CESifo Working Papers
10010 2022
October 2022

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
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CESifo *Working Paper No. 10010*

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Abstract

Financial aid decreases the cost of acquiring additional education. By using Italian administrative and survey data on financial aid recipients and exploiting sharp discontinuities in the amount of aid received, this paper identifies the causal effect of aid generosity on college performance and labor market outcomes. The results show that students with a higher cost of college earn more credits each year than those receiving higher financial aid. This gap generates a significant difference in the overall graduation time. No differences emerge in the GPA level or in the probability of working during college. After graduation, lower-aid recipients have a similar probability of continuing to study and of working after college as higher-aid beneficiaries. However, they secure a better job match in terms of working hours and payment but also in terms of skills matching.

JEL-Codes: H750, I220, I260, J240.

Keywords: human capital, financial aid, labor market outcomes, regression discontinuity design.

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I would like to thank Maria Bigoni, Massimiliano Bratti, Daniele Checchi, Margherita Fort, Osea Giuntella, Andrea Ichino, Enrico Rettore who gave useful suggestions in several discussions. I am also grateful to the seminar participants at the University of Milan, the University of Pittsburgh, the University of Bologna, the EALE 2021 Conference, and the 2nd Human Capital Workshop of the Bank of Italy, for their comments and suggestions. Finally, I would like to thank ER.GO and the University of Bologna for the data disclosure.

1 Introduction

Higher education is often promoted to foster individual development and to increase the wealth of society more generally. Given the extensive private and social returns resulting from human capital investments, many countries offer financial aid programs meant to broaden access to tertiary education (OECD, 2019), particularly through grants targeting low-income students.[1] From a theoretical point of view, financial aid programs, by decreasing the price of college, should induce an increase in the demand for tertiary education. While the relationship between these types of monetary incentives and enrollment is theoretically clear, the effects of this liquidity provision on performance after enrollment are more ambiguous, especially considering the interdependence between the effects generated by program generosity and the minimum academic requirements.[2] This is indeed a central problem in the design of an efficient financial aid policy since higher financial incentives attached to weak requirements may encourage the enrollment and persistence of students who underperform in college, creating moral hazard concerns. However, less generous incentives can have the unintended side effect of inducing some students to drop out or to work during college (Schudde and Scott-Clayton, 2016).

Despite the relatively extensive literature on the effects of financial aid, this is the first paper to isolate the sole impact of grant generosity on both short- and medium-run outcomes since previous empirical evidence usually captures the combined impacts of aid amounts and of the minimum academic requirements, focusing mostly on academic performance during college. One exception is Montalbán (2019), who uses a reform of the Spanish financial aid system to isolate the effect induced by a change in the minimum academic requirements from the total effect of financial aid on the performance of students during college; however, this study does not provide any evidence on the effect of the reform on the labor market outcomes of the recipients.[3] Therefore, relatively little is known about the long-run return on investments for

[1] Examples of financial aid grants based on students' parental income are the "Maintenance Grant" in the UK, the "Becas" grant in Spain, the "Pell Grant" in the US, the "Bourses sur critéres sociaux" in France, and the "Right to Study" program in Italy. Although all of these large-scale national programs typically grant tuition fee allowances and cash transfers to students based on their family income, they are subject to different eligibility criteria and minimum academic requirements for the renewal.

[2] For a detailed discussion on the effects of financial aid on after-enrollment performance see Fryer et al. (2011). While the trade-off between minimum academic requirements and performance has been analyzed in the principal-agent model build on Bénabou and Tirole (2000) and Bénabou and Tirole (2002) and extended with academic standards and financial aid by Schudde and Scott-Clayton (2016).

[3] The recent paper by Agasisti et al. (2021) also disentangles the effects induced by a change in the merit requirements in a need-based program in the Italian context, findings similar results to Montalbán (2019) on medium- and high-ability students. However, besides focusing only on a change in the requirements (and not in

these government inputs.

This paper aims to fill this gap by assessing the impact of Italy's single largest need-based aid program, called the "Right to Study" (RTS) program, using administrative and survey data on the universe of students applying for RTS aid over the period 2009-2013 at the University of Bologna, which is one of the largest public universities in Italy[4]. In particular, the administrative data have measures of performance during college – yearly credits, GPA, drop-out and re-enrollment rates, and graduation time – and they can be linked to the survey data on the RTS recipients' labor market outcomes after graduation – unemployment and full-time employment probabilities, monthly salary, and several measures on the skill-match between the job position and the graduating major.

By exploiting a sharp discontinuity in the amount of aid received across the eligibility threshold through a regression discontinuity design (RDD), this paper is able to identify the causal impact of aid generosity on student outcomes while controlling for the effects induced by the minimum academic requirements attached to the program and by other relevant factors. Furthermore, by linking administrative microdata with "AlmaLaurea" survey data on the labor market performance of the graduates, this paper also isolates the causal impact of financial aid generosity on the labor outcomes of recipients one year after graduation.[5] Notice that while this time span does not allow us to properly look at the earning profiles of the graduates, it offers the main advantage of studying the effect of financial aid on the quality of the job match at first employment, which indeed mainly depend on the educational path of the candidates – and it is not confounded, for example, by experience, know-how, or job-training practices – and it has large and persistent effects on future careers (Von Wachter, 2020).

The results show that receiving approximately €3,500 extra in terms of aid decreases the number of credits obtained in the first year of college by approximately 9 credits (about 1 and a half courses), which corresponds to 15% of the total credit load at the first year and to 28% of the baseline performance. This gap in performance persists over time, significantly slowing the

the generosity of the program, which is th main focus of this paper) also this study does not provide any evidence on after-graduation outcomes.

[4]The University of Bologna is one of the most prestigious universities in Italy, often appearing first in national rankings. In 2020 Bologna topped Italy's main ranking of the large public universities (> 40,000 students) for the eleventh year in a row (Censis, 2020). Each year, the university attracts more than 85,000 students, and it is the second biggest University in Italy in terms of the student population. See the last available data from the Ministry of Education, Research and University (MIUR): https://anagrafe.miur.it/php5/home.php?&anni=2019-20&categorie=ateneo&status=iscritti&tipo_corso=TT&&order_by=i

[5]Bagues and Labini (2009) show that the "AlmaLaurea" survey data on the labor market performance of the college graduates are representative of the underlying population under many levels (gender, age, high school grade) and institutional characteristics (number of students per university and course, share of delayed students).

degree completion of highly subsidized recipients. By the end of the last year of college, these students have indeed a higher graduation time by approximately 8-12 months (depending on the specification used).[6] In contrast, I find no strong effects of aid generosity on GPA or drop-out rates.[7] When looking at the after-graduation outcomes, I find that higher-aid recipients are equally likely to continue studying than lower aid recipients, and no differences emerge in the probability of working either before or after graduation. However, higher-aid recipients secure worse job matches, both in terms of working hours and payment and in terms of skills matching.

This paper contributes to the financial aid literature from several perspectives. In particular, previous studies analyzing the impact of need-based financial aid programs have often compared eligible candidates with ineligible candidates. However, these two groups of students not only receive distinct amounts of aid but are also subject to different minimum performance requirements. For example, for the Federal Pell Grant, which is the largest need-based financial aid program in the United States, initial eligibility is computed purely on the basis of financial need, but eligible candidates have to meet certain satisfactory academic progress (SAP) requirements. Therefore, the estimated effect of the Pell Grant on the performance of eligible candidates, when using ineligible students as controls, is a combination of two mechanisms: the cost-of-college and minimum academic requirements (Scott-Clayton and Schudde, 2020).[8] Another classical problem in the financial aid literature is indeed the difficulty in separating the unique effect of financial aid from all the other factors influencing college and labor market outcomes. For example, students with low socioeconomic backgrounds tend to attend lower-quality schools, have fewer learning inputs, and have less support from their parents for their education and initial labor marker experience (Checchi

[6]This result is indeed in line with Garibaldi et al. (2012), who study the effects of an increase in college cost on on-time completion rates at a private University in Italy. The authors find that those students, who may potentially pay a higher fee for an additional extra year of education, have higher incentives to finish on-time. The results are also in line with the literature showing that financial aid programs work through incentives on academic achievement, and not simply through the relaxation of the budget constraints (Montalbán, 2019; Scott-Clayton, 2011). In particular, since the RTS financial aid sets a minimum number of credits which, at the first year, is equal to 41%-50% of the total load, subsidized students target these requirements and under-perform with respect to those having a higher cost of college. Notice also that the RTS program do not impose any minimum requirements on the GPA level.

[7]This result is in line with Mealli and Rampichini (2012) and with Sneyers et al. (2016), who find no effects of the "Right to Study" grant on students' drop-out.

[8]See also Castleman and Long (2016). Notice that Scott-Clayton and Schudde (2020) and Schudde and Scott-Clayton (2016) also suggest that the high academic requirements attached to the Pell Grant makes this need-based program indirectly become a merit-based aid, therefore it becomes hard to disentangle the impact on performance induced by the aid generosity from that of the minimum academic requirements, per se. The study by (Anderson, 2020) instead looks at the effect of the Wisconsin Grant on students enrolled in technical colleges, but, as the author pointed out, the recipients could also apply for the Pell Grant (or federal loans) and be therefore subject to the SAP requirements.

et al., 1999). Moreover, more able students could self-select into the treatment. This is indeed a major concern for merit-based grants, which typically target high- or medium-achieving students, and it is the setting from which most of the current evidence is drawn (Barrow et al., 2014; Bettinger et al., 2019; Cornwell et al., 2006, 2005; Dynarski, 2008; Scott-Clayton, 2011; Scott-Clayton and Zafar, 2019). Consequently, it is often difficult to generalize these results to the full population of college students.[9] In the case of the RTS program, which is indeed the largest government intervention in Italy, financial aid for tertiary education is offered on the basis of parental income only. Aid is also renewable each year subject to meeting specific minimum academic requirements, which do not vary with the aid generosity. Furthermore, the comparison is made within very similar family income brackets. Therefore, the effects of aid generosity on performance are identified by looking at students with comparable family income, while controlling for their ex-ante ability, as captured by the final high school grade.

Moreover, most of the existing work on need-based grants captures the joint impact of financial aid generosity and of academic requirements on academic performance *during* college: enrollment, dropout, persistence, and graduation (Bettinger, 2015; Castleman and Long, 2016; Denning, 2018; Dynarski, 2003; Fack and Grenet, 2015; Goldrick-Rab et al., 2016; Modena and Tanzi, 2020; Murphy and Wyness, 2016). Few studies have examined how financial aid influences recipients' career paths. Some papers have looked at the likelihood that students awarded with merit-based aid continue to reside in the same location, finding small and sometimes insignificant results (Fitzpatrick and Jones, 2012; Sjoquist and Winters, 2013). The paper by Bettinger et al. (2019) finds that at ages 28-32, the "Cal Grant" merit-based grant recipients are more likely to live in California and to have higher earnings. The study by Scott-Clayton and Zafar (2019) shows that the merit-based "WV PROMISE" scholarship increased the likelihood of graduating, of buying a house, of living in a rich neighborhood, and of having better finances than nonrecipients, although the latter effect is imprecisely estimated. By using administrative data from Texas colleges, Denning et al. (2019) show that the eligibility for the Pell Grant – which, in addition to being attached to certain academic requirements, in their setting is also affecting the eligibility for the "TEXAS" Grant, for federal loans, and for other grants – increases the income tax payments of the awarded students, with the government grant expenditures being fully recovered within ten years. Notice, however, that, the vast majority of these studies – in addition to estimating the joint

[9] Not to mention that several evaluations focus on narrowly defined programs, implemented mostly in the US and in a specific University or State (Dynarski, 2008; Dynarski and Scott-Clayton, 2013) or they include the impact of other treatments – such as tutoring services – therefore making it difficult to isolate the sole effect of aid generosity (Angrist et al., 2009, 2014).

impact of aid generosity and of academic requirements – have focused on US merit-based programs, and on a limited set of labor market outcomes after graduation. Therefore, it is unclear whether these results would apply to a large-scale need-based program – awarded only on the basis of student financial need – in the European context, which has very different institutions and labor market structures. Moreover, while this paper does not study the long-run effects of financial aid on the earning profiles of graduates, it offers the main advantage of examining a broader set of first-employment outcomes, which are mainly determined by the educational career of the candidates and are not confounded by other factors (such as experience, know-how, or job-training practices).

Overall, this paper makes several contributions to the literature on financial aid. First, by linking administrative microdata on the universe of students applying for a need-based grant in one of the largest universities in Italy to labor market performance one year after graduation, this paper analyzes both the short-term (during college) and medium-term (after graduation) impacts of a large-scale policy covering low-income students in Europe. Second, this setting allows us to properly disentangle the impact of aid generosity from that induced by the minimum academic requirements, clarifying the extent to which aid amounts contribute to the total effect of financial aid. Third, when looking at the effects of financial aid on the labor market performance of the recipients, this paper looks at several outcomes – such as the type of employment contract (full-/part-time), the probability of being employed, and some indexes for over-education and skill mismatch – therefore better clarifying how financial aid affects both the extensive and intensive margins of the work decision, as well as the quality of the job matches.

The paper is organized as follows. Section 2 analyses the institutional framework and Section 3 describes the data and the methodology. In Section 4, I will present and discuss the causal effects of financial aid generosity on different measures of academic achievement and labor market performance. Section 5 presents the robustness checks performed, and Section 6 concludes.

2 The Institutional Framework

2.1 Higher education in Italy

Tertiary education in Italy is accessible to students with a high school diploma, independent of the type of diploma obtained (lyceum, technical, vocational), and it is mostly characterized by public institutions.[10] Students can decide to enroll either into a bachelor's degree program of three years, or five years (dentistry, veterinary medicine, pharmacy, architecture, construction engineering, law), or six years (medicine); after having completed the bachelor's degree, students can enroll in a two-year Master of Science degree or in a one-year Master of Arts degree; only the Master of Science grants access to a Doctoral degree, which typically lasts from three to four years. Public universities are not selective, as the only requirement for admission is to have graduated from high school. However, enrollment in certain majors is limited since there are only a fixed number of seats available.

The cost of tertiary education in Italy is mainly driven by tuition and by living expenses and was estimated to be approximately €12,000 per year in 2019 (OECD, 2019), representing, therefore, a potential constraint for low-income students' enrollment in tertiary education. To meet the goal of providing equal opportunity and fair access, all public universities in Italy must offer the RTS financial aid program. Generally, the program includes different types of services: services for people with a disability, vouchers for educational programs (master's degree, higher-level education, etc.), fiduciary loans, part-time working opportunities, and allowances for international mobility. In addition to these forms of aid, which cover only a tiny fraction of students, the program offers full scholarships and several levels of grants, as well as many tuition discounts to students enrolling in a public university.[11] The total cost for RTS scholarships and grants amounts to approximately €800 million in 2020 (Ghizzoni, 2021). From this perspective, it is quite important to know how these publicly financed benefits shape students' incentives and whether they have any effects on their academic achievement and subsequent labor market performance. This question is of paramount importance in Italy, given that student performance in higher education is below average. It has been estimated that 42% of students are "Fuori Corso" in bachelor's degree programs – i.e., they have stayed in the system beyond the legal length of the degree program – and that the average time to complete a bachelor's degree is 4.2 years instead of 3, and 2.8 years instead of 2 years for a master's degree.[12]

[10] In 2018, private institutions accounted for less than 12% of total enrollment in tertiary education (MIUR – Ministry of Education, University and Research).

[11] In Italy, the share of first-cycle full-time students taking out publicly-subsidized loans is less than 1%, while the share of students receiving a full scholarship and a grant jumps to around 18% for students – with a minimum of 10% to a maximum of 25% depending on the institution (Kocanova and Crosier, 2018).

[12] AlmaLaurea – Annual Report on University Graduates 2019.

2.2 The *Righ to Study* Financial Aid Program

The RTS financial aid program is offered at each public university, and the law entitled "DPCM April 9th 2001" established that each regional government has the right to set its own RTS eligibility thresholds but that all thresholds must lie within the range established by the central government.[13] In the Emilia-Romagna region, which is the region where the University of Bologna is located, the public entity in charge of RTS aid is called "ER.GO", and since 2008, the region has fully covered all financial aid applicants – a 100% coverage rate.[14]

In what follows, I describe the structure of the benefits offered by the RTS program, starting with the design of the grant assignments and then moving to the tuition discount scheme. The RTS program assigns different grant amounts using three eligibility thresholds, which are based on an index of family income, i.e., the Equivalent Economic Status Index (ISEE). Furthermore, eligibility is always conditional on being below a maximum value of the wealth index, the Equivalent Patrimonial Status Index (ISPE), which should not exceed €60,000.[15] In addition to this annual cash allowance, the recipients of the RTS grant are also exempt from paying any tuition, namely, they receive a full scholarship. Panel A of Table 1 summarizes how the RTS grants vary with the ISEE eligibility thresholds.[16] Notice that the grant amount also varies with the distance between the student residence and the University campus: "in sede", which identifies students who live in the city where the university campus is located or who do not live more than 45 minutes away from the campus (by public transport); "fuori sede" or students who live more than 90 minutes away from the campus; and "pendolari" or commuting students, identifying those who live from 45 to 90 minutes away.

