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Assessing the Efficacy of Debt Forgiveness Incentives in Promoting Higher Education Outcomes: Evidence from Colombia's National Student Loan Company

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This paper examines the impact of a debt forgiveness program implemented in 2011 on education and labour market outcomes for student loan holders who pursued university education in Colombia. The policy generated a sharp discontinuity in the eligibility criteria, which I exploit to identify the causal effect of debt forgiveness. Regression discontinuity estimates indicate an increase of 10 percentage points, equivalent to 19.5 percent, in the graduation rate of marginally eligible students. Additionally, the probability of graduating on time (within five years of enrollment) increased by 7.2 percentage points (25.4 percent). There is evidence that the policy had an effect on labour market outcomes. Eight years post-enrollment, eligible students are 19.5 percent more likely to be employed in the formal sector and have higher earnings.

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Highlights

- There is growing evidence of the role of financial aid in the extensive margin of higher education (enrollment). However, evidence on the intensive margin (persistence and graduation) and long-term outcomes (employment and earnings) remain more scarce and mixed.
- Using a Regression Discontinuity Design, I examine the effect of Colombia's 25% Debt Forgiveness upon Graduation Program on education and labour market outcomes.
- The results suggest that the policy increases the graduation rate by 10 percentage points (pp), equivalent to an increase of 19.5% in the probability of graduating from university. The effect on the probability of graduating on time (five years after enrolment) is a 7.2 pp. (25.4%) increase.
- Regarding labour market outcomes, eight years after enrolment, eligible students are 10.2pp (19.5%) more likely to be employed in the formal labour market and earn 383,000 COP (32.6%) more than their comparable peers.

Why does this matter?

Understanding how debt forgiveness impacts graduation and labour market outcomes is crucial for designing effective education policies that promote social mobility. Targeting financially disadvantaged students with well-structured loan relief programs can help reduce dropout rates, improve workforce participation, and enhance long-term earnings.

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March 4, 2025

Abstract

This paper examines the impact of a debt forgiveness program implemented in 2011 on education and labour market outcomes for student loan holders who pursued university education in Colombia. The policy generated a sharp discontinuity in the eligibility criteria, which I exploit to identify the causal effect of debt forgiveness. Regression discontinuity estimates indicate an increase of 10 percentage points, equivalent to 19.5 percent, in the graduation rate of marginally eligible students. Additionally, the probability of graduating on time (within five years of enrollment) increased by 7.2 percentage points (25.4 percent). There is evidence that the policy had an effect on labour market outcomes. Eight years post-enrollment, eligible students are 19.5 percent more likely to be employed in the formal sector and have higher earnings.

Keywords: Student Loans, Higher Education, Debt Relief, Financial Aid, Graduation, Employment.
JEL Codes: I22, I23, I28, J21, J31.

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1 Introduction

The first two decades of the 21st century saw a massive expansion of higher education, mainly driven by developing countries. In 2021 worldwide, roughly 220 million students were enrolled in formal post-secondary education, more than doubling the enrollment figure from 2000 (Malee-Basset and Murti, 2022). Nevertheless, there is evidence of a gap between enrollment and completion rates, which hinders countries' efforts to provide higher education (IESALC, 2020). In Latin America, Ferreyra et al. (2017) documented an enrolment growth pattern with notable issues in efficiency and quality, with roughly only half of students graduating on time.

Colombia experienced significant growth in higher education enrollment, more than doubling from 23.8% (approximately 873,000 students) in 2000 to 54.9% (around 2.3 million students) by 2022. Despite this expansion, over half of the students who enrol in university eventually drop out of the system. As reported by the MEN (2022), the national graduation rate for university-level students in 2020 was just 41.2%.[1] These figures highlight the persistent challenge of student retention in higher education and the need for targeted policy interventions.

This paper studies the effects of the *Debt Forgiveness upon Graduation Program*, introduced in 2011 by the Colombian National Student Loan Company (ICETEX) on education and labour market outcomes. The program consists of a 25% reduction in the total capital indebted for student loan holders with a vulnerability score below a certain threshold who complete their tertiary education studies.

Using linked administrative records with information on approximately 43,000 students who received financial support from ICETEX to enrol in higher education between 2011 and 2013, I leverage the policy's assignment mechanism, which relies on a well-defined threshold of the national vulnerability score.[2] This threshold generates a sharp discontinuity in the likelihood of assignment to the debt forgiveness program. Students below the vulnerability score threshold were eligible, while those above were not. Using a Regression Discontinuity (RD) design, I analyse the program's impact on graduation, employment, and earnings.

The empirical findings indicate significant effects of the policy. Marginally eligible students experienced a 10 percentage point (pp.) increase in the graduation rate, equivalent to a 19.5% rise. Moreover, eligible students were 7.2 pp. (25.4%) more likely to graduate on time. However, the policy did not influence other education outcomes, such as the SABER Pro score, the duration of enrollment, or the probability of postgraduate education enrollment.

[1] Colombia's gross enrollment rate in higher education remains relatively low compared to the OECD average of 79%. Tertiary education (29%) in Colombia is among the lowest in OECD countries (OECD, 2019).

[2] The score is the result of a means-tested survey that assigns households a score ranging from 0 to 100, representing their relative wealth based on factors like housing quality, possession of durable goods, access to public utilities, and human capital indicator (Londoño-Vélez et al., 2020).

Regarding the labour market, eight years after enrollment, there is compelling evidence that the policy significantly increases the probability of employment in the formal sector by 10.2 pp. (13.7%) and the monthly earnings levels by 32.6%. These findings underscore the policy's effectiveness in promoting higher education completion and enhancing future employment prospects and earnings.

This paper contributes to the literature on the effects of conditional debt forgiveness on higher education outcomes among tertiary education students. In Finland, Hämäläinen et al. (2017) found that the student loan forgiveness program did not affect graduation timing. In Canada, the graduate retention program increased by 5.3 pp. the graduation rate (relative to a pre-treatment mean of 57.7%)(Mikola and Webb, 2023). In Norway, Sten-Gahmberg (2020) found that loan forgiveness, coupled with support for at-risk students, improves academic performance and reduces the study duration, particularly for students from low socioeconomic backgrounds and those with weak academic records. In Denmark, Gunnes et al. (2013) analyse a student loan forgiveness program (to about 10% of the total loan amount) conditional on on-time graduation. Their results suggest an increase of 3.8 pp. (relative to a pre-treatment mean of 20%). This paper adds evidence on the effectiveness of debt forgiveness programs in promoting tertiary education completion for economically disadvantaged student loan holders in emergent market economies and, importantly, can follow these students into the labour market.

This work contributes to understanding how to enhance the effectiveness of student loans by integrating targeted interventions. It also adds evidence to the literature on the long-term impact of financial aid on labour market outcomes. The evidence suggests that students and prospective students respond to financial assistance, increasing the likelihood of enrolling and persisting in tertiary education (Dynarski and Scott-Clayton, 2013; Dynarski et al., 2022). Two recent systematic reviews of the literature assessing the overall impact of aid on persistence and degree completion—mainly in the US—estimate that grant aid programs increase the probability of persisting and degree completion from 0.4 to 3 pp. (LaSota et al., 2023; Nguyen et al., 2019). Regarding Latin America, in Chile, student loans have negative impacts on dropout (9.3 pp.) and positive impacts on completion (12 pp.) (Rau et al., 2013; Card and Solis, 2022). In Brazil, a cash transfer program increased the probability of graduation in 10 pp. (e Silva and Sampaio, 2023). In Colombia, Melguizo et al. (2016) found that student loans decreased college dropouts by around seven pp. Additionally, Londoño-Vélez et al. (2023) analyse the impacts of receiving financial aid on graduation and early labour market outcomes. The authors identified an increase in the probability of earning a postsecondary degree within seven years from high school completion (between 10.6 and 12.4 pp.), a 17% increase in Colombia's nationwide college graduation exam (SABER Pro) and a modest increase in monthly earnings for formal employees.

