Countering Moral Hazard in Higher Education: The Role of Performance Incentives in Need-Based Grants*

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Abstract

Large-scale financial aid programs cover a significant fraction of low-income college students. These programs often require meeting weak academic requirements for renewal, potentially leading to efficiency losses. I combine two sources of exogenous variation to identify the impact of eligibility to equal aid amounts under two different intensities of academic standards. I exploit sharp discontinuities in the Spanish need-based grant eligibility formula to identify the impact of aid on student performance outcomes, and dropout decisions. Using comprehensive administrative data on a large university, I utilize a unique reform in the national program to estimate the effect of aid under different intensities of academic requirements. I find that grant eligibility has no effects when academic requirements are comparable to those that characterize the typical need-based programs around the world. In contrast, I find strong positive impacts on student performance and degree completion rates when aid is combined with more demanding academic requirements, while no significant effects are found on dropout decisions.

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

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1 Introduction

To make higher 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). Large-scale national need-based grant programs typically provide fee waivers and award cash transfers to low-income students.[1] Initial eligibility to financial aid is typically need-based, whereas grant renewal requires to meet certain minimum academic requirements (i.e., having passed a certain number of credits). Whether academic requirements improve the effectiveness of financial aid remains an empirical question.[2] This issue is central in education policy debates since large-scale need-based grant programs cover a significant 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 (7 million) and accounted for 18% of the total federal student aid (28.2$ billion) in 2017/18 (Board, 2017).[3]

Despite the relatively extensive literature on the effects of financial aid (Dynarski, 2003; Castleman and Long, 2016; Goldrick-Rab et al., 2016; Denning, Marx and Turner, 2019), it remains unclear to what extent grants tied to academic requirements are more effective than those without.[4] One of the main challenges to identify the role of academic requirements is that typically the empirical evidence is only able to capture a combined impact of the awarded cash amounts and the impact of academic standards. Previous studies have not been able to separate the impact of academic standards from the impact of providing grant endowments. Generally, the lack of reforms on large-scale national programs and data availability make difficult to address

[1] Examples of such schemes are the US Pell Grant, the *Bourses sur critères sociaux* in France, or the *Becas de Carácter General* in Spain.

[2] The principal-agent theory suggests that financial incentives that are not attached to performance standards may encourage persistence of students who under-perform in college and who eventually may not be able to graduate, creating moral hazard concerns. Introducing instruments of student accountability, such as to linking grants to academic requirements for renewal, can serve as an effective tool to better monitor student effort. However, while academic requirements may mitigate moral hazard concerns by helping students to reduce failure rates on exams and time to graduation, they can also have the unintended side effect of inducing some students to drop out. This potential trade-off can be theoretically analyzed based on a principal-agent model building on Bénabou and Tirole (2000, 2002) and Scott-Clayton and Schudde (2019).

[3] Relatively low college completion rates are a public policy concern, particularly in the US. College attendance rates have risen substantially, while degree completion rates have remained stable over the last two decades (Deming, 2017; Deming and Walters, 2017). It seems to be remarkably salient for low-income students (Bailey and Dynarski, 2011). The debate regarding minimum academic requirements has focused on both the academic (Dynarski and Scott-Clayton, 2013; Goldrick-Rab et al., 2016; Patel and Rudd, 2012) and the public sphere (Reauthorization, 2013, Gates Foundation's Reimagining Aid Design and Delivery project).

[4] 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 about this statement, finding mixed evidence. For instance, Goldrick-Rab et al. (2016) find that grants with no strings attached seem to increase college persistence of low-income students using a randomized experiment in several public universities in Wisconsin.

this identification issue. Most of the existing literature focuses on narrowly defined rather than large-scale national programs, mostly implemented in the US for a specific university or state (Deming and Dynarski, 2009; Dynarski and Scott-Clayton, 2013). Such programs are usually merit-based, the vast majority of which are targeting high or medium achieving low-income students (Dynarski, 2008; Scott-Clayton, 2011), challenging the generalization to the broader population of low-income students.[5] Another main obstacle to identification is the difficulty of isolating the impact of grants on the intensive margin response of student performance since most programs affect both the extensive and intensive margins simultaneously.[6] The vast majority of the literature has focused on the extensive margin of enrollment, with several papers finding statistically significant impacts (Seftor and Turner, 2002; Fack and Grenet, 2015; Denning, Marx and Turner, 2019).[7] In such a case, the potential selection bias on those who access higher education challenges the interpretation of intensive margin effect.

This paper has two key methodological features that allow me to make stronger inferences about the specific contribution of minimum academic requirements to the impact of financial aid. First, I combine two sources of exogenous variation to identify how the impact of eligibility to *equal* cash aid amounts differs when combined with different intensities of academic standards. I use 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 outcomes. Besides, I use a policy reform in the Spanish large-scale need-based grant program undertaken in 2013. This reform raised the minimum academic requirements for renewal from a setting relatively comparable to those that characterize the typical need-based programs around the world (*weak* henceforth), such as the Satisfactory Academic Progress (SAP) in the US, to a more demanding requirement scheme (*strong* henceforth).[8] I take advantage of this policy reform to estimate the causal impact of financial aid under *weak*

[5]Several financial aid programs often include additional components, such as academic and support services, which make it difficult to isolate the specific role of academic requirements (Angrist, Lang and Oreopoulos, 2009; Angrist, Oreopoulos and Williams, 2014). Besides, most of studies 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, since they focus on non-enrolled or freshmen students, who report the highest probability of dropout.

[6]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 the 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).

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

[8]The SAP generally requires students to maintain a GPA of 2.0 or higher, and to complete at least two-thirds of the course credits they undertake to renew the Pell Grant (Scott-Clayton and Schudde, 2019).

and *strong* academic requirements. Second, taking advantage of the specific timing of grant application in Spain, I am able to isolate the impact of grant eligibility on the intensive margin responses of an exhaustive set of student performance measures.[9] In this unique framework, students are already enrolled in higher education when they apply for the grant, allowing to capture the effects on the intensive margin response since the extensive margin is essentially mute due to the timing of grant applications.[10] Finally, I use linked administrative data of the universe of undergraduate students applying for the Spanish national grant program in a large university over the period 2010–2015. This dataset allows me to test the impact of aid on a comprehensive set of outcomes that are common in previous studies (e.g., GPAs, degree completion rates, dropout decisions), but also on several unusual variables related to student effort (e.g., final exam attendance, fraction of subjects in retake, distinguishing between performance on mandatory and elective subjects) that are useful to test the different mechanisms at play.

I find that grant eligibility has no impact when academic requirements are comparable to those that characterize the typical need-based programs around the world. Results show no effect of neither moderate (675 euros relative to fee waiver) nor sizeable (about 3,000 euros relative to an average of 1,400 euros) discontinuous changes in cash allowances on student performance (e.g., GPA, fraction of credits earned, degree completion rates) and dropout decisions. I am able to reject effects on student performance as small as 0.5 percent. These results are consistent with papers finding limited effects of similar Pell Grant's cash amount on student GPA under a relatively comparable context to the *weak* academic requirements setting (Denning, Marx and Turner, 2019; Denning, 2018).

In contrast, I find large positive impacts of eligibility to first grant endowment when financial aid is combined with more demanding academic requirements (i.e., under the *strong* scheme). Results show that the provision of an *equally* moderate cash allowance of 825 euros (I cannot reject the null hypothesis that this amount is different from the previous 675 euros cash endowment) increases student average GPA by 0.45 points (on a 0 to 10 scale) and fraction of credits earned

[9] 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). These studies are mainly limited to testing the effects on graduation outcomes, earnings, and college persistence, while more comprehensive measures of student effort are still understudied.

[10] This framework has an inherent drawback. It is not possible to directly test the extensive margin effect on student initial college enrollment, but it is plausible to test college persistence and drop out once students are enrolled. I indirectly test college enrollment effects looking at the number of grant applicants over time (see Figure Appendix A1 in the online appendix, section A). The total number of applicants seems to slightly decrease in 2013, but the number of first-year applicants is reasonably flat over the period studied. This suggests no extensive margin changes in the number of applicants. Besides, the applicants' observable characteristics do not significantly change after the 2013's reform.

by 6 percentage points (corresponding to an increase of 7.3 and 7.6 percent with respect to the baseline mean, respectively). The effect size is of 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 merit-based experiments in a large Canadian university (Angrist, Oreopoulos and Williams, 2014). Results persist over time, enhancing the student cumulative average GPA and fraction of credits earned over two consecutive years, and increasing degree completion rates. The baseline results are robust to an exhaustive number of specifications and sample selection criteria. Results show that prospective undergraduate students only react if academic requirements are *strong* (relative to *weak*), when eligible to (*same*) moderate grant amounts. This points out the significant role that minimum academic requirements play on stimulating student performance and degree completion rates when combined with financial aid.

The impact of aid does not seem to depend on the amount of financial aid awarded. I find no further improvements in student performance for subsequent increments in the amount of awarded aid when students are already entitled to a modest amount of aid. The results suggest that the boost in student performance does not linearly depend on the amount received.[11]

To explore potential equity effects beyond the RDD estimates, I perform a Difference-in-Difference model (DID), a Difference-in-Discontinuity (RDD-DID) specification, and a Logit analysis to measure the propensity to dropout before and after the change in requirements. I find that combining financial aid with *strong* academic requirements does not necessarily lead to an increase in drop out from higher education. This result seems to contradict the heterogeneous discouragement effects of SAP failure in the US Pell Grant (Scott-Clayton and Schudde, 2019), and similar effects of being placed in academic probation (regardless of financial aid) for students at one large baccalaureate institution in Canada (Lindo, Sanders and Oreopoulos, 2010). Back of the envelope calculations suggest that the increase in non-eligible applicants due to the rise in academic standards is potentially attenuated with the simultaneous increase in student performance induced by the stronger academic requirement scheme. I rule out the hypothesis that eligible grant applicants are more positively selected in their observable characteristics after the 2013's policy reform. The institutional context, especially the cost of college, may be a relevant factor affecting the elasticity of dropout concerning academic requirements.

[11] Consistent with the findings of Gneezy and Rustichini (2000).

This paper explores several possible mechanisms.[12] I find that eligibility to relatively moderate grant endowment combined with *strong* academic requirements increases the final exams attendance rate, 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, suggesting a genuine increase in student performance. Besides, I investigate several potential confounding factors that may bias the baseline results, such as the student strategic selection of subjects. I can distinguish between mandatory subjects (i.e., those where students do not have the right to self-select) and elective (i.e., where students can choose a subset from a particular 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. However, the fact that student effort responds positively to actual amounts of aid combined with *strong* academic requirements, but it seems unrelated to the amount awarded, can serve as a potential indirect evidence to rule out this hypothesis.

Organization of the Paper. The remainder of this paper is structured as follows. Section 2 provides an institutional background on the Spanish higher education system and the national need-based grant program. Section 3 describes the data used in the paper, the sample restrictions, and descriptive statistics. Section 4 explains the empirical strategy. Section 5 discusses the internal validity of the research design, analyzes the main results, explores heterogeneous effects, and test several robustness checks. Section 6 examines the different mechanisms explaining the baseline results. Section 7 discusses external validity and rule out additional potential confounding factors. Section 8 concludes.

[12] 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. 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.

2 Institutional Background

2.1 Higher Education in Spain

In Spain, students choose whether to pursue higher education after graduating from high school.[13] The vast majority decide to enroll in college education.[14] Most of the higher education institutions are publicity funded (57%), and the vast majority of students decide to enroll in those universities (82%).[15] To access higher education, students must pass the standard access to university test (*PAU*), which consists of two-year college preparation courses and a standardized entry exam (*Selectividad*).[16] The vast majority of the students taking this test manage to pass it. For instance, 92 percent of the students who took the test passed it in 2015.[17] 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.

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 (*Comunidad Autónoma*), the degree program undertaken, and the repeated subjects' failures. The national average tuition fee for a full academic year was 1,100 euros for undergraduate students in 2015.[18] Most of the students face relatively high living costs, due to the fact that most of the universities are located in large urban areas.[19] The average cost of living expenses in Spain for a nine-month period in 2015 was 5,069 euros,[20] which represents a significant financial barrier for students to emancipate

[13] I use the terms higher and college education interchangeably.

[14] College education cover vocational undergraduate degrees (*CFGS*), academic undergraduate degrees (four-year degree called *Grado*), graduate degrees (*Master*) and doctoral studies. Outside these two undergraduate main tracks, a minority of students enroll in artistic education (e.g., arts, music, dance, dramatic arts), which offers undergraduate and graduate degrees.

[15] Currently, there are 50 publicly funded and 37 private universities. About 1.3 million of students decide to enroll in public institutions against 282 thousands who enroll on the private.

[16] The final grade of *PAU* is composed by a preponderated average of *Bachillerato* and *Selectividad*. *Selectividad* is divided into a mandatory and elective part. The elective part is not mandatory, and its used to increase student grade. The final grade of *PAU* for each student is defined as:

$$PAU = 0.6 * Bachillerato + 0.4 * Mandatory + a * E_1 + b * E_2$$

where *Bachillerato* is the average of two-year college preparation courses, *Mandatory* is the average grade in the mandatory part of the exam, and $\{E_i\}_{i=1,2}$ are the average grade of the two highest scored electives. The total *PAU* ranges between 0 and 14 points, where the threshold of pass is established at 5 points. The name changed in 2017 to *Evaluación de Bachillerato para el Acceso a la Universidad* (EBAU).

[17] See *Datos generales de las Pruebas de Acceso a la Universidad (PAU). 2015. Ministerio de Educación, Cultura y Deporte.*

[18] Public prices are detailed in *Estadísticas de precios públicos universitarios del MECD*. The average tuition fee for a full academic year for graduate students range between 1,634 and 2,347 euros.

[19] In 2011, a survey on living conditions of Spanish college students indicated that the vast majority were living with their parents and that only 6.3 percent were living in university residence halls (Ariño, 2011).

[20] 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*.

from their family home while enrolled in higher education.

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

The *Becas de Carácter General* (BCG hereafter) is the Spanish national financial aid program devoted to low-income students in post-secondary education.[21] About a quarter of the academic undergraduates and 15 percent of graduate students enrolled in higher education received this grant for a total cost of 829 million euros in 2014. 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.[22] Other types of financial support, such as loans or merit-based grants, are almost absent in the Spanish higher education system.[23]

Students are eligible to different endowments of financial aid depending on their parental taxable income and the number of household members. The BCG program consists on three main levels of grant. The first level exempts eligible applicants from paying tuition fees, but does not grant cash allowances. Besides the fee waiver, the second level provides eligible applicants to an average annual cash allowance of approximately 1,100 euros (or about 2,300 euros) for those living in (away from) their household primary residence. Finally, this annual cash endowment increases by approximately 3,000 euros (3,500 euros) for those who live in (away from) their household primary on the third level and last level of grant.[24] In addition to fee waiver, the maximum cash allowance may raise up to 6,000 euros.

Before 2013, the grant allowances were organized as fixed endowments. After 2013, the different fixed cash allowances were broken down into a smaller fixed cash amount and a variable component (applicant's dependent). The variable component of the grant is computed as an applicant's deterministic function that increases on the student's grades and decreases on household income.[25] Overall, the applicant is entitled to larger cash amounts as the lower her family

[21] 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.

[22] See EDU/2098/2011 *de 21 de julio*.

[23] A loan system was functioning in Spain from 2007 to 2011 only for Master and Ph.D. studies. The fraction of Master students covered by loans in 2010/2011 was only 2 percent.

[24] In addition to the three main cash allowances, the Displacement and Other Needs Grant (T3 grant hereafter) existed before 2013. This level of allowance provided students with different cash endowments, such as displacement to the university, urban transport, academic material, or final undergraduate degree project. A student who received this grant could obtain only one, or a combination of these different endowments.

[25] The variable component of the grant is set at a minimum amount of 60 euros. The deterministic function depends on the student's average GPA, the average GPA distribution of grant holders, the applicant's income, and the income distribution of all applicants. The exact formula of the variable component of the grant is provided in the online appendix (section H). The

income and the higher her grades. From now on, I refer to the three academic year of 2010–2012 (2010/2011 to 2012/2013) as Period I, and the years 2013–2015 (2013/2014 to 2015/2016) as Period II.

2.2.1 Eligibility Rules

Eligibility Rules: Need-based. 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.[26] Students are required to filed a new application every academic year, which both need and performance-based eligibility being reassessed each time.[27]

The need-based eligibility condition is evaluated based on the applicant's annual household income the year before application, which is based on after-tax household income.[28] Household income thresholds determine applicant's eligibility to the different levels of grant depending on the number of household members.[29] The grant can be denied based on non-compliance of household income thresholds, but also in the case when household wealth, family business activity, or capital returns exceed certain thresholds.[30]

Income eligibility thresholds change with the number of family members creating multiple discontinuities, which are graphically displayed in Figure 1. The identification strategy uses the discontinuities that are generated by these income-eligibility thresholds to estimate the causal effect of grant eligibility on students' outcomes. To be eligible to the first and second levels of grant (fee waiver and T1 grant), for a household with four members (the average family size), the annual family income must fall behind 38,831 and 36,421 euros respectively, which corresponds

Ministry of Education offers an online simulator for the variables amounts at the following website: *http://www.mecd.gob.es/educacion-mecd/mc/becas/2016/estudios-universitarios/simulador.html*

[26] 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 academic course application is detailed in the Oficial State Gazette (*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.*

[27] Students can receive a BCG grant up to a maximum of one additional year more than the length of the program in which they are enrolled (up to two additional years of the program length for students who are enrolled in a STEM -Science, Technology, Engineering and Mathematics- degree).