The RTS programs also allow students with an ISEE index just above €19,152.97 and an ISPE index below a maximum of €60,000 to apply for a tuition discount, following the scheme

[13]This indeed generates some differences across regions in tertiary education accessibility for low income students. Moreover, in some regions the call for application for the RTS benefits is carried out by the single institution (or by a group of institutions) and not by the central regional government – namely in the region of Abruzzo, Calabria, Sardinia, Sicily and Trentino Alto Adige, Veneto and Lombardy – therefore there might be some inequalities in access even within the same region Ghizzoni (2021).

[14]The University has a multi-campus structure, with eight campuses in the regional territory, and its main campus in Bologna.

[15]The ISEE represents the previous-year annual after-tax family income plus 20% of the family liquid assets, and it is adjusted by family size using an equivalence scale. The ISPE is instead an index based only on the family assets (financial assets and real properties), and it is also adjusted to family size by means of the same equivalence scale. The information on the family income and wealth indexes is subject to legal verification from the agency in charge of the financial aid program and the calculus of the indexes must be certified by a professional institution.

[16]Notice that the awarded cash amount of the RTS scholarship is similar to other European financial aid programs, such as the "Becas" grant in Spain and the "Bourses sur critéres sociaux" in France.

Table 1: RTS Financial Aid

Panel A: RTS Grant Assignment

ISEE Thresholds	"Fuori Sede"	"Pendolari"	"In Sede"
Up to €12,713.21	€5,073.78	€3,043.88	€2,255.11
From €12,713.21 to €15,386.29	€3,942.83	€2,420.89	€1,828.83
From €15,386.29 to €19,152.97	€2,811.88	€1,796.93	€1,402.53

Panel B: RTS Tuition Fee Discount Assignment

ISEE Thresholds	Fess Discount
From €19,152.98 to €22,500	50%
From €22,501 to €26,000	40%
From €26,001 to €30,000	30%
From €30,001 to €35,000	20%
From €35,001 to €40,000	10%

described in Panel B of Table 1.[17] To summarize, all the students with an ISEE below €19,152.97 are exempted from paying any tuition, and they receive a grant.[18] Those students with a family income index greater than €19,152.97 do not receive any grant and they have to pay a share of the total tuition fees – from 50% to 90% depending on the family income index. Therefore, students positioned slightly above and below the €19,152.97 threshold receive extremely unequal benefits: on average, the difference in financial aid is approximately €3,500, given by an average grant of €2,004 plus the 50% percent difference in the tuition fee discount, namely approximately €1,500.[19] Figure 1 summarizes how the RTS financial aid amount changes with the level of the family income indicator, ISEE.

The aid discontinuity at the €19,152.97 of the ISEE threshold provides the main source of exogenous variation that this paper exploits to identify the effect of financial aid generosity on the performance of students during and after college. Notice that the RTS aid application opens each year in early June and closes at the end of August, just before the start of the academic year. The preliminary eligibility results are published in early November, while the final results are published online around mid-December. The first installment of the benefit (50% of the yearly aid) is paid at the end of the calendar year, while the second half of the incentive is paid around mid-March. As previously discussed, all RTS aid recipients are subjected to the same minimum performance requirements, which are known ex ante and do not vary with the level of benefit received. Therefore, if students do not satisfy the requirements they must return the aid received and they could not apply as second- (or third-) year enrollees. Table 2 shows the total credit load and the minimum credit requirements at each year of study and by type of degree. Specifically, bachelor's students must obtain 25 credits (out of 60) by the end of the first academic year, and master's students must obtain 30 credits (out of 60) by the end of the first academic year. By the end of the second year, recipients are required to have a cumulative sum of at least 80 credits, both at the bachelor's and master's levels. At the end of the third year, bachelor's students can obtain additional aid to cover an extra six-month period, but they must have obtained at least 135 credits (out of a total of 180) in the previous three years.

[17] The eligibility thresholds of the tuition fee discounts slightly increased in the academic year 2010/2011, see table A1 of the Appendix. However, these changes do not represent a problem for the estimation, since they are unannounced and modest in value.

[18] The grant amount varies with the ISEE index and the student status, and it goes from a minimum of €1,402.53 to a maximum of €5,073.78, see Panel A of Table 1.

[19] The average grant amount is computed by taking into account the population share of the "Fuori Sede","Pendolari" and "In Sede" students within each income bracket. While the estimate of the average tuition fee discount is computed using the data on the average tuition from the *7th Report on the costs of the Italian universities* of the national non-profit organization "Federconsumatori".

Table 2: Credits Load and Requirements by Years and Programs

Panel A: Credit Load

Type of course	1st Year	2nd Year	3rd Year
Bachelor	60	120	180
Master	60	120	-

Panel B: Credit Requirements

Type of course	1st Year	2st Year	3rd Year
Bachelor	25	80	135
Master	30	80	-

3 Data and Methodology

3.1 Data

The administrative data are provided by the regional entity in charge of the RTS program in the Emilia-Romagna region (ER. GO) and by the University of Bologna. The data include the universe of financial aid recipients enrolled in any of the twenty-three faculties of the University of Bologna and it contains detailed information on the characteristics of the recipients: their family income and wealth indexes – i.e., the ISEE and the ISPE – their academic performance – measured both in terms of quantity (credits) and quality (GPA)– their demographic characteristics (age and gender), their high school grade, their macroregion of origin (north, center, south, or the Islands), their major of study and degree level (master or bachelor), the type of grant obtained ("in sede", "fuori sede", or "pendolari"), and the tuition discount received ("100%","50%","40%", etc.). The data cover the students enrolled in the 2009/2010 and 2010/2011 academic years, following them up to the 2013/2014 academic years.

Table 3 provides some descriptive statistics of the students enrolled in the first year of their studies both in the full sample and around the €19,152.97 threshold of the ISEE index (i.e., third threshold, see Table 1). On average, 59% of the students are female, and the students are approximately 21 years old. The geographical distribution is quite mixed, as 46% of students reside in the north, approximately 19% of students reside in the central regions, 7% are from southern Italy and 8% come from the Islands (Sicily and Sardinia). The average high school grade is approximately 80 points.[20] The average number of credits obtained at the end of the first year of enrollment is about 32 credits, and the average weighted GPA is approximately 26 points in the full sample.[21]

To analyze the impact of financial aid on the labor market outcomes of the recipients, I match the administrative records on the financial aid recipients with the "AlmaLaurea" survey data following the three-step procedure by Britto (2020), described in more detail in Section 4.2.[22] "AlmaLaurea" is an interuniversity consortium established in 1994 and supported by the Ministry of Education and the National Agency for the Assessment of the University and Research System (ANVUR). Currently, the consortium includes 79 Italian universities – representing approximately 90% of the Italian graduates. Most importantly, every year, "AlmaLaurea" conducts the "Profile and the Employment Conditions" survey, which collects data on all graduates one year after graduation. These data are representative of the full population down to the level of a single major program. Table A2 shows the summary statistics of the University of Bologna graduates enrolled in the 2009/2010 and 2010/2011 academic years and graduating in the 2011/2012, 2012/2013, 2013/2014, and 2014/2015 years. Note that 65% of the students are bachelor's degree graduates and that 60% of the graduates are female with an age (at enrollment) of approximately 21 years old.[23] The average graduation time is approximately 3 years and 6 months, while the mean High-School final grade is equal to 82 and the mean final graduation mark is approximately 101. The share of graduates who work after obtaining a bachelor's degree is around 38%, while a similar share of graduates continue to study. The working graduates subsample (Column 2 of Table A2) is fairly similar to the full sample in terms of High-School final grade, final graduation mark, age, gender, graduation time and graduating campus. However, there are fewer bachelor's degree graduates compared to the full sample (56% versus 65%). When comparing the fraction of students working during college in the full sample with the one in the working-graduates subgroup, I notice that those who had some work experience during college are more likely to choose to work after graduation. The working-graduate subsample mostly earns less than

[20] In Italy the High School grade ranges from 60 to 100 points.

[21] Grades in the Italian university system range from a minimum of 18 to a maximum of 31 points.

[22] Indeed, this procedure allows the matching between the administrative records and the "AlmaLaurea" survey data using the common observable characteristics in the two datasets when there is no unique identifier.

[23] Notice that the gender and the age (at enrollment) distributions are well in line with the national statistics: the share of female graduates is of about 58% and the average age at enrollment is of around 21 years old in the academic year from 2011/2012 to the 2014/2015 years in the full population of graduates (AlmaLaurea, 2015; MIUR, 2015).

€1000 net per month (54%) and 43% of them work part-time. The average time to find a job was approximately 4 months. These labor market statistics are in line with the full population averages of the graduates entering the "AlmaLaurea" national repository (AlmaLaurea, 2015) further suggesting that data on the University of Bologna graduates could be used to derive fairly general implications.[24]

3.2 Empirical Strategy

The methodology used to study the effect of financial aid on students' academic and labor market performance, is a Regression Discontinuity Design (henceforth RDD). RDD has been widely used in economics and it was first introduced by Thistlethwaite and Campbell (1960). The attractiveness of this design is that it allows to identify treatment effects in a context similar to a formal randomized experiment. The RDD identification was formalized in the work of Hahn et al. (2001), which shows the minimum set of conditions under which it is possible to non-parametrically identify a treatment effect. The idea behind the RDD is to exploit discontinuities in the relationship between an assignment variable and a treatment variable. In the present context, these are the family income index, i.e., the ISEE index, and the level of benefit received, respectively. The intuition is that if the treatment (financial aid) has an effect on certain outcomes, for example, on the number of earned credits and GPA, there should also be a discontinuous relationship between the outcomes of interest and the assignment variable. To identify the average treatment effect on the treated (ATT) in the data, this paper presents the main results using a parametric approach and by running local linear regressions using different specifications. However, as shown in Section 5, the results are robust to the use of different functional forms, and to the adoption of the most recent non-parametric techniques with optimal bandwidth computation. Specifically, the main results are derived using the following parametric model:

$$Y_i = \alpha + \gamma_1 D_i + \gamma_2 F(Z_i - c) + \gamma_3 D_i * F(Z_i - c) + \epsilon_i \text{ where } |Z_i - c| \leq h \tag{1}$$

where the set of outcome variables, Y_i, is composed by the number of credits and the GPA obtained at the end of each year of study, the re-enrollment and drop-out rates, the on-time

[24] In the "AlmaLaurea" national repository the average net monthly income is of around €872 for the Bachelor-degree graduates and of €1065 for the Master-degree graduates. While the share of part-time working graduates is of about 50%.

graduation probability, the graduation time, and the labor market outcomes after graduation. Z_i is the ISEE index centered around the threshold c, $F(\cdot)$ is the polynomial function of the regressor $Z_i - c$, h is the bandwidth used and D_i is a dummy variable taking the value 1 for $(Z_i - c) \leq 0$.[25] Given the above specification, it is possible to demonstrate that:

$$\gamma_1 = E[Y_i|Z_i - c = 0^+] - E[Y_i|Z_i - c = 0^-]$$

identifies the mean change in the outcome variable at the discontinuity and it is an unbiased estimator of the ATT under certain validity conditions. The first condition is that the conditional expectations of all the characteristics determined ex-ante must be smooth around the eligibility thresholds. While, the second condition requires that there are no discontinuities in the density of the assignment variable. These two conditions have direct testable implications. Specifically, to test whether the first condition is satisfied in this context, I exploit the information on several observable characteristics of the recipients, like the age, gender, high school grade, and region of origin, and I show in Figure 4 the results on the pre-treatment continuity tests, namely whether these covariates are smoothly distributed aver the ISEE index. The graphs do not display any sharp discontinuities around any of the program thresholds.

The second testable implication asses whether there are any discontinuity in the density of the assignment variable around each threshold. In particular, this test may fail if students manipulate their ISEE to obtain a higher benefit. First, one must consider that in this context, the ISEE index must be certified by a professional agency and that violations are legally prosecuted. Moreover, the ISEE index is calculated on the basis of the family income in the previous year, so any ISEE manipulations must have been undertaken two years before applying to the financial aid program. Finally, the exact formula used to calculate the index is neither well known nor easily traceable. To run this continuity check I use the non-parametric density test developed by Cattaneo et al. (2016). Figures 2 and 3 confirm that there is indeed no such manipulation of the ISEE index, either in the 2009 or in the 2010 cohorts, as the observations are smoothly distributed around each threshold.

Finally, a specific features of the RTS financial aid program is that there are multiple eligibility thresholds. The next section will present the main results by looking at the third threshold, i.e. $c = 19,152.97$, which is where I observe the highest discontinuity in the amount of aid.[26]

[25] Notice that the results are robust to the use of different functional forms. Results are shown in the Appendix and will be discussed in Section 5.

[26] Notice that in the Appendix I also include the other-thresholds results for transparency purposes.

4 Results

4.1 The Effect of Financial Aid on College Performance

Following Imbens and Lemieux (2008), this section first presents the results by graphically plotting the relationship between the running variable and the outcomes of interest and then by presenting the results more formally using regression analysis. To explore the effects of RTS generosity on recipient performance, persistence and success, I start by plotting the relationship between the ISEE index and several outcome variables: the enrollment density, the number of credits and GPA level at the end of each year of education, the drop-out and re-enrollment rates after the first and second years, the probability of on-time graduation and the graduation time.

Figures 2 and 3 show how the generosity of the RTS financial aid program affected student enrollment in the 2009/2010 and 2010/2011 academic years at the University of Bologna. These figures plot the density of the observations around each threshold, which it could be interpreted as a proxy for enrollment.[27] The figures show the results of the local polynomial density estimator developed by Cattaneo et al. (2016), which represent an improvement over the previous approaches available in the literature.[28] The visual inspection of the data suggests that the generosity of the RTS financial aid program has no effect on enrollment. In particular, the figures show that there are no significant discontinuities in the density of the observations near each of the thresholds, suggesting that higher benefits do not significantly change the probability of enrollment at the University of Bologna. This is not surprising since in Italy the financial aid application is submitted before enrollment, but the notice of acceptance is generally communicated a few months later. Moreover, several studies analyzing the effects of the Pell Grant in the US also find null effects on enrollment (Denning et al., 2019; Kane, 1995; Marx and Turner, 2018; Turner, 2017).

The following graphs instead explore how the first-year performance of the financial aid recipients is affected by the generosity of the RTS program. Notice that in the following analysis the effects are interpreted by pooling the two cohorts and by not distinguishing by student status

[27] The data do not include those students who applied for the RTS but did not enroll, or those who enrolled in a university degree but did not apply for the RTS. However, these share of students should not vary with the level of the benefit received and they should represent a small fraction of the full population since all the financial aid applicants at the University of Bologna received the benefits in these and the previous academic years, i.e, 100% coverage rate, and the coverage rate did not vary with the level of the benefit.

[28] McCrary (2008) introduced a test based on the non-parametric local polynomial density estimator of Cheng et al. (1997), which requires pre-binning of the data and hence introduces additional tuning parameters. The Cattaneo et al. (2016) improves this method.

("Fuori sede", "Pendolari", "In sede"). In particular, Figure 5 shows how the data on the credits earned by the end of the first year correlate with the ISEE. This graph shows that the number of credits obtained by students at the end of their first year of study is relatively flat both above and below the €19,152.97 threshold and that the mean performance of the higher-aid recipients is mainly centered around the 25-30 level, which is equal to the level of the first-year minimum credit requirement (see Table 2). In contrast, I observe a jump in the performance among the students on the right-hand side of the third threshold, even though they are receiving a significantly smaller aid and are subject to the same minimum credit requirements. Notice that the performance is somewhat noisier as we move up on the ISEE index, but this is consistent with having less observations on the top of the income distribution (see Figures 2 and 3). Figure 5 also includes the local polynomial fit of the underlying individual observations, computed with a triangular kernel and the optimal bandwidth selection from Calonico et al. (2014b).

To investigate whether the results on the number of credits earned may have generated any side effect on the quality dimension of student performance, Figure 6 shows the effects of the RTS program on the GPA level. The figure shows a flat performance in terms of GPA, so no clear discontinuities emerge. However, it is possible to notice a positive relationship between the GPA and the ISEE index, which is a result in line with a pure income effect: students on the right tail of the income distribution may have better living conditions or more educated parents than those at the bottom. In addition, the null effect of financial aid on the GPA could be reconciled with the fact that the RTS financial aid is not conditioned to a minimum GPA; therefore, students are not expected to target any GPA level. It is worth noting that the results are confirmed when plotting the raw data averaged in bins of €200 of the family income index in Figures A1 and A2 of the Appendix. Moreover, they are not specific to the freshmen of a particular cohort, either when looking at the number of credits or at the GPA, since both cohorts behave similarly (see Figures A1 and A2 in the Appendix). Finally, Figures A3 and A4 of the Appendix confirm the above evidence for all the RTS eligibility thresholds nonparametrically.

Overall, the graphical evidence has shown that there is a significant difference in the number of credits obtained at the end of the first year of college around the €19,152.97 threshold, where fully subsidized students are compared with freshmen who have a positive cost of college, even though they all face the same credit requirements.