This paper is organised as follows. Section 2 discusses the institutional background and describes the policy intervention. Section 3 describes the data used for the analysis. Section 4 explains the regression discontinuity design used as the methodology to disentangle the causal effects. Section 5 presents the program's effects on education and labour market outcomes. Section 6, concludes.

2 Policy Context

ICETEX, which is the Colombian National Student Loan Company, promotes access -and retetention- to higher education through the provision of loans, grants, and subsidies targeted to the most vulnerable population.[3] Aiming at improving the graduation rates, it introduced the *Debt Forgiveness upon Graduation Program* in 2011, that consists of a reduction of 25% of the outstanding debt to the student loan holders who successfully graduate from tertiary education.

Eligible students must be economically disadvantaged, as measured by the national vulnerability score (SISBEN), which ranges from 0 (poorest) to 100 (richest). The program's SISBEN score thresholds differ across three geographical regions: Principal Cities, Other urban areas, and Rural Areas.

Principal Cities includes the 14 most economically important cities in the country without their metropolitan areas (i.e, Bogotá, Medellín, Cali, Barranquilla, Cartagena, Cúcuta, Bucaramanga, Ibagué, Pereira, Villavincencio, Pasto, Montería, Manizales, and Santa Marta.) and *Other Urban* comprises all the urban areas outside the Principal Cities (i.e, including population centres and the scattered rural area of the 14 Principal Cities). The rest of the country is labelled as *Rural*, which are the poorest zones in Colombia. The threshold for *Urban (50.45)*, *Principal Cities (52.66)* and *Rural (40.75)* aimed to make eligible percentiles 60, 55, and 80 of the surveyed population, respectively.[4]

According to LEE (2023), there are significant educational disparities between urban and rural areas regarding availability, access, and quality. Urban areas have higher literacy rates and educational attainment, with more advanced education levels and better infrastructure than rural areas, which often lack basic resources like internet and electricity. Many rural youths do not attend school due to financial constraints and lack of motivation, with girls and young women facing additional barriers such as teenage pregnancy and housework. Rural students

[3] For more information about ICETEX and its role in the higher education system, see Appendix A.

[4] See Appendix A for more information about policy eligibility criteria and changes in the qualifying conditions over time.

also perform worse on standardized tests, limiting their access to higher education.

Due to the low representation of rural areas in the ICETEX population sample (i.e., less than 8%) and the structural differences between urban and rural areas, the analysis primarily focuses on urban areas, aggregating both Principal Cities and Other urban areas. Appendix B, provides a separate analysis for Rural areas.

3 Data

The paper relies on rich administrative records from the Colombian National Student Loan Company (ICETEX) —linked to socioeconomic, education, and labour market information— to construct a repeated cross-section dataset of approximately 43,000 urban students who accessed university from 2011 to 2013 with financial support from ICETEX. These data allow me to track each student, their socioeconomic status, type of funding, education trajectory (e.g., whether they graduate or not, how many semesters they were enrolled in higher education, and their results in national standardised university tests, among others), their labour outcomes after graduation (i.e., employment status and earnings) and a rich set of covariates including individual, household, and school information.

3.1 National Student Loan Company (ICETEX)

Data comprises individual information on ICETEX's student loan beneficiaries from 2011 to 2013. The data provides information on the loan, including the total amount disbursed —corresponding to tuition fees—, estimated loan duration (in semesters), and the starting semester of the loan. They also have information on student characteristics (e.g., gender and date of birth) and the academic program to be funded (e.g., University, tuition fees). I group students in cohorts by year (e.g. the 2010 cohort corresponds to all students who first took out a loan in the year 2010).

3.2 Elegibility Criteria from SISBEN

The *System for Selecting Beneficiaries of Social Spending* (SISBEN) is a survey that assesses the living and monetary conditions of households. In 2014, the SISBEN database held information on more than 34 million people, more than 70% of the national population (ILO, 2015). After the assessment, households are assigned a SISBEN score ranging from 0 to 100. A lower score indicates a higher level of vulnerability and a greater need for social assistance.

Every social program using SISBEN choose the maximum eligibility score threshold (and other qualifying conditions) that best suits its budget and policy design. According to the ILO (2015), in 2013, ten institutions running several social protection and employment programmes each used the SISBEN to identify potential beneficiaries. Thus making it difficult for the surveyed population to anticipate the thresholds for any particular policy and try to manipulate the score accordingly.

Equation (1) defines a new variable X_i which, for each individual i, subtracts the policy threshold for their area a from their raw SISBEN Score and then multiply it by -1 to reverse it. This running score is centred and characterises eligible individuals for the policy as those with a score above 0.

$$X_i = (SISBENScore_{ia} - PolicyThreshold_{ia}) \times (-1) \tag{1}$$

Figure 1 presents the distribution of the X_i for the *Urban Pooled* sample and for the *Principal Cities* and *Other Urban*. The median score for *Urban Pooled* is 10.59, while the mean is 8.11. The minimum value is -45.17, and the maximum is 52.08. The figure shows that the distribution is left-skewed, with most of the observations concentrating on the upper part of it. This is consistent with the above explanation, where surveyed households tend to be more vulnerable and in greater need of social assistance. There is no signal of bunching around the corresponding thresholds, which supports the hypothesis that the assignment variable is not manipulated. I provide formal evidence to support this assumption in Section 4.

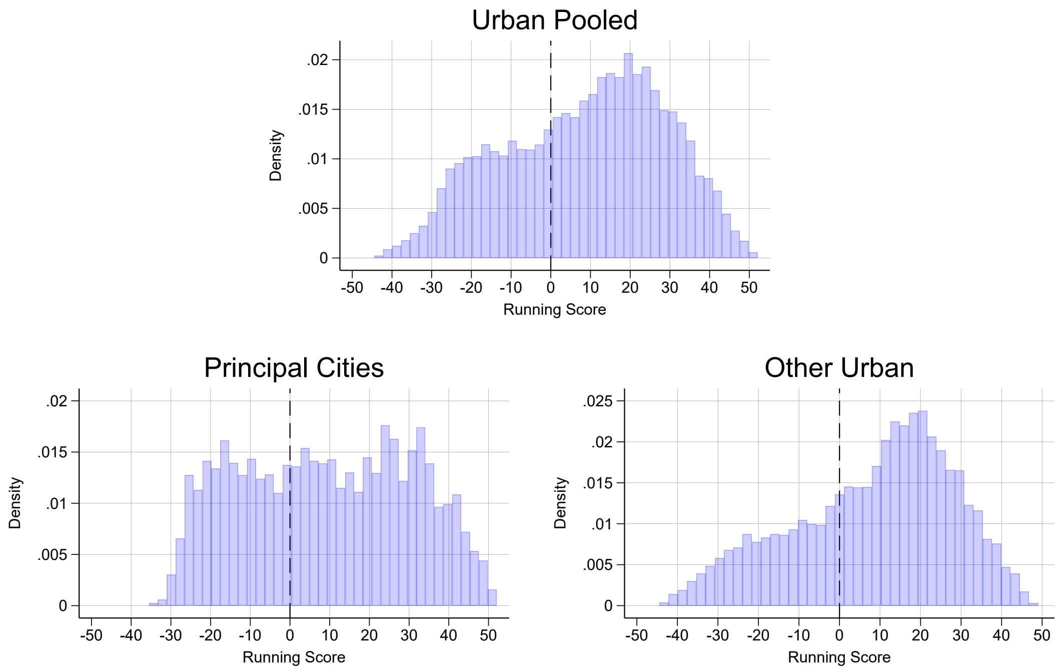
3.3 Graduation and Dropout from SNIES/SPADIES

