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The effects of financial aid on graduation and labor market outcomes: New evidence from matched education-labor data

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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 facing 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 the probability of graduating from college.

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 & Scott-Clayton, 2016).

Despite the relatively extensive literature on the effects of financial aid, previous empirical evidence usually captures the combined impacts of aid amounts and of the minimum academic requirements. Furthermore, the current literature mostly focus on academic performance during college. One exception is Montalbán (2023), 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 these government inputs.

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[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 Minaya, Agasisti, and Bratti (2022) 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 (2023) on medium- and high-ability students. However, besides focusing only on a change in the requirements (and not in 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.

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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 tentatively looks at the 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, and some of the results are imprecisely estimated, this analysis is still informative about the labor market participation choice of the graduates, and 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. Notice that the extra aid covers a quite large share of the educational costs, namely around 28,4%.[6]

This gap in performance persists over time, significantly slowing the 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).[7] In contrast, I find no strong effects of aid generosity on GPA or drop-out rates.[8] When looking at the after-graduation outcomes, although some of the results are imprecisely estimated, 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 & Schudde, 2020).[9] 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, Ichino, & Rustichini, 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, Richburg-Hayes, Rouse, & Brock, 2014; Bettinger, Gurantz, Kawano, Sacerdote, & Stevens, 2019; Cornwell, Lee, & Mustard, 2005; Cornwell, Mustard, & Sridhar, 2006; Dynarski, 2008; Scott-Clayton, 2011; Scott-Clayton & Zafar, 2019). Consequently, it is often difficult to generalize these results to the full population of college students.[10] 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.

[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) here.

[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).

[6] The cost of higher education in Italy is mainly driven by tuition and by living expenses. Tuition costs vary by program, from a minimum of €1,258 to a maximum of €4,400 at the University of Bologna in 2016 (link). The average living expenses in Bologna in 2016 was about €1,025 per month, including rent — these estimates are taken from the *Numbeo Quality of Life Index* (link) for Bologna in 2016 and from *Immobiliare* observatory (link), making to a total of €12,300 per year. Therefore, the share of the college cost covered by the average grant is given by €3,500/€12,300.

[7] This result is indeed in line with Garibaldi, Giavazzi, Ichino, and Rettore (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, 2023; 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.

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

[9] 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.

[10] 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 & 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, Lang, & Oreopoulos, 2009; Angrist, Oreopoulos, & Williams, 2014).

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 & Long, 2016; Denning, 2018; Dynarski, 2003; Fack & Grenet, 2015; Goldrick-Rab, Kelchen, Harris, & Benson, 2016; Modena, Rettore, & Tanzi, 2020; Murphy & Wyness, 2023). 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 & Jones, 2012; Sjoquist & 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, Marx, and Turner (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 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. While this paper does not study the long-run effects of financial aid on the earning profiles of graduates, and some of the post-graduation results are imprecisely estimated (making the analysis not fully definitive), it is one of the first attempt 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, 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. Second, this setting also allows to separate the effect of financial aid from other factors typically influencing college performance, like students' ex-ante ability and 'socio-economic backgrounds. Indeed, previous studies have mostly focused on merit-based programs, which typically target high- or medium-achieving students. In particular, this paper identifies the effects of financial aid generosity on performance by looking at students with comparable family income, while controlling for their ex-ante ability, as captured by the final high school grade. Third, 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 is one of the first attempts in examining both the short-term (during college) and medium-term (after graduation) impacts of a large-scale policy covering low-income students in Europe, better clarifying how financial aid might affect 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 analyzes 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.[11] 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.[12] 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.[13]

2.2. The right 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

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

[12] 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 & Crosier, 2018).

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

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%		
Panel C: Credits Requirements over Credit Load by Years and Programs			
Type of course	1st Year	2nd Year	3rd Year
Bachelor	25 credits out of 60	80 credits out of 120	135 credits out of 180
Master	30 credits out of 60	80 credits out of 120	–

the central government.[14] 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.[15]

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.[16] 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.[17] 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 min away from the campus (by public transport); "fuori sede" or students who live more than 90 min away from the campus; and "pendolari" or commuting students, identifying those who live from 45 to 90 min 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 described in Panel B of Table 1.[18] To summarize, all the students with an ISEE below €19,152.97 are exempted from paying any tuition, and they receive a grant.[19] 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.[20] Fig. 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. The minimum credit requirements at each year of study are set as follows: bachelor students must obtain 25 credits (out of 60) by the end of the first academic year, and master students must obtain 30 credits (out of 60) by the end of the first academic year. By the end of the second year, recipients

[14] 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).

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

[16] 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.

[17] 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.

[18] 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.

[19] 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.

[20] 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 University of Bologna (link).