In what follows, I look at how financial aid affects performance in the second year of college and graduation timing more generally. However, before looking at these outcomes, it is important to check whether the RTS program has differentially changed the drop-out and the re-enrollment decisions of the freshmen at the end of their first year of college and around each threshold. Table 3 shows that on average, 32% of students drop out and approximately 8% re-enroll in the first year. However, Figures A5 and A6 show that while no difference across thresholds emerges in the drop-out probability, receiving higher aid induces more students to re-enroll in the first year at the third threshold. The next section properly addresses this self-selection problem when interpreting the effects of financial aid on second-year performance outcomes. Note that in the second year of college, students must obtain a cumulative number of 80 credits to avoid repaying the benefit received and to be able to apply for the RTS scholarship as a third-year student in the following academic year. This requirement does not change with the level of the family income index, and even in the second year, there are no GPA requirements attached to the benefits. Figures 7 and 8 plot the nonparametric data-driven second-year performance, both in terms of the total number of credits and of GPAs. Notice that the gap in the total number of credits between the higher-aid recipients and the students receiving only a 50% tuition allowance still persists in the second year. In particular, the former group's performance is centered on the yearly requirement, i.e., 80 credits; therefore, it is lower by approximately 10 credits than the latter group's outcome. However, the GPA level is similar across the two groups of recipients. These results suggest that, even at the end of the second year, the fully subsidized students are not taking fewer credits to improve their GPA, or at least not significantly so. Given the persistence of this gap in performance in the second year of college, I now examine how the average graduation time differs between the two groups of recipients. Figure 9 shows how the nonparametrically adjusted graduation time (measured in years) is distributed around the third threshold. As it is possible to notice from the figure, there is a significant discontinuity in the average graduation time at the €19,152.97 threshold, since higher-aid recipients take approximately a year longer to finish college.

In the next part of the section, I present the regression results by pooling all the cohorts and by using the model presented in equation 1.

The regression results on the effects of financial aid generosity on performance are reported in Tables 4 and 5, which show the estimates at the €19,152.97 threshold. Tables A3 and A4 of the Appendix look instead at the regression results at each threshold separately. Tables 4 and 5 show the treatment effects of receiving extra €3,500 in terms of financial aid on the number of credits and GPA level at the end of the first year. The estimates confirm what the graphical inspection of the data first suggested. The performance of those students positioned below the €19,152.97 threshold is centered around the minimum requirements in terms of credits (30 credits). On the other hand, the number of credits obtained by those students positioned above the third threshold is significantly higher by approximately 9 credits, which correspond to one and a half courses. Additionally, Table 5 shows that, while the highly subsidized students earn 9 credits less, their GPA does not differ from that of the lower-aid recipients. On the one hand, this result suggests that while more generous financial aid has induced a significant difference in the quantity of the study effort, this does not translate into an increase in quality. On the other hand, this evidence also implies that, in this setting, imposing a minimum performance requirement on the number of credits does not induce any side effects on GPA level. Notice that the results are stable even when the full set of controls is included in the regressions or when the nonparametric estimator by Calonico et al. (2014b) is adopted, as shown in Table A5 of the Appendix.

At the end of their first year, students could decide to drop out of college, to re-enroll in their first year or to continue their education. As the graphical analysis shows, there is no systematic difference in drop-out rates near the third threshold, which is confirmed by the nonparametric estimates of the first column of Table A6. Table A6 also confirms that the lower-aid recipients re-enroll significantly less often as first-year students than those receiving higher aid. This result could indeed be indeed explained by the incentives offered by the financial aid policy. In particular, if students do not satisfy the credit requirements at the end of the first year, they could decide to re-enroll again as first-year students and reapply for financial aid, since for college freshmen, aid is assigned only on the basis of the family income index. Therefore, given that the opportunity cost of losing financial aid is higher for the students positioned below the third threshold, it is straightforward to expect higher re-enrollment rates among these. To further confirm this intuition, the third column of Table A6 looks at how the probability of not satisfying the credit requirement is distributed around the third threshold: as expected, higher-aid recipients have a significantly higher probability of not meeting the requirements by approximately 30 percentage points.

To formally estimate the effects of financial aid on the second-year outcomes while controlling for this differential self-selection in the re-enrollment rates, I implement the Lee bounds procedures (Lee, 2009), which it has been proposed in the literature to have a nonparametric estimation of the bounds of the treatment effects when nonrandom sample selection is present. The results shown in Tables A8 and A9 are very consistent with the graphical analysis. Notice that both the upper and lower bounds of the treatment effect on the number of credits obtained in the second year are significantly negative and non too wide: higher-aid recipients obtained from 7 to 13 credits less than lower-aid students in the second year of college. On the other hand, the confidence interval of the treatment effect on the second-year GPA is centered around zero, meaning that the Lee bounds identify a null effect of a more generous financial aid on the GPA level.

Finally, Table 6 shows that this gap in the annual number of credits generates a significant difference in the graduating time between the students positioned above and below the third threshold. Specifically, the table shows that higher-aid recipients take 1 year and 3 months longer to finish college. This result could be explained by a combination of two mechanisms: on the one hand, higher-aid recipients proceed more slowly each year since they are more likely to target the minimum credit requirements, and on the other hand, they stay longer since they are more likely to re-enroll as first-year students at the end of the first year, as shown in Table A6.

Taking this evidence together, this paper finds that the RTS financial aid program works through the cost-of-college channel since students who pay a higher cost for their education have lower graduation time, starting from the first year (Garibaldi et al., 2012). In addition, given that subsidized students target the minimum credit requirements each year – which are indeed set at a low level – these results also confirm that financial aid recipients are indeed highly responsive to the academic requirements attached to their program (Scott-Clayton and Zafar, 2016).

4.2 The Effects of Financial Aid on Labor Market Outcomes

To analyze the impact of financial aid on the labor market outcomes of the graduates, I match the administrative records on the financial aid recipients with the "AlmaLaurea" survey data following the three-step procedure by Britto (2020). This matching procedure, linking the survey data to the administrative records, is based on clusters of students identified by several individual characteristics: year of enrollment, age, gender, degree (bachelor or master), numeric code of their graduating major, numeric code of their graduating campus, and high school final grade.[29] First, the administrative records on the financial aid recipients are restricted to bachelor's degree graduates only since information on high school final grades is not available in the "AlmaLaurea" repository for master degree graduates.[30] Moreover, the administrative records are restricted to financial aid recipients lying close to the third threshold to avoid matching students offered with different incentives and to clusters containing no more than one individual, as in Britto

[29] There are two years of enrollment observed, 2009 and 2010, 88 majors, 8 campuses, 41 possible values of the high-school final grade, and age ranges from a minimum of 17 to a maximum of 67.

[30] Notice that restricting the sample to the bachelor graduates may decrease the external validity of the results, however, it does not seems to be a severe problem in Italy since 93% of the 25-34 employed adults hold a short-cycle degree only (OECD, 2020).

(2020). Specifically, I focus on the financial aid recipients with an ISEE index above €15,386 and below €22,500, who are uniquely identified by their year of enrollment, age, gender, degree, graduating major and campus, and high school final grade. Interestingly, approximately 85.2% of the financial aid recipients are uniquely identified within each cluster. Second, following Britto (2020), I restrict the "AlmaLaurea" survey data to observations belonging to clusters identifying no more than ten graduates, which correspond to about 97.5% of observations. Notably, because the "AlmaLaurea" survey was conducted on the entire population of graduates from the University of Bologna, the cluster size is significantly larger than that in the financial aid recipient sample. The choice of the cluster size involves a trade-off between increasing the precision of the match against losing the information on the dropped observations. In Section 5, I present a robustness check that shows that the main findings are fairly robust to this choice, as in Britto (2020). Finally, the administrative records are matched with the "AlmaLaurea" survey sample, whereby 1068 observations in the administrative data are associated with 1318 counterparts in the survey. Then, I use this matched sample to estimate the treatment effect of receiving a higher aid on the labor market performance of the graduates in the 2012-2015 period using the same RDD methodology as described later in this Section and in Section 3. Note that this is clearly an inexact matching procedure since some graduates from the AlmaLaurea survey data may be incorrectly associated with the administrative data. However, as shown in Britto (2020), under the assumption that the probability of an incorrect linkage is continuous around the cutoff, this matching procedure still leads to an unbiased estimate of the treatment effects on labor market outcomes.[31] Notice by combining these two data sources, it is also possible to estimate the share of financial aid recipients who did not graduate in this time period (i.e., approximately 11%) and to assess what is the share of students who graduated but did not participate in the "AlmaLaurea" survey (i.e., approximately 15%). Furthermore, by comparing the distribution of these shares of students above and below the €19,152.97 threshold, I can also infer if there has been any differential self-selection along these two choice margins. Table A10 in the Appendix shows that there are indeed no discontinuities either in the share of students who graduate in this period or in the share of graduates who participated in the "AlmaLaurea" survey. Notice that this evidence further supports the robustness of the above matching procedure, given that no imbalances emerge in the distribution of these students above and below the €19,152.97 threshold. Following Britto (2020), in Section 5, I provide another two sets of evidence supporting the matching procedure.

[31] In particular, Britto (2020) shows that if the probability of incorrect linkage is continuous around the threshold, the estimate may suffer from an attenuation bias only, and that the degree of attenuation exclusively depends on the share of incorrect matches.

To analyze the impact of financial aid on the labor market outcomes of the recipients, I follow the three-step procedure described above, and I use the matched sample to estimate the nonparametric RDD effect of receiving a more generous financial aid on the labor market outcomes of the observed college graduates in the 2012-2015 period.[32] The summary statistics of the matched sample are shown in Table A11, while the main RDD results are presented in Tables 7, 8 and 9.

As shown in Table A11, the matched graduates are 64% female with an age (at enrollment) of approximately 19 years old. The average graduation time is about 4 years, while the mean High-School final grade is equal to 84. The share of graduates who work after obtaining a bachelor's degree is approximately 33%, while about 47% continue to study. The working graduates subsample (Column 2 of Table A11) has similar characteristics to the full sample in terms of high school final grade, age, gender, graduation time and campus and major choices. However, when comparing the fraction of students working during college in the full sample with the one in the working-graduates subgroup, I notice a 26 percentage point difference. This suggests that among all bachelor's degrees, those who have some work experience during college are more likely to choose to work after graduation rather than continuing to study. The working-graduate subsample also reports to have found – for the majority (51%) – a part-time job after almost 4 months from graduation and 65% of them earn less than €1000 net per month.[33] When thinking about the job match, most of the working graduates (72%) state that they are using the skills acquired during college, but only 23% report that the degree was effective for finding the job. Notice that this share is indeed similar to the fraction of graduates who report that the bachelor's degree is required by law to perform the job (23%). Finally, only 11% of the working graduates state that the bachelor's degree was indeed necessary to perform the job, even if it is not required by law.

The following analysis will further test whether receiving higher financial aid has any effects on the labor market participation choice both before and after graduating from college, as well as on the quality of the job match. In particular, in Table 7, I look at the full sample of financial aid graduates, and I estimate the treatment effects of receiving higher aid on graduation time, the probability of continuing studying, and labor market participation both before and after graduation using the nonparametric estimator by Calonico et al. (2014a). The table confirms

[32]Notice that the non-parametric approach allows to use a covariate-adjusted RDD estimator with optimal bandwidths and point estimators (Calonico et al., 2019) and it is intended to increase the precision of the RDD treatment effect estimator in the matched sample.

[33]The net income statistic is in line with the data on the full working population in the 25-29 age range: https://www.inps.it/osservatoristatistici/15.

nonparametrically that the students who received a lower amount of aid took approximately 8 months less to graduate. Column 2 instead shows that students positioned below and above the €19,152.97 financial aid threshold are equally likely to continue their educational career. In Columns 3 and 4 of Table 7, I look at the probability of working after and during college, respectively. Interestingly, no differences emerge in the two extensive margins of the work choice, potentially ruling out, on the one hand, the possibility that delayed graduation has significant consequences on the probability of finding a job and, on the other hand, that higher-aid recipients graduate later since they are more likely to work during college. Of course, some differences may emerge if we look at the intensive margin of the work choice, such as the number of working hours or salaries. While unfortunately, I do not have information on the hours of work, the "AlmaLaurea" survey asks if the job is a part- or full-time contract, which clearly allows us to proxy the number of hours worked. Column 2 of Table 8 shows the results on the probability of working part-time for the subsample of the working graduates. Notably, while higher-aid recipients have a similar probability of finding a job to students receiving a lower benefit, they are approximately 70% more likely to work part-time. Interestingly, Column 1 of Table 8 shows that among the subsample of working graduates, higher-aid recipients take approximately 3 months more to find a job than unsubsidized graduates, but the results are not statistically significant. Column 3 of Table 8 shows that, in the subsample of working graduates, the probability of earning less than €1,000 per month is significantly lower for the lower-aid recipients, further signaling that the higher-aid recipients secured a worse job match both in terms of working hours and salary. To test this intuition more directly, in Table 9, I look at how the working graduates answer the survey questions directly related to the job and skill match. Specifically, Column 1 of Table 9 shows the results on the probability of using the skills acquired during college in the job position. Notably, despite the broad definition used in this outcome variable, lower-aid recipients are approximately 43% more likely to report that they are using the skills acquired during college. Given that there is no systematic sorting of low-skilled students around each financial aid threshold, as shown in the previous section, it may be that the jobs obtained by the higher-aid recipients offer a lower return on the bachelor's degree skill investment. This line of reasoning is indeed supported by the results shown in Columns 2,3 and 4 of Table 9. Specifically, the lower-aid recipients have a 43% higher probability of reporting that their degree was effective for finding the job and a 33% higher probability of stating that the bachelor's degree is necessary to perform the job (even if not required). Although these estimates are only marginally significant, both the magnitudes and the signs are quite consistent across specifications, pointing toward the same interpretation. Namely, it seems that higher-aid recipients might have secured a worse job match, both in terms of hours worked and payments but also in terms of skill matching. In addition, notice that these effects are not driven by a differential selection of graduates into the labor market since graduates located below the third threshold are equally likely to continue to study or to work both before and after graduation as shown in Table 7. Furthermore, when testing for differences in the observable characteristics of the working graduates lying near the third threshold, no significant results emerge; see Table A12 in the Appendix.

5 Robustness Checks

As discussed in Section 3.2, the main treatment effects in Tables 4-5 are estimated while allowing for different linear relationships on either side of each threshold. In the Appendix, Table A13 evaluates the sensitivity of the first-year estimates with respect to the functional form of the ISEE index, i.e., the term $F(Z_i - c)$ included in equation 1. Specifically, the table includes the second- and third-degree polynomials of the parametric estimation that are on either side of the third threshold. This robustness exercise supports the validity of the main results reported in Tables 4-5. However, given the small size of the ISEE windows around each threshold and the plots of the raw data, the local linear estimation is preferred.

To further check the robustness of the results, nonparametric estimates are reported in Table A5 of the Appendix, following the procedure in Calonico et al. (2014b) and Calonico et al. (2014a). This estimation strategy generates strongly significant results around the third threshold and in the direction expected based on the graphical analysis and the parametric estimation. Furthermore, these nonparametric estimates are also highly robust to the choices of the kernel and the bandwidth used in the estimation; see Tables A14 and A15 in the Appendix. Finally, when using two placebo cutoffs of the running variable close to the third threshold – at the levels of ISEE of 16,000 and of 21,000 – no effect is detected; see Table A16 in the Appendix.

Following Britto (2020), I provide two sets of evidence supporting the procedure adopted to match the administrative data on the financial aid recipients with the labor market information from the "AlmaLaurea" survey. First, in Figure A10, I show that the distributions of the variables used in the matching procedure – gender, age at enrollment, high school grade, code for the graduating major, and code for the graduating campus – are indeed similar between the administrative records and the "AlmaLaurea" survey data. This evidence supports the idea that the matching procedure adopted successfully matches the same graduates across samples, even if the linkage is imperfect. To further ensure that this matching procedure does not bias the RDD estimates, I test whether these observable characteristics and the cluster size are smooth across the financial aid threshold of interest. Indeed, Table A12 in the Appendix shows that there is no significant discontinuity in any of the covariates or in the cluser size around the cutoff in the matched sample, further supporting the validity of the matching procedure and of the RDD.

6 Conclusions

This paper studies the effects of financial aid generosity on students' academic achievement and labor market outcomes. The main finding is that those students who receive a lower benefit and, therefore, have a positive cost of college perform better than those whose costs are completely subsidized. Given that students face the same requirements for the renewal of their financial aid (independent of the aid level awarded), the results can be explained through the cost-of-college mechanism. Receiving a lower benefit increases the cost of attending college relative to receiving a higher level of aid and consequently motivates students to finish early to avoid paying extra costs due to delayed graduation.

It is interesting to compare the overall findings with the results in the literature. The null enrollment effect is in line with some of the previous findings. Indeed, while theoretically, there should be an inverse relationship between the price of college and enrollment, the empirical evidence is only partially consistent with this prediction. Several studies looking at Pell Grant program eligibility or generosity indeed find no impact on enrollment.[34] The prevailing explanations are mainly related to the complexity of the application process and to the late notice of grant eligibility.[35] In the context of the RTS program, it is indeed the case that students know about their eligibility only around December of each year, while most of the bachelor's and master's programs typically start around mid-September. This lag between the start of the program and notifications of eligibility might explain why I find no effect of RTS program generosity on enrollment. Among higher-aid recipients, I find that a higher benefit does not generate any differences in yearly performance in terms of either GPA or accumulated credits. This result is in line with the literature showing that financial aid programs work through incentives for academic achievement and not simply by relaxing budget constraints

[34] See Kane (1995); Carruthers and Welch (2019); Turner (2017); Marx and Turner (2018); Denning (2018).

[35] See Bettinger et al. (2012); Dynarski and Scott-Clayton (2006); Dynarski and Scott-Clayton (2008); Dynarski and Wiederspan (2012);Dynarski and Scott-Clayton (2013).