The Colombian Ministry of Education keeps data on enrollment patterns, student demographics, educational outcomes, and educational spending in the National Higher Education Information System (SNIES). From this source, I use the graduates' report (up to December 2021) to characterise which and when students graduated from university. Focusing on ICETEX students enrolled for the first time in university from 2011 to 2013, the graduation rate is 59.5% (18.7 percentage points higher than the national graduation rate).

I use historical individual information on enrollment from the System for the Prevention and Analysis of School Dropouts in Higher Education (SPADIES) to construct the dropout mark that characterises students who pause their studies for three or more consecutive semesters.[5] Additionally, I construct a variable describing the last time dropout students' were enrolled in higher education. Jointly, the graduation year-semester and the last year-semester enrolled allow the calculation of enrollment duration into tertiary education for students in the sample.

[5]This calculation follows the methodology of the Ministry of Education to calculate the dropout rate.

Figure 1: SISBEN vulnerability score



Notes: This figure shows the histogram of the Running scores for the Urban Pooled, Principal Cities and Other Urban areas. The distribution includes information for cohorts from 2011 to 2013.
Source: Author's calculation based on DNP data.

3.4 High School and University Exit Exam from SABER11 and SABERPRO

I use data from the national exit school exam SABER 11, which is mandatory for every student about to graduate from secondary school and a prerequisite to access tertiary education, to extract several individual and household covariates, as well as the test scores.

The SABER 11 measures students' skills in 13 areas, including Mathematics, Spanish, Physics, Chemistry, Biology, and English, among others. I use the Overall, Math, and Spanish scores as covariates because previous studies have shown their relation to college success (Mariño et al., 2021).

I employ data from the national exit university exam, SABER Pro, which is mandatory for all graduating higher education students. This exam provides a thorough assessment of students' skills, preparedness for the workforce, and potential for further academic studies, enabling the construction of an outcome measure that captures students' effective learning.

3.5 Labour market indicators from PILA

The Integrated Social Security Contribution Form (PILA) facilitates the collection of social security contributions, including pension and health contributions, from employers or independent employees. From this source, I extracted information about employment and earnings. Specifically, it is possible to know if an individual was employed in the formal sector and the corresponding earnings level.

4 Methods

The most suitable quasi-experimental methodology to estimate the impact of the *Debt Forgiveness upon Graduation Program* is the Regression Discontinuity (RD) design. The three fundamental components in the RD design are well defined: The score (X), the cutoff (a sharp policy eligibility threshold) and the treatment (25% debt forgiveness upon graduation). In this particular setting, I use a continuity-based framework for the RD analysis with noncumulative multiple cutoffs to disentangle the causal effects (Cattaneo et al., 2020b).[6] I use a local polynomial RD to estimate the following specification for the Urban Pooled sample:

$$Y_i = \alpha + \beta \times Policy_i + \eta_- \times X_i + \eta_+ \times Policy_i \times X_i + \omega Cohort_i + \epsilon_i, \tag{2}$$

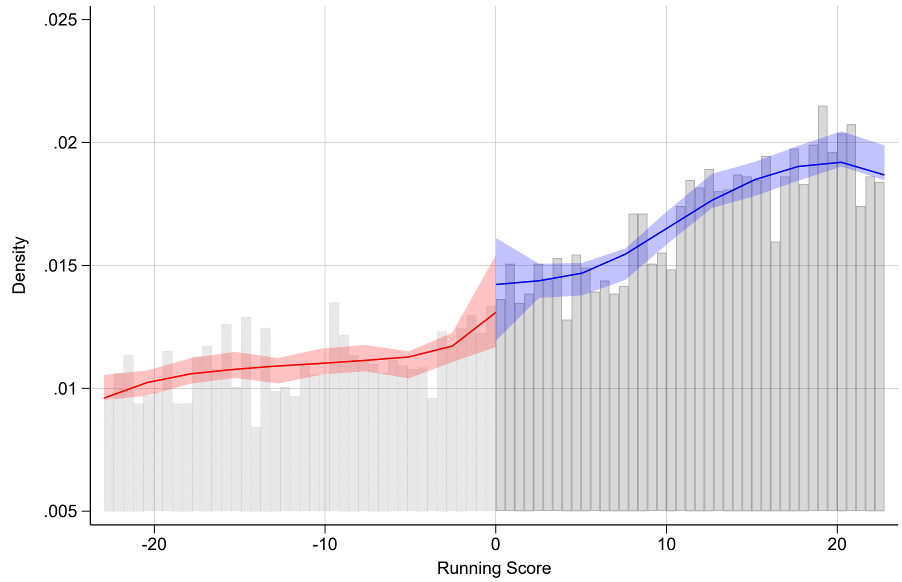
where Y_i is the outcome variable of interest for student i, and X_i is the running variable that measures the distance between a student's SISBEN Score and the cut-off (0). $Policy_i$ is an indicator variable that takes on the value 1 for students who are exposed to treatment (e.g. those whose Running Score is above the threshold) and 0 otherwise. $Cohort_i$ is a control indicator for the student cohort. ϵ_i is the error term. β is the coefficient of interest as it describes the RD causal impact of the *Debt Forgiveness upon Graduation Program*.

The local polynomial RD estimator leverages the sharp discontinuity in eligibility conditions to allocate the treatment. It capitalizes on the fact that the 25% forgiveness policy is defined for those who fall above $X = 0$ to compare individuals just below the threshold with those just above it. It assumes that students whose Running Scores are the closest to the cutoff are most similar regarding covariates and unmeasured confounders. Therefore, I apply a triangular kernel to place greater weights on observations close to the cutoff and use data-driven optimal bandwidths following Calonico et al. (2020, 2014). I estimate the RD model using STATA command rdrobust (Calonico et al., 2017).

To ensure the identification of the RD effect, there should be no manipulation of the

[6] Students in different SISBEN areas are assigned a univariate score known as the SISBEN Score. However, the RD cutoff point varies depending on the specific area.