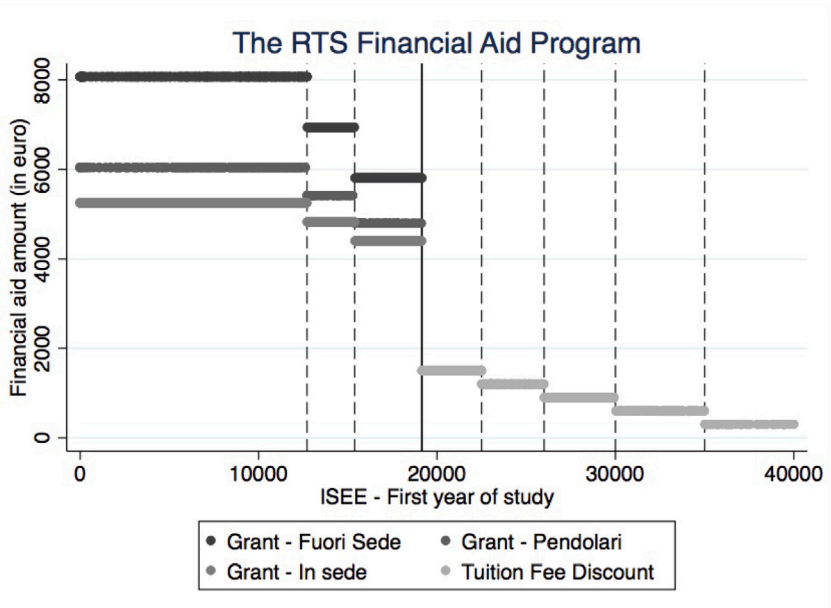

Fig. 1. The RTS benefit level schedule.
Notes: The graph plots how the total amount of aid change with the level of the family income indicator, ISEE. The recipients positioned below the €19,152.97 threshold receive a grant, which varies with the ISEE index and the student'status – "Fuori sede", "Pendolari", "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.

are required to have a cumulative sum of at least 80 credits (out of 120), 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.

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 2 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.[21] 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.[22]

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.[23] "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.[24] 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

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

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

[23] 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.

[24] 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).

Table 2
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: 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.

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 €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.[25]

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).

In the present context, the assignment variable is the family income index, i.e., the ISEE index, and the treatment variable is the level of benefit received. The intuition is that, by exploiting the fact that the level of financial aid received is determined by several income-eligibility thresholds, if the level of the treatment (financial aid amount) has an effect on academic performance (for example, on the number of earned credits and GPA), I should observe a discontinuity in the performance between students whose parental income is located just above or below the income-eligibility thresholds.

To identify the average treatment effect on the treated (ATT) in the data, this paper presents the main results using the most recent non-parametric techniques with optimal bandwidth computation (Calonico, Cattaneo, Farrell, & Titiunik, 2017, 2019; Calonico, Cattaneo, & Titiunik, 2014a, 2014b). However, as shown in Section 5, the results are robust to the use of a parametric approach using different functional forms (linear, quadratic, or cubic regressions), and to the inclusion/exclusion of other controlling variables. Specifically, the parametric results are derived using the following model:

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

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 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 $(Z_i - c) \leq 0$.[26] 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 Fig. 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, Jansson, and Ma (2016). Figs. 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.[27]

[25] 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%.

[26] 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.