(Scott-Clayton, 2011). In particular, since the academic requirements for the renewal of financial aid are set at a low level, subsidized students target these requirements and underperform with respect to students who pay a higher cost of college. This effect has indeed been formalized in the principal-agent model developed by Bénabou and Tirole (2000) and Bénabou and Tirole (2002) and in the extension by Schudde and Scott-Clayton (2016). The overall evidence is also in line with the findings by Belot et al. (2007), who show that a reduction in the maximum duration of a Dutch grant increases performance. The idea is that students react positively in terms of their study effort to an increase in the cost of a delayed graduation. Garibaldi et al. (2012) propose a similar explanation in the context of a private Italian university. In addition, in line with Mealli and Rampichini (2012), the RTS program is not found to generate any difference in the drop-out decisions of the recipients.

When looking at the after-graduation outcomes, I find that higher-aid recipients are equally likely to continue their educational careers, and no differences emerge in the probability of working before or after graduation. This suggests that, on the one hand, delayed graduation has no significant consequences on the probability of finding a job (the extensive margin of the work choice) and that on the other hand, higher-aid recipients do not graduate later because they work more during college. However, I find that higher-aid recipients secure worse job matches, both in terms of hours worked and payment received but also in terms of skill matching.

This paper shows that when considering changes in financial aid generosity, one should consider the spillover effects of these changes on the graduation time of financial aid recipients, since this observable characteristic might be used by employers to screen potential job candidates, generating significant labor market value for on-time graduates.

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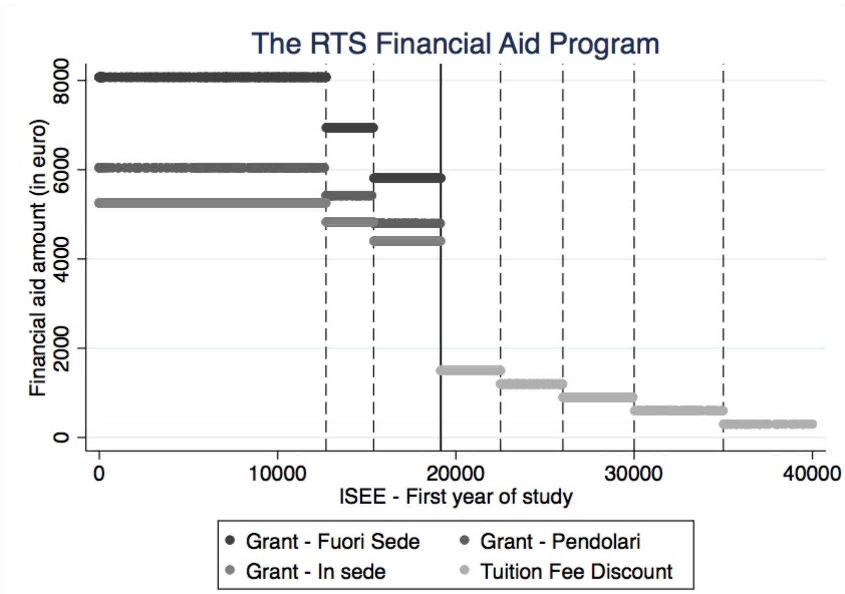
7 Tables and Figures

Figure 1: The RTS Benefit Level Schedule



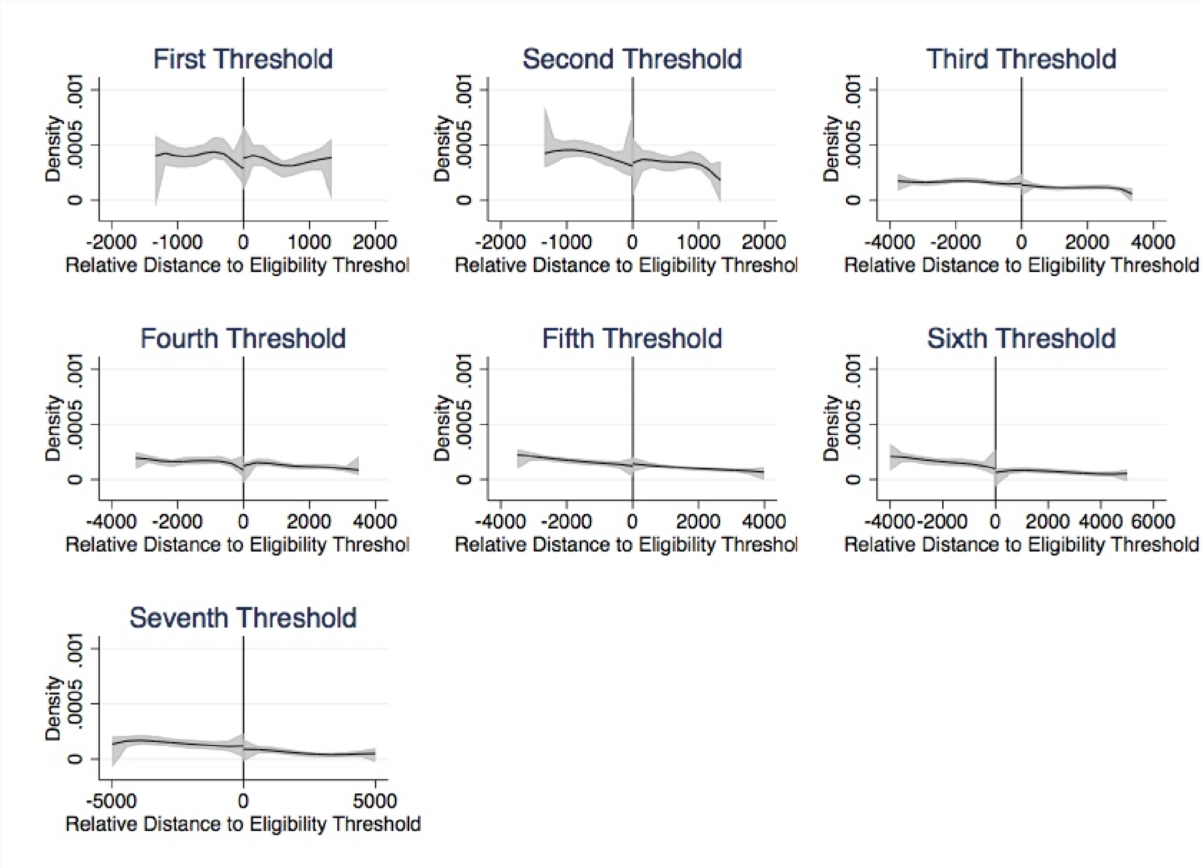
Notes: The graph plots how the total amount of aid change with the level of the family income indicator, ISEE. The recipients positioned below the €19,152.97 threshold receive a grant, which varies with the ISEE index and the student'status – "Fuori sede", "Pendolari", "In sede" (see Panel A of Table 1). They also receive a full tuition exemption, which is equal to around €3,000 according to the *7th Report on the costs of the Italian universities* of the national non-profit organization "Federconsumatori". While the students with an ISEE index above €19,152.97 threshold receive a tuition discount, which varies with the family income index, only – from a maximum of %50 to a minimum of %10.

Table 3: Summary Statistics

	Full Sample	Third Threshold
Undergraduate students	0.72	0.70
	(0.45)	(0.46)
Age	21.41	21.20
	(3.92)	(3.55)
Area (share)		
Center	0.19	0.22
	(0.39)	(0.41)
Islands	0.08	0.07
	(0.28)	(0.26)
North	0.46	0.51
	(0.50)	(0.50)
South	0.07	0.01
	(0.25)	(0.08)
High-School Grade	79.54	80.47
	(13.20)	(13.20)
ISEE	13946.70	18579.74
	(8384.83)	(2026.98)
ISPE	10260.49	10466.86
	(13094.75)	(9807.44)
Gender		
Female	0.59	0.58
	(0.49)	(0.49)
Credits 1st	32.17	33.33
	(17.15)	(16.28)
GPA 1st	26.05	26.46
	(2.80)	(2.62)
Drop-out	0.32	0.36
	(0.46)	(0.48)
Re-Enrollment	0.08	0.07
	(0.27)	(0.26)
Observations	9621	2107

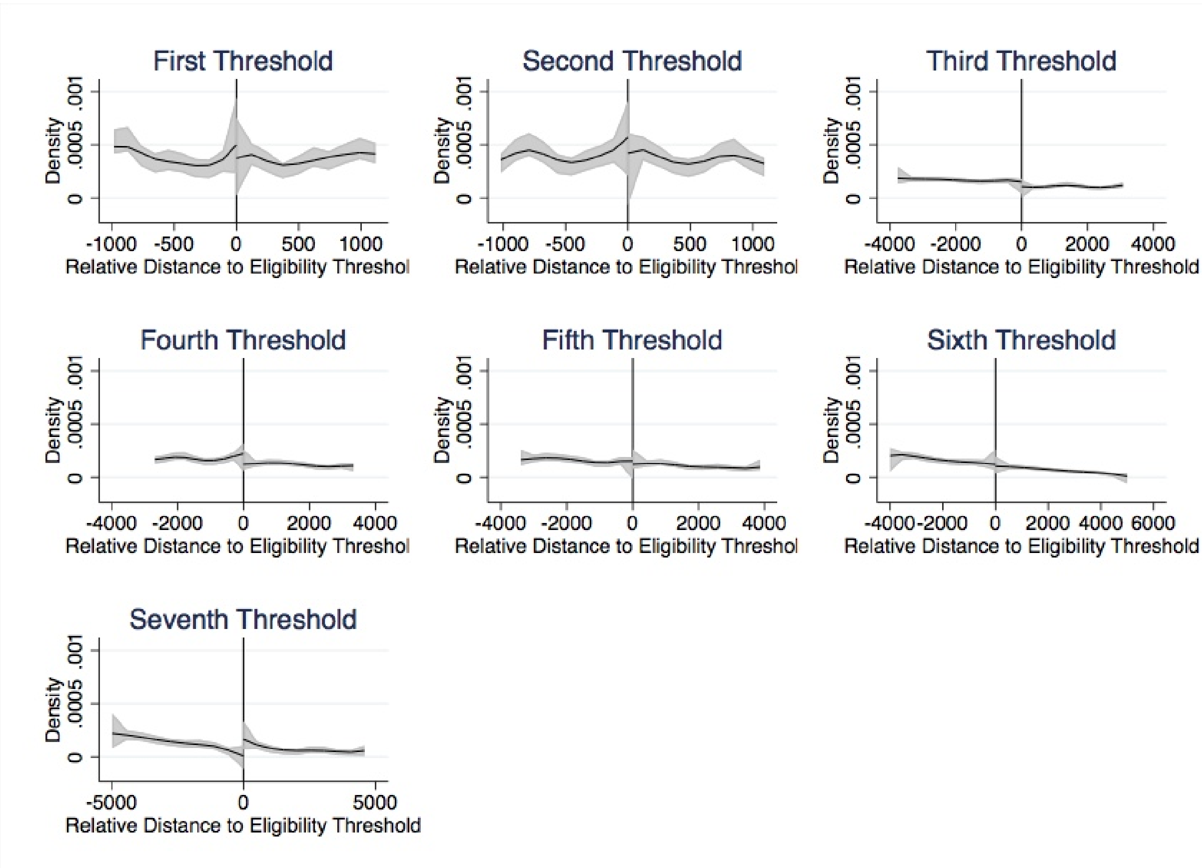
Notes: Note: Statistics for the freshman who enrolled at University of Bologna in the 2009/2010 and 2010/2011 academic years in the full sample and around the third threshold, namely with an ISEE between €15,386.29 and €22,500.

Figure 2: Cattaneo, Jansson, and Ma (2017a) density tests 2009: individual thresholds



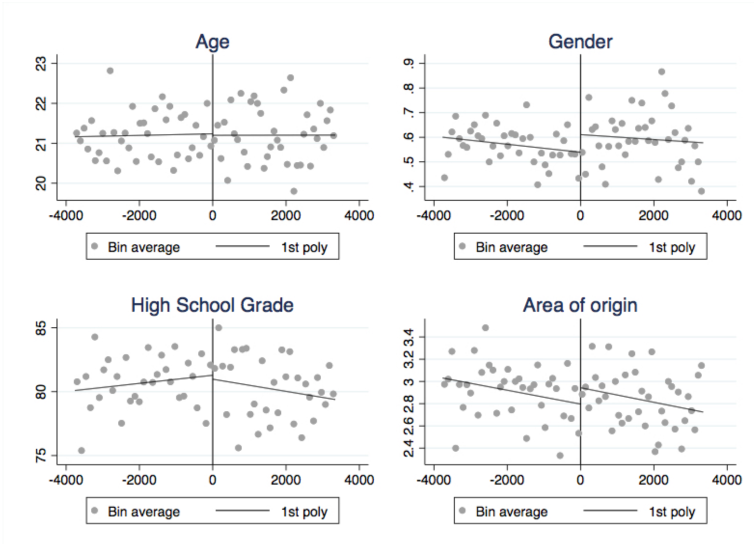
Notes: The graph implements density testing procedures using the local polynomial estimators to construct test statistics and p-values given a pre-specified cutoff, using data-driven bandwidth selection as in (Calonico and Titiunik, 2017).

Figure 3: Cattaneo, Jansson, and Ma (2017a) density tests 2010: individual thresholds



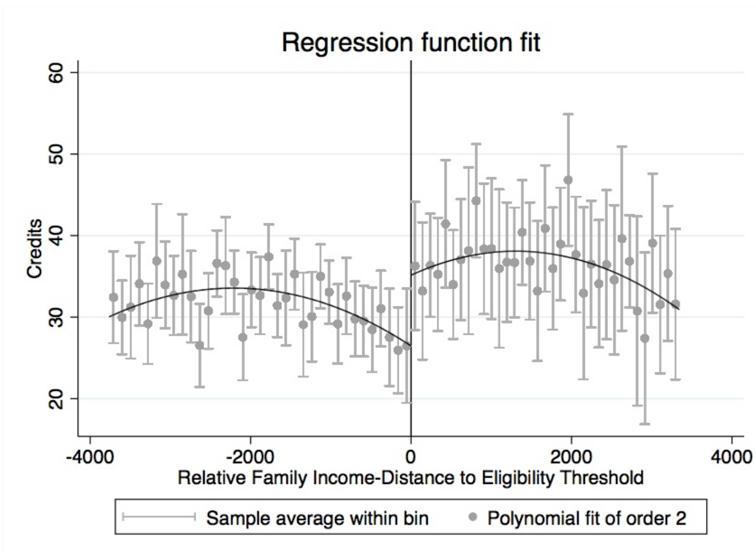
Notes: The graph implements density testing procedures using the local polynomial estimators to construct test statistics and p-values given a pre-specified cutoff, using data-driven bandwidth selection as in (Calonico and Titiunik, 2017).