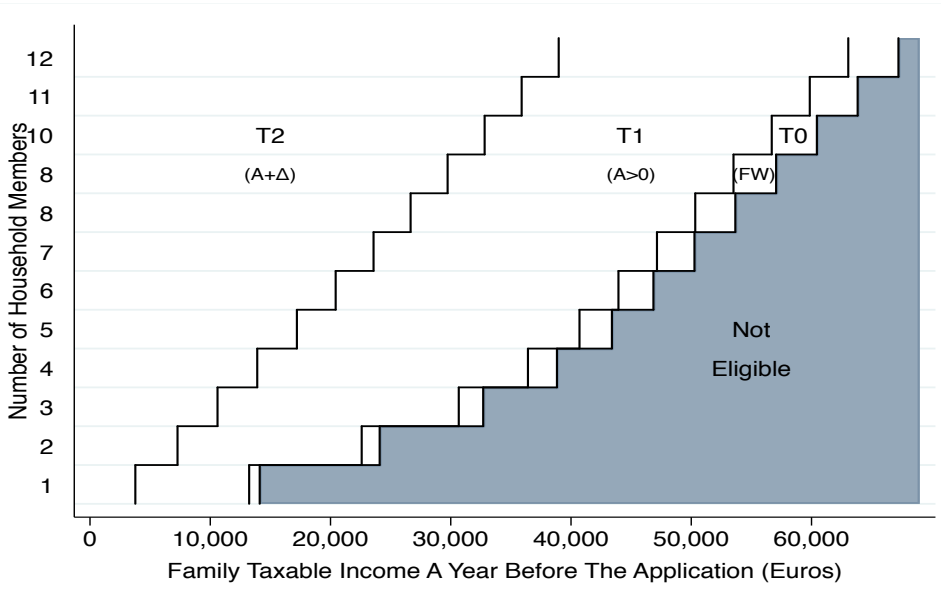
[28] The applicant's annual household income is computed as the household taxable income minus several specific quantities to which student may qualify (e.g., large family or disability).

[29] 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 if they live in the same family dwelling. In the case of parental divorce, only the household members who live with the applicant are considered.

[30] Only a tiny fraction of the total number of applicants was not eligible due to household wealth (5.3 percent), and business activities (0.3 percent) over 2010–2015.

approximately to the fourth and top quintiles of the Spanish income distribution.[31] To be eligible to the highest level of grant (T2 grant), the same household must earn less than 13,909 euros, placed in the bottom quintile of the Spanish income distribution.

Figure 1: Income Eligibility Thresholds for the Different Levels of the BCG Need-Based 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.

Eligibility Rules: Performance-based (minimum academic requirements). Applicants must be enrolled in at least 60 ECTS credits (The European Credit Transfer and Accumulation System), which corresponds to the number of credits obtained in a typical academic year.[32] Eligibility to the BCG grant is conditional on meeting certain minimum academic requirements the year before application. Those academic requirements are essentially based on having earned a certain fraction of credits (over 60 credits).

Table 1 displays a summary of the performance requirements to grant eligibility. In Period I (2010-2012), the minimum academic requirements were relatively comparable to those set out in the typical need-based grant programs around the world (e.g., the SAP of Pell Grants in the US). Students were required to have earned 60 percent (80) of the credits the year before application if enrolled in a STEM (Non-STEM) degree. In Period II (2013-2015), the academic requirements

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

[32] There are several exceptions where students are allowed to be enrolled in less than 60 credits, such as when the attended a program that counts with less than 60 credits per year or when the student is affected by a disability.

became more stringent.[33] Overall, two main changes were undertaken in 2013: (i) the required minimum fraction of credits earned increased; (ii) the average GPA was incorporated as an additional factor to be combined with the fraction of credits earned.[34] Generally, the required fraction of credits earned increased by 41 (25) percent in Period II relative to Period I for a student enrolled in STEM (non-STEM) degree. However, the actual increase is of about 8 (9) percent for a student enrolled in STEM (non-STEM) if combine the minimum fraction of credits with the average GPA. College entrants are required to have passed the access to university exam (PAU). This requirement increased in Period II, but this raise is unlikely to be binding for university entrants.[35]

Table 1: BCG Grant Minimum Academic Requirements.

	Fraction of Credits Earned		**Average GPA**		**Grant**
	STEM	Humanities & SS	STEM	Humanities & SS	
Period I (2010-2012)	0.6	0.8	.	.	All
2012	0.65	0.9	.	.	All
Period II (2013-2015)	0.85	1	.	.	All
	0.65	0.9	>=6	>=6.5	All
	0.65	0.9	<6	<=6.5	Only Fee Waiver

Notes: 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 an A+. STEM refers to Science, Technology, Engineering and Mathematics degree. SS refers to Social Sciences degrees.

[33]Note that the minimum academic requirements were slightly increased in 2012. I do not find any statistically significant effects of this minor modification (see online appendix, section D).

[34]Note the grant's variable component (described above) incorporated another performance related incentive since students are awarded with larger cash amounts if obtained higher GPAs. I cannot disentangle the specific contribution of each of these changes from the total effect of financial aid in Period II.

[35]In Period II, college entrants must have a GPA of 5.5 (6.5) in the PAU exam to be eligible for fee waiver (all grant levels). This increase is unlikely to have a sizeable positive selection on college entrants who apply for a grant, since only 4.7% of the college entrants in Spanish public universities scored between 5-5.5 in PAU in 2015 (see *Datos y cifras del sistema universitario español. Curso 2015-2016, Ministerio de Educación, Cultura y Deporte*), and hence would not been eligible. Before the reform (2010-2012), only 2% of college entrants in my treatment sample score below 5.5, implying that 98% of them would comply with performance standards for incoming students at Period II. Note that this would be an identification threat to the internal validity of the empirical strategy only if there is differential positive selection of grant applicants at the income-eligibility thresholds. Internal validity is extensively discussed in Section 5.1, showing that this does not seem to be the case. Note also that if there is positive selection of grant applicants across periods, it would not be an identification threat, but a matter for interpretation regarding the comparability of results across periods. This concern is discussed on Section 3, and section F of the online appendix.

2.2.2 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 income document transfer is needed since the Ministry contacts directly the institutions concerned, i.e., the Tax Authority (AEAT, *Agencia Tributaria*), 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. On average, awarded and denied grants are notified around the start of the Spring term of the academic year (in February–March). The total amount granted is transferred to the students one month after the notification.[36]

The unique application process of this program allows me to estimate the causal effect of eligibility to cash allowance on the intensive margin effect on student performance. This is due to the fact that students are already enrolled in a higher education institution when they apply, hence extensive margin is essentially mute due to the timing of grant applications. This setting may seem to some extent peculiar, but it is a unique framework that is useful to measure "intensive" rather than "extensive" margin responses.

Applicants' potential manipulation of information can be an identification threat for this type of allowances. It should be noted, however, that the authority handle in the grant applications directly contacts the Tax Agency and the university to check both applicants' household income and academic requirements. Hence, students have only limited ability to misreport this information. Another potential 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 used to change every year, thus complicating applicant's knowledge of their actual grant-eligibility situation, but over 2010–2015, income thresholds remained unchanged. Discontinuities in application rates would be more likely to occur at the first level of grant (fee waiver), since at higher levels of grants students remain eligible for some

[36] Figure Appendix H1 (online appendix, section H) presents the application process graphically.

form of financial aid. Then, students have strong incentives to apply even if they anticipate being below the corresponding cutoffs. The existence of multiple income reductions for the computation of 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 about whether they meet the eligibility criteria. Potential manipulation around the income-eligibility threshold is discussed extensively in Section 5.1.

3 Data and Descriptive Statistics

The analysis of this paper is based on linked individual-level administrative data that allows me to track the academic progress of all students enrolled in Carlos III University of Madrid who filled an application for a BCG grant over 2010–2015.

Data. The data used in this paper are a combination of different administrative micro-data of the universe of BCG grant applicants enrolled in Carlos III University of Madrid over the six academic-year period 2010–2015. I exploit the *SIGMA* database, which consists of four administrative data files, which can be matched using an encrypted student identifier: (i) household information; (ii) grants; (iii) university enrollment; (iv) college grades. First, the household information database contains the set of variables that determine grant eligibility (e.g., household taxable income, number of family members, household wealth, family business, large family condition or whether a family member suffers a disability), the administrative status of the grant (e.g., grant final status, reason for denial or the type of allowance), and parental occupation. Second, the grants database provides details about the BCG grant amounts, the type of allowance, and the date of award. Third, the university enrollment database embraces information about grant applicants at the time they enter university, such as gender, nationality, postal code of the household's primary residence, or the score in the *PAU* entrance exam. Fourth, the database on university grades covers all academic curricula of students who have applied at least once to the BCG grant between 2010 and 2015. It provides information on the program and subjects undertaken, as well as detail information of each subject's course undertaken. This exhaustive data allows me to compute many relevant variables related to student performance (e.g., GPA, final exam attendance, or whether the student had to retake a particular subject).

Sample Restrictions. On average, about 5,300 students apply for a BCG grant in a given year at Carlos III University. Table 2 displays the number of BCG applicants by year and degree program. The analysis is centered on 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 to make the regression discontinuity design sharper.[37]

Table 2: Number of BCG applicants (2010–2015).

		Undergraduate	**Graduate**	**Other Programs**	**Total**
2010	%	97	3.09	0	100
	N	5,235	167	0	5,402
2011	%	95.24	4.76	0	100
	N	5,240	257	0	5,497
2012	%	93.07	6.07	0.86	100
	N	5,088	332	47	5,552
2013	%	92,73	7.03	0.24	100
	N	4,721	358	12	5,174
2014	%	91.07	8.89	0.18	100
	N	4,601	449	9	5,128
2015	%	88.88	10.97	0.17	100
	N	4,723	582	9	5,314
Total	%	93	6.76	0.24	100
	N	29,500	2,145	77	31,722

Notes: Total number of BCG applicants enrolled at Carlos III University over the period studied 2010–2015. The sample is constructed by the administrative database of undergraduate applicants to the BCG grant in Carlos III University over 2010–2015. Undergraduate students studied are the addition of applicants in the old and new system. The undergraduate new system constitutes of typically four years degree program, harmonized with the European Union, using ECTS credits.

Summary Statistics. I split the estimation sample into two groups: (i) the T1 grant sample (Threshold 1) includes applicants who are in the vicinity of the T1 grant threshold, where students become eligible to both cash allowance and fee waiver; (ii) the T2 grant sample (Threshold 2) includes applicants whose relative household income is close to the T2 grant threshold, where students become eligible for a larger additional cash allowance. Table 3 shows summary statistics

[37]Students excluded from the sample of analysis represented 25 percent of the total applicants over the six years covered by the study. From this 25 percent, 16 percent corresponds to problems with the Tax Agency or exceeding the wealth or 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 these reasons is discontinuous at the income-eligibility cutoffs, potentially leading to sample selection. This potential threat to identification is not a concern in this case since probabilities are continuous on either side of the cutoffs (results available upon request). Moreover, discarding students who did not meet the minimum academic requirements do not change the statistical significance nor the magnitude of baseline results (see Table D6 in online appendix, section D).

on the sample of BCG grant applicants who are considered in the analysis. Most of the applicants are Spanish, live with their parents when they entered university, and 60 percent 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 of four members, and more than 11 percent of applicants in the treatment samples qualify for the large family bonus. The majority of applicants' family head works as a blue-collar.

Applicants' background characteristics across periods. Tightening the minimum academic requirements may have changed the composition of grant applicants, making difficult to compare the samples across periods. For instance, the policy change may discourage low ability students for applying, and hence making them more positively selected relative to the population of grant applicants who applied before the change. In the online appendix (section F), I show summary statistics of the applicants' background characteristics at T1 and T2 grant samples by period. The main aspect to note is the applicants' background similarity across periods within grant sample, particularly at T1 grant. There are somewhat larger differences in background applicants' characteristics at T2 grant, but the differences are minor.

Table 3: Summary Statistics on Applicants to BCG Need-Based Grant at T1 and T2 Discontinuities (2010–2015).

Treatment sample: (Income Eligibility Thresholds)	**T2 Discontinuity** $(A + \Delta/\mathrm{A})$ (1)	**T1 Discontinuity** (A/0) (2)
Applicants		
Female	0.48	0.47
Spanish	0.92	0.98
Access to University Exam Percentile rank (PAU)	52.40	55.40
	(28.60)	(28.46)
STEM degree	0.34	0.38
Applications		
Household taxable income (euros)	14,250	32,182
	(5,689)	(10,111)
# Family members	3.7	3.6
	(0.970)	(0.843)
Frac. Disability	0.024	0.013
Frac. Large family condition	0.17	0.11
Frac. Living outside the family primary residence	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 (0–1)	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
Academic year		
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 a relative distance of 50 percent of the eligibility thresholds between fee waiver and T1 Grant allowance. The T2 treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between T1 and T2 Grants allowances. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence, using the student's postal code when 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 enrolled at Carlos III University from 2004-2015. Household taxable income is expressed in constant 2015 euros. Standard deviations are in parenthesis.

4 Empirical Strategy

The goal is to estimate the causal effect of being eligible for a need-based grant on student performance and dropout decisions under two different academic requirement frameworks. I exploit the sharp discontinuities in the amount of cash allowances awarded to grant applicants depending on their household income, using a regression discontinuity design (RDD).

The estimates of a simple OLS regression of college performance 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 or predetermined measures of student ability, this approach would not account for unobservable determinants of student performance that are likely to be correlated with financial aid status (e.g., motivation).

To estimate the treatment effect of being entitled to the BCG grant, I exploit the fact that the grant eligibility formula generates two different discontinuities at the T1 and T2 grant income-eligibility thresholds. Since those cutoffs are endogenously given, and under the assumption that applicants can not manipulate the information regarding household income (the forcing variable), I can focus on applicants whose parental income is located at the vicinity of the income-eligibility thresholds considering those just below as very similar to those just above the cutoffs. The amount of allowance granted to these students can be considered as "locally" randomly assigned. Assuming that in the absence of the treatment the outcome variable is a smooth function of parental income, the causal effect of being eligible for a grant is identified by comparing outcomes for applicants who are close but below the income-eligibility threshold (treatment group) with those who are near but above (control group).

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 household taxable income c_{it}, and the number of family members, m_{it}:

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

where $\mathbb{1}\{\cdot\}$ 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. I define $p = 1$ for Period I (2010–2012), and

$p = 2$ for Period II (2013-2015), such that:

$$A_{it} = \mathbb{1}\{t \leq 2012\} * \sum_{k=1}^{2} \alpha_{k,1} E_{i,k,t} + \mathbb{1}\{t \geq 2013\} * \sum_{k=1}^{2} \alpha_{k,2} E_{i,k,t}; \tag{2}$$

The allowance increments in Period I and Period II are:

$$\alpha_{k,1} = \gamma_{k,1}; \tag{3}$$

$$\alpha_{k,2} = \gamma_{k,2} + z_i(c_i, \overline{c_i}, g_i, \overline{g_i}); \tag{4}$$

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

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

$$Y_{it} = \alpha + \mathbb{1}\{t \leq 2012\} * \sum_{k=1}^{2} \beta_{k,1} E_{i,k,t} + \mathbb{1}\{t \geq 2013\} * \sum_{k=1}^{2} \beta_{k,2} E_{i,k,t} + \epsilon_{it}; \tag{5}$$

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 (5), the parameters $\beta_{k,p}$ are the treatment effects of being eligible for a need-based grant k at period p.

Under the assumption that the conditional distribution function is smooth in household income at the income-eligibility cutoffs, 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 by:

$$\beta_{k,p} = \lim_{c \uparrow \bar{c_k}(m)} E[Y \mid c, m, p] - \lim_{c \downarrow \bar{c_k}(m)} E[Y \mid c, m, p]; \tag{6}$$

A specific feature of the BCG need-based grant design is the existence of multiple income-eligibility thresholds. In total, there are 22 distinct discontinuity cutoffs for the T1 and T2 grants (see Figure 1). To have sufficient statistical power, I pool all thresholds that are associated to a given

level of grant.[38] Then, I use the relative distance to the income-eligibility threshold as forcing variable.

The treatment samples are defined as follows: (i) The first sample combines the eleven household 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 (I cannot reject the null hypothesis that the amounts are different) in Period I and II respectively, relatively to being eligible to fee waiver only. Hence, $\beta_{1,1}$ and $\beta_{1,2}$ measure the causal effect of *equal* discontinuous changes in the average grant amounts (relative to eligibility for only fee waiver) under *different* academic requirements (*weak* and *stronger*, respectively). (ii) The second sample combines the eleven household income thresholds of the 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 (the difference being statistically significant) in Period I and II respectively, relative to being eligible for about 1,400 euros on average. Thus, $\beta_{2,1}$ and $\beta_{2,2}$ measure the causal effect of *different* discontinuous changes in the average grant amounts (relative to eligibility for about 1,400 euros cash allowance) under *different* academic requirements (*weak* and *stronger*, respectively). Figure 2 shows the amount of annual cash amounts awarded to applicants with four family members as a function of their parents' income in both periods.