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

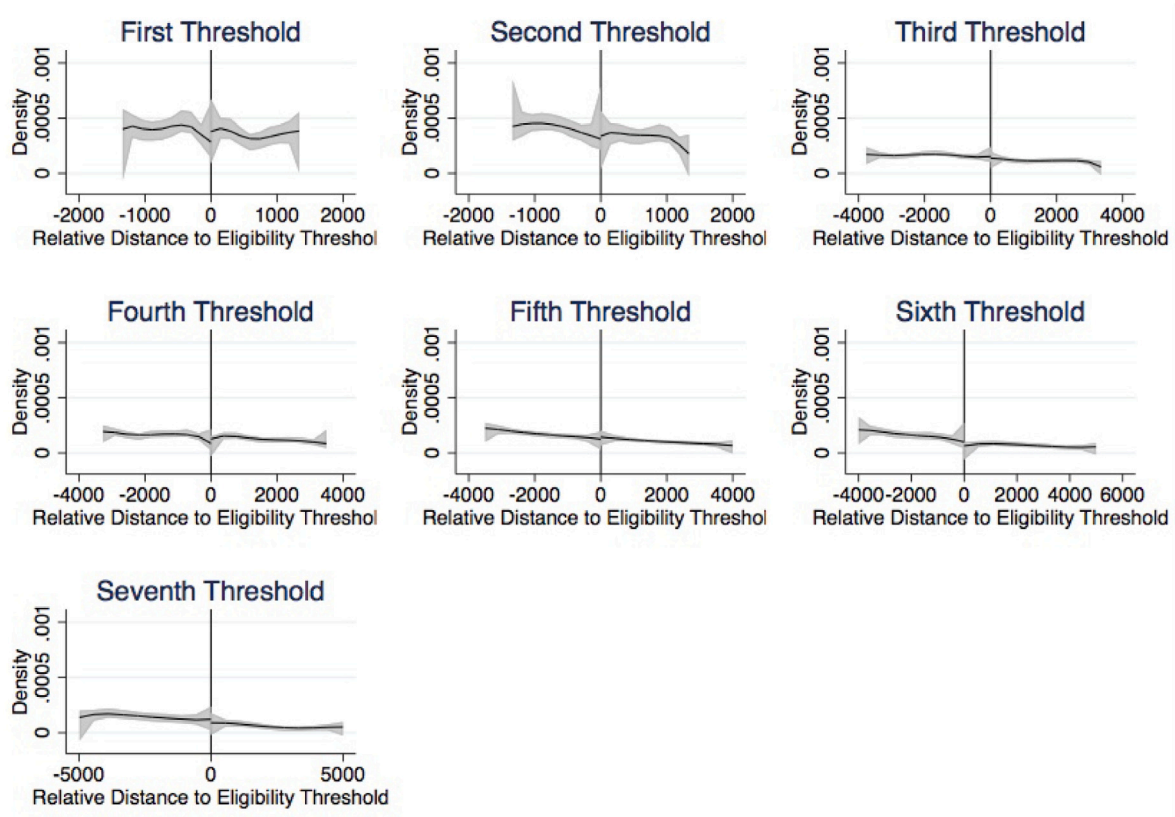

Fig. 2. Cattaneo, Jansson, and Ma (2017a) density tests 2009: individual thresholds.
Notes: The graph implements density testing procedures using the local polynomial estimators to construct test statistics and p-values given a pre-specified cutoff, using data-driven bandwidth selection as in Calonico et al. (2017).

4. Results

4.1. The effect of financial aid on college performance

Following (Imbens & 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.

Figs. 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.[28] 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.[29] 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 final notice of financial aid eligibility is generally communicated only around December, which is a few months after the start of the academic year (mid-September). 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 & 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 (“Fuori sede”, “Pendolari”, “In sede”). In particular, Fig. 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 Panel C of Table 1). 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

[28] 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.

[29] 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.