Figure 4: Pre-treatment Continuity in relevant Covariates



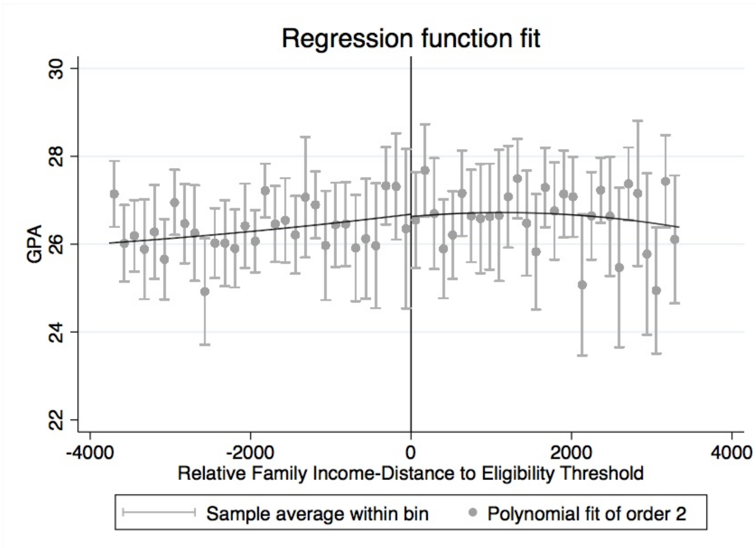
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Figure 5: Credits – First Year of Study



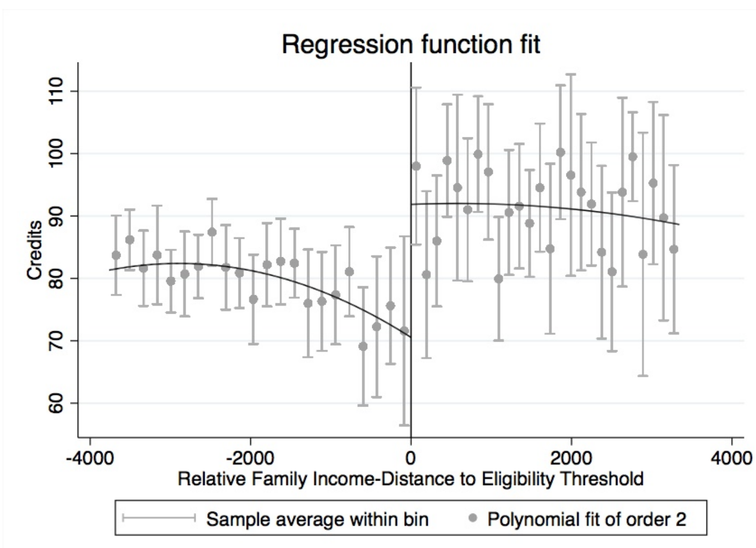
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Figure 6: GPA – First Year of Study



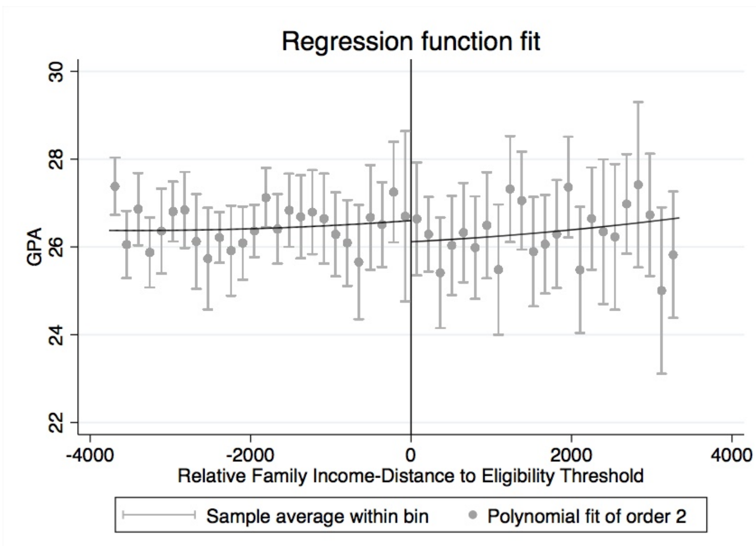
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Figure 7: Credits – Second Year of Study



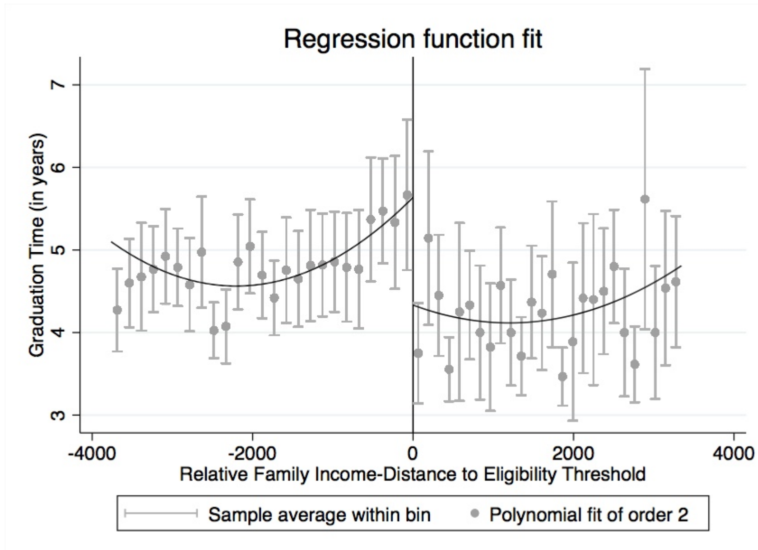
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Figure 8: GPA – Second Year of Study



Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Figure 9: Average Graduation Time (in years)



Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Table 4: Effects of higher aid on Credits – First year

	Credits 1st	Credits 1st	Credits 1st	Credits 1st
3rd **Threshold** - Effect of higher aid	-8.314***	-9.034***	-8.369***	-9.019***
	(1.479)	(1.680)	(1.560)	(1.726)
ISEE	-0.001***	-0.001**	-0.001*	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Effect of higher aid x ISEE			0.000	-0.000
			(0.001)	(0.001)
Constant	38.105***	18.818***	38.207***	18.778***
	(0.858)	(4.122)	(1.259)	(4.248)
Observations	1940	1479	1940	1479
Mean Dependent Variable	33.332	32.563	33.332	32.563
Controls	No	Yes	No	Yes
$Adj.R_2$	0.021	0.116	0.020	0.115

Notes: *Credits* is the outcome variable, which measures the number of credits obtained at the end of the first year of college. *ISEE* is the running variable index of the student's family income. Columns 1 and 2 show the point estimates of the linear effect of receiving a higher benefit at the third threshold, with and without controls, respectively. Columns 3 and 4 report the local linear effects of receiving a higher benefit at the third threshold, with and without controls, respectively. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 5: Effects of higher aid on GPA – First year

	GPA 1st	GPA 1st	GPA 1st	GPA 1st
3rd **Threshold** - Effect of higher aid	-0.103	-0.132	-0.145	-0.116
	(0.295)	(0.330)	(0.296)	(0.330)
ISEE	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000*	0.000**
			(0.000)	(0.000)
Constant	26.547***	19.845***	26.798***	20.200***
	(0.155)	(0.774)	(0.210)	(0.791)
Observations	1448	1113	1448	1113
Mean Dependent Variable	26.463	26.065	26.463	26.065
Controls	No	Yes	No	Yes
$Adj.R_2$	0.002	0.096	0.003	0.099

Notes: *GPA* is the outcome variable, which measures the number of credits obtained at the end of the first year of college. *ISEE* is the running variable index of the student's family income. Columns 1 and 2 show the point estimates of the linear effect of receiving a higher benefit at the third threshold, with and without controls, respectively. Columns 3 and 4 report the local linear effects of receiving a higher benefit at the third threshold, with and without controls, respectively. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 6: Effects of higher aid on Graduation Time

	Graduation Time	Graduation Time	Graduation Time	Graduation Time
3rd **Threshold** - Effect of higher aid	1.125***	1.441***	1.071***	1.413***
	(0.199)	(0.214)	(0.213)	(0.219)
ISEE	0.000***	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	0.000
			(0.000)	(0.000)
Constant	3.990***	5.607***	4.081***	5.685***
	(0.116)	(0.509)	(0.174)	(0.525)
Observations	1339	1036	1339	1036
Mean Dependent Variable	4.623	4.842	4.623	4.842
Controls	No	Yes	No	Yes
$Adj.R_2$	0.025	0.131	0.025	0.130

Notes: *Graduation Time* is the outcome variable, which measures the time elapsed between enrollment and graduation (in years). *ISEE* is the running variable index of the student's family income. Column (1) and (2) show the point estimates of the linear effect of receiving a higher benefit at each threshold, with and without controls respectively. Columns (3) and (4) report the local linear effects of receiving a higher benefit at the third threshold, with and without controls respectively. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 7: Effects of higher aid after graduation – Full sample

	Graduation Time	Continue studying	Working after	Working during
Conventional	-0.70***	-0.056	0.0057	0.11
	[0.20]	[0.10]	[0.093]	[0.084]
Bias-corrected	-0.67***	-0.092	0.043	0.14
	[0.20]	[0.10]	[0.093]	[0.084]
Robust	-0.67**	-0.092	0.043	0.14
	[0.24]	[0.12]	[0.11]	[0.097]
Observations	1318	1318	1318	1318
Conventional p-value	0.00053	0.58	0.95	0.19
Robust p-value	0.0056	0.43	0.69	0.15
Order Loc. Poly. (p)	1	1	1	1
Order Bias (q)	2	2	2	2
BW est. (h)	1295.6	1210.3	1007.4	953.2
BW bias (b)	1890.8	2037.1	1743.8	1593.1

Notes: Non-parametric estimates of the effect of receiving lower aid on several outcome variables. *Graduation Time* measures the difference from the graduation year and the year of enrollment. *Continue studying* is a dummy variable equal to 1 if the student continues to study after graduating with the Bachelor's degree. *Working after* is a dummy variable equal to 1 if the student works after graduation. *Working during* is a dummy variable equal to 1 if the student works during college. Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the distance of the ISEE index from the threshold value €19,152.97: $(Z - c)$. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 8: Effects of higher aid after graduation – Working sample

	Months to find a job	Part-time	Monthly salary <1000
Conventional	-2.35	-0.58*	-0.39*
	[1.74]	[0.27]	[0.18]
Bias-corrected	-2.85	-0.71**	-0.52**
	[1.74]	[0.27]	[0.18]
Robust	-2.85	-0.71*	-0.52*
	[2.11]	[0.32]	[0.24]
Observations	284	434	422
Conventional p-value	0.18	0.031	0.034
Robust p-value	0.18	0.028	0.029
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
BW est. (h)	1039.7	568.7	712.1
BW bias (b)	1738.6	1020.8	1187.6

Notes: Non-parametric estimates of the effect of receiving lower aid on several outcome variables. *Months to find a job* measures the number of months it took the graduate to find a job. *Part-time* is a dummy variable equal to 1 if the student works part-time. *Monthly salary < 1000* is a dummy variable equal to 1 if the student earns less than €1,000 per month. Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the distance of the ISEE index from the threshold value €19,152.97: $(Z - c)$. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 9: Effects of higher aid after graduation – Working sample

	Skills: used	Degree: required	Degree: effective	Degree: necessary
Conventional	0.34*	0.36	0.35**	0.23
	[0.16]	[0.20]	[0.13]	[0.13]
Bias-corrected	0.43**	0.42*	0.43***	0.33*
	[0.16]	[0.20]	[0.13]	[0.13]
Robust	0.43*	0.42	0.43**	0.33*
	[0.19]	[0.25]	[0.15]	[0.15]
Observations	434	434	429	434
Conventional p-value	0.028	0.078	0.0055	0.082
Robust p-value	0.023	0.093	0.0042	0.029
Order Loc. Poly. (p)	1	1	1	1
Order Bias (q)	2	2	2	2
BW est. (h)	894.6	756.3	1235.8	721.8
BW bias (b)	1405.6	1399.1	2144.9	1278.6

Notes: Non-parametric estimates of the effect of receiving lower aid on several outcome variables. *Skills: used* is a dummy variable equal to 1 if the working graduate reports to use at least some of the acquired skills in the job.*Degree: required* is a dummy variable equal to 1 if the degree is required by law in the working position. *Degree: effective* is a dummy variable equal to 1 if the working graduate reports that the degree was at least somehow effective for finding a job. *Degree: necessary* is a dummy variable equal to 1 if the degree is not required by law but it is necessary to perform the job. Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the distance of the ISEE index from the threshold value €19,152.97: $(Z - c)$. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

8 Appendix A

Table A1: Assignment of Tuition Fees Discount – 2010

ISEE Thresholds	Fess Discount
From €19152.98 to €22838	50%
From €22839 to €26390	40%
From €26391 to €30450	30%
From €30451 to €35525	20%
From €35526 to €40600	10%

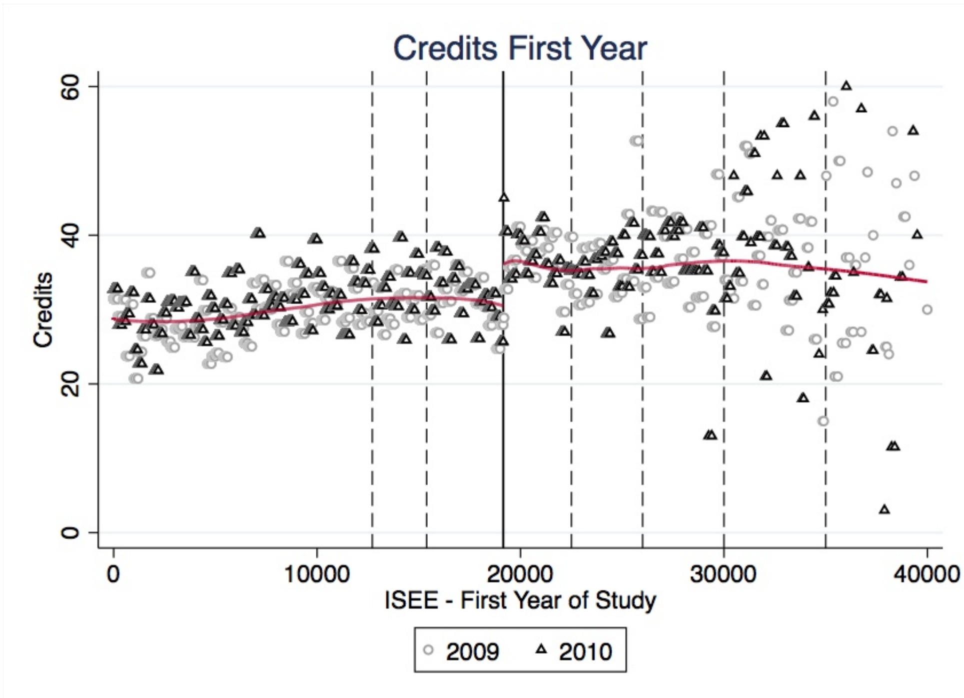
Notes: Schedule of tuition fee discounts assignment in the academic year 2010/2011.

Table A2: Summary Statistics on the Full sample

	All Graduates	Working Graduates
Bachelor student	0.65	0.56
	(0.48)	(0.50)
High-School Grade	81.9	81.4
	(12.3)	(12.4)
Female	0.60	0.61
	(0.49)	(0.49)
Final Graduation Mark	101.0	100.9
	(8.19)	(8.06)
Age	21.6	22.7
	(6.91)	(10.1)
Graduating Campus - Code	3.00	3.08
	(2.98)	(3.02)
Graduation Time	3.56	3.57
	(0.87)	(0.90)
Continue to study	0.38	
	(0.49)	
Working after graduation	0.38	
	(0.49)	
Working before graduation	0.26	0.49
	(0.44)	(0.50)
Months to find a job		4.20
		(3.58)
Part-time Job		0.43
		(0.50)
Monthly salary <1000€		0.54
		(0.50)
Skills used in the job		0.75
		(0.44)
Degree: required by law		0.19
		(0.40)
Degree: very effective		0.25
		(0.43)
Degree: necessary		0.17
		(0.37)
Observations	22457	8616

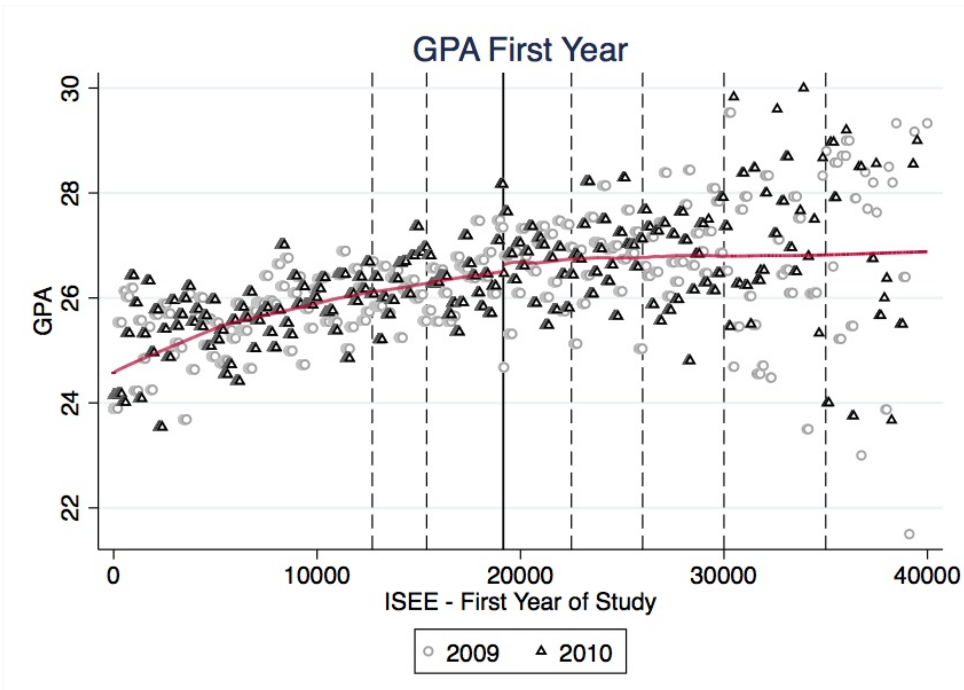
Notes: The Table shows the summary statistics on the full sample of students enrolled in the 2009/2010 or 2010/2011 academic years and graduating in the 2011/2012, 2012/2013, 2013/2014, 2014/2015 years. *Bachelor student* is a dummy variable equal to 1 for Bachelor-degree graduates. *High School Grade* takes value from 60 to 100. *Female* is a dummy variable equal to 1 for female graduates. *Final Graduation Mark* takes value from 66 to 110. *Age* measures age at enrollment. *Graduating Campus - Code* is a categorical variable taking values from 1 to 8. *Graduation Time* measures the time elapsed between enrollment and graduation (in years). *Continue studying* is a dummy variable equal to 1 if the student continues to study after graduating with the Bachelor's degree. *Working after* is a dummy variable equal to 1 if the student works after graduation. *Working during* is a dummy variable equal to 1 if the student works during college. *Months to find a job* measures the number of months it took the graduate to find a job. *Part-time* is a dummy variable equal to 1 if the student works part-time. *Monthly salary < 1000* is a dummy variable equal to 1 if the student earns less than €1,000 per month. *Skills: used* is a dummy variable equal to 1 if the working graduate reports to use at least some of the acquired skills in the job. *Degree: required* is a dummy variable equal to 1 if the degree is required by law in the working position. *Degree: effective* is a dummy variable equal to 1 if the working graduate reports that the degree was at least somehow effective for finding a job. *Degree: necessary* is a dummy variable equal to 1 if the degree is not required by law but it is necessary to perform the job. Column 1 shows the mean value and the standard deviation of the observable characteristics in the full sample. Column 2 shows the mean value and the standard deviation of the observable characteristics in the working graduates only.