The treatment effects are estimated using a triangular kernel.[39] The standard errors are clustered at the student level.[40] The bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012).

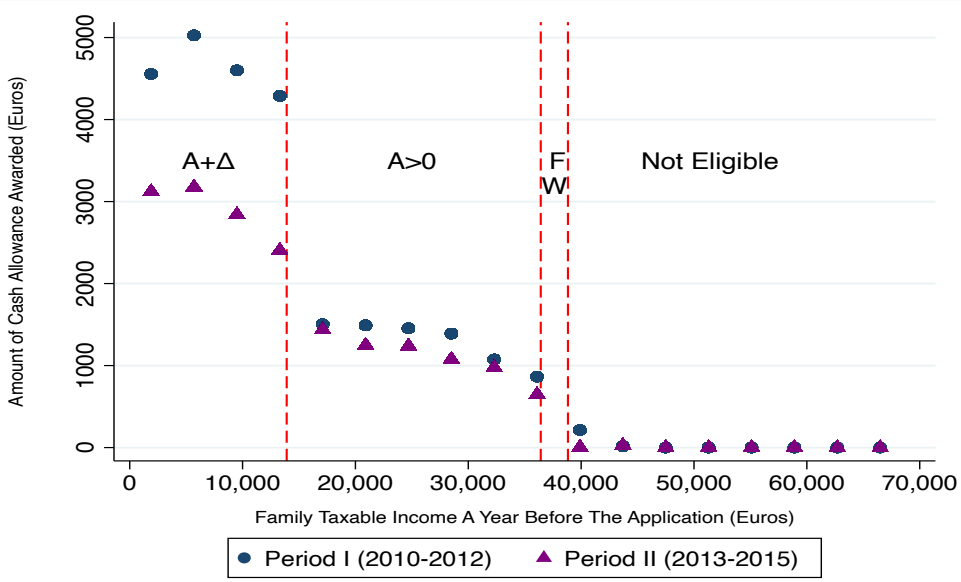
There are several advantages on using a uni-dimensional RDD on income cutoffs rather than on minimum academic requirement thresholds. First, substantial body of research finds endogenous sorting on one of the sides of general academic thresholds with the density of students bunching at the cutoff. The typical reasons behind this behavior comes by the fact that students are aware of their grades and they can compute their exact distance to the cutoff (deciding to apply only if they are eligible), or by teachers manipulating students' grades to surpass

[38] Note that the fee waiver eligibility threshold is close to the eligibility cutoff of the T1 grant (see Figure 1) making difficult to construct two treatment samples (with sufficient number of observations) between T1 grant and fee waiver that do not overlap. The discontinuity induced by the tuition fee eligibility cutoff is therefore ignored in the principal analysis. However, as a robustness check, I conduct a separate analysis of the treatment effect of tuition fee eligibility. The results show no evidence of statistically significant effects on student outcomes at the fee waiver income-eligibility threshold (see online appendix, section D).

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

[40] Standard errors are clustered at the student level since the same student may be observed several times in the same treatment sample if she applied more than once within the same period.

Figure 2: Amount of Annual Cash Allowance Awarded to Applicants with 4 Family Members 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, and $A + \Delta$ to students awarded with fee waiver and larger cash amount than A.

the required threshold. In contrast, students' face difficulties to precisely compute the exact distance to the income cutoffs. There exists multiple income reductions and after-tax income is more difficult to manipulate than income (especially with frequent tax code changes, such as in Spain). The complexity of the eligibility rules may encourage students to apply even in cases when they are unsure about whether they meet the eligibility criteria, alleviating the concerns for endogenous sorting around the cutoffs. Second, the multiple academic requirement thresholds are not constant across periods. The second period incorporated additional thresholds and changed the pre-existent ones. This may originate that when comparing students at the vicinity of academic thresholds across periods, it is very likely that those students are not a similar set of compilers, and hence comparing results across periods would be difficult to interpret. However, the fact that income-eligibility thresholds remain unchanged since 2010 (and inflation rates close to zero), I am able to compare students at the same household income range before and after the reform. Hence, under certain conditions, such as the "type" of students do not significantly change with the reform,[41] applicants at the vicinity of the cutoffs before and after the reform are a reasonable comparable set of compliers. Third, one of the main goals of the paper is to identify how eligibility to *equal* cash aid amounts differs when combined with different intensities

[41] See Section 3 and online appendix section F.

of academic standards. Eligibility to *equal* discontinuous changes in cash endowment across periods is provided at the income-eligibility thresholds, but this is not necessarily guaranteed when focusing on the academic requirement thresholds. This is due to the fact that students may have similar academic performance but eligible to very different cash amounts (determined by their distinct household income).

5 Results

5.1 Internal Validity of the Empirical Strategy

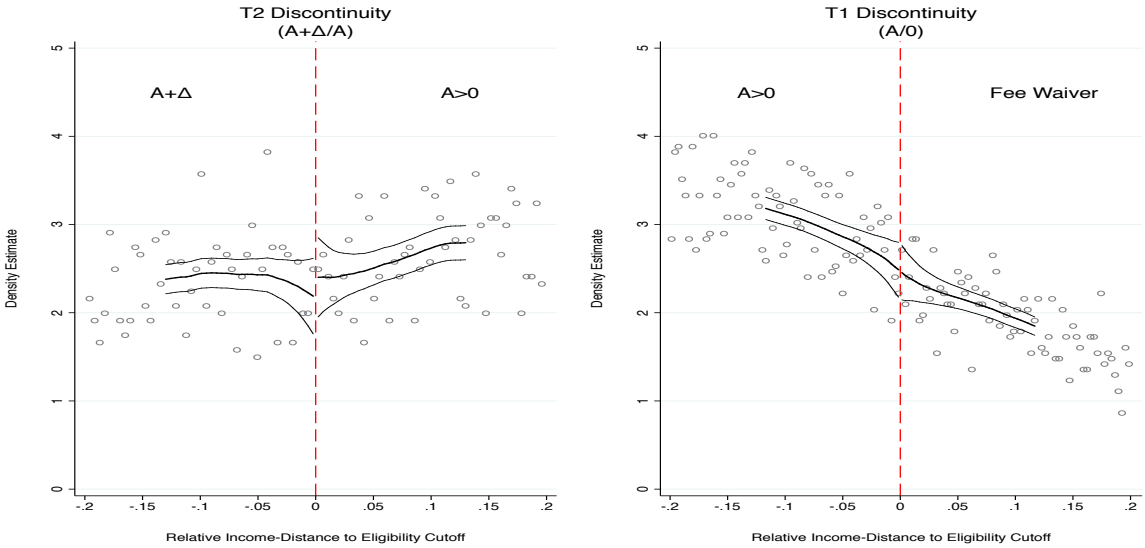
The internal validity of the RDD requires that there is no endogenous sorting on either side of grant eligibility cutoffs. This type of endogenous sorting is more likely to occur in the typical case where the treatment assignment rule is public knowledge (Imbens and Lemieux, 2008), as in the case of this paper. There is a concern of manipulation at the cutoffs, especially for the first income-eligibility threshold (fee waiver) since the precise cutoffs are public information and have not changed since 2010. In contrast, manipulation is less likely at higher level cutoffs since students have incentives to apply anyway, given the fact that applicants are eligible for some amount of aid on both sides. Montalvo (2018) highlights 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 BCG applicants' density estimates at the vicinity of the cutoffs, displaying that it does not seem to be a systematic manipulation of parental household income around the thresholds. The density of applicants increases as parental income decreases in the T1 grant, given the fact that more students may be encouraged to apply when they are closer to the cutoff. Density estimates at T2 grant are roughly constant since applicants have incentives to apply on both sides as they are eligible for positive cash allowance. McCrary (2008) test fails to reject a statistically significant jump at the eligibility cutoffs for every treatment sample used in this paper, such as within each period, gender, predetermined ability, or residence status (see online appendix, section B).

‘

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 since treatment assignment cannot influence variables that are predetermined to the treatment.

Figure 3: McCrary (2008) test for Manipulation of Household Income at TI and T2 Discontinuities in 2010–2015



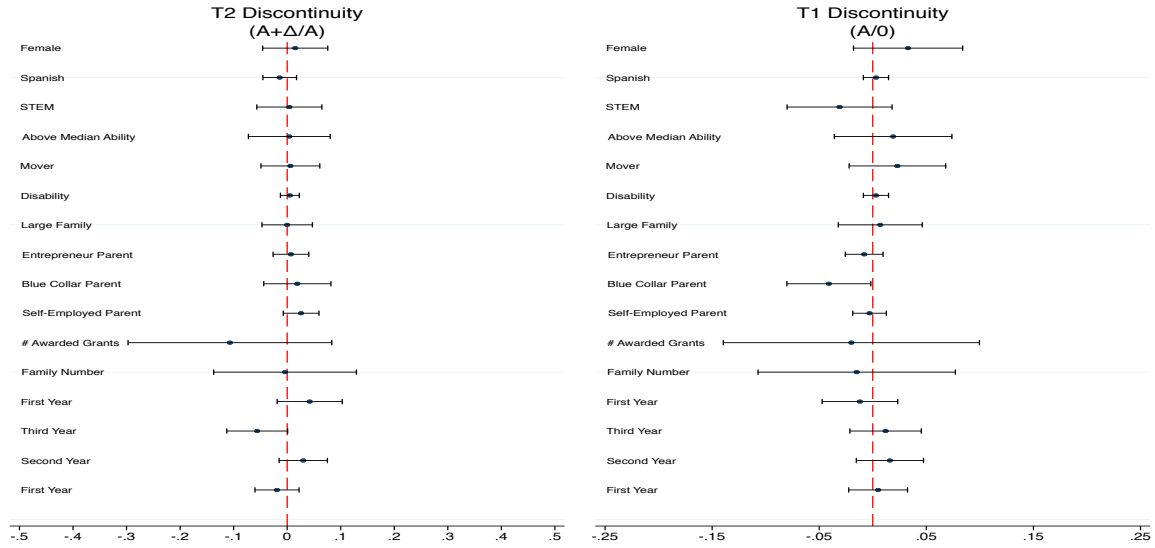
Notes: The figure shows the results of the test proposed by McCrary (2008). The weighted kernel density estimates are plotted, computed separately for each of the sides of the income thresholds T1 and T2. The T1 treatment sample includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and T1 Grant allowances. The T2 treatment sample includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between T1 and T2 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.

Local linear regressions are performed for each of the applicants' observable characteristics (e.g., gender, nationality, parental income, PAU score, parents' occupation) as the dependent variable. Table 4 (Panel A) and Figure 4 present the regression results, showing that the observable characteristics of applicants are well balanced on both sides of the cutoffs since less than 10 percent of the coefficients are statistically significant at the 10 percent level. Furthermore, a chi-squared test based on a system of seemingly unrelated regression with as many equations as baseline characteristics are performed indicates that the null hypothesis that the discontinuity gaps are jointly equal to zero cannot be rejected (see Panel B).

Furthermore, a potential concern may arise if students who were awarded a grant in a given academic year might be more likely to reapply the next year. Since students are required to filed a new application every academic year, this may lead to a persistent sorting of re-applicants below the cutoffs, potentially confounding the effects of the current year with those from previous years. A formal test rejects this hypothesis, showing that the null hypothesis of no discontinuity in the density of re-application cannot be rejected.[42] This may be explained by the fact that parental

[42]See online appendix, section B.

Figure 4: Balance of Applicants' Baseline Characteristics at T1 and T2 Discontinuities (2010–2015).



Notes: The dots represent the point estimates of the RDD non-parametric regressions. Horizontal lines depict confidence intervals at the 95% level of confidence. The red stripes reflect the two income-eligibility thresholds for T1 and T2 Grants. Red vertical lines identify a zero effect.

income is highly correlated over time[43], however, there is substantial variation in parental income over time since only 3.2 percent of applicants registers the exact same parental income than the one registered the year before.

The empirical evidence discussed supports the internal validity of the RDD design to test the effects of BCG grant on student performance, degree completion rates, and dropout decisions. The next subsections show the main results.

[43]Regressing applicants' income (at constant prices of 2015) in a given year on income the year before leads to a coefficient estimate of 0.73.

Table 4: Balance of Applicants' 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	0.46	0.033
		(0.031)		(0.026)
Spanish	0.94	-0.014	0.99	0.003
		(0.016)		(0.006)
Access to University Percentile rank	53.41	-2.044	56.36	3.46**
		(1.858)		(1.594)
STEM degree	0.35	0.004	0.41	-0.031
		(0.031)		(0.025)
Households taxable income (euros)	17,282	-1.882	42,126	123.971
		(233.841)		(308.907)
Disability	0.015	0.005	0.012	0.003
		(0.009)		(0.006)
Large family condition	0.13	-0.000	0.13	0.007
		(0.024)		(0.020)
#Family members	3.664	-0.004	3.651	-0.015
		(0.068)		(0.047)
Live outside the family home	0.3	0.006	0.3	0.023
		(0.028)		(0.023)
Entrepreneur Parent	0.073	0.007	0.04	-0.008
		(0.017)		(0.009)
Blue Collar Parent	0.45	0.019	0.22	-0.041**
		(0.032)		(0.020)
Self-Employed Parent	0.061	0.026	0.021	-0.003
		(0.017)		(0.008)
# Awarded Grants	0.061	-0.107	0.37	-0.020
		(0.097)		(0.061)
First year	0.295	0.042	0.338	-0.012
		(0.031)		(0.018)
Second year	0.225	-0.056*	0.238	0.012
		(0.029)		(0.017)
Third year	0.204	0.030	0.182	0.016
		(0.023)		(0.016)
Fourth year	0.173	-0.019	0.148	0.005
		(0.021)		(0.014)
B. All baseline charcteristic jointly				
X2-stat		14.37		22.99
P-value		0.57		0.11

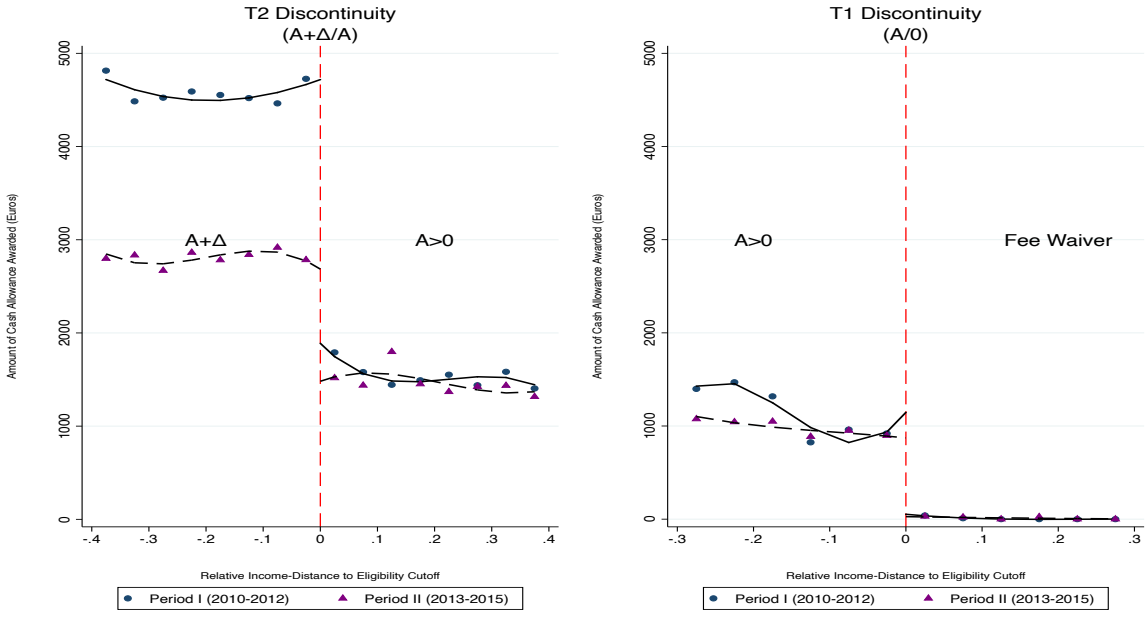
Notes: The table shows the RDD non-parametric estimates for the different applicants' observable variables. The treatment effect is estimated using a triangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) for each separated regression. Baseline mean refers to the average value of the variable above the income-eligibility threshold. The T1 treatment sample (columns 2 and 3) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Discontinuities in Grant Amounts

In this subsection, I examine the discontinuities in average grant amounts awarded at the different income-eligibility thresholds. Figure Appendix B2 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 receive the grant (either only fee waiver or fee waiver plus cash endowments).

Figure 5 presents the average conditional grant amount as a function of applicants' relative distance to the thresholds separately for the two periods under study. Figure 5 and Table 5 (Panel A) shows discontinuities on the average conditional cash allowance for T1 and T2 grants in both periods. In T1 income-eligible cutoffs, applicants are granted an average cash amount of 675 and 825 euros (I cannot reject the null hypothesis that the amounts are different) in Period I and Period II, respectively (relatively to been awarded with only fee waiver). In T2 income-eligible cutoffs, applicants are granted an average cash amount of 2,955 and 1,240 euros (the difference being statistically significant) in Period I and Period II, respectively (relatively to been awarded about 1,400 euros).

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.