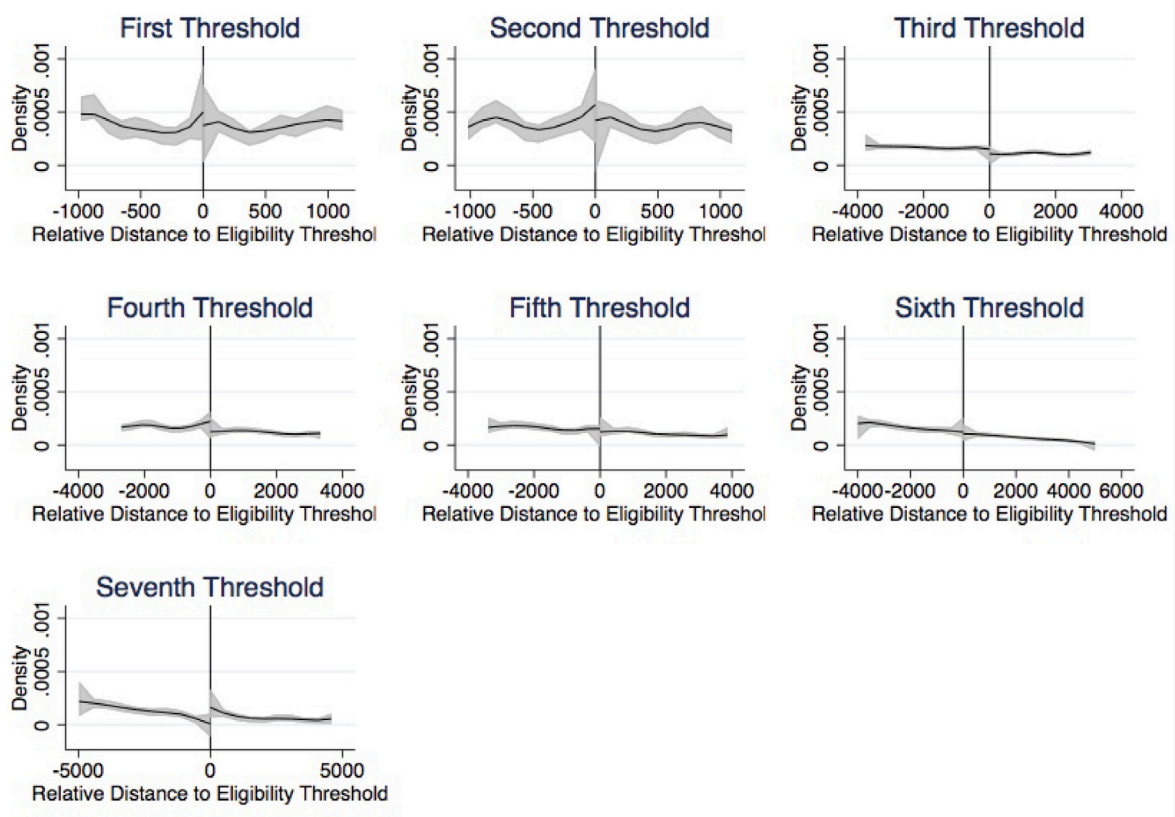

Fig. 3. Cattaneo, Jansson, and Ma (2017a) density tests 2010: individual thresholds.
Notes: The graph implements density testing procedures using the local polynomial estimators to construct test statistics and p-values given a pre-specified cutoff, using data-driven bandwidth selection as in Calonico et al. (2017).

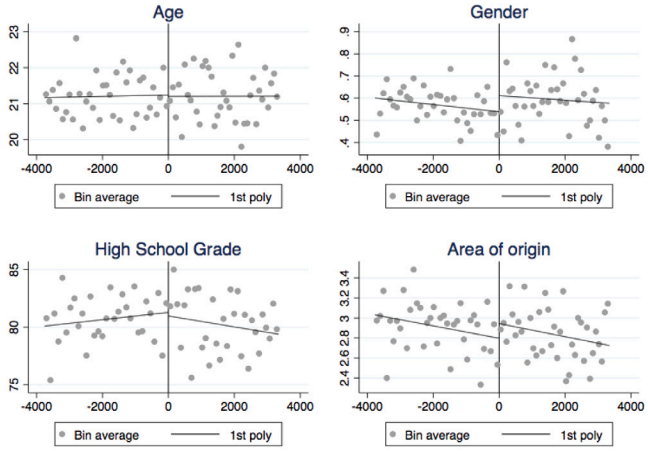

Fig. 4. Pre-treatment continuity in relevant covariates.
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

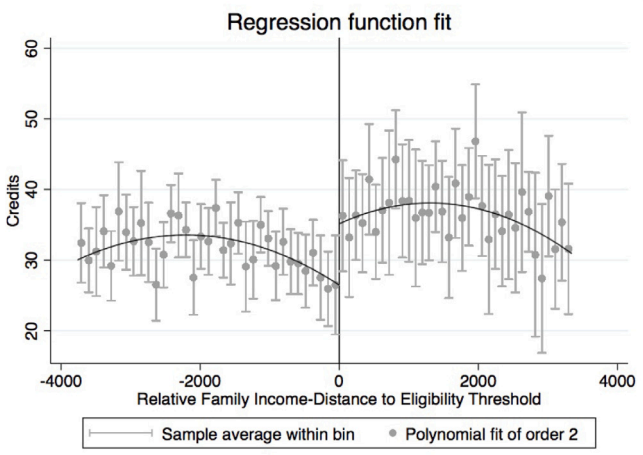

Fig. 5. Credits – First year of study.
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

observations on the top of the income distribution (see Figs. 2 and 3). Fig. 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, Fig. 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

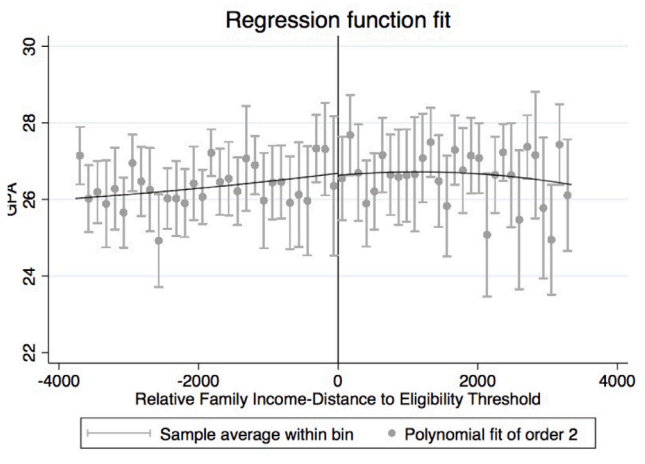

Fig. 6. GPA – First year of study.
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

Table 3
Effects of higher aid on Credits, GPA and Graduation Time at the third threshold – Non parametric.

	Credits 1st	GPA 1st	Graduation Time
Conventional	−8.801**	0.124	1.371***
	[3.016]	[0.608]	[0.363]
Bias-corrected	−8.778**	0.136	1.445***
	[3.016]	[0.608]	[0.363]
Robust	−8.778*	0.136	1.445***
	[3.650]	[0.733]	[0.433]
Observations	1970	1476	1355
Robust 95% CI	[−15.931 ; −1.624]	[−1.301 ; 1.574]	[.597 ; 2.293]
Kernel Type	Triangular	Triangular	Triangular
Mean Dep. var	36.4	26.6	4.27
Conventional p-value	0.0035	0.84	0.00016
Robust *p*-value	0.016	0.85	0.00084
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
BW est. (h)	1177.4	963.1	1418.7
BW bias (b)	1793.3	1507.6	2200.9

Notes: Non-parametric estimates of the effect of receiving higher aid on performances: credits obtained, GPA reached at the end of the first year of college, and overall Graduation Time. 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.