Figure A1: Bin average plot of Credits – First Year of Study



Notes: Scatter plot over the ISEE indicator of the number of credits obtained at the first year averaged over bins of size €200 of ISEE in academic year 2009/2010 and 2010/2011. The red line shows the locally weighted regression of the outcome variable over the ISEE indicator.

Figure A2: Bin average plot of GPA – First Year of Study



Notes: Scatter plot over the ISEE indicator of the GPA level at the first year averaged over bins of size €200 of ISEE in academic year 2009/2010 and 2010/2011. The red line shows the locally weighted regression of the outcome variable over the ISEE indicator.

Table A3: Effects of higher aid on Credits per threshold – First year

	Credits 1st	Credits 1st	Credits 1st	Credits 1st
1st **Threshold** - Effect of higher aid	0.175	-2.052	0.171	-2.044
	(2.124)	(2.224)	(2.124)	(2.226)
ISEE	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Effect of higher aid x ISEE			0.001	-0.000
			(0.003)	(0.003)
Constant	31.695***	20.700***	32.111***	20.554***
	(1.194)	(6.101)	(1.511)	(6.212)
Observations	1040	748	1040	748
Mean Dependent Variable	31.788	30.166	31.788	30.166
2nd **Threshold** - Effect of higher aid	1.531	2.769	1.499	2.708
	(2.149)	(2.513)	(2.151)	(2.516)
ISEE	0.001	0.002	0.000	0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Effect of higher aid x ISEE			0.001	0.002
			(0.003)	(0.003)
Constant	31.671***	12.713*	32.025***	13.045**
	(1.203)	(6.522)	(1.549)	(6.550)
Observations	1015	711	1015	711
Mean Dependent Variable	32.441	30.640	32.441	30.640
3rd **Threshold** - Effect of higher aid	-8.314***	-8.948***	-8.369***	-8.870***
	(1.479)	(1.652)	(1.560)	(1.697)
ISEE	-0.001***	-0.001***	-0.001*	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Effect of higher aid x ISEE			0.000	-0.000
			(0.001)	(0.001)
Constant	38.105***	20.602***	38.207***	20.412***
	(0.858)	(4.349)	(1.259)	(4.451)
Observations	1940	1479	1940	1479
Mean Dependent Variable	33.332	32.563	33.332	32.563
4th **Threshold** - Effect of higher aid	-0.304	-0.097	-0.102	0.085
	(1.962)	(1.944)	(1.964)	(1.949)
ISEE	-0.000	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Effect of higher aid x ISEE			-0.002	-0.001
			(0.001)	(0.001)
Constant	36.228***	6.162	34.748***	5.037
	(1.116)	(5.528)	(1.437)	(5.609)
Observations	1179	1003	1179	1003
Mean Dependent Variable	36.130	35.869	36.130	35.869
5th **Threshold** - Effect of higher aid	-0.373	-2.616	-0.425	-2.644
	(2.267)	(2.301)	(2.269)	(2.304)
ISEE	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Effect of higher aid x ISEE			0.001	0.000
			(0.001)	(0.001)
Constant	36.480***	5.792	37.261***	6.226
	(1.310)	(6.351)	(1.653)	(6.501)
Observations	875	731	875	731
Mean Dependent Variable	36.188	35.919	36.188	35.919
6th **Threshold** - Effect of higher aid	-3.268	-3.518	-3.325	-3.765
	(2.733)	(3.068)	(2.760)	(3.126)
ISEE	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Effect of higher aid x ISEE			0.000	0.001
			(0.001)	(0.001)
Constant	38.926***	23.790***	39.137***	24.457***
	(1.635)	(8.501)	(2.124)	(8.655)
Observations	538	450	538	450
Mean Dependent Variable	37.203	36.684	37.203	36.684
7th **Threshold** - Effect of higher aid	-0.701	-1.933	0.021	-1.008
	(4.151)	(4.780)	(4.310)	(5.087)
ISEE	-0.000	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Effect of higher aid x ISEE			-0.001	-0.001
			(0.002)	(0.002)
Constant	37.110***	20.115	35.609***	17.943
	(2.396)	(13.415)	(3.370)	(14.032)
Observations	252	202	252	202
Mean Dependent Variable	37.234	36.733	37.234	36.733
Controls	No	Yes	No	Yes

Notes: *Credits* is the outcome variable, which measures the number of credits obtained at the end of the first year of college. *ISEE* is the running variable index of the student's family income. Columns 1 and 2 show the point estimates of the linear effect of receiving a higher benefit at each threshold, with and without controls, respectively. Columns 3 and 4 report the local linear effects of receiving a higher benefit at each threshold, with and without controls, respectively. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A4: Effects of higher aid on GPA per threshold – First year

	GPA 1st	GPA 1st	GPA 1st	GPA 1st
1st **Threshold** - Effect of higher aid	0.786**	0.577	0.789**	0.573
	(0.383)	(0.409)	(0.383)	(0.409)
ISEE	0.001***	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.001	0.001
			(0.000)	(0.001)
Constant	25.614***	20.873***	25.782***	21.121***
	(0.216)	(1.183)	(0.271)	(1.206)
Observations	815	564	815	564
Mean Dependent Variable	26.002	25.255	26.002	25.255
2nd **Threshold** - Effect of higher aid	-0.007	0.418	-0.060	0.335
	(0.392)	(0.435)	(0.393)	(0.434)
ISEE	-0.000	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.001*	0.001**
			(0.001)	(0.001)
Constant	26.266***	21.076***	26.596***	21.201***
	(0.221)	(1.172)	(0.287)	(1.168)
Observations	761	502	761	502
Mean Dependent Variable	26.271	25.426	26.271	25.426
3rd **Threshold** - Effect of higher aid	-0.103	-0.160	-0.145	-0.143
	(0.295)	(0.315)	(0.296)	(0.314)
ISEE	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000*	0.000**
			(0.000)	(0.000)
Constant	26.547***	20.077***	26.798***	20.381***
	(0.155)	(0.790)	(0.210)	(0.803)
Observations	1448	1113	1448	1113
Mean Dependent Variable	26.463	26.065	26.463	26.065
4th **Threshold** - Effect of higher aid	-0.468	-0.234	-0.459	-0.238
	(0.307)	(0.306)	(0.308)	(0.307)
ISEE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			-0.000	0.000
			(0.000)	(0.000)
Constant	26.964***	18.607***	26.899***	18.633***
	(0.175)	(0.872)	(0.226)	(0.886)
Observations	1111	942	1111	942
Mean Dependent Variable	26.718	26.451	26.718	26.451
5th **Threshold** - Effect of higher aid	0.185	-0.100	0.193	-0.084
	(0.347)	(0.346)	(0.347)	(0.346)
ISEE	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			-0.000	-0.000
			(0.000)	(0.000)
Constant	26.746***	19.472***	26.638***	19.232***
	(0.200)	(0.958)	(0.253)	(0.979)
Observations	824	684	824	684
Mean Dependent Variable	26.841	26.540	26.841	26.540
6th **Threshold** - Effect of higher aid	0.272	0.365	0.220	0.235
	(0.463)	(0.476)	(0.467)	(0.485)
ISEE	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	0.000
			(0.000)	(0.000)
Constant	26.562***	18.798***	26.754***	19.172***
	(0.274)	(1.323)	(0.357)	(1.348)
Observations	516	428	516	428
Mean Dependent Variable	26.733	26.431	26.733	26.431
7th **Threshold** - Effect of higher aid	-0.381	-0.053	-0.434	0.062
	(0.729)	(0.803)	(0.756)	(0.849)
ISEE	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	-0.000
			(0.000)	(0.000)
Constant	26.986***	18.456***	27.102***	18.171***
	(0.418)	(2.159)	(0.588)	(2.263)
Observations	243	193	243	193
Mean Dependent Variable	26.751	26.354	26.751	26.354
Controls	No	Yes	No	Yes

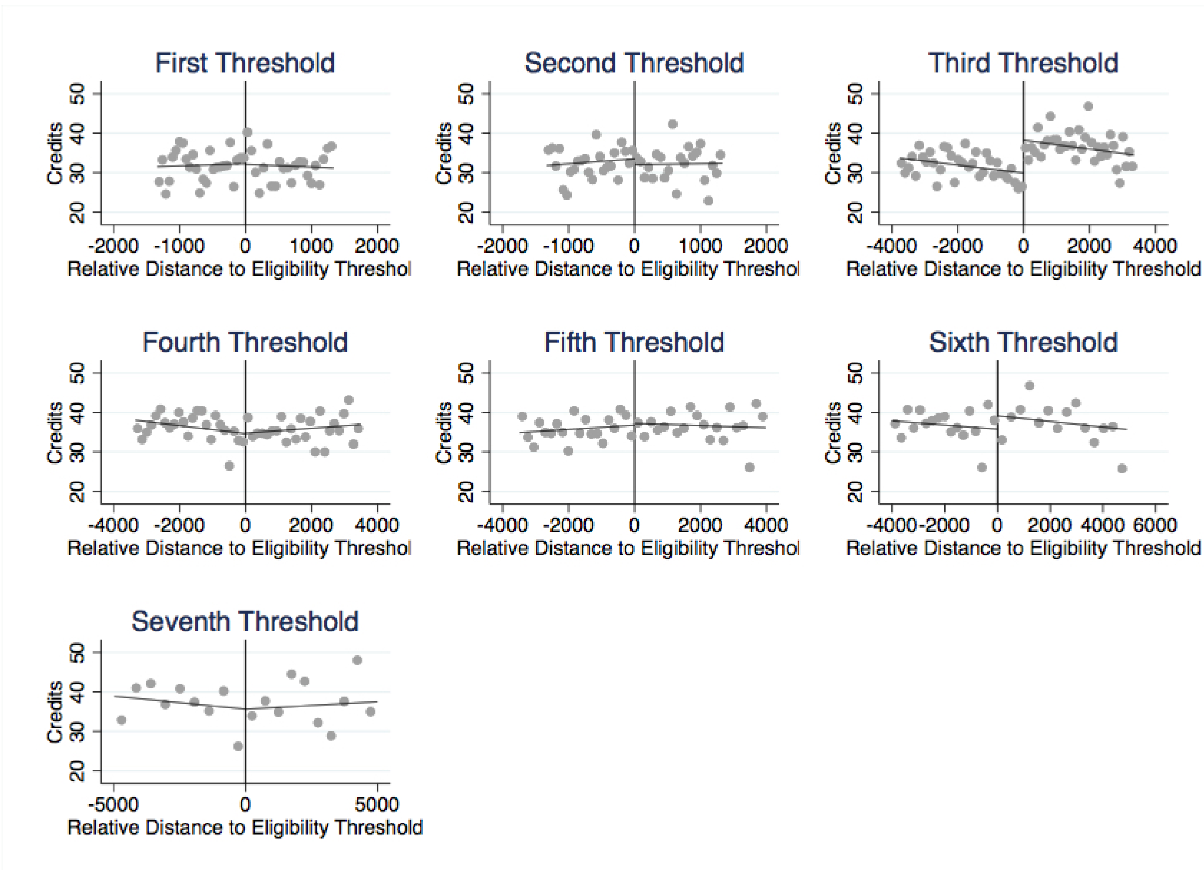
Notes: *GPA* is the outcome variable, which measures the number of credits obtained at the end of the first year of college. *ISEE* is the running variable index of the student's family income. Columns 1 and 2 show the point estimates of the linear effect of receiving a higher benefit at each threshold, with and without controls, respectively. Columns 3 and 4 report the local linear effects of receiving a higher benefit at each threshold, with and without controls, respectively. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A5: Effects of higher aid on Credits and GPA third threshold – Non parametric

	Credits 1st	GPA 1st
Conventional	8.804**	-0.123
	[3.012]	[0.609]
Bias-corrected	8.780**	-0.136
	[3.012]	[0.609]
Robust	8.780*	-0.136
	[3.643]	[0.733]
Robust 95% CI	[1.639 ; 15.92]	[-1.574 ; 1.301]
Kernel Type	Triangular	Triangular
Observations	1970	1476
Conventional p-value	0.003	0.839
Robust p-value	0.016	0.853
Order Loc. Poly. (p)	1.000	1.000
Order Bias (q)	2.000	2.000
BW est. (h)	1178.623	962.511
BW bias (b)	1794.551	1507.867

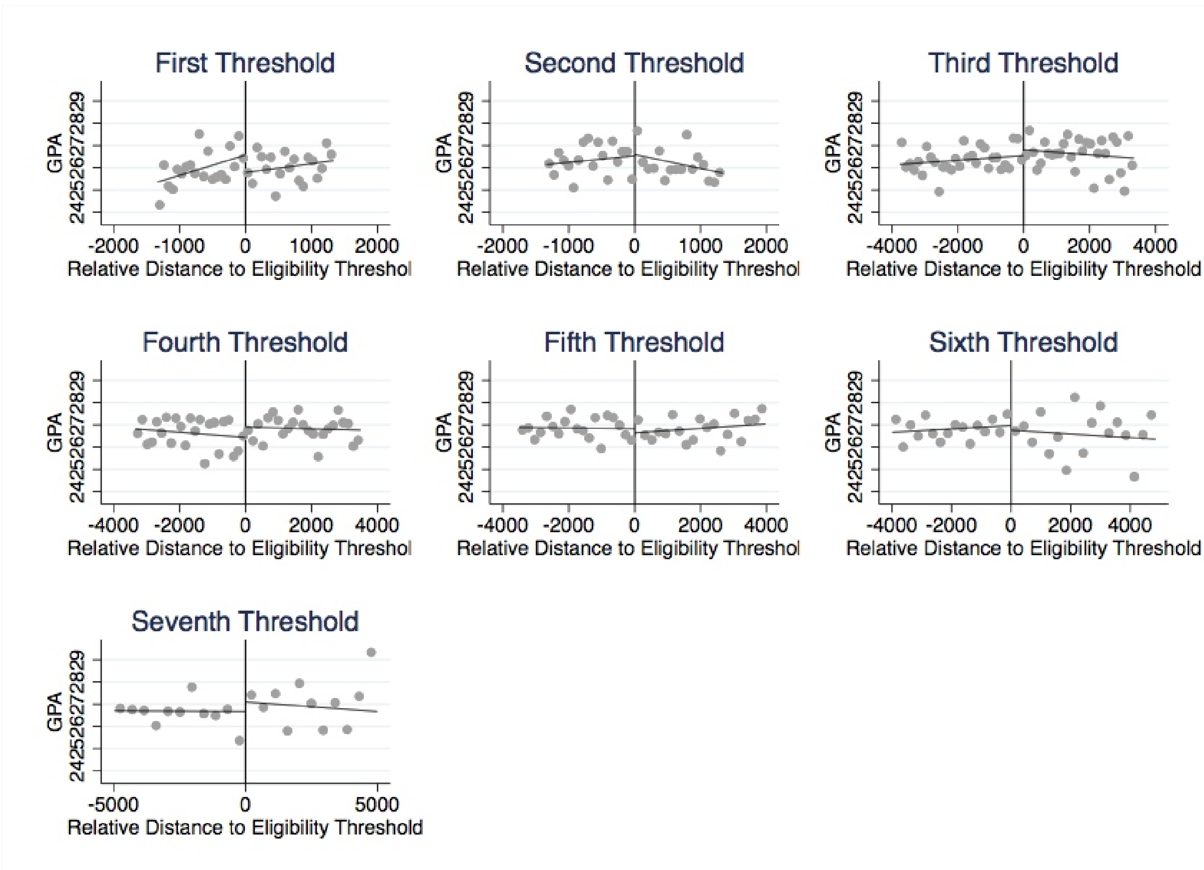
Notes: Non-parametric estimates of the effect of receiving higher aid on performances: credits obtained and GPA reached at the end of the first year of college, columns (1) and (2). Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the relative distance of the ISEE index from the threshold value €19,152.97: $(Z - c)$. Significance levels: * at 10%; ** significant at 5%; *** significant at 1% or better.