5.3 Impact on Student Performance

In this subsection, I explore to what extent being awarded different cash allowances impact student performance of the full sample of applicants. I measure the general student performance using two variables: average GPA, and the fraction of credits earned among the total attempted.

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. The solid black lines are the fitted values from a linear projection. The average GPA and the fraction of credits earned are 6 points and 0.77 in Period I, respectively. These measures of student performance marginally increase in Period II (4 and 2.6 percent, respectively). Table 5 presents the non-parametric RDD estimates for the average allowance amounts, average GPA, fraction of credits earned, and the accumulated effects over two consecutive years.

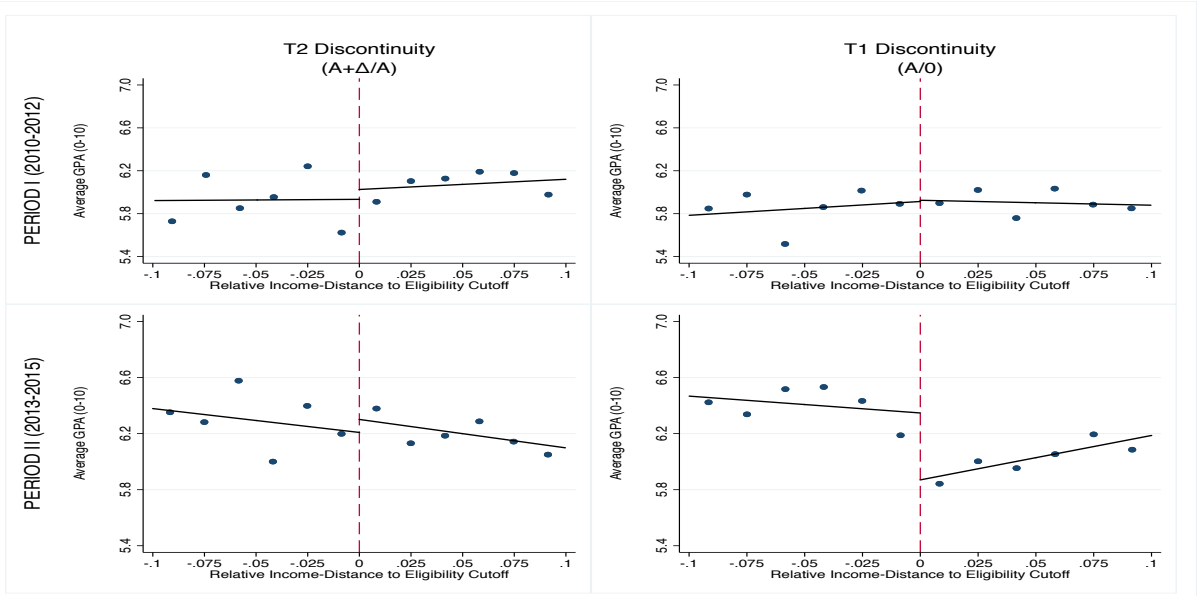
I find no effect of neither modest nor sizeable discontinuous change in grant amounts when interacted with academic requirements comparable to those that characterize the typical need-based programs around the world. I find no effect of being eligible to 675 (relative to fee waiver) or 3,000 euros (relative to an average of 1,400 euros) on neither average GPA nor fraction of credits earned when minimum academic requirements are *weak*. I am able to reject effects on student performance as small as 0.5 percent. This result is especially relevant since a discontinuous change of 3,000 euros is a relatively large differential amount in comparison to what is found on the literature of financial aid. Thus, student performance does not seem to be particularly sensitive to monetary incentives. This result may potentially rule out, or at least partially, the cost-of-college channel, though I cannot test this hypothesis directly in this paper.[44]

In contrast, I find large positive impacts of eligibility to first grant endowment when financial aid is combined with more demanding academic requirements. Results show that the provision of an *equally* moderate cash allowance of 825 euros (I cannot reject the null hypothesis that this amount is different from the previous 675 euros cash endowment) interacted with *strong* academic requirements, increases student average GPA and fraction of credits earned by 0.45 points and 6 percentage points (corresponding to an increase of 7.3 and 7.6 percent with respect to the baseline mean, respectively). These effects correspond to about 25 percent of the standard deviation of the dependent variable. Results are statistically significant at the 1 percent. The T1 grant threshold offers a unique opportunity to analyze the role of minimum academic requirements

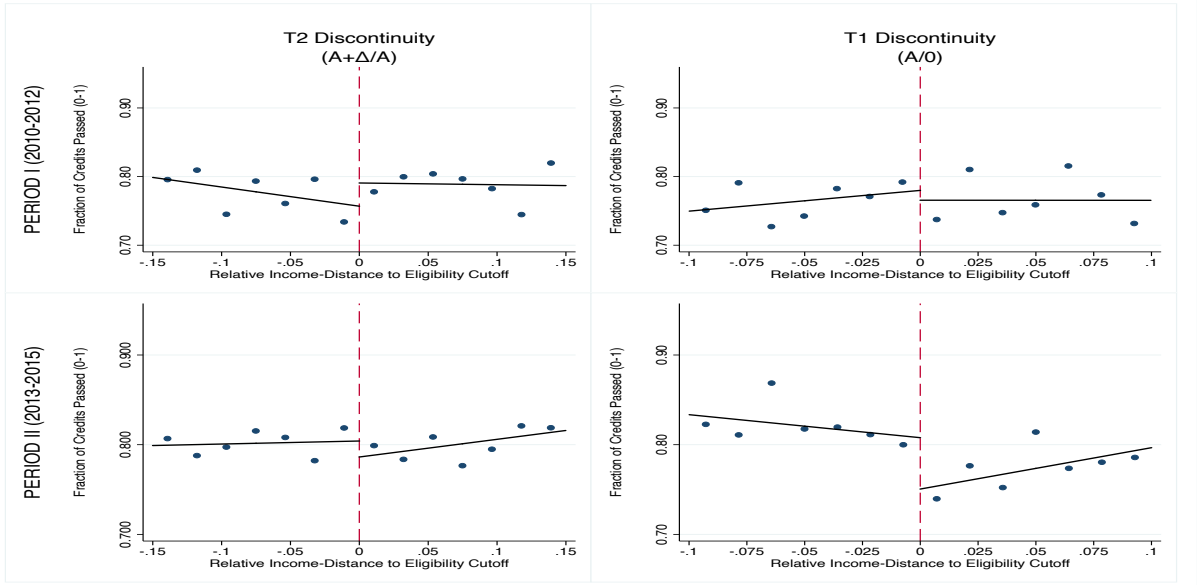
[44]This channel implies that the relaxation of budget constraints may prevent financially constrained students from working part-time, inducing them to devote more time to study.

Figure 6: Average GPA (0-10) and Fraction of Credits Earned for T1 and T2 Discontinuities by Period.

(a) Average GPA (0-10)



(b) Fraction of Credits Earned (0-1)



Notes: The dots represent the average GPAs and fraction of credits earned per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a linear approximation 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.

on the effect of eligibility to financial aid on student performance. Since average grant amounts are not statistically significantly different between Period I and Period II, I can test the causal effect of eligibility to *same* average grant amounts under two different intensities of minimum academic requirements. I use a Difference-in-Discontinuities (RDD-DID) to test whether the discontinuous jumps in student performance are different across periods. Table E1 show that the

Table 5: 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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)
A. Average Allowance Amounts (euros)				
Non-parametric	2,955***	1,240***	675***	825***
Estimates	(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	-0.092	0.057	-0.031	0.455***
Estimates	(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	-0.017	0.016	0.006	0.059***
Estimates	(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	-0.017	-0.246	0.048	0.511**
Estimates	(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	-0.008	0.021	0.025	0.063***
Estimates	(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 student performance over two years (Panel D and E). 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 of the variable above the eligibility threshold. The T1 treatment sample (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. Robust standard errors are clustered at the student level and displayed in parenthesis. Total number of observations are presented in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

null hypothesis that the discontinuous changes in average GPA and fraction of credits earned are equal across periods is rejected at the 1 percent confidence level.[45] Therefore, results show that prospective undergraduate students only react if academic requirements are *strong* (relative

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

to *weak*), when eligible to (*same*) moderate grant amounts. This points out the significant role that minimum academic requirements play on stimulating student performance when combined with financial aid.

Eligibility for a need-based grant may have dynamic effects over the students' academic career. Grants awarded in a given year may produce longer-lasting effects, impacting students' outcomes in several subsequent years. I compute the effect of being eligible for a grant in year t on cumulative student performance in t and t+1.[46] I find that results seem to persist over two consecutive academic years. Local linear regression estimates indicate that grant eligibility to 825 euros increases the cumulative average GPA and fraction of credits earned over two consecutive years by 0.5 points and 6.3 percentage points per year (8 and 7 percent per year with respect to the baseline mean, respectively). Hence, grant eligibility for moderate cash allowance combined with *strong* academic standards have a positive impact on student performance that lasts for two consecutive years.

In addition, I find no further improvements in student performance for subsequent increments in the amount of awarded aid when students are already entitled to a modest amount of aid. Subsequent 1,240 euros increment in the amount of cash allowance (with respect to an average of 1,400 euros) is estimated to have a non-statistically significant impact on student performance. Point estimates are highly precisely estimated, being able to reject effects as small as 1-2 percent. Although results may suggest that the effect on student performance is not linear to the size of grant amounts, I cannot reject the possibility that the impact is in fact, linear. Three hypotheses may help to interpret this result.

First, the null impact of the grant could alternatively be due to the fact that students at the bottom of the family income distribution (those at the vicinity of T2 grant income-eligibility threshold) may not be as able as their peers to respond to performance incentives, even under reasonably large cash amounts granted.[47] Potentially, 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,

[46] This method would provide unbiased estimates and limited concern for sample selection. The challenge regards that the first stage would decrease over time due to the variability of students' application status and household income. For instance, note that the average grant amount awarded in the next consecutive year for T1 grant in Period II is statistically significant at the 1 percent level but of much shorter amount (406 euros on average) and non-significant for subsequent years. A test for the discontinuity of the average grant amount at the cutoffs are presented in the online appendix, section C.

[47] 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.

students' behavioral responses to incentives may be more powerful when they start receiving the first grant endowment, with the intensity fading out with subsequent allowance increments. This result is consistent with Fack and Grenet (2015), showing that the most significant effects of the French national need-based grant program are concentrated on those students receiving the first endowment of cash allowance, but more limited on students entitled to higher levels of grant. Third, the quasi-experimental variation is not the same for those students at the bottom of the parental income distribution (T2 grant) with respect to those at higher levels of the distribution (T1 grant), since both cash amounts and minimum 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* minimum academic requirements. I cannot reject the hypothesis that the large decrease in average amounts in Period II (relative to the Period I) may offset the positive effect induced by stronger minimum academic standards.

Overall, I find no effect of relatively high cash amounts on student performance in a setting with 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 minimum academic requirements (Denning, Marx and Turner, 2019; Denning, 2018). In contrast, I find that an average provision of 825 euros cash allowance (relatively to receiving only fee waiver) increase student performance in a setting with more demanding minimum academic requirements, 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). Then, results suggest that tightening minimum academic requirements may be a useful tool to make a national grant program more effective through improving student performance at least partially.

5.4 Robustness Checks

In the online appendix (section D), I perform an exhaustive number of tests to check the robustness of the baseline estimates. First, I investigate the sensitivity of estimates to the choice of bandwidth. Second, I perform the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014). Third, I run the baseline regressions adding student individual observable characteristics and year fixed effects to capture year specific trends. Fourth, I test for jumps at non-discontinuity income-eligibility

threshold points by running placebo regressions. Fifth, I check for the effect of being eligible for only fee waiver. Sixth, I investigate the effect of being eligible for the Displacement and Other Needs Grant (T3 grant) in Period I. Seventh, I analyze the potential effects of being eligible for a need-based grant in 2012, where minimum academic requirements were slightly modified. Eight, I test for grades manipulation by university instructors. If instructors have the information on whether a student is awarded a need-based grant in year t, a potential concern may arise if they marginally modify applicants' GPAs to make them be above the minimum academic requirement threshold (to increase their chances to be eligible for a need-based grant in year t+1). If that is the case, bunching would be observed at the minimum academic GPA requirements. I test for significant discontinuities in the density of students at minimum academic GPA requirements, finding no statistically significant jump.[48] Finally, I test for multiple-hypothesis testing of the baseline results computing Benjamini and Hochberg (1995) q-values.

I find that baseline estimates are robust to all the different robustness checks undertaken. Point estimates vary from 0.27 to 0.5 GPA points, which corresponds to about 4.5 to 8.3 percent to the baseline mean. The direction and the statistical significance of the effects are robust to all the different specifications. Therefore, the baseline estimates capture the full impact of eligibility on need-based grants on student performance.

5.5 Heterogeneity of Student Performance

I explore heterogeneous effects of being eligible for a need-based grant on student performance. First, I investigate the existence of heterogeneous results by academic term (Fall vs. Spring grades). Second, I perform separate regressions by different subgroups of applicants (i.e., gender, predetermined academic ability, residency status, and undergraduate year).

Student Performance by Academic Term. Students are already enrolled in higher education when they apply for a need-based grant. Applicants' face a different timing of acceptance/rejection disclosure. The vast majority of grant decisions are notified after the end of the Fall term of

[48] Grades in mandatory subjects at Carlos III University constitutes of a weighted average between mid-term exams, and a final term exam. The final term exam is the same across the different classes and typically set out by all the senior instructors (i.e., assistant, associate, full, or postdocs) teaching on a specific subject. In many cases, the grading of the final exam is split into parts/questions that are corrected by these different senior instructors. Students enrolled in mandatory subjects are often substantially large (about a hundred). Most mandatory subjects consist of a weekly lecture that is attended by all students and is typically taught by senior instructors. Besides, students are required to participate in smaller-size sections that typically meet once per week that is typically taught by teaching assistants (e.g., postdocs, Ph.D. students, lecturers, or graduate students). The relatively large class size and the grading structure substantially limits instructors' flexibility for grade manipulation in this respect.

the academic year (see Section 2.2.2.). The effects are expected to be stronger in the Spring term since most of the students received the notification after the Fall term. I test the impact of eligibility to a need-based grant on student performance by academic term (Fall and Spring).[49] Table 6 presents the non-parametric estimates by academic term. I find that being eligible for an average grant of 825 euros combined with *strong* academic requirements has a positive and significant impact on student performance of Fall and Spring terms. The effect sizes are twice larger for the Spring than for the Fall term. Although the differences between Fall and Spring term student performance are not statistically significant, the point estimates of Spring doubled the Fall term ones, and the estimates of the latest seem to be more sensitive to the functional form (see Figure 7).

Student Performance by Subgroups of Population. Table D7 and Table D8 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 in Period II is found for both males and females (Panel A). The point estimate is larger for males than for females, although the difference is not statistically significant. Panel B explores heterogeneous effects by level of academic ability, splitting the samples into two groups based on applicants' percentile rank on PAU exam. The positive effect on student performance seems to be mainly driven by students above the median percentile rank of the PAU exam score distribution. However, the null hypothesis that coefficients are equal across groups below and above the median cannot be rejected. Panel C presents the results divided by the different applicants' residence status. The impacts are positive and statistically significant for both both applicants who were living in their parent's primary residence in the Region of Madrid (non-movers hereafter) and those students who were living away from their family primary residence (movers hereafter). The null hypothesis of equality of coefficients cannot be rejected.[50] Moreover, there are no statistically significant heterogeneous effects across

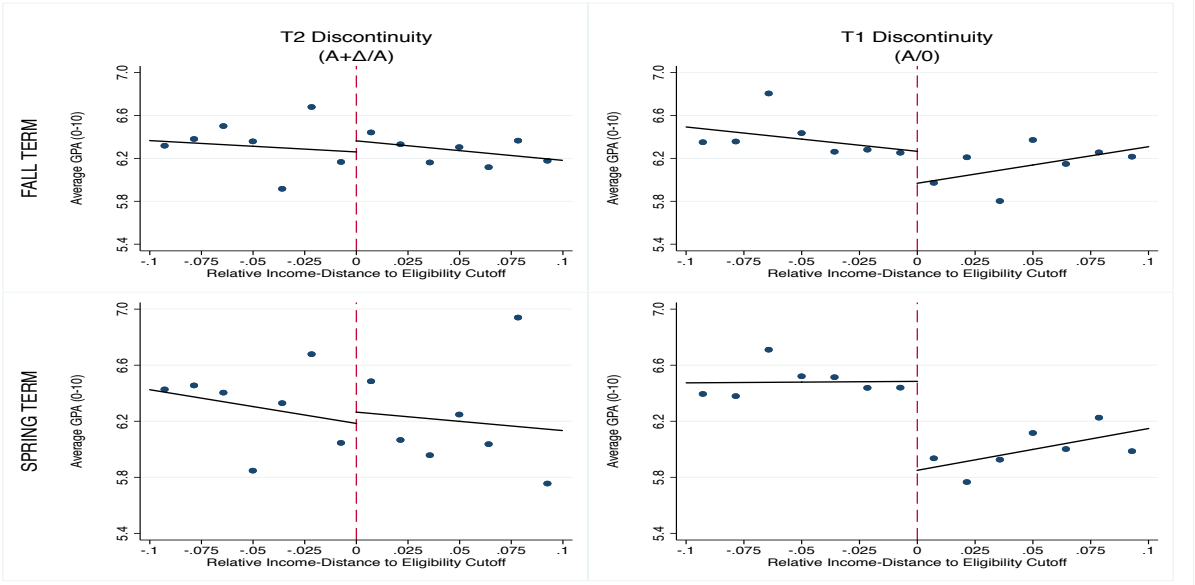
[49] An ideal way to test for heterogeneous effects on student performance before and after the student received the notification would be to compare the effect on students who received it before the term final exams versus those who were informed after. Unfortunately, this sample split creates endogenous selection at the eligibility cutoffs, since on average, denied grants are disclosed before accepted grants, leading to a significant break in the density at income-eligibility thresholds. Notice that student disclosure time is not a perfect continuous variable, but discrete, since notifications are sent divided into weekly blocks.