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.

In the next part of the section, I present the regression results by pooling all the cohorts and by using the nonparametric estimator by Calonico et al. (2014a, 2014b). The regression results on the effects of financial aid generosity on performance are reported in Table 3, which shows the estimates at the €19,152.97 threshold. The first two columns of Table 3 show the treatment effects of receiving about 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 the students positioned below the €19,152.97 threshold is centered around the minimum requirements in terms of credits (around 28 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 corresponds to one and a half courses. Additionally, Column 2 of Table 3 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 reduced-form model presented in Eq. (1) is adopted, or when the full set of controls is included in the regressions, as shown in Tables A3 and A4 of the Appendix. Instead, Tables A5 and A6 of the Appendix look at the regression results at each threshold, separately. It is worth noting that the results are confirmed also 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 and the formal analysis have 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 2 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. As this graphical analysis has shown, there is no systematic difference in drop-out rates near the third threshold, when looking at the nonparametric estimates in the first column of Table A9. Table A9 also confirms that the higher-aid recipients re-enroll significantly more often as first-year students than those receiving lower aid. This result could indeed be 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 re-apply 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 A9 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. Notice, also, that the main results on the GPA shown in Table 3, are confirmed when dropout is taken into account more directly: the last column of Table A9 indeed shows that higher-aid recipients seem to be about 4 percentage points more likely to have a GPA higher than 26, i.e. the median value, where for those who drop out this outcome variable takes value zero, but this difference is not significant.

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

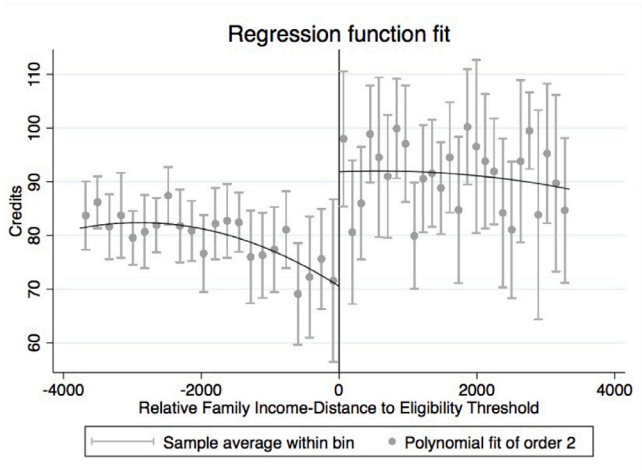

Fig. 7. Credits – Second year of study.
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

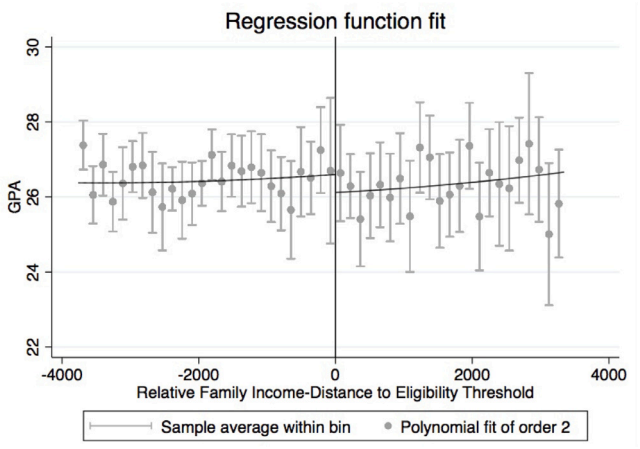

Fig. 8. GPA – Second year of study.
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

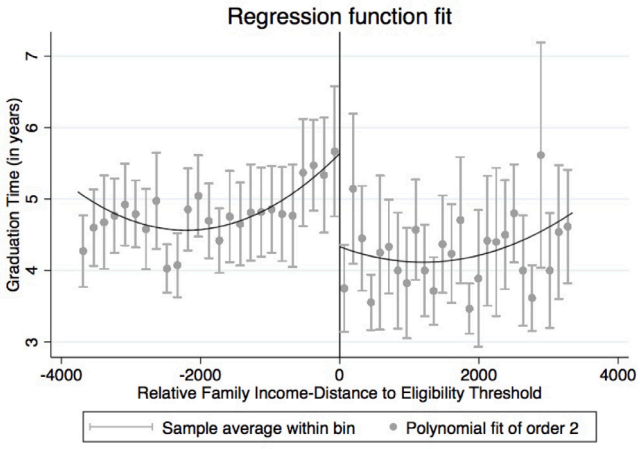

Fig. 9. Average graduation time (in years).
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

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. Figs. 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. 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, and for a general dropout, 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 A10 and A11 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 not 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. This is also confirmed, when looking at the treatment effects on the GPA level at the third year using the Lee' Bounds in Table A12. The Table shows that both the bounds, and the confidence interval of the treatment effect at the third year are also centered around zero, suggesting that the null effect on the GPA persist for the entire education path.