Figure A3: Non-parametric plot of Credits – First Year



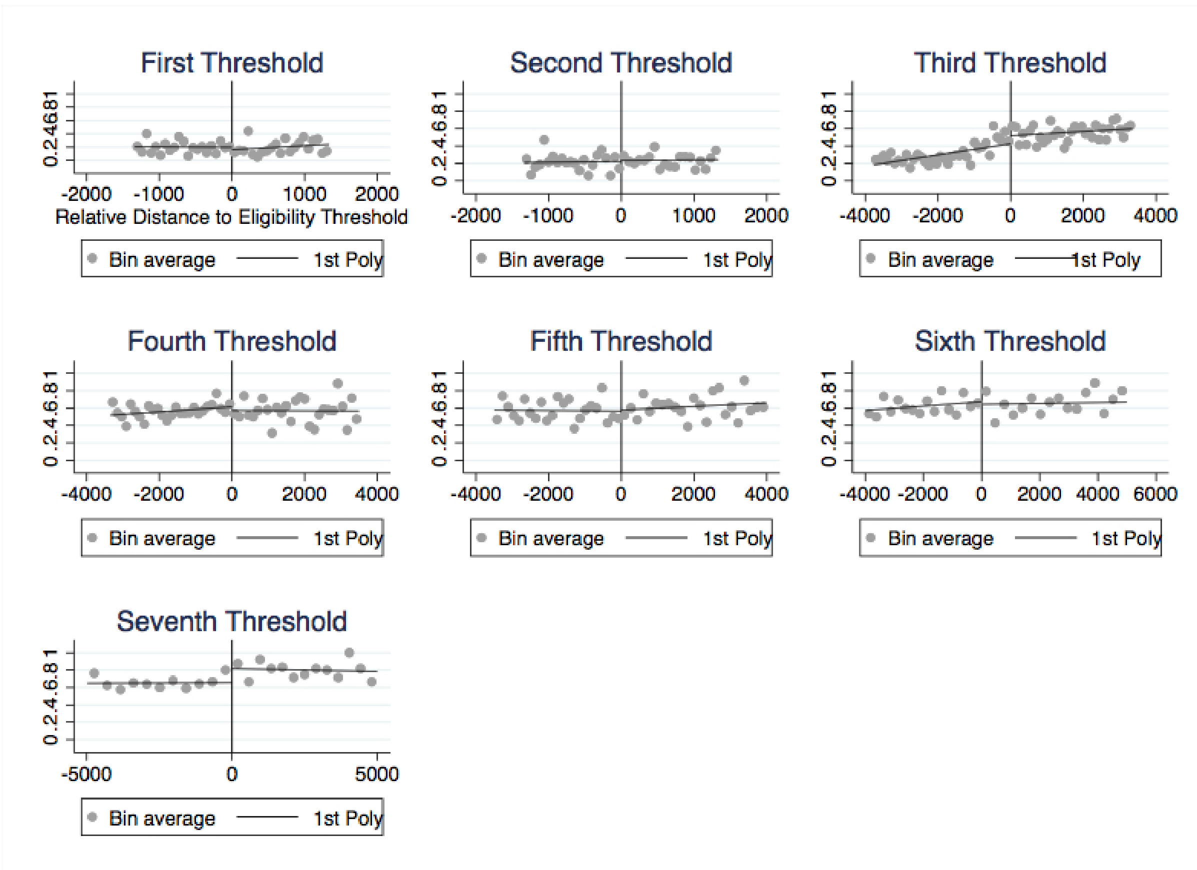
Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Figure A4: Non-parametric plot of GPA – First Year



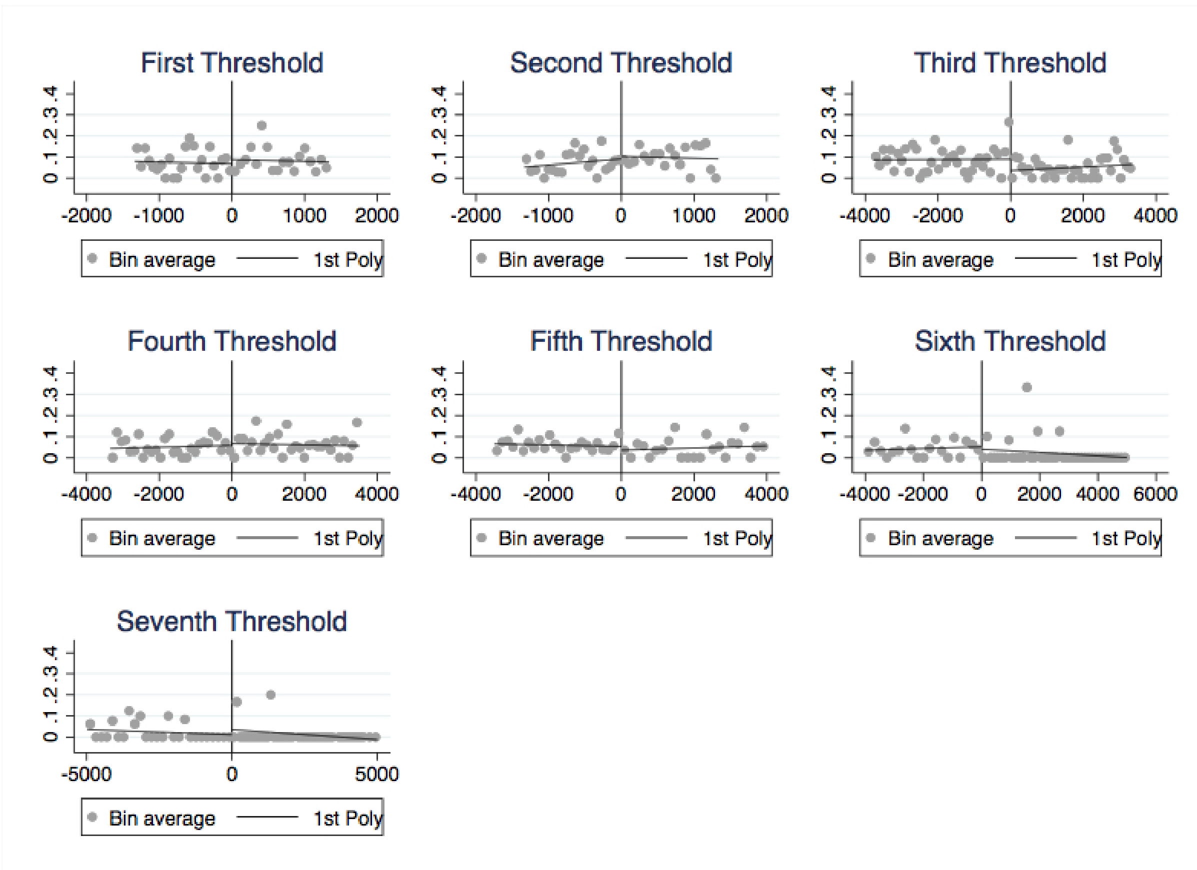
Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Figure A5: Drop-out rates



Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Figure A6: Re-enrollment rates



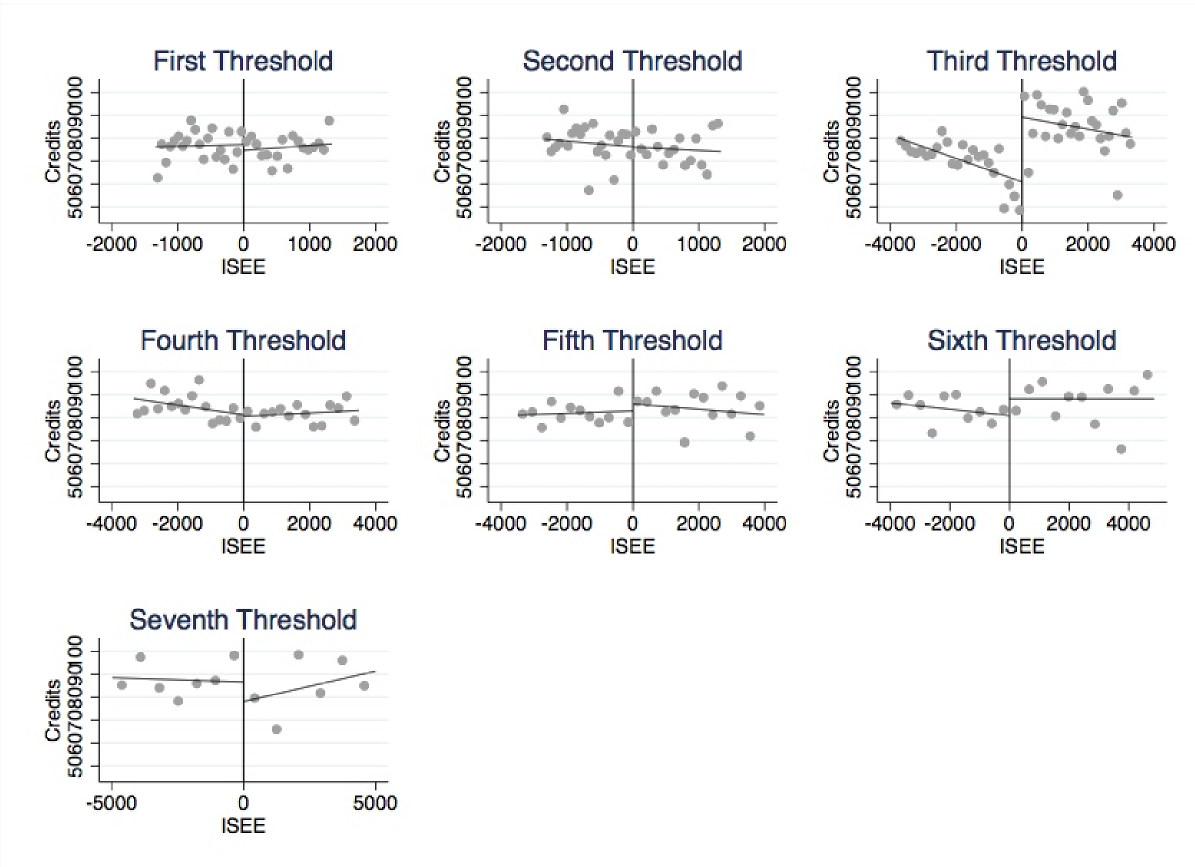
Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Table A6: Effects of higher aid on Dropout and Re-enrollment rates, and on the Probability of Not Satisfying the Minimum Requirements – Non parametric

	Drop-out	Re-Enrollment	P(No Req)
Conventional	0.060	-0.143**	-0.287***
	[0.092]	[0.055]	[0.079]
Bias-corrected	0.076	-0.163**	-0.313***
	[0.092]	[0.055]	[0.079]
Robust	0.076	-0.163*	-0.313***
	[0.111]	[0.064]	[0.091]
Robust 95% CI	[-.142 ; .293]	[-.288 ; -.037]	[-.492 ; -.134]
Kernel Type	Triangular	Triangular	Triangular
Observations	1991	2150	2150
Conventional p-value	0.516	0.010	0.000
Robust p-value	0.494	0.011	0.001
Order Loc. Poly. (p)	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000
BW est. (h)	1138.244	931.019	1008.460
BW bias (b)	1770.215	1591.505	1700.733

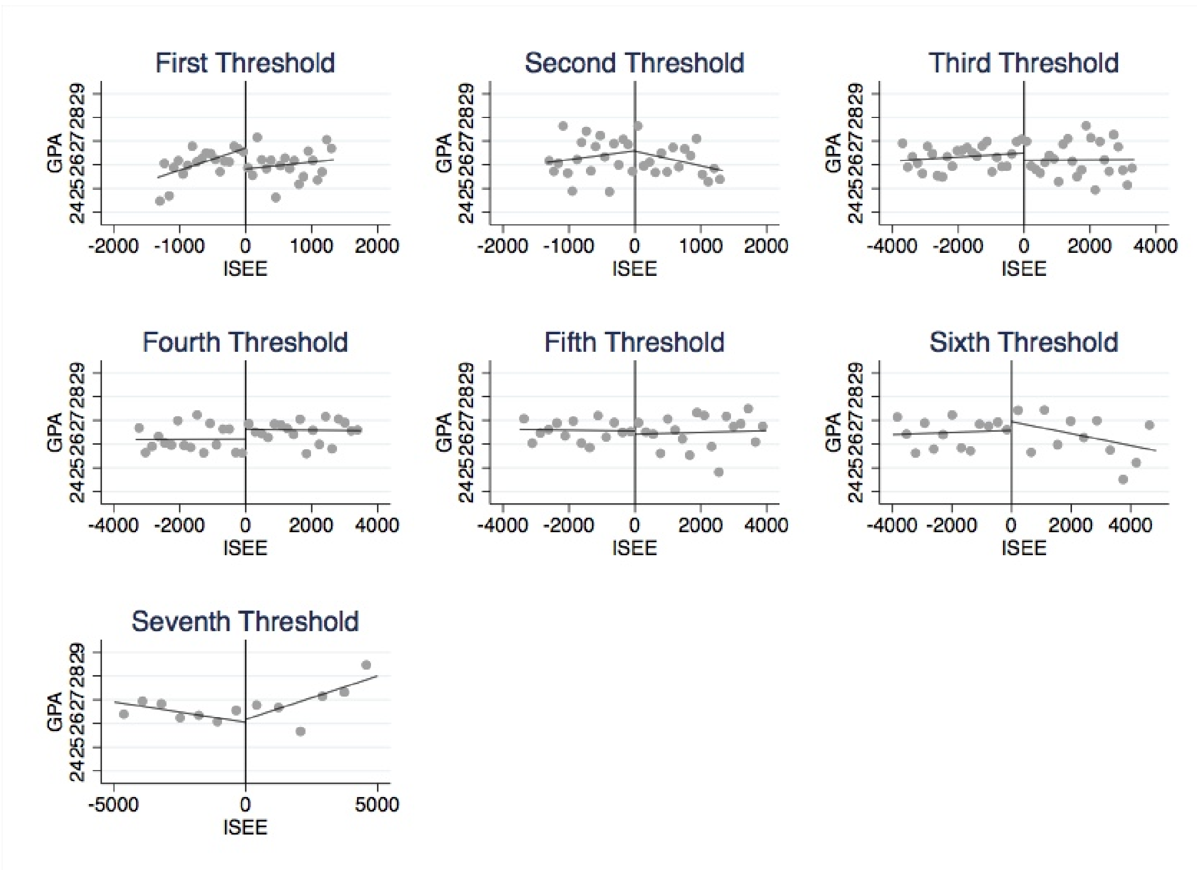
Notes: Non-parametric estimates of the effect of higher benefit on the first year dropout and re-enrollment rates. and on the probability of obtaining less than 25 (30) credits at the end of the first year of college for Bachelor (Master) students. Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the distance of the ISEE index from the threshold value €19,152.97: $(Z - c)$. Significance levels: * at 10%; ** significant at 5%; *** significant at 1% or better.

Figure A7: Non-parametric plot of Credits – Second Year



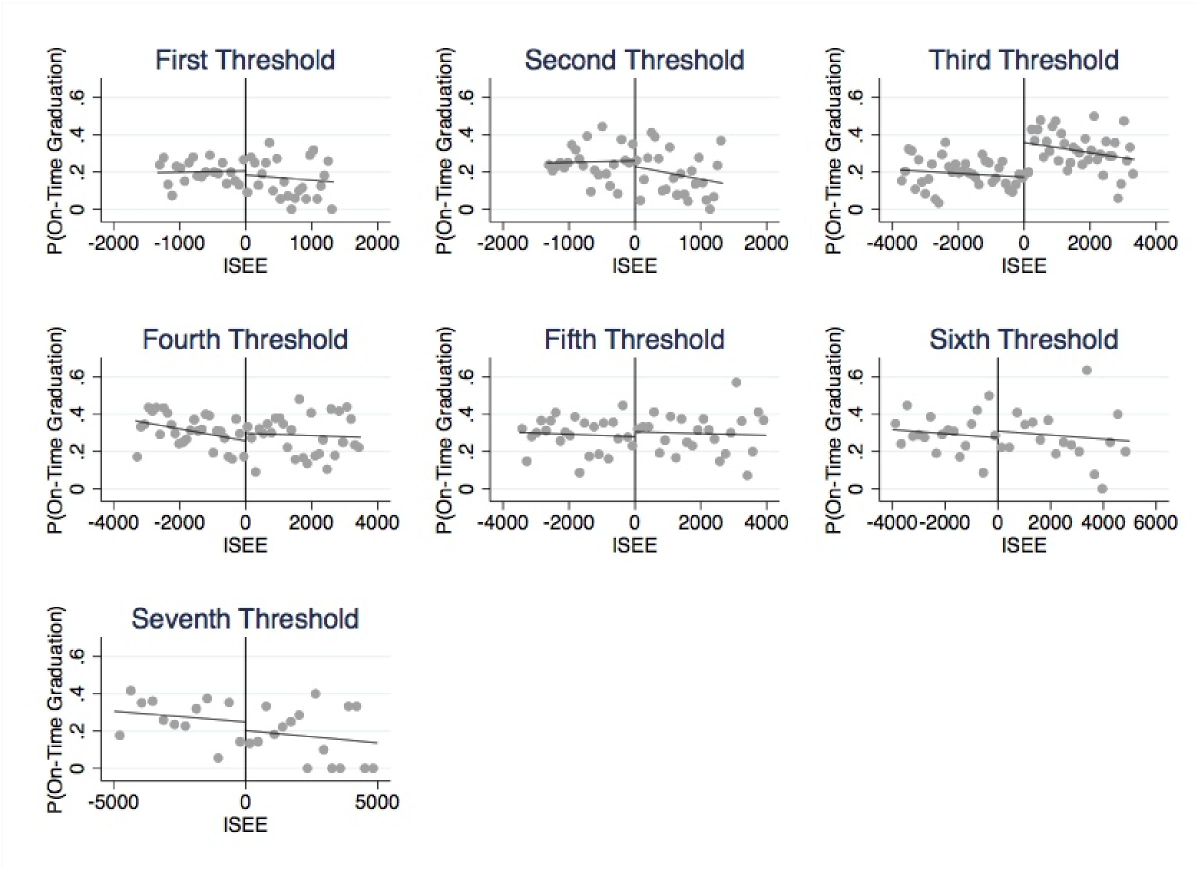
Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Figure A8: Non-parametric plot of GPA – Second Year



Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Figure A9: Non-parametric plot of the Probability of On-Time Graduation



Notes: Regression Discontinuity plots showing RD point estimates in the the neighborhood around the cutoff determined by the bandwidth used. Notice that this plot allows for weighted polynomial fits and for possibly different bandwidths on either side of the cutoff when computing the global polynomial fits (Calonico and Titiunik, 2017).