[50] Note that these subgroups receive substantially different average grant amounts. While movers receive actual amounts decreasing in the second period (from 2,858 to 1,673 euros on average), non-mover applicants were awarded zero cash amount in Period I, and with 445 euros on average in Period II (see online appendix, section C). Then, the grant structure allows considering the non–movers in Period I as a placebo test. See online appendix, section D, for a graphical representation of the RDD Estimates by subgroup of population at T1 Discontinuity in Period II.

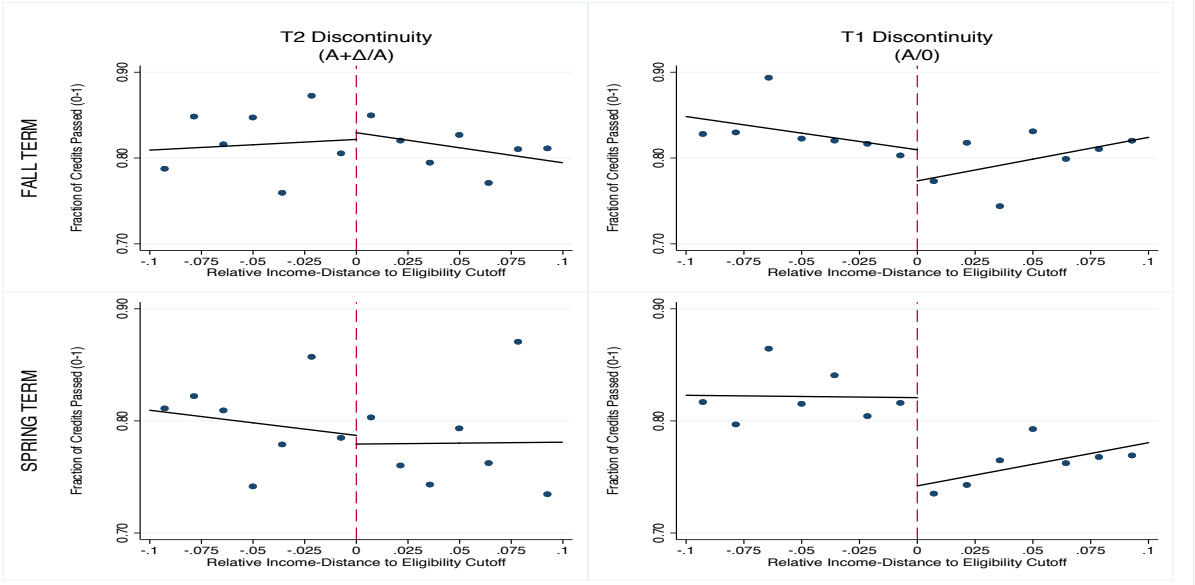
Figure 7: Average GPA (0-10) and Fraction of Credits Earned for T1 and T2 Discontinuities by Term in Period II.

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(a) Average GPA (0-10)



(b) Fraction of Credits Earned (0-1)



Notes: The dots represent the average GPAs and fraction of credit earned per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a linear approximation 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.

undergraduate course year.[51]

[51] See online appendix section, section D.

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 (0.190) [3,402]	0.057 (0.157) [3,549]	-0.031 (0.124) [6,093]	0.455*** (0.144) [5,868]
Baseline mean	5.97	6.29	5.91	6.15
A.2. First Term (Fall)				
Non-parametric Estimates	-0.024 (0.213) [3,299]	0.020 (0.159) [3,470]	0.030 (0.127) [5,904]	0.282** (0.136) [5,703]
Baseline mean	6.01	6.33	5.91	6.20
A.3. Second Term (Spring)				
Non-parametric Estimates	-0.187 (0.222) [3,282]	0.050 (0.190) [3,400]	-0.118 (0.138) [5,885]	0.560*** (0.154) [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 (0.028) [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.2. First Term (Fall)				
Non-parametric Estimates	-0.010 (0.029) [3,299]	-0.003 (0.023) [3,470]	0.018 (0.023) [5,904]	0.037** (0.018) [5,703]
Baseline mean	0.79	0.82	0.77	0.80
B.3. Second Term (Spring)				
Non-parametric Estimates	-0.019 (0.031) [3,282]	0.029 (0.034) [3,400]	-0.012 (0.020) [5,885]	0.073*** (0.022) [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) by academic term. 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 of the variable above the eligibility threshold. The T1 treatment sample (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. Robust standard errors are clustered at the student level and displayed in parenthesis. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.6 Impact on Dropout

In this paper, dropout decisions are a related measure of college persistence. Due to the timing of grant applications, students are already enrolled in higher education when they apply for a need-based grant. Then, dropout is defined as a dummy variable equal to one if a student does not re-enroll in higher education on the following academic years. Conditional of being enrolled in higher education in year t, I compute the probability of dropout within years t+1 and t+2. This measure of dropout presents a proxy about how much students persist in higher education, conditional on being enrolled in the first place. Thanks to the richness of the dataset, I can precisely identify whether a student dropout higher education or whether she transferred the files to another higher education institution. Table 7 displays the RDD estimates on student dropout from higher education. The RDD non-parametric estimates show that there is no impact of grant eligibility on student dropout regardless of the intensity of the two minimum academic requirements examined nor the level of grant. Panel A and B show that the null hypothesis of a zero effect of being eligible for a need-based grant on dropout cannot be rejected neither within one nor two academic years.[52]

Finding a null effect may have two potential alternative explanations. First, tightening the academic requirements may have changed the composition of students (at the vicinity of the cutoff) across periods. Leading to a more positively selected sample of applicants after the reform, potentially less sensitive to college costs. I rule out this hypothesis on Section 3, and section F of the online appendix. Second, increasing minimum academic requirements may have limited effects on dropout at the vicinity of the income-eligibility thresholds (at the local level), but significant impact on other parts of the grant applicants' distribution. I broader the scope of grant eligibility impact on the average dropout effects on the full population of applicants. Besides the scope of the RDD estimates to observe differential changes in dropout at the income-eligibility cutoffs, I perform a Difference-in-Difference model (DID), an RDD-DID specification, and a Logit analysis to measure the propensity to dropout before and after the change in minimum academic requirements.[53] Overall, I do not find significant average equity effects of tightening the minimum academic requirements. Results of he RDD-DID specification shows no evidence of a significant change in dropout across periods at the vicinity of income-eligibility cutoffs.[54] These results show

[52]Note that due to the fact that data is available until 2015, I can only test the effect of a need-based grant at most within the two following academic years (re-enrollment in t+2) in Period II.

[53]Results are displayed in the online appendix (section E and G).

[54]Results do not present significant heterogeneity by gender, the predetermined measure of student ability, and

Table 7: Discontinuities in Dropout from higher education 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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)
A. Dropout within one academic year				
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
B. Dropout within two academic year				
Non-parametric Estimates	0.007	0.027	0.026	-0.016
	(0.015)	(0.018)	(0.019)	(0.019)
	[3,402]	[3,549]	[6,095]	[5,87]
Baseline mean	0.04	0.04	0.04	0.06

Notes: The table shows the RDD non-parametric estimates for 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 (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. Robust standard errors are clustered at the student level and displayed in parenthesis. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

local average treatment effects but do not provide average effects for the total distribution of grant applicants. To address the concern on 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 pre-reform period minimum academic requirements but not overcame the Period II standards (treatment group), with students who do not meet the minimum academic requirements of both periods (control group), before and after the reform.[55] I find no effect of tightening the minimum academic requirements on dropout of the group of students who would not meet those requirements due to the reform. Finally, an additional Logit analysis on the full population of grant applicants shows that the probability of dropout does not significantly change after the reform.[56] Therefore, the change in academic requirements does not do not seem to have a significant equity effect on applicants to the national need-based financial aid.

residence status.

[55] In other words, I compare the behavior of those students who are eligible before but not after the reform, with those who are never eligible due to their academic performance.

[56] These results are robust to separately analyze the model for first and non-first year students. Besides, 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.

These results seem to contradict the evidence showing that minimum academic requirements may have a negative impact on student persistence presented by Scott-Clayton and Schudde (2019) 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 in the Spanish context. The institutional context, especially the cost of college, may potentially be a relevant factor affecting the elasticity of dropout to minimum academic requirements. Reconciling the results on student performance and dropout, a setting with stronger academic requirements appears to be more cost-effective, at least partially.

5.7 Impact on Degree Completion Rates

Table 8 expands the analysis by investigating the impact of financial aid on degree completion rates. The non–parametric estimates indicate that being eligible for 825 euros (relatively to fee waiver only) in the period when minimum academic requirements are more stringent, increases student probability of obtaining a degree in 12.5 and 11 percent to the baseline mean for all applicants and applicant in the graduation year, respectively.

Table 8: 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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(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 applicants' probability of graduation. 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 (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. Robust standard errors are clustered at the student level and displayed in parenthesis. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Mechanisms

Baseline results show that eligibility for 825 euros cash allowance when combined with *strong* academic requirements increase student performance and degree completion rates. Crucial further investigation is needed to understand the mechanisms behind these results. First, I investigate whether the increase in student performance is due to an increase in performance genuinely, or a change in student's strategic behavior in the choice of subjects. Second, I analyze which channels may be driving the limited adverse effects on student persistence to the increases in minimum academic standards.

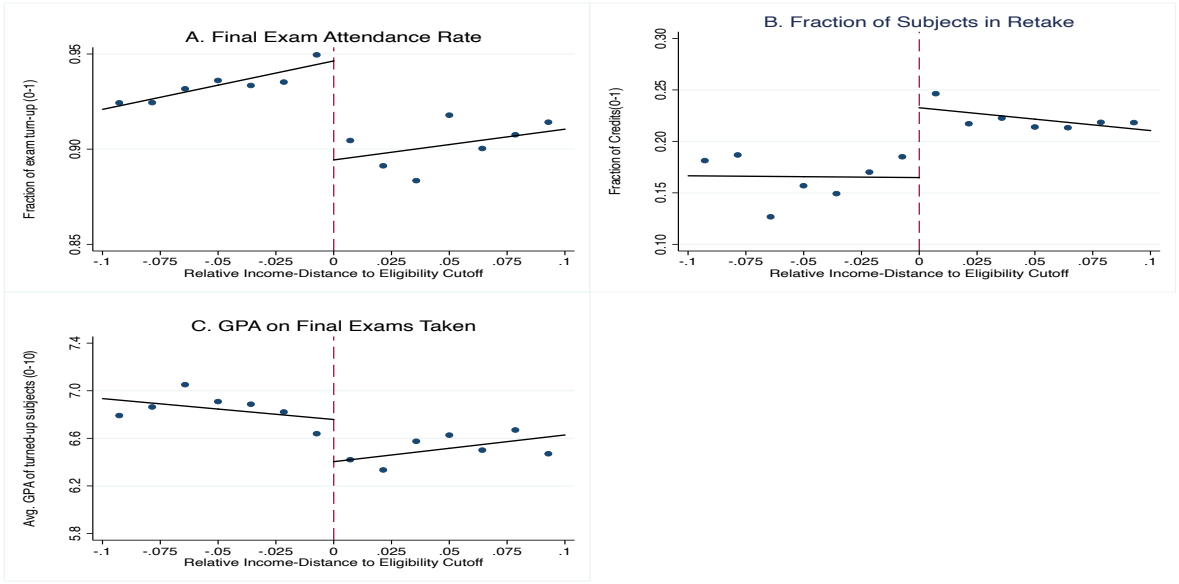
Is the increase in student performance genuinely? The increase in student performance documented in the previous section may be due to an actual rise in student genuinely performance, or alternatively, to other confounding factors, such as students' self-selection in subjects with higher probability of passing. Thanks to the detailed information of the administrative data, I can compute different variables to precisely test the effect on different genuine performance measures (e.g., fraction of subjects in retake or GPA on final exams taken), and rule-out strategic selection of subjects (comparing the effects on compulsory vs. elective subjects). Table 9 presents the results of the RDD estimates on these different outcomes for T1 and T2 by period, and Figure 8 plots these channels. Results reinforce the hypothesis of an increase in genuinely student performance. Panel A shows that eligibility for 825 euros cash allowance when minimum academic requirements are *strong* increases the final exam attendance rate in 3.2 percentage points (about 3 percent to the baseline mean). Eligible students might increase their final exam attendance rate by attending more often to retakes. Panel B presents that students decrease the fraction of subjects on retake in 4.6 percentage points (25 percent to the baseline mean). This shows that they seem to be also increasing their fraction of credits earned in final exams, reducing retakes. Then, eligible students may attend to final exams more often, but their performance on them may remain unchanged.[57] To test this hypothesis, I examine the grant eligibility effects on the average GPA computed over the final exams precisely taken. I find that students improve their average GPA in final exams taken in 0.35 points (5 percent to the baseline mean). The null hypothesis of zero effect is rejected at the 1 percent confidence level. Results support the hypothesis that the observed improvement in student performance seems to be due to a genuine

[57] The fact that students show-up more often to final exams may enhance their total average GPA mechanically due to the less frequent graded subjects with zero points (grade given to students who fail to attend), rather than to an actual improvement in their performance.

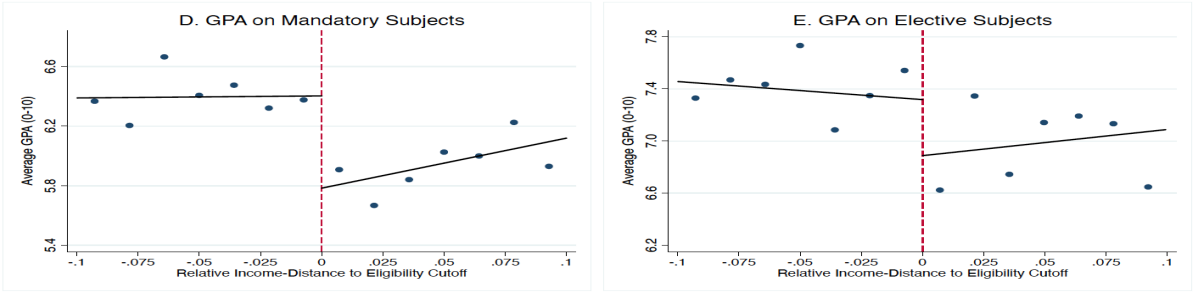
increase in student effort.

Figure 8: Mechanisms for Spring term at T1 Discontinuity (2013–2015).

(a) Measures of Genuine Student Performance



(b) Ruling out strategic selection of subjects



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 linear approximation 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.

Ruling out strategic selection of subjects. To test the hypothesis of potential student strategic selection of subjects, I investigate the differential results on student performance for mandatory and elective courses. To obtain a university degree, students must pass certain mandatory and elective subjects. Mandatory subjects are compulsory and degree-specific. Elective subjects are chosen from a subset of subjects that are degree specific.[58] If applicants would self-select in subjects with a higher probability of passing (students have only room to select elective subjects, but not mandatory), the effects may be due to a change in the composition of subjects instead of an actual increase in student performance. Panel E and F of Table 9

[58]The vast majority of Carlos III University degrees are typically composed of three academic years with almost full mandatory subjects, and the last academic year is devoted to elective subjects.

Table 9: Discontinuities for Genuine Student Performance and Strategic Selection of Subjects 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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)
1) Measures of Genuine Student Performance				
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
2) Ruling out strategic selection of subjects				
D. 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
E. 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 (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. Robust standard errors are clustered at the student level and displayed in parenthesis. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

analyze the effects of grant eligibility on the average GPA for mandatory and elective courses. Eligibility for 825 euros cash allowance combined with *strong* academic requirements increase their average GPA on those subjects which are mandatory by 0.46 points (7.5 percent to the baseline mean). Despite the fact that the higher baseline average GPA on elective courses compared with mandatory, the null hypothesis of zero grant effect on average GPA in elective courses cannot be rejected.[59] Therefore, results rule out the hypothesis that the increase in student performance is confounded by student strategic selection of less demanding courses.

What could drive the limited effect on student persistence? It is critical to elucidate whether the increase in minimum 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.[60] However, I use back on the envelope computations to shed suggestive evidence on the potential channels at play.[61] For the total income-eligible applicants who apply in the pre-reform period (2010 and 2011), 23 percent would not meet the minimum academic requirements for renewal given their performance in year t of Period I. This percentage increases to between 35–43 when the academic requirements would be those of Period II.[62] Although these estimates contain measurement error, they seem to indicate that the policy was binding, or at least relevant for some students. The increase in the minimum academic requirements may mechanically make some applicants ineligible, but at the same time, some students may increase their performance to meet the new threshold (inducing them to be *more ambitious*). Back on the envelope computations show that 11 (14) percent of all (first year) students would have meet the new academic requirements as a consequence of being affected by the average effect of the grant on student performance.[63] Therefore, back on the

[59] The point estimate and the standard errors show that it seems plausible that the null hypothesis on the average GPA of elective courses cannot be rejected potentially due to limited statistical power caused by relatively small sample size.