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. Fig. 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 more than a year longer to finish college. The third column of Table 3 shows, indeed, that the initial 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 approximately 1 year and 4 months longer to finish college. This results is also confirmed by the different parametric specifications of Table A7, and it 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 A9. Interestingly, receiving higher aid does not significantly affect the probability of graduating. In particular, the fourth column of Table A9 shows that the share of financial aid recipients who did not graduate in this time period is about 12 percentage points lower among the higher-aid recipients, but this difference is not statistically significant. This result is also confirmed by the nonparametric plot reported in Fig. 10.

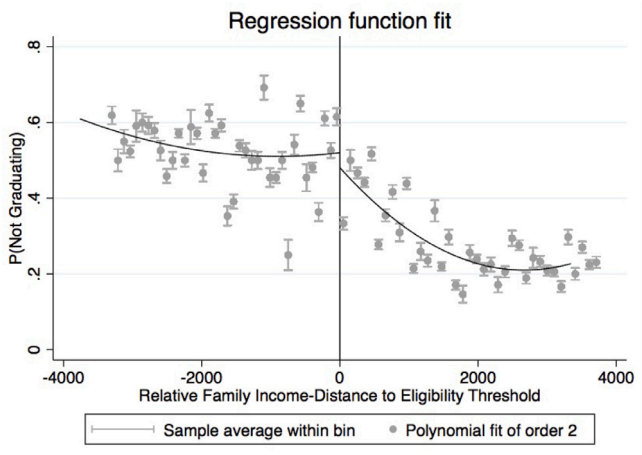

Fig. 10. P(Not graduating).
Notes: The graph implements a data-driven Regression Discontinuity (RD) plot. Two type of RD plots are constructed: (i) RD plots with binned sample means tracing out the underlying regression function, and (ii) RD plots with binned sample means mimicking the underlying variability of the data. For technical and methodological details see Calonico et al. (2014b).

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 & 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.[30] 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.[31] 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 (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 the University of Bologna graduates, 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.[32] By combining these two data sources, it is also possible to assess what is the share of students who graduated but did not participate in the "AlmaLaurea" survey (i.e., approximately 16%). Furthermore, by comparing the distribution of this share of students above and below the €19,152.97 threshold, I can also infer if there has been any differential self-selection in the participation margin. Table A18 in the Appendix shows that students below the threshold are about 15 percentage points more likely to participate in the "AlmaLaurea" survey. However this difference is not statistically significant from zero.[33] This evidence further supports the robustness of the above matching procedure, given that no imbalances emerge in the survey participation 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.

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. Note, however, that due to a reduction in the number of observations in the matched sample, driven by the fact that only some of the graduates decide to work after graduation (33%), and/or a small share of them did not participate in the "Almalaurea" survey (16%), some of the results presented in this Section are imprecisely estimated, making this analysis not fully definitive. The summary statistics of the matched sample are shown in Table A13, while the main RDD results are presented in Tables A14, A15 and A16.

As shown in Table A13, 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 A13) has similar characteristics to the full sample in terms of high school final grade, age, gender, graduation time and campus and major choices.

[30] 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.

[31] 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).

[32] 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.

[33] Notice that, following the literature on power estimation for Regression Discontinuity Design, as in Cattaneo, Titiunik, and Vazquez-Bare (2019), even the difference in the survey participation is not statistically significant from zero, this estimate is indeed under-powered.