Figure 2: Manipulation Test



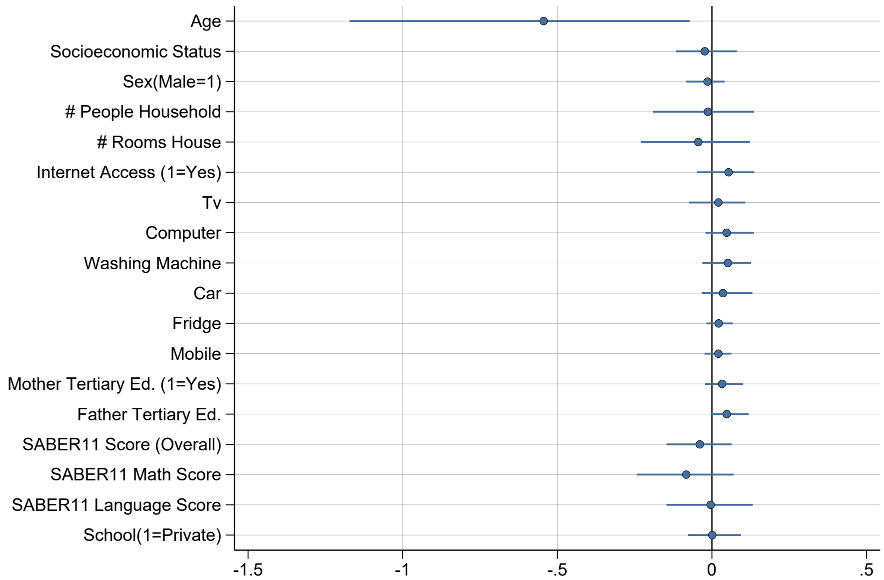
Notes: This figure shows the histogram of the Running score in dark grey and solid line for the treatment group and in light grey and dotted line for the control group. The red and blue lines are the local polynomial density estimation following Cattaneo et al. (2020a), and the shaded areas are their corresponding confidence intervals at the 95% level.
Source: Author's calculation based on DNP data.

Running score so that students have no control over the treatment assignment. Despite no graphical evidence of breaks in the density function from Figure 1, I use the polynomial density estimator from Cattaneo et al. (2020a) to support this assumption formally. The results, presented in Figure 2, confirm no statistical evidence of manipulation of the Running score with a robust-corrected p-value of 0.7401.

The second assumption for the validity of the RD design requires that there should not be significant differences in the observable characteristics around the discontinuity. I provide evidence to support this assumption using individual, household and school covariates as outcome variables in Equation (2). Figure 3 shows the results from the estimation. The statistical evidence demonstrates that there is balance for all but one of the 18 baseline characteristics[7]. There is a negligible difference found in the variable Age of -0.5 years (from a baseline mean of 18.85). The results suggest that students with scores above and below are comparable, and any difference found in the outcomes could be attributed to the eligibility for the policy.

[7]These potential confounders include Age, Socioeconomic Status, Sex, Starting Semester, Attended private school, Mother or Father with tertiary education, Results in the SABER11 Score (Overall, Math and Language), Number of people living or rooms in the household, and whether or not the household had access to Internet, TV, Computer, Washing Machine, Car, Fridge or Mobile phone.

Figure 3: Balance Test around the Eligibility Threshold



Note: This plot presents the coefficients and robust confidence intervals (at the 95% level) from a RD specification using predetermined covariates as the outcome and the Running Score as the running variable. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

5 Results

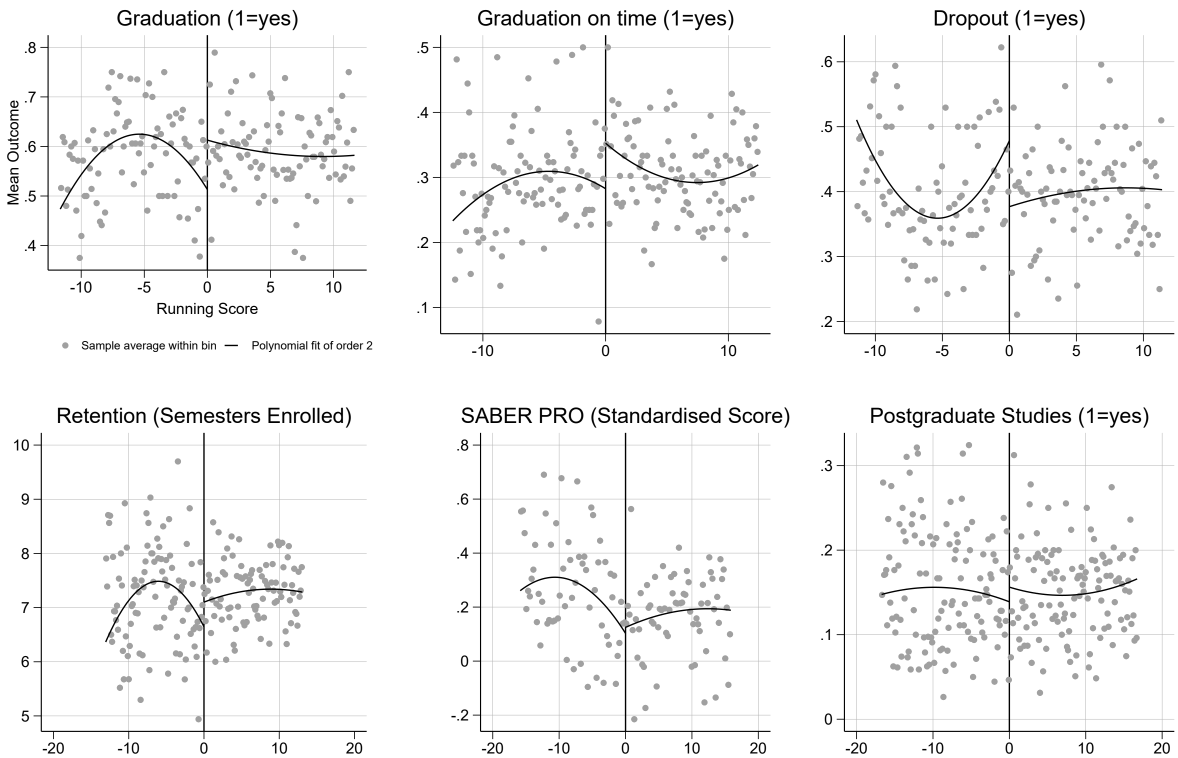
5.1 Education outcomes

Figure 5 displays the RD plots for all education outcomes analysed in this study. Each grey dot represents the outcome average within a small bin in these plots, while the solid line shows a second-order polynomial fit. Graphically, one can observe clear discontinuities for graduation, on-time graduation (within five years), and dropout. In contrast, the plot indicates only a modest jump in student retention and postgraduate enrollment, and no discernible discontinuity in the Saber Pro examination scores.

I begin by examining if there were any statistically significant impacts on the probability of graduation derived from the debt forgiveness policy. Given that the policy was designed exclusively to encourage graduation among student loan holders, graduation remains the primary outcome of interest. Table 1 presents the results. At the margin, the local impact of debt forgiveness eligibility is an increase of 10 percentage points (pp.), equivalent to 19.5%, in the probability of graduating from university.

Moreover, the impact on the probability of Graduating on time (5 years since enrollment) is a 7.2 pp. (25.4%) increase. Using the variable Dropout —which comes from another data

Figure 4: RD plots on Education Outcomes



Notes: This graph displays the discontinuity of education outcomes around the policy threshold. Each grey dot represents the outcome average within a small bin, and the solid line is a polynomial fitted line of order 2. The Centered and Reversed SISBEN Score (Running Score) is used as the running variable. The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017)
Source: Author's calculation based on ICETEX, MEN and DNP information

source— as the outcome variable mimics the results with a decrease in the probability of dropping out of university of 10.2 pp. (21.3%).