Table A7: Effects of higher aid on the Probability to Graduate on Time

	(1)	(2)	(3)	(4)
$1st$ **Threshold** - Effect of higher aid	0.021	-0.003	0.021	-0.003
	(0.048)	(0.047)	(0.048)	(0.047)
ISEE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	0.000
			(0.000)	(0.000)
Constant	0.173***	0.238*	0.185***	0.251**
	(0.027)	(0.122)	(0.034)	(0.124)
$2nd$ **Threshold** - Effect of higher aid	0.034	0.034	0.031	0.033
	(0.052)	(0.051)	(0.052)	(0.051)
ISEE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	0.000
			(0.000)	(0.000)
Constant	0.203***	0.251*	0.229***	0.264**
	(0.029)	(0.130)	(0.037)	(0.132)
$3rd$ **Threshold** - Effect of higher aid	-0.189***	-0.181***	-0.195***	-0.186***
	(0.037)	(0.036)	(0.038)	(0.037)
ISEE	-0.000**	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	0.000
			(0.000)	(0.000)
Constant	0.344***	0.445***	0.358***	0.456***
	(0.021)	(0.095)	(0.029)	(0.097)
$4th$ **Threshold** - Effect of higher aid	-0.045	-0.047	-0.041	-0.045
	(0.047)	(0.045)	(0.047)	(0.045)
ISEE	-0.000*	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			-0.000	-0.000
			(0.000)	(0.000)
Constant	0.322***	0.257**	0.298***	0.239**
	(0.027)	(0.119)	(0.035)	(0.121)
$5th$ **Threshold** - Effect of higher aid	-0.027	-0.038	-0.027	-0.038
	(0.054)	(0.052)	(0.054)	(0.052)
ISEE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			-0.000	-0.000
			(0.000)	(0.000)
Constant	0.308***	0.263**	0.306***	0.259*
	(0.031)	(0.131)	(0.039)	(0.133)
$6th$ **Threshold** - Effect of higher aid	-0.036	-0.030	-0.036	-0.027
	(0.068)	(0.067)	(0.068)	(0.068)
ISEE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			-0.000	-0.000
			(0.000)	(0.000)
Constant	0.310***	0.500***	0.310***	0.487***
	(0.040)	(0.167)	(0.052)	(0.171)
$7th$ **Threshold** - Effect of higher aid	0.047	0.070	0.046	0.070
	(0.090)	(0.093)	(0.091)	(0.094)
ISEE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE			0.000	-0.000
			(0.000)	(0.000)
Constant	0.201***	0.214	0.203***	0.211
	(0.050)	(0.228)	(0.067)	(0.233)
Observations	388	388	388	388
Controls	No	Yes	No	Yes
$Adj.R_2$	0.009	0.013	0.007	0.010

Notes: *P(On-time)* is the outcome variable, which measures the probability to graduate on time for Bachelor students (within 3 years) and for Master students (within 2 years). *ISEE* is the running variable index of the student's family income. Column (1) and (2) show the point estimates of the linear effect of receiving a higher benefit at each threshold, with and without controls respectively. Columns (3) and (4) report the local linear effects of receiving a higher benefit at each threshold, with and without controls respectively. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A8: Lee' Bounds of Treatment Effects on Credits 2^{nd}

	Credits 2^{nd}
Lower Bound	-13.102***
	[3.924]
Upper Bound	-7.588*
	[6.292]
Effect 95% CI	[-20.687 -0.505]]
Number of obs.	1339
Number of selected obs.	156
Trimming porportion	0.097

Table A9: Lee' Bounds of Treatment Effects on GPA 2^{nd}

	GPA 2^{nd}
Lower Bound	-1.390*
	[0.727]
Upper Bound	0.406
	[0.927]
Effect 95% CI	[-2.7308 1.8735]
Number of obs.	1286
Number of selected obs.	103
Trimming porportion	0.237

Table A10: Effects of higher aid on the Probabilities of Not Graduating and of Not Participating in the "AlmaLaurea" Survey – Non parametric

	P(Not Graduating)	P(No Survey)
Conventional	0.032	-0.139
	[0.662]	[1.786]
Bias-corrected	0.025	-0.156
	[0.662]	[1.786]
Robust	0.025	-0.156
	[0.805]	[2.096]
Robust 95% CI	[-1.553 ; 1.603]	[-4.264 ; 3.951]
Kernel Type	Triangular	Triangular
Observations	1543	1318
Conventional p-value	0.962	0.938
Robust p-value	0.975	0.941
Order Loc. Poly. (p)	1.000	1.000
Order Bias (q)	2.000	2.000
BW est. (h)	1168.865	1335.106
BW bias (b)	1802.825	2170.883

Notes: Non-parametric estimates of the effect of higher benefit on *P(Not Graduating)* and on *P(No Survey)*. *P(Not Graduating)* measures the probability of not graduating between 2012 and 2015. *P(No Survey)* measures the probability of not participating in the "Almalaurea" survey, conditional on graduating. Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the distance of the ISEE index from the threshold value €19,152.97: $(Z-c)$. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

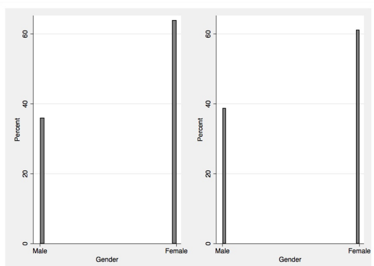
Table A11: Summary Statistics on the Matched Sample

	All Graduates	Working Graduates
High-School Grade	84.0	83.2
	(12.1)	(11.9)
Female	0.64	0.69
	(0.48)	(0.46)
Age	19.4	19.6
	(1.98)	(2.57)
Graduating Major - Code	6.44	6.53
	(2.70)	(2.80)
Graduating Campus - Code	3.19	3.44
	(3.08)	(3.16)
Graduation Time	4.33	4.48
	(1.46)	(1.48)
Continue to study	0.47	
	(0.50)	
Working after graduation	0.33	
	(0.47)	
Working before graduation	0.24	0.50
	(0.42)	(0.50)
Months to find a job		3.90
		(3.47)
Part-time Job		0.51
		(0.50)
Monthly salary <1000€		0.65
		(0.48)
Skills used in the job		0.72
		(0.45)
Degree: required by law		0.24
		(0.43)
Degree: very effective		0.23
		(0.42)
Degree: necessary		0.11
		(0.32)
Observations	1318	434

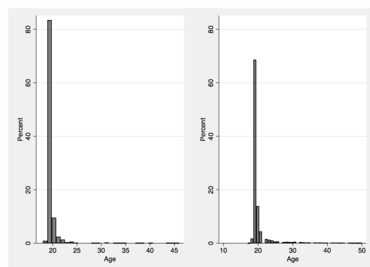
Notes: The Table shows the summary statistics in the matched sample. *Bachelor student* is a dummy variable equal to 1 for Bachelor-degree graduates. *High School Grade* takes value from 60 to 100. *Female* is a dummy variable equal to 1 for female graduates. *Final Graduation Mark* takes value from 66 to 110. *Age* measures age at enrollment. *Graduating Campus - Code* is a categorical variable taking values from 1 to 8. *Graduation Time* measures the time elapsed between enrollment and graduation (in years). *Continue studying* is a dummy variable equal to 1 if the student continues to study after graduating with the Bachelor's degree. *Working after* is a dummy variable equal to 1 if the student works after graduation. *Working during* is a dummy variable equal to 1 if the student works during college. *Months to find a job* measures the number of months it took the graduate to find a job. *Part-time* is a dummy variable equal to 1 if the student works part-time. *Monthly salary < 1000* is a dummy variable equal to 1 if the student earns less than €1,000 per month. *Skills: used* is a dummy variable equal to 1 if the working graduate reports to use at least some of the acquired skills in the job. *Degree: required* is a dummy variable equal to 1 if the degree is required by law in the working position. *Degree: effective* is a dummy variable equal to 1 if the working graduate reports that the degree was at least somehow effective for finding a job. *Degree: necessary* is a dummy variable equal to 1 if the degree is not required by law but it is necessary to perform the job. Column 1 shows the mean value and the standard deviation of the observable characteristics in the matched sample for all the graduates. Column 2 shows the mean value and the standard deviation of the observable characteristics in the matched sample for the working graduates only.

Figure A10: **Characteristics of Graduates: Administrative vs. Survey Data**

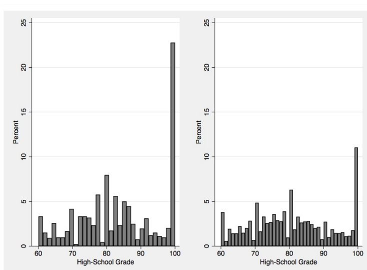
(a) Gender



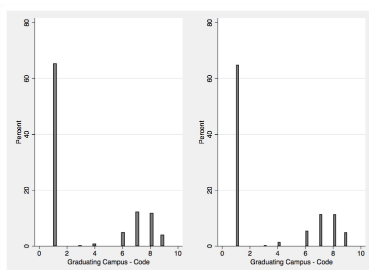
(b) Age at enrollment



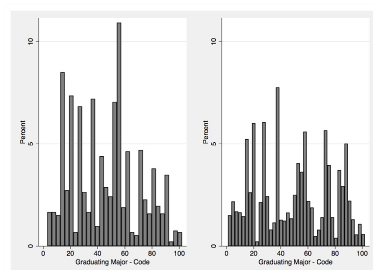
(c) High-School Grade



(d) Graduating Campus - Code



(e) Graduating Major - Code



Notes: The graphs on left present the distribution of the variable in the administrative data. The graphs on the right present the same distribution of the variable in the survey data.

Table A12: Balance of Covariates: Administrative and Survey Matched Sample

	High-School	Female	Age	Humanistic	Campus	Cluster
Conventional	0.97	-0.13	0.013	-0.090	-0.49	-0.17
	[2.03]	[0.081]	[0.090]	[0.094]	[0.53]	[0.35]
Bias-corrected	0.28	-0.11	-0.0019	-0.088	-0.35	-0.27
	[2.03]	[0.081]	[0.090]	[0.094]	[0.53]	[0.35]
Robust	0.28	-0.11	-0.0019	-0.088	-0.35	-0.27
	[2.40]	[0.095]	[0.11]	[0.11]	[0.64]	[0.42]
Observations	1318	1318	1318	1318	1318	1318
Conventional p-value	0.63	0.099	0.89	0.34	0.36	0.64
Robust p-value	0.91	0.27	0.99	0.44	0.59	0.52
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
BW est. (h)	700.9	809.5	729.9	710.3	777.2	731.5
BW bias (b)	1202.9	1385.1	1426.1	1113.8	1289.9	1036.7

Notes: Non-parametric estimates of the effect of being above the third threshold on the distribution of the covariates (in the matched administrative-Almalaurea sample: high-school grade, gender, age, type of major (humanistic studies vs scientific majors) and the numeric code of the campus of enrollment. The last column shows the estimates of the effect of being above the third threshold on the distribution of the cluster size in the matched administrative-Almalaurea sample. Following Calonico et al. (2014b) and Calonico et al. (2014a), I report the optimal bandwidth for the local polynomial (h) and for the bias (b). The treatment effects are computed for: the local polynomial estimator (conventional), the bias-corrected estimator proposed by Calonico et al. (2014b) and the same estimator with robust standard errors. The running variable is the distance of the ISEE index from the threshold value €19,152.97: $(Z - c)$. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A13: Robustness: Choice of the local polynomial

	(1) Credits 1st b/se	(2) Credits 1st b/se	(3) Credits 1st b/se	(4) Credits 1st b/se	(5) GPA 1st b/se	(6) GPA 1st b/se	(7) GPA 1st b/se	(8) GPA 1st b/se
3rd **Threshold** - Effect of higher aid	-8.619***	-9.012***	-8.897***	-9.886***	0.523	0.476	0.090	-0.252
	(2.355)	(2.567)	(3.172)	(3.487)	(0.468)	(0.500)	(0.646)	(0.696)
ISEE	0.004	0.005*	0.006	0.006	0.000	0.001	-0.000	-0.001
	(0.003)	(0.003)	(0.007)	(0.007)	(0.000)	(0.000)	(0.001)	(0.001)
Effect of higher aid x ISEE	-0.010***	-0.011***	-0.014*	-0.016*	0.000	-0.000	0.000	0.000
	(0.003)	(0.003)	(0.008)	(0.009)	(0.001)	(0.001)	(0.001)	(0.002)
ISEE_2	-0.000**	-0.000**	-0.000	-0.000	-0.000	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Effect of higher aid x ISEE_2	0.000	0.000	0.000	-0.000	0.000*	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ISEE_3			0.000	0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Effect of higher aid x ISEE_3			-0.000	-0.000			-0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Constant	35.327***	17.625***	34.891***	17.149***	26.568***	19.925***	26.713***	20.252***
	(1.893)	(4.705)	(2.540)	(5.029)	(0.318)	(0.842)	(0.429)	(0.890)
Observations	1940	1479	1940	1479	1448	1113	1448	1113
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj.R_2	0.026	0.162	0.025	0.161	0.004	0.201	0.003	0.201

Notes: The Table displays the robustness of the discontinuity estimates to the choice of the local polynomial around the third threshold. Standard errors in parentheses. Significance levels: $*p < 0.10, **$ $p < 0.05, ***p < 0.01$.

Table A14: Robustness: Choice of Kernel – Non-parametric

	Credits 1st	Credits 1st	GPA 1st	GPA 1st
Conventional	8.385**	9.631***	-0.197	-0.331
	[3.011]	[2.750]	[0.599]	[0.616]
Bias-corrected	8.310**	10.089***	-0.239	-0.337
	[3.011]	[2.750]	[0.599]	[0.616]
Robust	8.310*	10.089**	-0.239	-0.337
	[3.638]	[3.287]	[0.719]	[0.730]
Robust 95% CI	[1.18 ; 15.439]	[3.648 ; 16.531]	[-1.649 ; 1.171]	[-1.768 ; 1.095]
Kernel Type	Epanechnikov	Uniform	Epanechnikov	Uniform
Observations	1970	1970	1476	1476
Conventional p-value	0.005	0.000	0.743	0.591
Robust p-value	0.022	0.002	0.739	0.645
Order Loc. Poly. (p)	1.000	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000	2.000
BW est. (h)	1105.573	1179.867	919.173	785.327
BW bias (b)	1756.715	2054.632	1500.130	1396.645

Notes: The Table displays the robustness of the effects to the choice of kernel of the non-parametric estimate around the third threshold. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A15: Robustness: Choice of Bandwidth – Non-parametric

	Credits 1st	Credits 1st	Credits 1st	GPA 1st	GPA 1st	GPA 1st
Conventional	8.801**	8.804**	8.801**	-0.117	-0.123	-0.123
	[2.966]	[3.012]	[2.966]	[0.630]	[0.609]	[0.609]
Bias-corrected	8.765**	8.780**	8.765**	-0.130	-0.136	-0.145
	[2.966]	[3.012]	[2.966]	[0.630]	[0.609]	[0.609]
Robust	8.765*	8.780*	8.765*	-0.130	-0.136	-0.145
	[3.528]	[3.643]	[3.528]	[0.740]	[0.733]	[0.730]
Robust 95% CI	[1.85 ; 15.681]	[1.639 ; 15.92]	[1.85 ; 15.681]	[-1.581 ; 1.321]	[-1.574 ; 1.301]	[-1.577 ; 1.286]
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Observations	1970	1970	1970	1476	1476	1476
Conventional p-value	0.003	0.003	0.003	0.852	0.839	0.839
Robust p-value	0.013	0.016	0.013	0.861	0.853	0.842
Order Loc. Poly. (p)	1.000	1.000	1.000	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000	2.000	2.000	2.000
BW est. (h)	1249.418	1178.623	1249.418	908.031	962.511	962.511
BW bias (b)	1942.024	1794.551	1942.024	1517.797	1507.867	1517.797

Notes: The Table displays the robustness of the effects to the choice of the bandwidth in the non-parametric estimate at the third threshold. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A16: Robustness: Placebo Cutoffs– Non-parametric

	Credits 1st	Credits 1st	GPA 1st	GPA 1st
Conventional	-1.058	-0.268	-0.299	-0.298
	[1.103]	[1.427]	[0.200]	[0.235]
Bias-corrected	-1.077	-0.631	-0.359	-0.365
	[1.103]	[1.427]	[0.200]	[0.235]
Robust	-1.077	-0.631	-0.359	-0.365
	[1.325]	[1.687]	[0.235]	[0.270]
Robust 95% CI	[-3.675 ; 1.521]	[-3.937 ; 2.676]	[-.8200000000000001 ; .103]	[-.895 ; .165]
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	8956	8956	7082	7082
Conventional p-value	0.337	0.851	0.135	0.205
Robust p-value	0.416	0.709	0.127	0.177
Order Loc. Poly. (p)	1.000	1.000	1.000	1.000
Order Bias (q)	2.000	2.000	2.000	2.000
BW est. (h)	6047.838	6504.898	5990.920	5946.226
BW bias (b)	9590.375	10692.604	9888.407	10114.463

Notes: The Table displays the non-parametric estimate on the robustness of the effect to the use of two placebo cutoffs before and after the third threshold: Column 1 and 3 at a level of ISEE=16,000 and Column 2 and 4 at a level of ISEE=21,000. Standard errors in parentheses. Significance levels: $*p < 0.10, **p < 0.05, ***p < 0.01$.