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.[34] 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 A14, 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 first column of Table A14 confirms nonparametrically the result found in the full sample: the students who received a higher amount of aid took significantly more time to graduate from college (approximately 9 months). Column 2 instead shows that students positioned below the €19,152.97 financial aid threshold are 15 percentage points more likely to continue their educational career, even if this difference is not statistically significant. In Columns 3 and 4 of Table A14, I look at the probability of working after and during college, respectively. Interestingly, while students receiving higher aid seem to be 16 percentage points less likely to work during college, and 2 percentage points less likely to work after graduation, no statistically significant 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.[35] 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 A15 shows the results on the probability of working part-time for the subsample of the working graduates. Notably, while the difference in the probability of finding a job between higher-aid recipients and students receiving a lower benefit is not statistically significant (although it is not precisely estimated), higher-aid recipients are approximately 62 percentage points more likely to work part-time. Interestingly, Column 1 of Table A15 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.[36] Column 3 of Table A15 shows that, in the subsample of working graduates, the probability of earning less than €1,000 per month is significantly higher for the higher-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 A16, I look at how the working graduates answer the survey questions directly related to the job and skill match. Specifically, Column 1 of Table A16 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, higher-aid recipients are approximately 37 percentage points less likely to report that they are using the skills acquired during college. Given that there is no systematic sorting of low-skilled students (as measured by their GPA or high shool final graduation mark) 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 A16. Specifically, the higher-aid recipients are 55 percentage points more likely to report that their degree was not effective for finding the job, and of stating that the bachelor's degree is not necessary to perform the job (by 30 percentage points), even if not required.[37] Although some of these results are imprecisely estimated (making the analysis not fully definitive), and 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. This is indeed in line with previous literature showing negative effects of delayed graduation on employment and earnings in Italy (Aina, Baici, & Casalone, 2011; Aina & Casalone, 2020; Aina & Pastore, 2020; Domnisoru, 2023; Piazzalunga, 2018). In addition, notice that these effects seems to be not driven by a significant differential selection of graduates into the labor market, as shown in Table A14, even if this part of the analysis not fully definitive. Furthermore, when testing for differences in the observable characteristics of the working graduates lying near the third threshold, no significant results emerge; see Table A17 in the Appendix.

5. Robustness checks

As discussed in Section 3.2, the main treatment effects in Table 3 are estimated by using the nonparametric estimator by Calonico et al. (2014a, 2014b). While, the parametric estimates reported in Tables A3-A4 are derived allowing for different linear relationships on either side of each threshold. In the Appendix, Table A19 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 Eq. (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 parametric results reported in Tables A3-A4. 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.

Furthermore, the main nonparametric estimates are highly robust to the choices of the kernel and the bandwidth used in the estimation; see Tables A20 and A21 in the Appendix. In addition, 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 A22 in the Appendix.

Moreover, students enrolled in tertiary education in Italy choose degrees with a predefined curriculum rather than courses. Indeed, for

[34] 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.

[35] Notice that, following the literature on power estimation for Regression Discontinuity Design, as in Cattaneo et al. (2019), even if the effects presented in Column 2, 3 and 4 are not statistically significant from zero, these estimates are indeed under-powered.

[36] Notice that, following the literature on power estimation for Regression Discontinuity Design, as in Cattaneo et al. (2019), the effects presented in Column 1 are indeed under-powered.

[37] Notice that, following the literature on power estimation for Regression Discontinuity Design, as in Cattaneo et al. (2019), the effects presented in Columns 1 and 4 are indeed under-powered.

each degree, more than 55% of course content and number of credits is fixed: students can freely allocate only from 6% to 11% of all credits and mostly at the third year of the Bachelor Degree; the remaining credits are divided between any compulsory internships and thesis periods in varying proportions.[38] Therefore, the results on the number of credits and on the GPA level obtained at the end of the first and second years are not likely to be driven, for example, by course shifting (see for example, Huntington-Klein and Gill (2021)). Anyway, to check whether the main results are driven from the fact that higher-aid recipients are less likely to shift courses toward easier (higher GPA) subjects – or to lower their GPA in order to obtain more credits – I perform two additional robustness checks. First, when looking at the effects of financial aid generosity on the number of credits, I contextually control for the GPA level. Second, I have constructed a combined index of performance which is given by a weighted sum of the number of credits and the final year GPA (using equal weights), to understand weather there is still a difference in performance when I jointly account for the quantity and quality of the students' studying effort. Both robustness checks are shown in Table A23, and they confirm that the observed difference in the number of credits is not entirely explained by the GPA level, since I observe a statistically significant gap in performance, similar in magnitude to the main estimate.

Finally, notice that the parametric estimates of the treatment effects do not vary much when I add the set of controls, which also includes the field of study (Law, Political Science, Economics, Literature, etc.). This suggests that the treatment effects on the number of credits, or on the GPA, are not driven by the major choice. In line with Gurantz (2021), I also looked at differences in performance among students enrolled in STEM and non-STEM degrees, but no significant heterogeneity emerges (see Table A24). In line with Castleman and Long (2016), I also checked at how the treatment effects change between students with a high or low high school final grade ("high" is defined as being greater than 80, which is the median value). Overall, I find that, even if high-ability students have a higher GPA and obtain a higher number of credits at the end of the first year, they do not react differently to the financial aid incentives (see Table A25).

In addition, to check whether the main results are driven from the fact that higher-aid recipients are less likely to shift courses toward easier (higher-GPA) subjects – or to lower their GPA in order to obtain more credits – I perform two additional robustness. First, when looking at the effects of financial aid generosity on the number of credits, I contextually control for the GPA level. Second, I have constructed a combined index of performance which is given by a weighted sum of the number of credits and the final year GPA (using equal weights), to understand weather there is still a difference in performance when I take into account the quantity and quality of the students' studying effort, jointly. Both robustness are shown in Table A23, and they confirm that the observed difference in the number of credits is not entirely explained by the GPA level, since I observe a statistically significant gap in performance, which is similar in magnitude to the main estimate.