To assess whether this improvement is driven by a general enhancement in student retention or by a targeted effect on those near the margin, I analyze the policy's impact on the number of semesters enrolled. Column (4) suggests null effects on overall student retention. This indicates that the mechanism operates through a subgroup of students who actively engage with the policy, completing their studies and ending in graduation rather than a broad-based surge in university attainment that propels the cohort toward the graduation threshold.

Finally, while new graduates may have enhanced academic performance due to their engagement with the policy, the evidence clearly aligns with the policy's targeted focus on graduation rather than on learning outcomes or academic quality, as the Saber Pro scores do not exhibit a jump at the threshold. In addition, I explore whether the policy affects enrollment

Table 1: RD Effects on Education Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Graduation	Graduation On Time	Dropout	Retention	SABER PRO	Postgrad
Treatment Effect	0.100***	0.072**	-0.102***	0.453	0.028	0.017
	(0.042)	(0.036)	(0.042)	(0.358)	(0.096)	(0.025)
Control Mean	0.513	0.283	0.478	6.648	0.104	0.138
Effective Obs	6,953	7,898	6,789	7,728	4,559	10,858
MSE Bandwidth	11.666	12.455	11.409	13.075	15.863	16.739

Notes: This table presents the effect of debt forgiveness eligibility on the probability of graduation using a RD design. The Centered and Reversed SISBEN Score is used as the running variable (Running Score). Hence, a positive effect would be described as a positive coefficient in the outcome variable. The RD coefficient for the Urban Pooled sample suggests that, for students above the threshold, the 25% debt forgiveness eligibility increases Graduation by 10 percentage points (19.5 percent), and Graduation on time (5 years) by 7.2 percentage points (25.4 percent). The policy decreases Dropout by 10.2 percentage points (21.3 percent). I find no effects on Retention (number of semesters enrolled in Higher Education), SABER Pro (National Standardized Exit University Exam), and the probability of being enrolled in Postgraduate studies. The sample comprises newly enrolled students from Urban areas from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017)
***,** and * denote significance at the 1%, 5% and 10% levels, respectively
Source: Author's calculation based on ICETEX, MEN and DNP information

in postgraduate education and find no significant effect.

To ensure the validity and robustness of the results obtained from the RD design, I conduct four robustness checks. First, I estimate a placebo cohort before the policy intervention to verify that the RD effect observed is not spurious around the discontinuity. Second, I apply a placebo cutoff to test the continuity of the outcome variables at different points along the running variable. Third, I perform a donut-hole test to assess the sensitivity of the point estimates and confidence intervals to influential observations near the cutoff. Finally, I evaluate the sensitivity of the effects to different bandwidth selections.

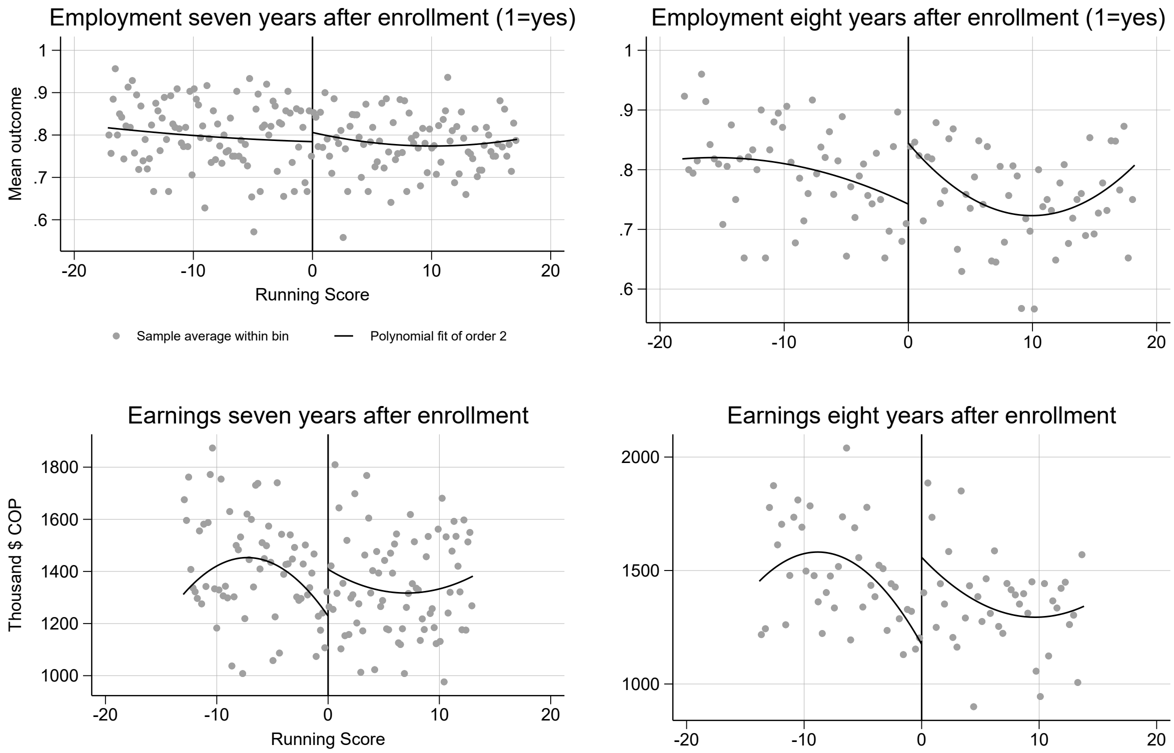
The results are robust in magnitude and statistical significance in all robustness checks (See Appendix C for further discussion, figures, and tables). As expected, there are no effects before the intervention. There are no significant differences in the local polynomial regression (rather than the cutoff) at any other point. The results are robust to excluding influential variables near the cutoff and different bandwidth levels.

5.2 Labour market outcomes

Figure 5 provides the RD plots for labour market outcomes after seven and eight years from enrollment. The graphical evidence reveals a clear discontinuity in formal sector employment eight years after enrollment and earnings seven and eight years after.

I extend the analysis by estimating Equation (2) for each year after enrollment to track the timing of these effects. This allows me to compare students from different cohorts at the exact same time in their education path. I begin by examining Employment in the formal sector.