[60] Students can quickly compute their fraction of credits earned and average GPA, but it is not the case for household income due to the reasons discussed in Section 2.2.2. and 5.1. Then, about 26 percent of applicants were not eligible due to performing below the minimum academic requirements before the policy reform, but this number was reasonably constant after the policy reform.

[61] Note that this is not an internal validity concern, but a procedure to address whether the policy was binding.

[62] Schudde and Scott-Clayton (2016) calculate that between 25-40 percent of first-year Pell recipients at public institutions were placed at risk of losing financial aid. I find that the first year that would not be eligible for a renewal of financial aid were about 30 and 47–55 percent with academic requirements of Period I and II, respectively.

[63] These estimates are based on the counterfactual of those students who are income-eligible but entitled to fee waiver only (the comparison group for T1 grant). Under the assumption that the average effect is constant on the distribution of income-eligible students, back on the envelope computations show that 8 (11) percent of all (first year) students would have meet the new academic requirements as a consequence of being affected by the average effect of the grant on student performance.

envelope, results suggest that the increase in non-eligible applicants due to the rise in academic standards may be attenuated with the simultaneous increase in student performance induced by the stronger minimum academic requirements.

7 External Validity

The estimates of this paper 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 score higher in the standardized university access exam, report higher graduation rates, and present lower dropout rates than their counterparts in the rest of Universities in Spain. However, the group of students who drive these differences is non-BCG grant recipients, while the targeted population of need-based programs are BCG 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, while slightly higher average score in the university access exam.[64] The sample of need-based grant applicants used in this paper can be seen as reasonably representative of the general population of low-income students in Spain, but with slightly higher ability. This group can be considered as comparable to the typically targeted population of most large-scale need-based grant programs around the world (e.g., students who 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.[65]

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

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

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

eligible to fee waivers (e.g., the Pell Grant) since they present substantially more substantial levels of debt, higher tuition fees, and larger 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 waivers and need-based grants.

8 Conclusion

In this paper, I estimate the causal effect of the Spanish large-scale need-based grant program on student performance (average GPA and fraction of credits earned), student dropout from higher education, and degree completion rates. I exploit the sharp discontinuities in the amount of grant at the income-eligibility thresholds using a regression discontinuity design. 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 rates in a setting with more demanding minimum academic requirements than those set out by the typical need-based grant programs around the world. 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. Results show that the increase in student performance is due to a genuine increase in performance, finding no evidence of significant student strategic course selection. Besides, I find that tightening minimum academic requirements have a limited effect on dropout from higher education. However, I find no effects on student performance of non-statistically different cash amounts interacted with minimum academic requirements relatively comparable to those of the typical need-based grant programs around the world. Interestingly, I find that additional increments in the grant amount does not lead to further improvements in student performance.

This paper points out the significant role that minimum academic requirements to renew the grant play on stimulating student performance and degree completion rates in the national large-scale need-based grant programs. Student performance seems to be weakly correlated with monetary incentives, but more reactive when combined with academic incentives. It seems that grants attached to the typical need-based grant programs' minimum academic requirements do not affect student performance, while grants with stronger requirements provide significant and positive effects for those students who receive the first cash allowance. Results indicate that the intensity and design rather than the sole existence of minimum academic requirements matter for stimulating student performance. The mechanisms indicate that a setting with stronger

academic requirements may reduce costs for taxpayers on repeated subjects failures and high attainment time rates, and improve the educational benefit of eligible students by enhancing their performance. A higher education financial aid framework with stronger minimum academic standards may be a useful tool to make a national grant program more effective, 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 the 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 student performance and dropout along the different possible minimum academic requirements (from zero strings attached to full accountability). Understanding how the impact of a grant changes when attached to all different possible minimum academic requirements turns out to be a crucial research question to improve the effectiveness of large-scale financial aid programs. Establishing the optimal lines of academic standards and the amount of financial aid that is socially optimal remains a topic for future research.

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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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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 and disuss other confunding factors (section A), the validity of the research design (section B), the discontinuities in BCG grant amounts awarded to applicants (section C), the robustness of baseline estimates (section D), the RDD-DID reduced-form model (section E), the comparability between Period I and Period II (section F), the additional Logit and Difference-in-Difference model (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 are computed for the cohort of students who enrolled in Spanish higher education in the academic year 2010/2011 (which expected graduation from the undergraduate program was 2013/2014 or 2014/2015).

The summary statistics presented in **Table A1** shows 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, but with slightly higher ability. 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 who 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.

A.1 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; Barrera-Osorio, De Barros and Filmer, 2018) 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. In this paper, it is unlikely that the labeling effect may be a confounding factor of the results since both the targeted population and label of the program remain constant before and after

the policy reform.

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.[66] 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 with the number of re-registrations in a particular module.[67] 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 GPAs. 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. Three reasons rule out this concern. First, being eligible for only fee waiver is not statistically significant in both periods.[68] Second, the significant effects on T1 eligibility threshold are mainly comparing students who got fee waiver with 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. Third, this paper focuses on applicants for a need-based grant, a population of students that is different in many dimensions to the standard student enrolled at college (the focus of the study previously mentioned). Besides, a loan system was functioning in Spain from 2007 to 2011 for postgraduate studies. 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 Ph.D. students, while this paper focuses on undergraduate students.

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

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 parental household income around the thresholds.

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

[67] 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.

[68] See online appendix, section D.

Table B1 shows the results of the 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 of no density break at income-eligibility thresholds for more than 90 percent of contrasts. The only contrasts that do not fail to reject the null hypothesis at the 10 percent confidence level are movers at T1 Grant in Period I, and T2 Grant at Period II. The results of the McCrary (2008) test for Fee Waiver (FW) and Displacement and Other Needs Grant (T3) grant are presented in **Table B2**. McCrary test statistics confirm that the null hypothesis of no density jump at the eligibility cutoffs cannot be rejected for these income-eligibility cutoffs. Besides, **Figure B1** displays the fraction of the 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 may be driven by this group of students, with no density break for all poled applicants at the cutoffs but so for re-applicants. The null hypothesis of the density break of re-applicants cannot be rejected. Overall, these tests suggest that the probability of applying does not change discontinuously at the income eligibility threshold. Thus applicants immediately above the cutoff are not able to manipulate their parental household income to be eligible for higher levels of grant.

C Discontinuities in Awarded Grants

This section tests 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 substantial 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 cash allowances at this specific threshold and period. **Table C2** shows the average cash amount at T1 and T2 grants for being eligible for a grant in t+1, conditional on household income in t. Conditional on applying for a grant at time t with an individual household income, it is possible to compute the average allowance amounts awarded in t+1. This method provides limited sample selection concerns. The discontinuous jump in the average grant amount decreases over time due to the variability

of applicants' application status and household income over the years. The discontinuities in the actual amount of conditional grant awarded to applicants are about 300 euros for the T1 grant on both periods, and similar estimates for T2 grant but not statistically significant for Period I.

D Robustness Checks

In this section, I perform several tests to check the robustness of baseline estimates. First, I investigate the sensitivity of estimates to the choice of bandwidth. Second, I perform the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014). Third, I run the baseline regressions adding student individual observable characteristics and year fixed effects to capture year specific trends. Fourth, I test for jumps at non-discontinuity income-eligibility threshold points by running placebo regressions. Fifth, I check for the effect of being eligible for only fee waiver to zero cash amount and fee waiver. Sixth, I investigate the effect of being eligible for the Displacement and Other Needs Grant (T3 grant) in Period I. Seventh, I analyze the potential effects of being eligible for a need-based grant in 2012, where minimum academic requirements were slightly modified. Eight, I test for grades manipulation by university instructors. Finally, I test for multiple-hypothesis testing of my baseline results computing Benjamini and Hochberg (1995) q-values.

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 point estimates are larger when using half the optimal bandwidth instead of 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** and **Table D2** presents non-parametric estimates very close to the baseline estimates.

D.3 Individual Control Variables and Year Fixed Effects

I investigate the robustness 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. Panel D in **Table D1** and **Table D2** shows that results are statistically significant at the 5 percent confidence level, but point estimates are smaller than baseline estimates.

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 at T1 and T2 cutoffs. Since these midpoints do not correspond to any change in applicants' grant eligibility status, I should expect to find no significant jumps in student performance. Panel E in **Table D1** and **Table D2** presents that the points estimates are close to zero and non-statistically significant in all specifications.

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. Note that the fee waiver eligibility threshold is close to the eligibility cutoff of the T1 grant (see Figure 1), making it difficult to construct two treatment samples (with a sufficient number of observations) between T1 grant and fee waiver that do not overlap. The discontinuity induced by the tuition fee eligibility cutoff is therefore ignored in the main analysis.

As a robustness check, I have conducted a separate analysis of the treatment effect of being eligible for only tuition fees. **Table D3** reports the discontinuities in the average cash amount awarded and the 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 the 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.

An ideal test would be a similar amount of cash awarded for non-movers at Period I and II for the 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 the grant's minimum academic requirements. The key advantages of using 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 since it offers a scenario where entitlement to the grant, cash allowances, and compliers are comparable. However, minimum academic requirements are different in the two periods.

Table D3 shows that 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.

Student performance was not impacted by eligibility to the T3 grant in Period I, and it was positively impacted in Period II by the T1 grant, under approximately the same cash allowance amounts but different minimum academic requirements. This finding suggests that academic standards components seem to play a crucial role in 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 specific cash allowance and strong minimum academic requirements as primary drivers of the grant's effect on performance.

D.7 Differential effects on 2012

This section tests for specific effects of grant eligibility in 2012. The paper focus on the results on two periods, Period I and Period II. While minimum academic requirements in Period II were homogeneous throughout the three academic years, Period I reported a change in 2012. Students had to pass 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.[69] **Table D4** 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.

D.8 Multiple hypothesis testing

I test for multiple-hypothesis testing of baseline results computing Benjamini and Hochberg (1995) q-values. **Table D5** shows the p-values of T1 Grant in Period II adjusted for multiple hypothesis testing. I find that baseline results are robust to multiple hypothesis testing for both testing all hypothesis by each outcome variable (four statistical hypotheses, one per period), and testing all hypothesis of every outcome variable jointly (twenty-eight statistical hypothesis).

D.9 Manipulation of grades by university instructors

I test for grades manipulation by university instructors. If instructors have the information on whether a student is awarded a need-based grant in year t, a potential concern may arise if they marginally modify applicants' GPAs to make them be above the minimum academic requirement threshold (to increase their chances to be eligible for a need-based grant in year t+1). If that is the case, bunching would be observed at the minimum academic GPA requirements. **Figure D4** tests for significant discontinuities in the density of students at minimum academic GPA requirements, finding no statistically significant jump.[70]

D.10 Mechanisms by academic term

I test for the robustness of results on measures of genuine student performance by academic term. **Table D6** shows that baseline estimates are robust to heterogeneous effects by academic

[69] See online appendix, section H.

[70] Grades in mandatory subjects at Carlos III University constitutes of a weighted average between mid-term exams, and a final term exam. The final term exam is the same across the different classes and typically set out by all the senior instructors (i.e., assistant, associate, full, or postdocs) teaching on a specific subject. In many cases, the grading of the final exam splits into parts/questions that are corrected by these different senior instructors. Students enrolled in mandatory subjects are often substantially large (about a hundred). Most mandatory subjects consist of a weekly lecture that is attended by all students and is typically taught by senior instructors. Also, students are required to participate in smaller-size sections that typically meet once per week that is typically taught by teaching assistants (e.g., postdocs, Ph.D. students, lecturers, or graduate students). The relatively large class size and the grading structure substantially limits instructors' flexibility for grade manipulation in this respect.

term. **Figure D3** and **Figure D5** show the robustness of heterogeneous effects by applicants' subgroups of the population and undergraduate course year.

E RDD-Difference-in-Difference

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}:

$$E_{i,k,t} = \mathbb{1}\{c_{it} \leq \bar{c_k}(m_{it})\} \tag{7}$$

$$Y_{it} = \alpha + \sum_{k=1}^{2} \beta_k E_{i,k,t} + c_{it} + c_{it} * E_{i,k,t} + \epsilon_{it} \tag{8}$$

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

$$Y_{it} = \alpha + c_{it} + c_{it} * E_{i,k,t} + c_{it} * \text{Period II} + c_{it} * E_{i,k,t} * \text{Period II} + E_{i,k,t} + \text{Period II} + \sum_{k=1}^{2} \beta_k E_{i,k,t} * \text{Period II} + \epsilon_{it} \tag{9}$$

Note that in this model, the coefficient estimates do not change. They are the same that perform an RDD separately by each period than RDD-DID (standard errors can slightly vary due to a change in degrees of freedom). The advantage of this model is the fact that this method allows us to compute the standard errors of the difference in changes directly. **Table E1** shows that the jump in average grant and dropout from higher education at T1 grants are not statistically significantly different across periods. The jumps in student performance and degree completion are significantly different across periods.

F Comparability between Period I and Period II

A principal 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 periods. **Table F1** presents the results of this analysis. I show that three out of sixteen contrasts are significant at the 10% level at the T1 and T2 discontinuities. Grant applicants seem to be highly comparable across periods at both discontinuities. The sub-population of applicants present a slightly higher fraction of movers and lower second-year students in Period II to Period I at the vicinity of T1 discontinuity. Slightly higher fraction of applicants are enrolled in STEMs degree, a larger fraction of students which parents work as blue-collar in Period II to Period I at the vicinity of T2 discontinuity.

G Additional Equity Effects: Logit and Difference-in-Difference model

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 7. The analysis explores two different dropout variables: (i) Yearly dropout, signaling the flow of students who dropout at the end of particular 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 the six-year period to see how dropout changed before and after the reform.[71] The regressions control for all available student predetermined observable characteristics.

I analyze the differences in the dropout rates between two cohorts of students (before and after the reform):

$$\Pr(\text{Dropout} = 1 \mid \text{X}) = \frac{\exp(X\beta)}{1 + \exp(X\beta)} = \psi(X\beta) \tag{10}$$

Where vector X includes explanatory variables such as gender, family income, score in the access to university exam, nationality, parental education, etc. **Table G1** and **Table G2** shows

[71] 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 biased, due to the fact that the undergraduate program covers four years of education, and this cohort has only attended 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 attractive since it was the first increase in minimum academic requirements.

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 dropout. However, both dropout measures do not significantly change after the reform, neither when controlling for student individual observable characteristics nor when they do not. These results are robust for non-first year and first-year students, which is the sub-population of students with the highest probability of dropping out.

The Difference-in-Difference 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 met the academic requirements of Period I (Control Group), before and after the reform:

$$\text{Dropout}_{it} = \alpha + \beta \text{Treatment}_{it} * \text{Period II}_t + \gamma \text{Treatment}_{it} + \delta \text{Period II}_t + \nu \text{X}_{it} + \epsilon_{it} \qquad (11)$$

where Treatment_{it} is a dummy variable that takes value one if the students belong 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 of **Table G3** show that 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 seems to be consistent for first and non-first year students. The increase in the minimum academic requirements does not seem to be high enough to induce these students to dropout of higher education.

H Academic requirements for BCG grant

This section summarizes the minimum academic requirements for being eligible for a BCG grant over the six years studied (2010–2015). 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 H1** shows a summary of the different performance standards required by

year, degree, and cohort.

First-year students must report an average grade in *PAU* of at least 5/10 points (roughly corresponding to having passed the university entrance exam) to be eligible for all grant levels in Period I, while students need to reach at least 6.5/10 (5.5/10 to be only eligible for the fee waivers) in Period II.[72] Non-freshmen students must have earned at least:

- *Period I (2010–2012)*: 60 percent of the total full-year credits if enrolled on a STEM degree, and 80 percent in non-STEM degree the year before application.

- *Period II (2013–2015)*: After 2013, students may combine a fraction of credits earned with average GPA the year before application. To qualify for all grant levels, students must have earned at least either: (i) 85 (100) percent of the total full-year credits if enrolled on a STEM (non-STEM) degree; or (ii) 65 (90) percent of the total full-year credits if enrolled on a STEM (non-STEM) degree, but combined with an average GPA of at least 6/10 (6.5/10) respectively for STEM (non-STEM) degree the year before application. If students do not meet the minimum average GPA in (ii), they would only be entitled to fee waivers.[73] For a student enrolled in a non-STEM degree, the policy reform in Period II implies an increase in the minimum fraction of credits earned of 25 and 12.5 percent with respect to Period I to be entitled to all grant levels and only fee waiver, respectively. For a student enrolled in a STEM degree, the policy reform in Period II implies an increase in the minimum fraction of credits earned of 41 and 8 percent with respect to Period I to be entitled to all grant levels and only fee waiver, respectively. However, this increase is only 12.5 (8) percent if combined with the minimum average GPA incorporated in Period II for a student enrolled in a non-STEM (STEM) degree.

[72] 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 an A+.