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 of the graduating major, and code of 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 A17, and the second column of Table A18 in the Appendix shows that there is no significant discontinuity in any of the covariates, or in the cluster 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. Furthermore, by matching the administrative data on college performance with survey information on the recipients' labor market outcomes one year after graduation, this paper also tentatively looks at the impact of financial aid generosity on post-graduation outcomes. The main finding is that those students who receive a lower benefit and, therefore, have a positive cost of college perform better during college 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.[39] The prevailing explanations are mainly related to the complexity of the application process, and to the late notice of grant eligibility.[40] In the context of the RTS program, it is indeed the case that students know about their eligibility only around December each year, while most of the bachelor and master programs typically start around mid-September of the same calendar year. 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 (Montalbán, 2023; 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, 2002) and in the extension by Schudde and Scott-Clayton (2016). The overall evidence is also in line with the "cost-of-college" mechanism, which predicts that students should increase their studying effort if they face a (potentially) higher cost of college. Belot, Canton, and Webbink (2007) indeed show that a reduction in the maximum duration of a Dutch grant increases students' performance, even in a merit-based context, and when the control group is composed by students in higher professional education. Garibaldi et al. (2012) also show evidence in line with this mechanism in the context of a private Italian university, where students who may pay a higher tuition fee

[38] See the description of the tertiary education in Italy, here. Moreover, the database with the full list of degrees offered at the University of Bologna can be found here. In the description of the activities, within each degree it is possible to see the number of credits that the students can freely choose (typically at the third year of the program).

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

[40] See Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012), Dynarski and Scott-Clayton (2006, 2008, 2013), Dynarski and Wiederspan (2012).

for an additional extra year of education, are more likely to finish on-time. While focusing on private university students, this study also differs since it only measures delayed graduation among students in their *final* year of college, and who face a *potential* higher cost. This paper, however, finds similar results, starting from the *first* year of study, and when there is a *current* difference in the cost of college.[41]

Few papers have also looked at the effects of financial aid *loss*. Carruthers and Özek (2016) examine the effects of scholarship loss among the Tennessee's HOPE Scholarship recipients, finding only modest changes in enrollment, and no long-term effects on graduation. Jones, Kreisman, Rubenstein, Searcy, and Bhatt (2022) also looked at aid reduction of the HOPE Scholarship in Georgia, finding no evidence on persistence nor graduation among wealthier students. Marx and Turner (2019) instead find in an intervention increasing loan take-up and loan amount, that this improves students' GPA and number of completed credits. However, Barr, Bird, and Castleman (2021) find that a campaign on borrowing, led students to reduce their unsubsidized loan, and this generated worse academic performance. While, these studies have looked at changes in the amount of aid offered by loans or merit-based programs, which are indeed subject to specific selection-criteria and requirements, the present paper finds results in line with the cost-of-college mechanism in a need-based context, and where students are all subjects to the same academic requirement.

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 slightly more likely to continue their educational careers, and less likely to work before or after graduation, even if these differences are not statistically significant nor precisely estimated. This suggests that, on the one hand, delayed graduation might have 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 might not graduate later because they work more during college. However, it seems that higher-aid recipients secure worse job matches, both in terms of hours worked and payment received but also in terms of skill matching. Nonetheless, even if some of these latter results seems to be well-powered, they are drawn on a smaller sample: some of the graduates have not participated in the survey, and/or they have not yet entered the labor market one year after graduation. While, I do not find a significant differential attrition below and above the cutoff, this part of the analysis on post-graduation outcomes is not fully definitive. Future research on this topic should indeed consider these losses of observations in the pre-analysis plan, or when calculating the ex-ante power of similar analysis.

Overall, 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. This observable characteristic might indeed be used by employers to screen potential job candidates, generating significant labor market value for on-time graduates (Aina et al., 2011; Aina & Casalone, 2020; Aina & Pastore, 2020; Domnisoru, 2023; Piazzalunga, 2018).

[41] Previous evidence, although based on the exogenous variation generated by a policy change, it is not fully able to account for other confounding factors. For example, the study of Häkkinen and Uusitalo (2003), evaluates a reform of the financial aid system in Finland aimed at reducing incentives for delayed graduation, finding small positive effects on performance. The paper by Kifmann, Martin, and Normann (2006) evaluate a German reform, which introduced a fee for students enrolled beyond the regular completion time, finding ambiguous results. While, Groen, Jakubson, Ehrenberg, Condie, and Liu (2008) look at the effect of the Graduate Education Initiative (GEI), which had the explicit goal of reducing students' attrition and time to degree, finding modes impact.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econedurev.2023.102444.

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