Figure 5: RD plots on Labour Market Outcomes



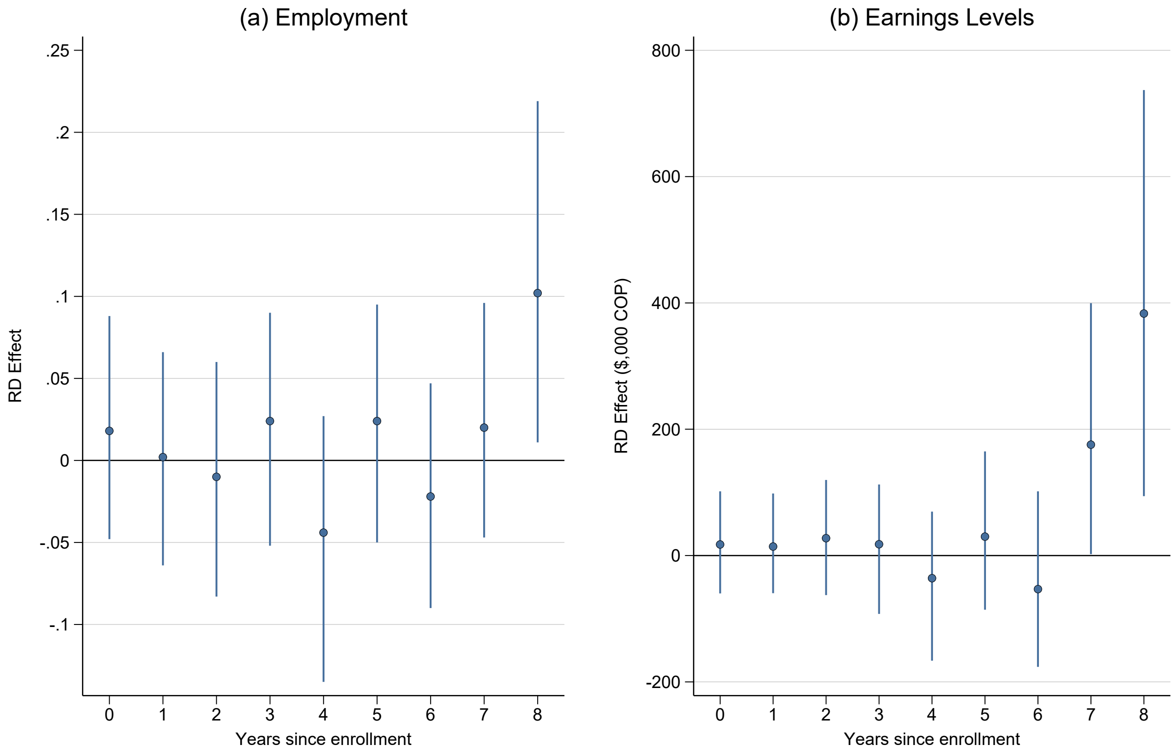
Notes: This graph displays the discontinuity of labour market outcomes around the policy threshold. Each grey dot represents the outcome average within a small bin, and the solid line is a polynomial fitted line of order 2. The Centered and Reversed SISBEN Score (Running Score) is used as the running variable. The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017)
Source: Author's calculation based on ICETEX, MEN and DNP information

Figure 6 (panel a) shows an increase in employment eight years after enrollment by 10.2 pp. (19.5%). In contrast, earlier periods show no effect, further supporting the expected delay between graduation and labour market entry.

At last, I estimate the impact on earnings. Figure 6 (panel b) indicates that debt forgiveness eligibility is associated with a 176,000 COP increase (14.3%) in earnings after seven years of enrollment, and a 383,000 COP increase (32.6%) after eight years. In this analysis, individuals without formal earnings (due to informal work or economic inactivity) are coded as zero.

The same set of robustness tests are conducted on labour market outcomes. The earnings results are robust in magnitude and statistical significance in all of the robustness checks (See Appendix C for further discussion, figures, and tables).

Figure 6: RD effect on Labour Market Outcomes



Notes: This plot displays the effect of debt forgiveness eligibility on employment (panel a) and earnings (panel b) in the formal sector using a regression discontinuity design. The Centered and Reversed SISBEN Score (Running Score) is used as the running variable. Hence, a positive effect would be described as a positive coefficient in the outcome variable. The RD coefficient for the Urban Pooled sample suggests that, for students above the threshold, the 25% debt forgiveness eligibility increases Employment after seven years of enrollment by 2 percentage points (2.6 percent), and by 10.2 percentage points (19.5 percent) eight years after. The program increases Earnings after seven years of enrollment by 176,000 COP (14.3%), and by 383,000 (32.6%) eight years after. The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017)
Confidence Intervals are at the 95% level
Source: Author's calculation based on ICETEX, MEN and DNP information

6 Conclusion

This paper assesses the effectiveness of the *Debt Forgiveness upon Graduation Program* implemented by ICETEX in 2011 on education and labour market outcomes. I use a RD design that leverages the sharp discontinuity generated by the eligibility conditions to estimate if there is any difference in the outcomes of interest for students just above and below the assignment threshold. I construct a repeated cross-section dataset containing extensive information about around 43,000 students who received financial support from ICETEX and were enrolled in higher education between 2011 and 2013. The data covers loan characteristics, educational history, socio-demographics, employment and earnings.

The findings indicate that the policy had a positive, robust and significant effect of 10 percentage points (pp), equivalent to 19.5%, increase in the graduation rate of eligible students. Moreover, there is a significant increase in the probability of graduating on time (within five years from enrollment) of 7.2pp (25.4%). Regarding labour market outcomes, eight years after enrollment, eligible students are 10.2pp (19.5%) more likely to be employed in the formal labour market and earn 383,000 (32.6%) more than their comparable peers.

Despite the positive and robust effects, there may be at least two channels through which the effects of the policy could have been attenuated or may have failed to materialise. First, the size of the incentive might be too low to exert a boost in completion. In the country, roughly 50% of total university dropouts occur within the initial two years of study (Ferreyra et al., 2017). Hence, the incentive's binding nature could be limited for early leavers students for whom the decision to remain in the system might not be perceived as cost-effective. This channel, coupled with present bias behaviour (Levitt et al., 2016), where students might hesitate to invest in education initiatives with substantial future returns if those returns are not immediately evident, could deter broader impacts. Future research could address this issue experimentally by modifying the incentive structure. One approach would be to increase the size of the incentive, making it more substantial to influence students' decisions to persist in their studies. Another strategy could involve offering partial loan forgiveness or financial rewards as students accomplish critical milestones in their higher education journey, such as completing the first two or four semesters. By breaking down the incentive into smaller, more immediate benefits tied to progress, this approach could motivate students to continue their studies and reduce early dropout rates. Testing these variations would provide valuable insights into how different incentive structures impact student retention and completion.

Second, economically disadvantaged students face additional barriers (e.g. fewer academic skills or the "know-how") to achieve academic success (Stephens and Townsend, 2015). This is particularly true for the rural areas in Colombia, which are the poorest and have the lowest quality of primary and secondary education. For them, even exerting more effort (i.e. engaging with the policy) could not translate into completion.

This paper examines the causal effect of the "Debt Forgiveness upon Graduation Program" on educational, debt and labour market outcomes. Nevertheless, the literature has identified other dimensions related to lower debt levels upon completion of the study period, such as life satisfaction, mental health, and happiness, among others (Elliott and Lewis, 2016; Tay et al., 2017). These variables are not included within the scope of this study, but addressing them in future research can contribute to a more comprehensive analysis of the impacts of the policy.

Acknowledging the limitations of this study, the dataset used in this research lacks specific critical indicators of student engagement and effort within the higher education path. Metrics such as GPA, credit-taking patterns, and courses taken are not included, making it challenging to fully comprehend the mechanisms through which the policy may have incentivized students to graduate. This lack of information questions how the program influenced student behaviours and motivations. Despite the valuable insights derived from this study, certain aspects of the program's effects and mechanisms remain empirical questions requiring further investigation.

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Appendices

A Policy Context and Background

ICETEX is the Colombian National Student Loan Company. It was created in 1950, making it the world's first formally constituted Student Loan Provider (Chapman et al., 2019). Its primary goal is to promote tertiary education —focusing on individuals from disadvantaged socioeconomic backgrounds— facilitating individuals' access and continuation of higher education studies. This objective is accomplished by allocating national and international resources through subsidized loans, scholarships, and other forms of support (ICETEX, 2023b).