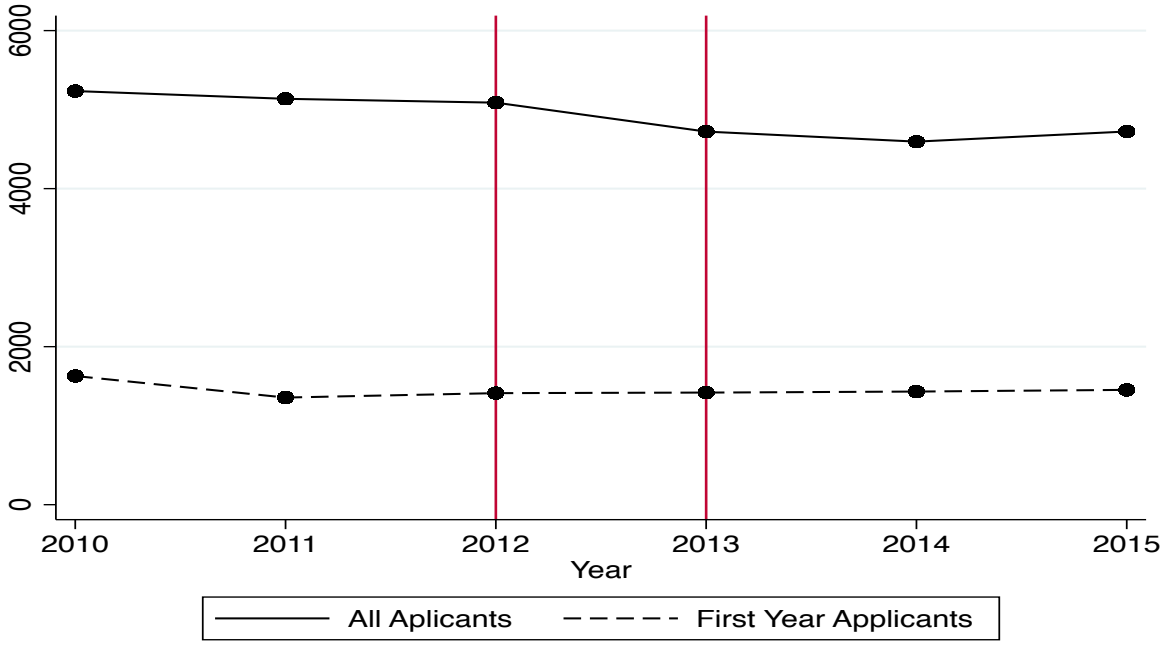
[73] A detailed summary of the policy change regarding minimum academic performance requirements is provided in the online appendix, section H.

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.

Figure Appendix A1: Number of applicants to BCG Grant between 2010–2015.



Notes: Total number of BCG applicants enrolled at Carlos III University over the period studied 2010–2015. The sample is constructed by the administrative database of undergraduate applicants to the BCG grant in Carlos III University over 2010–2015.

Table Appendix B1: McCrary (2008) Test for Manipulation of the Forcing Variable for the 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 (2010-2012)	.13 (.22)	.60	.06	.006	-.079 (.12)	.647	.10	.004
Total Applicants	Period II (2013-2015)	.18 (.23)	.79	.07	.006	-.107 (.13)	.80	.10	.004
B. By Gender									
Females	Period I (2010-2012)	-.14 (.43)	.33	.05	.009	-.06 (.17)	.34	.096	.006
	Period II (2013-2015)	.29 (.36)	.81	.05	.009	.004 (.23)	.02	.072	.006
Males	Period I (2010-2012)	.16 (.25)	.61	.07	.009	-.11 (.2)	.55	.074	.006
	Period II (2013-2015)	.18 (.36)	.49	.06	.008	-.03 (.18)	.16	.10	.006
C. By PAU Percentile Rank									
Above Median	Period I (2010-2012)	-.05 (.27)	.19	.07	.008	-.14 (.19)	.75	.07	.005
	Period II (2013-2015)	.05 (.28)	.17	.07	.008	-.096 (.19)	.48	.08	.005
Below Median	Period I (2010-2012)	.28 (.34)	.83	.07	.01	-.016 (.24)	.07	.06	.007
	Period II (2013-2015)	.20 (.43)	.47	.06	.009	-.016 (.22)	.07	.08	.007
D. By residence condition									
Living with parents	Period I (2010-2012)	.12 (.26)	.45	.07	.007	.075 (.14)	.52	.09	.005
	Period II (2013-2015)	-.11 (.29)	.39	.07	.007	.054 (.16)	.32	.09	.005
Living outside the family home	Period I (2010-2012)	.14 (.38)	.38	.07	.012	-.65 (.37)	1.76	.059	.008
	Period II (2013-2015)	.62 (.33)	1.87	.09	.01	-.46 (.29)	1.56	.078	.008

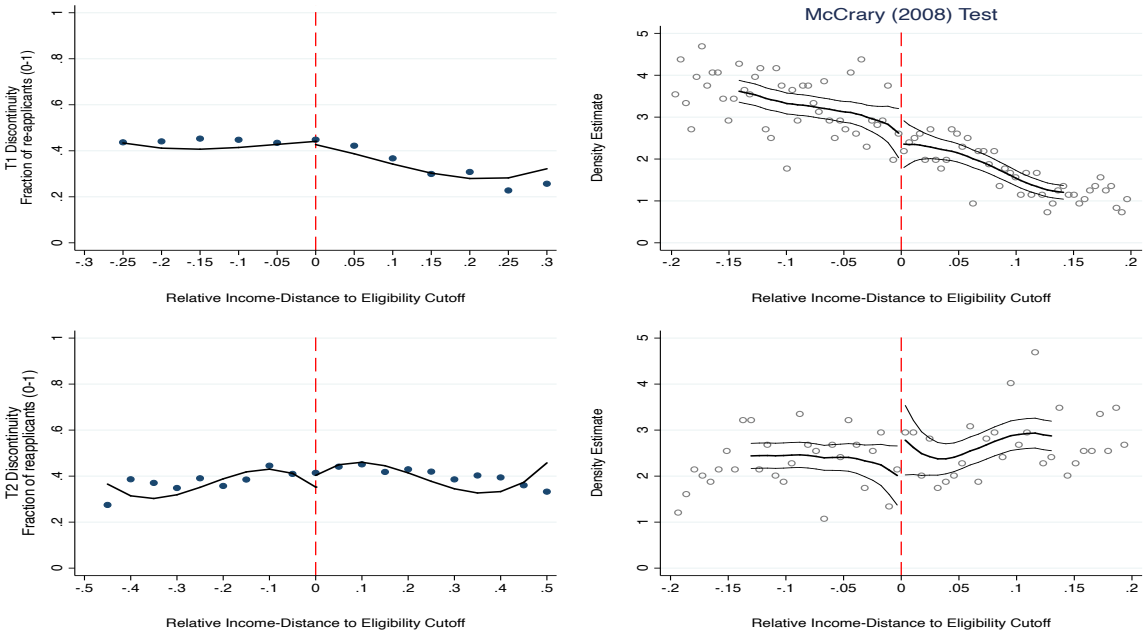
Notes: The McCrary test is performed separately for each treatment sample. The T1 treatment sample (columns 5, 6, 7 and 8) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1, 2, 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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 B2: 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

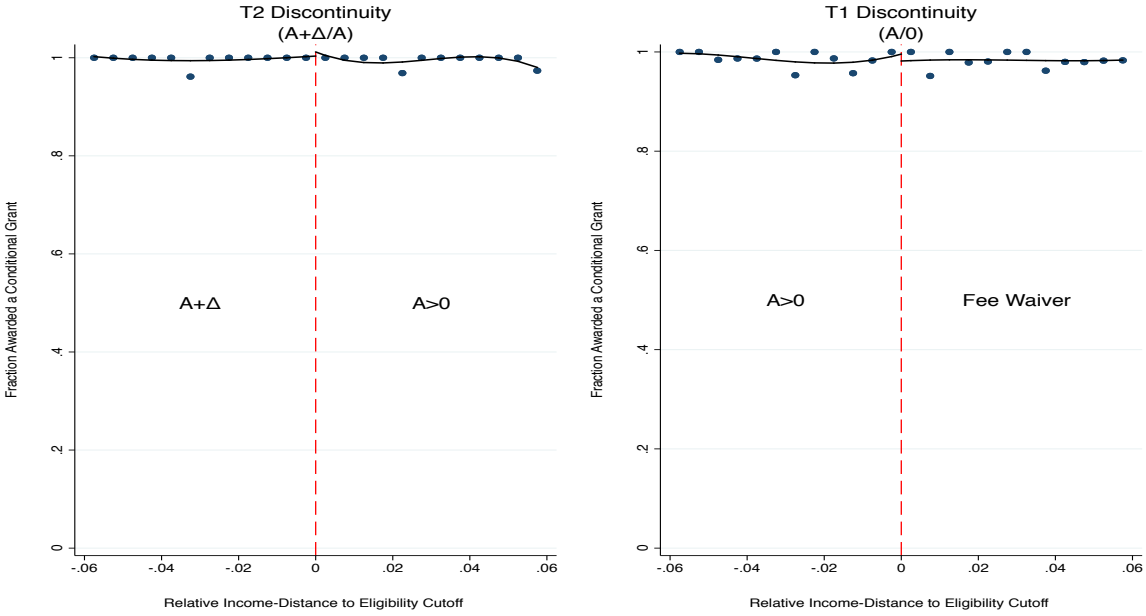
Notes: The McCrary test is performed separately for each treatment sample. The FW treatment sample includes applicants whose household parental taxable income is at the vicinity of the FW eligibility threshold. The T3 treatment sample includes applicants whose household parental taxable income is at the vicinity of T3 Grant eligibility threshold. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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.

Figure Appendix B2: 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.

Table Appendix C1: Average Allowance Amounts (in euros) at T1 and T2 Discontinuitys by Period and Subgroup Sample.

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. 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 subsamples. 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 (columns 2 and 3) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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 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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(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 (columns 2 and 3) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. 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 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	-0.092	0.057	-0.031	0.455***
Estimates	(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	-0.131	0.087	-0.054	0.490**
Estimates	(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	-0.158	0.013	-0.021	0.363***
Estimates	(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	-0.135	0.088	-0.001	0.501**
Estimates	(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 student individual controls and year fixed effects				
Non-parametric	-0.065	0.013	-0.159	0.273**
Estimates	(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	0.0026	0.1386		
Estimates	(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. Results are 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 above the eligibility threshold. The T1 treatment sample (columns 2 and 3) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. 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 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	-0.017	0.016	0.006	0.059***
Estimates	(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. Sensitivity Analysis				
B. 1 Half of the optimal bandwidth				
Non-parametric	-0.035	0.013	0.017	0.059**
Estimates	(0.041)	(0.037)	(0.028)	(0.030)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	0.779	0.805	0.769	0.787
B. 2 Twice of the optimal bandwidth				
Non-parametric	-0.021	0.002	0.003	0.046***
Estimates	(0.020)	(0.018)	(0.016)	(0.016)
	[3,400]	[3,284]	[6,087]	[5,855]
Baseline mean	0.779	0.805	0.769	0.787
C. RD Robust				
Non-parametric	-0.035	0.020	0.017	0.060**
Estimates	(0.041)	(0.029)	(0.028)	(0.030)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	0.779	0.805	0.769	0.787
D. Baseline estimates with student individual controls and year fixed effects				
Non-parametric	-0.010	0.012	-0.014	0.037**
Estimates	(0.024)	(0.024)	(0.017)	(0.019)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	0.779	0.805	0.769	0.787
E. Placebo test with midpoint between T1 and T2				
Non-parametric	0.0021	0.0150		
Estimates	(0.017)	(0.016)		
	[3,833]	[5,829]		
Baseline mean	0.777	0.809		

Notes: The table shows the RDD non-parametric estimates for applicants' fraction of credits earned. Results are 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 above the eligibility threshold. The T1 treatment sample (columns 2 and 3) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. 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 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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)
A. Baseline Estimates				
Non-parametric	143*	-75.927	0.146	-0.235
Estimates	(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)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(5)	(6)	(7)	(8)
A. Total Sample				
Non-parametric	730***	123	0.115	0.149
Estimates	(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	693***	56	0.200	0.172
Estimates	(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	888***	-240.677	0.095	-0.014
Estimates	(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 at the vicinity of FW eligibility thresholds. The T3 treatment sample includes applicants whose household parental taxable income is at vicinity of T3 Grant eligibility thresholds. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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 D4: Discontinuities in Average Awarded Grant, Average GPA, Fraction of Credits Earned and Dropout at T1 and T2 Grants in 2012.

Treatment Sample: (Income Eligibility Threshold)	**T2 Discontinuity** (A/0) (1)	**T1 Discontinuity** ($A + \Delta$/A) (2)
A. Average Allowance Amounts (euros)		
Non-parametric Estimates	2,792*** (213.989) [1,035]	657*** (141.691) [2,038]
Baseline mean	1,461	14.20
B. Average GPA (0-10)		
Non-parametric Estimates	-0.660 (0.401) [1,035]	-0.392 (0.298) [2,037]
Baseline mean	6.28	5.98
C. Fraction of Credits Earned (0-1)		
Non-parametric Estimates	-0.078 (0.054) [1,035]	0.017 (0.029) [2,037]
Baseline mean	0.81	0.77
E. Dropout from higher education		
Non-parametric Estimates	0.013 (0.011) [1,035]	-0.000 (0.010) [2,038]
Baseline mean	0.02	0.02

Notes: The table shows the RDD non-parametric estimates for the average allowance amount received and outcome variables at T1 and Te Grants 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: Multiple Hypothesis Testing for Outcome Variables. T1 Discontinuity in Period II.

Outcome Variable	**Effect**	**Naive p value**	**FDR 4 Hyp. p value**	**FDR All Hyp. p value**
Average GPA	0.455 (0.144)	.00154	.007	.024
Fraction of Credits Earned	0.059 (0.021)	.00485	.02	.034
Final Exam Attendance Rate	0.032 (0.010)	.00172	.007	.024
GPA on final exams taken	0.351 (0.129)	.00646	.026	.037
Fraction of Subjects in Retake	-.046 (0.018)	.0129	.052	.061
GPA on Mandatory Subjects	0.462 (0.152)	.00248	.01	.024
GPA on Elective Subjects	0.553 (0.385)	.152	.304	.532

Robust standard errors are clustered at the student level and displayed in parenthesis.

Notes: The table shows the adjusted p-values of baseline results using Benjamini and Hochberg (1995). "FDR 4 Hyp." refers to the adjusted p-values testing for all hypothesis by each outcome variable (four statistical hypothesis, one per period). "FDR All Hyp." shows p-values for all hypothesis of every outcome variable jointly (twenty-eight statistical hypothesis).

Table D6: Discontinuities in Average Awarded Grant, Average GPA, and Fraction of Credits Earned at T1 and T2 Grants including those students who were denied a grant for not meeting the academic criteria.

Treatment Sample: (Income Eligibility Thresholds)	**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)
	(1)	(2)	(3)	(4)
A. Average Allowance Amounts (euros)				
Non-parametric	2,798***	1,219***	569***	760***
Estimates	(148.626)	(115.425)	(85.439)	(34.873)
	[3,694]	[3,910]	[6,503]	[6,306]
Baseline mean	1,367	1,286	25.27	10.46
B. Average GPA (0-10)				
Non-parametric	-0.1948	0.0450	-0.1119	0.4627***
Estimates	(0.153)	(0.153)	(0.119)	(0.141)
	[3,694]	[3,910]	[6,503]	[6,306]
Baseline mean	5.9	6.14	5.9	6.1
C. Fraction of Credits Earned (0-1)				
Non-parametric	-0.0020	0.0129	-0.0051	0.0454**
Estimates	(0.025)	(0.025)	(0.019)	(0.019)
	[3,694]	[3,910]	[6,503]	[6,306]
Baseline mean mean	0.77	0.79	0.77	0.78

Notes: The table shows the RDD non-parametric estimates for the average allowance amount received and outcome variables at T1 and T2 Grants 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 D7: Discontinuities in Average GPA (0-10) at Different Income Eligibility Thresholds and Periods by 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					
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 on average GPA for the different subgroups of applicants. 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 (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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 D8: Discontinuities in the Fraction of Credits Earned (0-1) at Different Income Eligibility Thresholds and Periods by 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

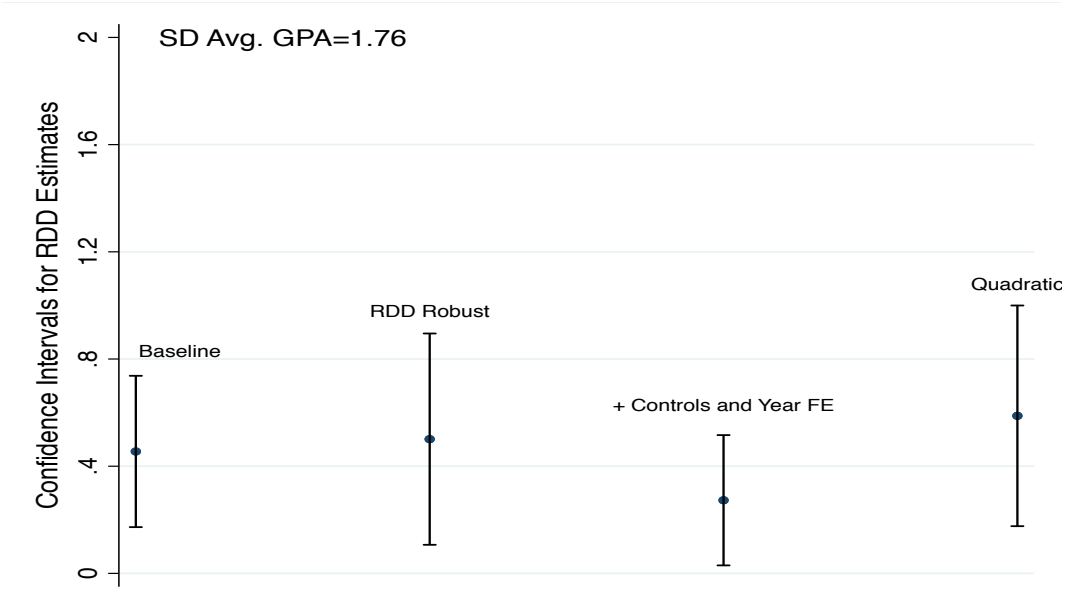
Notes: The table shows the RDD non-parametric estimates on fraction of creadits earned the different applicants' subgroups. The treatment effect is estimated using a triangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. The T1 treatment sample (columns 3 and 4) includes applicants whose household parental taxable income is at the vicinity of cutoff of T1 Grant. The T2 treatment sample (columns 1 and 2) includes applicants whose household parental taxable income is at the vicinity of cutoff of T2 Grant. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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 D9: Discontinuities for the mechanisms variables at T1 and T2 grants by period and term.

Treatment Sample: (Income Eligibility Thresholds)	**First Term (Fall)**				**Second Term (Spring)**			
	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) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)	**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								
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

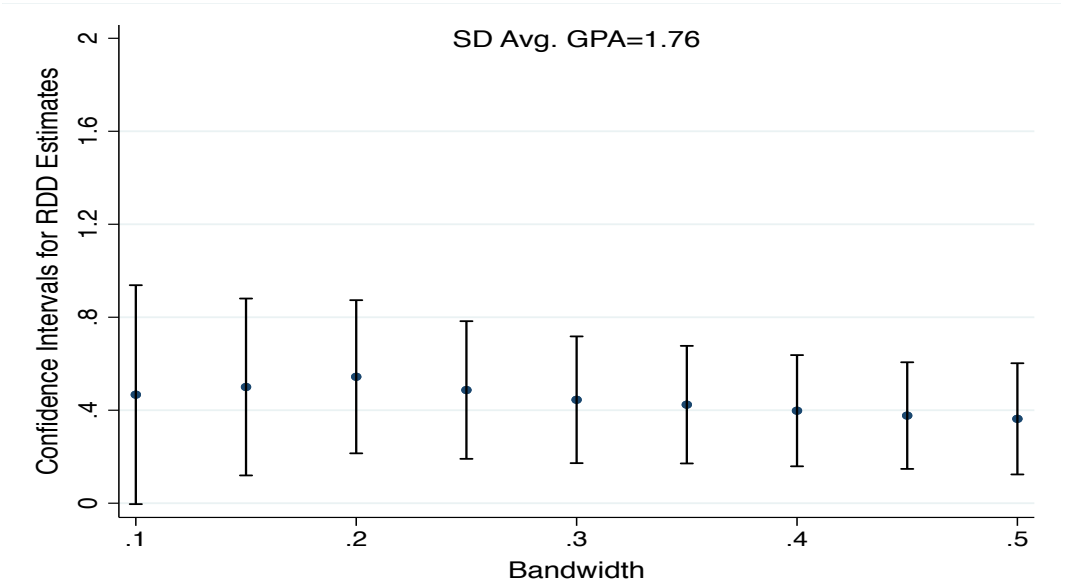
Notes: The table shows the RDD non-parametric estimates for the student performance variables. The treatment effect is estimated using a triangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. Robust standard errors are clustered at the student level and displayed in parenthesis. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure Appendix D1: RDD Estimates for Different Specifications at T1 Discontinuity in Period II.



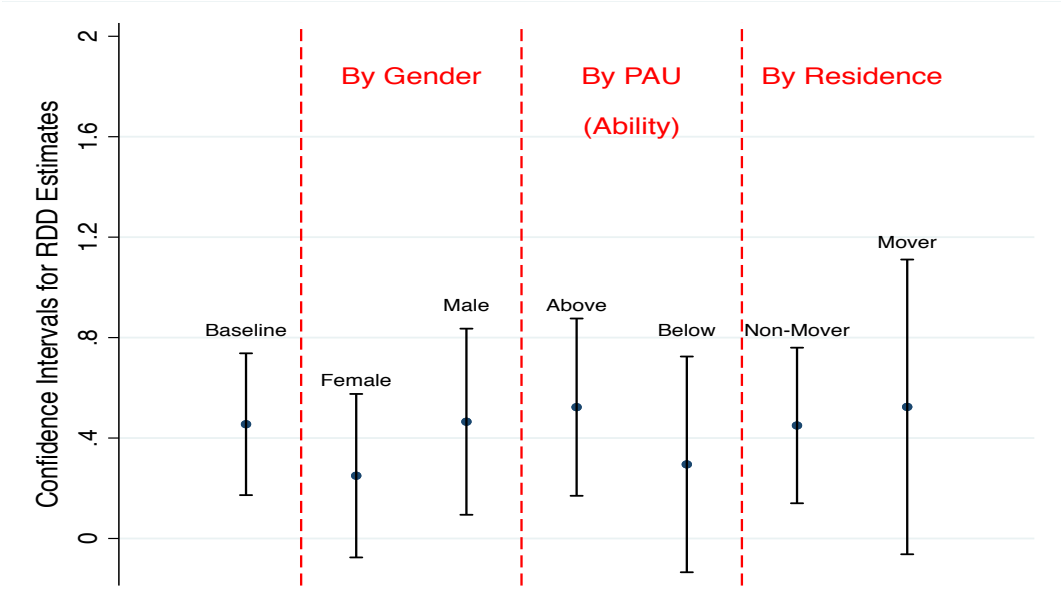
Notes: The dots represent the point estimates of the RDD non-parametric regressions. Vertical lines depict confidence intervals at the 95% level of confidence.

Figure Appendix D2: RDD Estimates for Different Bandwidths Size at T1 Discontinuity in Period II.



Notes: The dots represent the point estimates of the RDD non-parametric regressions. Vertical lines depict confidence intervals at the 95% level of confidence.

Figure Appendix D3: RDD Estimates for Subgroup of Population at T1 Discontinuity in Period II.



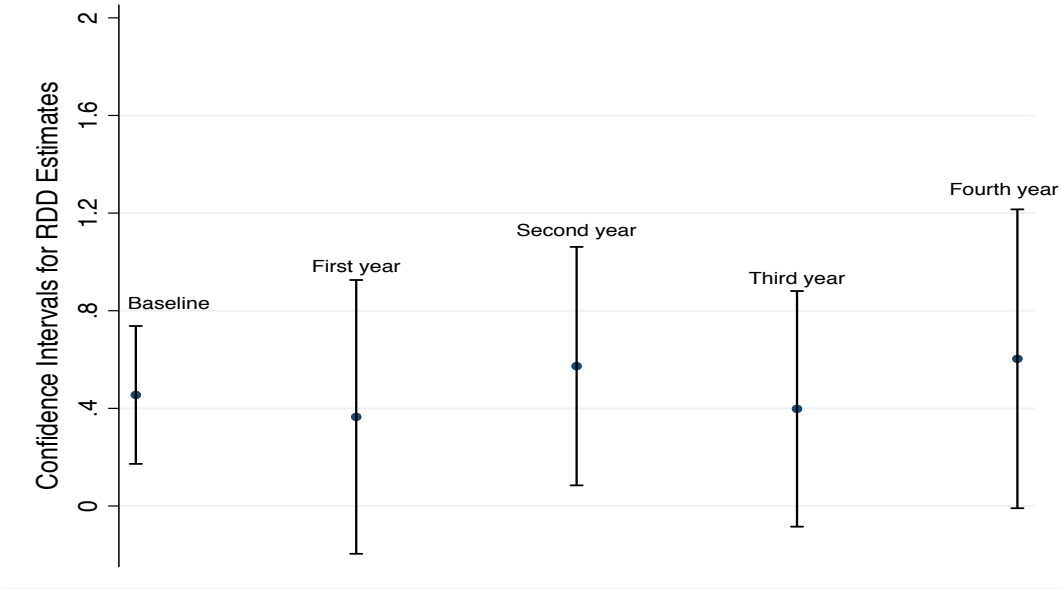
Notes: The dots represent the point estimates of the RDD non-parametric regressions. Vertical lines depict confidence intervals at the 95% level of confidence.

Figure Appendix D4: McCrary (2008) test at the GPA cutoff.



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 GPA cutoffs. Optimal bandwidth and bin size are computed by McCrary (2008) selection procedure. 'Relative Academic-Distance to Eligibility Cutoff" refers to the relative distance of student academic performance to the minimum GPA thresholds.

Figure Appendix D5: RDD Estimates for Undergraduate Course at T1 Discontinuity in Period II.



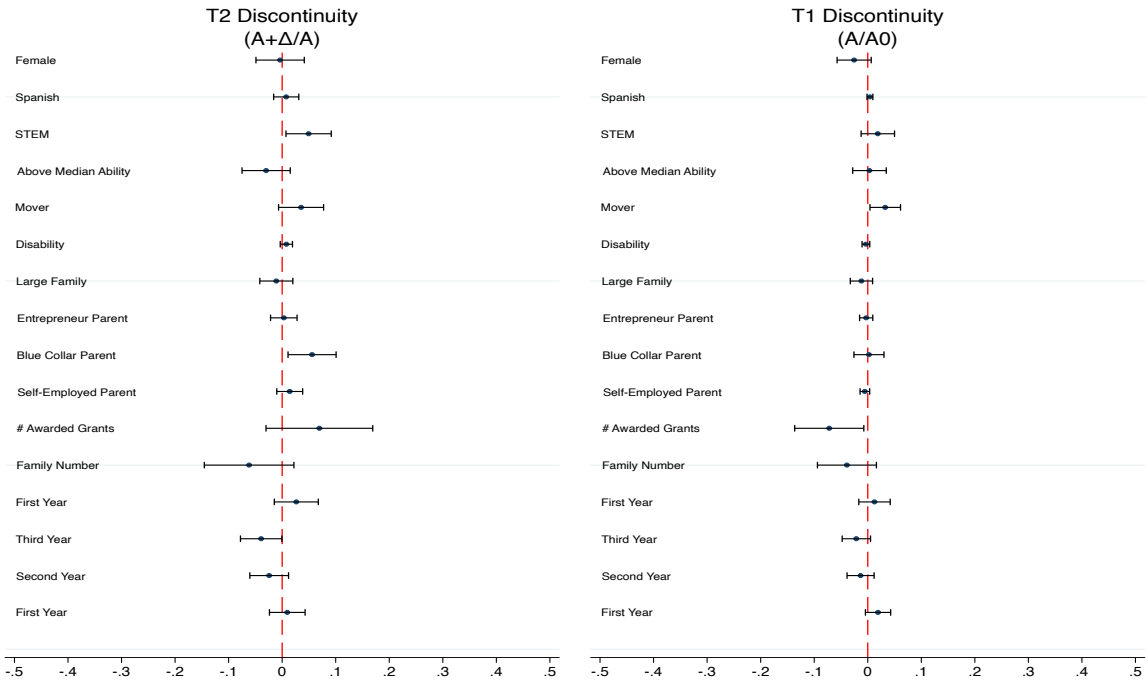
Notes: The dots represent the point estimates of the RDD non-parametric regressions. Vertical lines depict confidence intervals at the 95% level of confidence.

Table E1: RDD-DID Estimates at T1 and T2 Discontinuities.

Treatment Sample (Income Eligibility Thresholds)	**T2 Discontinuity** ($A + \Delta$/A)	**T1 Discontinuity** (A/0)
A. Average Allowance Amounts (euros)		
Non-parametric Estimates	-1,693*** (173.432)	121.9168 (85.365)
Baseline mean	1,481	25.89
B. Average GPA (0-10)		
Non-parametric Estimates	0.1389 (0.232)	0.3162** (0.148)
Baseline mean	5.971	5.908
C. Fraction of Credits Earned (0-1)		
Non-parametric Estimates	0.0307 (0.028)	0.0505** (0.023)
Baseline mean	0.779	0.769
D. Official Dropout (0-1)		
Non-parametric Estimates	0.0149 (0.015)	-0.0190 (0.018)
Baseline mean	0.02	0.03
E. Degree Completion (0-1)		
Non-parametric Estimates	0.0075 (0.047)	0.0964* (0.056)
Baseline mean	0.93	0.91
N	6,951	11,965

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

Figure Appendix F1: T-test of Applicant's Observable Characteristics across Periods at T1 and T2 Discontinuities.



Notes: The dots represent the point estimates of the RDD non-parametric regressions. Horizontal lines depict confidence intervals at the 95% level of confidence. The red stripes reflect the two income-eligibility thresholds for T1 and T2 Grants. T1 and T2 discontinuities treatment samples are defined as 15 percent of the relative distance to the income-eligibility thresholds, the typical optimal bandwidth proposed by Imbens and Kalyanaraman (2012).

Table F1: Summary Statistics by Period and Treatment Sample.

	T2 Discontinuity		**T1 Discontinuity**	
	Period I (2010-2012) (1)	**Period II (2013-2015)** (2)	**Period I (2013-2015)** (3)	**Period II Period II** (4)
Frac. Female	0.48	0.48	0.47	0.47
Frac. Spanish	0.93	0.92	0.98	0.98
Frac. STEM	0.33	0.35	0.38	0.38
Frac. Above Median Ability (PAU)	0.56	0.51	0.59	0.57
Frac. Living outside family primary residence	0.31	0.33	0.27	0.3
Frac. Disability	0.02	0.03	0.01	0.01
Frac. Large Family	0.15	0.16	0.12	0.12
Frac. Entrepreneur Parent	0.07	0.09	0.05	0.05
Frac. Blue Collar Parent	0.42	0.45	0.31	0.33
Frac. Self-Employed Parent	0.07	0.08	0.03	0.03
# Awarded Grants	1	1	0.80	0.8
# Family Number	3.7	3.7	3.6	3.6
Frac. First Year	0.29	0.31	0.31	0.31
Frac. Second Year	0.24	0.21	0.23	0.22
Frac. Third Year	0.21	0.20	0.20	0.19
Frac. Fourth Year	0.16	0.18	0.15	0.18
N	3,402	3,549	6,095	5,870

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 a relative distance of 50 percent of the eligibility thresholds between fee waiver and T1 Grant allowance. The T2 treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between T1 and T2 Grants allowances. The variable "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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.

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 "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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 "Living outside the family primary residence" refers to the fraction of applicants who live outside the family primary residence , 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

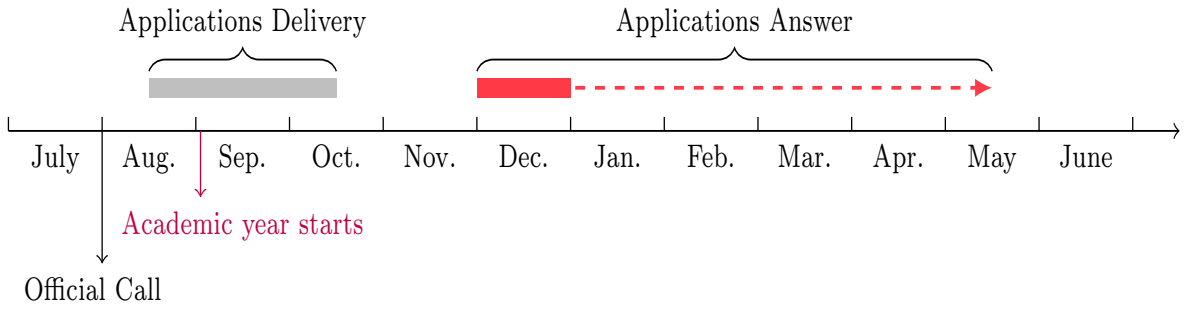
Notes: Treatment refers to the group of students whose performance is in between academic requirements of Period II (2012) and Period I. These students would meet the requirements in Period I, but not in Period II (2012). Student controls include all the student predetermined observable characteristics 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 Minimum Academic Requirements.

	Fraction of pass credits in the last academic year over 60 ECTS		Average GPA		Grant rights
	STEM	Humanities and Social Sciences	STEM	Humanities and Social Sciences	
A. Non-First year students					
Before 2012	60%	80%	None	None	All
2012	65%	90%	None	None	All
2013 onward	85%	100%	None	None	All
	65%	90%	>=6	>=6.5	All
	65%	90%	<6	<=6.5	Only Fee Waiver
B. First year students					
	Average Grade in PAU				Grant rights
Before 2013	5/10				All
2013 onward	6.5/10				All
	5.5/10				Only Fee Waiver

Notes:

Figure Appendix H1: BCG Grant Application Process.



Variable component formula.

$$C_j = C_{min} + \left[(C_{total} - S * C_{min}) * \frac{(N_j/N_{max} * (1 - (\frac{R_j}{R_{max}}))}{\sum_{i=1}^{S} (N_i/N_{max}) * (1 - (\frac{R_i}{R_{max}})} \right] \tag{12}$$

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.