In 2020, from the total population enrolled in higher education in the country (approximately 2.35 million students), ICETEX provided financial support of any kind (i.e. subsidized reimbursable loans and forgivable loans funded by special funds) to 21 percent of them (MEN and ICETEX, 2022).

The *Debt Forgiveness upon graduation program* was implemented in 2011. Under the historic regulatory framework, the policy has undergone several modifications that preserved the nature of the debt forgiveness program but changed the eligibility criteria. Usually, these changes obeyed budget constraints and political decisions (the public legal agreements do not disclose why they modify the thresholds). Table A.1 summarizes the relevant changes to the qualifying conditions in 2013 and 2015. By increasing the margin in 2013, ICETEX held constant the eligibility percentile in the three areas. In 2015, they lowered the thresholds to 54 for *Main Urban*, 52.72 for *Other Urban*, and 34.79 for *Rural* (no distributional arguments were presented in the legal agreement). Since then, it remained stable until the methodology upgrade to SISBEN IV in 2021.

From 2013 to 2023, 74,656 students received debt forgiveness upon graduation, for a total cost of USD 136 million. Only in 2023, 11,025 people benefited from the debt forgiveness program because they graduated from higher education and met the corresponding vulnerability threshold. The total cost for ICETEX was USD 26.61 million[8]

[8] See Table A.2 for a breakdown of beneficiaries and costs by year

Table A.1: Policy Eligibility Criteria

Area	**SISBEN III Threshold**		
	From 2011-1 to 2013-1	**From 2013-2 to 2015-1**	**From 2015-2 to 2020-2**
Principal Cities	52.66	57.21	54
Urban	50.45	56.32	52.72
Rural	40.75	40.75	34.79

Notes: The dates describe year-semester (e.g. 2011-1 comprises the months from January to June 2011). From 2021 onwards, the prioritization uses the classification (A to D) of the new SISBEN IV methodology.

Source: Author's adaptation based on ICETEX's Agreement 017 of 2011, 009 of 2013, and 013 of 2015

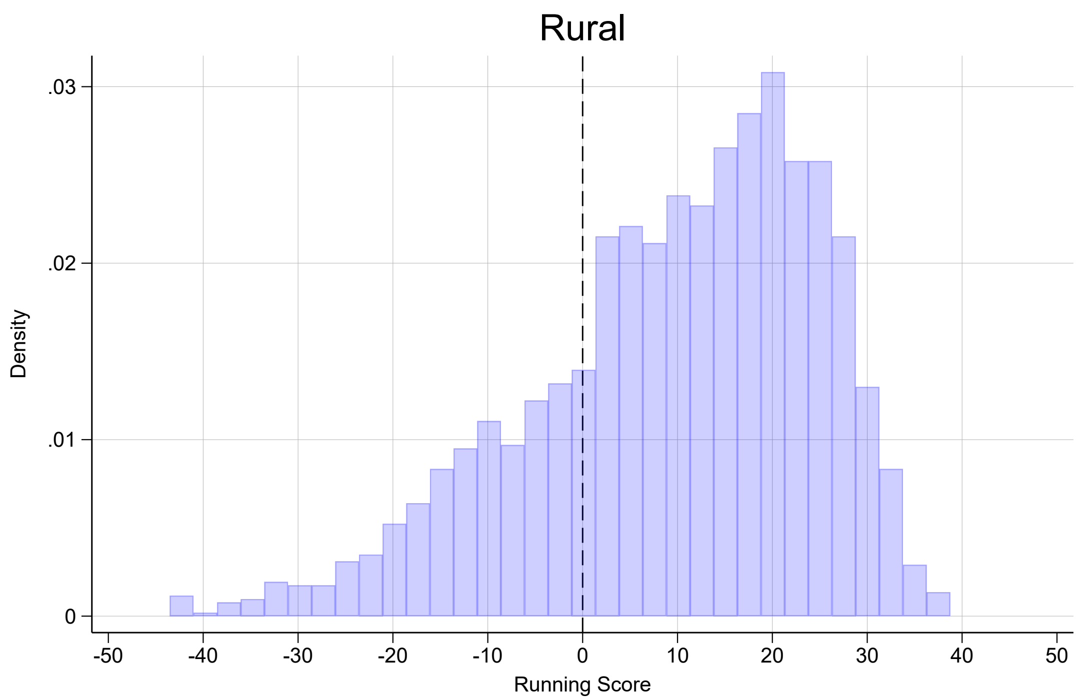
Table A.2: Number of recipients of the debt forgiveness and total cost

Year	**Beneficiaries**	**Total**	
		($ million COP)	**($ million USD)**
2023	11,025	$ 109,825	$ 26.61
2022	11,558	$ 112,006	$ 27.14
2021	9,551	$ 95,867	$ 23.23
2020	6,691	$ 58,954	$ 14.28
2019	7,490	$ 42,338	$ 10.26
2018	11,425	$ 81,618	$ 19.77
2013-2017	16,916	$ 64,000	$ 15.51
Total	74,656	$ 564,608	$ 136.79

Notes: COP in nominal values. The exchange rate used is 4,127.6 USD-COP As of 12:00 AM EDT 08/25/23 from Bloomberg. The information from 2013-2017 was taken from ICETEX (2018a)

Source: Author's adaptation based on ICETEX's Public Management reports (ICETEX, 2018b, 2019, 2020, 2021, 2022, 2023a).

Figure B.1: SISBEN vulnerability score



Notes: This figure shows the histogram of the Running score for the Rural areas. The distribution includes information for cohorts from 2011 to 2013.
Source: Author's calculation based on DNP data.

B Analysis for Rural Area

Figure B.1 presents the distribution of the X_i for the *Rural* sample. The figure shows that the distribution is left-skewed, with most of the observations concentrating on the upper part of it. There is a signal of bunching to the right of the threshold. Nonetheless, the p-value associated with the manipulation test is 0.769, suggesting no statistical evidence of manipulation of the score.

Debt forgiveness eligibility does not affect the probability of graduating or graduating on time from university. It also has null effects on the probability of dropping out, the number of semesters enrolled, or the probability of enrolling in postgraduate studies.

The results show null and imprecise effects by extending the analysis to employment and earnings.

Table B.1: RD Effects on Education Outcomes

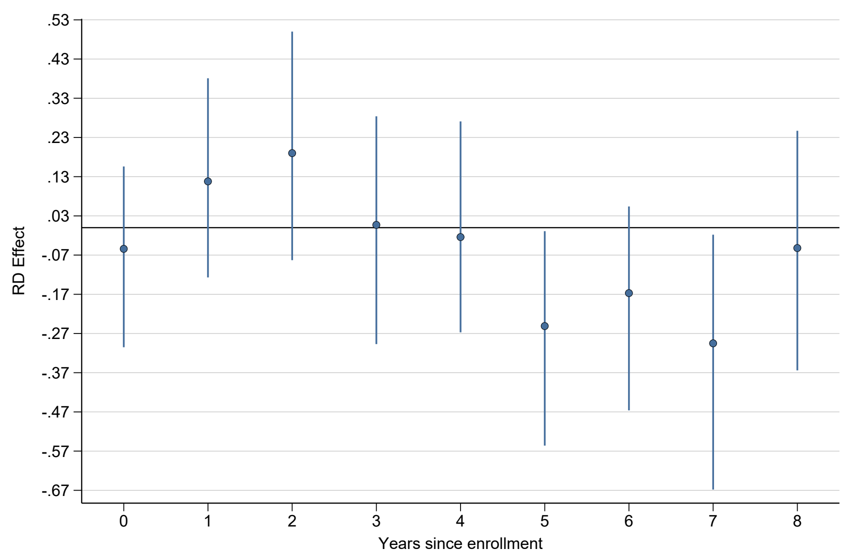
	(1)	(2)	(3)	(4)	(5)	(6)
	Graduation	**Graduation On Time**	**Dropout**	**Retention**	**SABER PRO**	**Postgrad**
Treatment Effect	-0.041	-0.100	0.043	-0.289	0.871**	-0.030
	(0.132)	(0.116)	(0.129)	(1.325)	(0.404)	(0.093)
Control Mean	0.579	0.374	0.420	6.480	-0.354	0.141
Effective Obs	887	958	920	678	311	861
MSE Bandwidth	13.773	14.106	14.260	10.862	10.219	12.666

Notes: This table presents the effect of debt forgiveness eligibility on the probability of graduation using a RD design. The Centered and Reversed SISBEN Score is used as the running variable (Running Score). Hence, a positive effect would be described as a positive coefficient in the outcome variable.The sample comprises newly enrolled students from Rural areas from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017)

***,** and * denote significance at the 1%, 5% and 10% levels, respectively

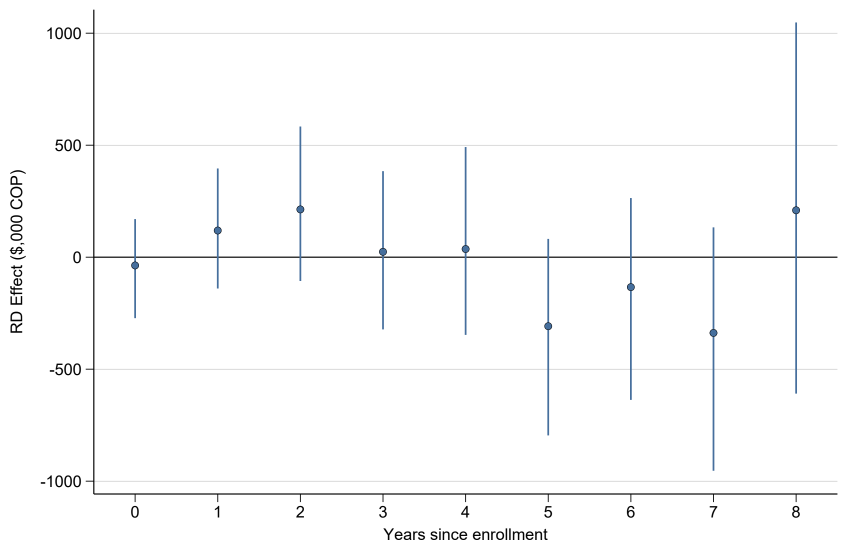
Source: Author's calculation based on ICETEX, MEN and DNP information

Figure B.2: RD effect on Employment



Notes: This plot displays the effect of debt forgiveness eligibility on employment in the formal sector using a regression discontinuity design. The Centered and Reversed SISBEN Score (Running Score) is used as the running variable. Hence, a positive effect would be described as a positive coefficient in the outcome variable. The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017)
Confidence Intervals are at the 95% level
Source: Author's calculation based on ICETEX, MEN and DNP information

Figure B.3: RD effect on Earnings Levels



Notes: This plot displays the effect of debt forgiveness eligibility on earnings using a regression discontinuity design. The Centered and Reversed SISBEN Score (Running Score) is used as the running variable. Hence, a positive effect would be described as a positive coefficient in the outcome variable. The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017) Confidence Intervals are at the 95% level
Source: Author's calculation based on ICETEX, MEN and DNP information

Table C.1: RD Effects on Education Outcomes - Placebo Cohort

	Graduation	**Graduation On Time**	**Dropout**	**Retention**	**SABER PRO**	**Postgrad**
Treatment Effect	-0.018	-0.027	0.014	-0.664	0.232	0.012
	(0.059)	(0.056)	(0.060)	(0.633)	(0.217)	(0.045)
Control Mean	0.545	0.207	0.449	7.105	-0.215	0.144
Effective Obs	4,109	2,865	3,956	3,799	983	3,322
MSE Bandwidth	21.572	14.140	20.756	20.503	13.778	16.196

Notes: This table presents the effect of debt forgiveness eligibility on the probability of graduation using a RD design. The Centered and Reversed SISBEN Score is used as the running variable (Running Score). Hence, a positive effect would be described as a positive coefficient in the outcome variable. To facilitate the reading, significant effects are in bold. The sample comprises newly enrolled students from Urban areas in 2010. All results are estimated with package rdrobust (Calonico et al., 2017)

***,** and * denote significance at the 1%, 5% and 10% levels, respectively

Source: Author's calculation based on ICETEX, MEN and DNP information

C Robustness Checks

C.1 Placebo Cohort

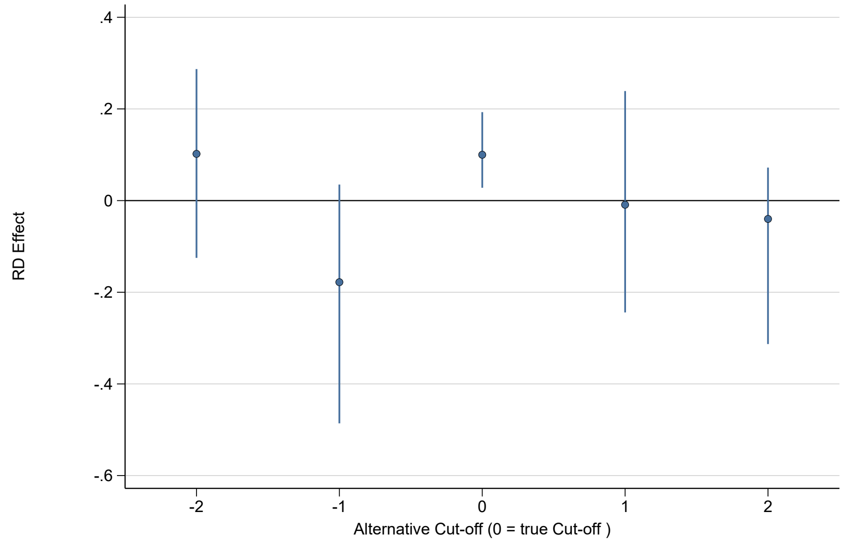
Since the introduction of the policy was in 2011, the 2010 cohort is a natural placebo sample to check the robustness of the findings presented in Section 5. Without the policy, one would expect negligible differences in the RD coefficient at the corresponding threshold. To shed light on this, Table C.1 summarizes the results of the RD design (Equation 2) using only the 2010 Cohort. As expected, the results confirm the absence of any discernible difference between treatment and control units.

C.2 Placebo Cutoffs

In the continuity framework used for the RD analysis in this paper, the key identifying assumption is the continuity of the regression functions for treatment and control units at the cutoff in the absence of the treatment (Cattaneo and Titiunik, 2022). According to Cattaneo et al. (2019), while the continuity assumption is untestable at the cutoff, one can estimate the regression function at any other point (other than the cutoff) to test whether it is continuous. Ideally, no significant difference should be found at placebo cutoff values.

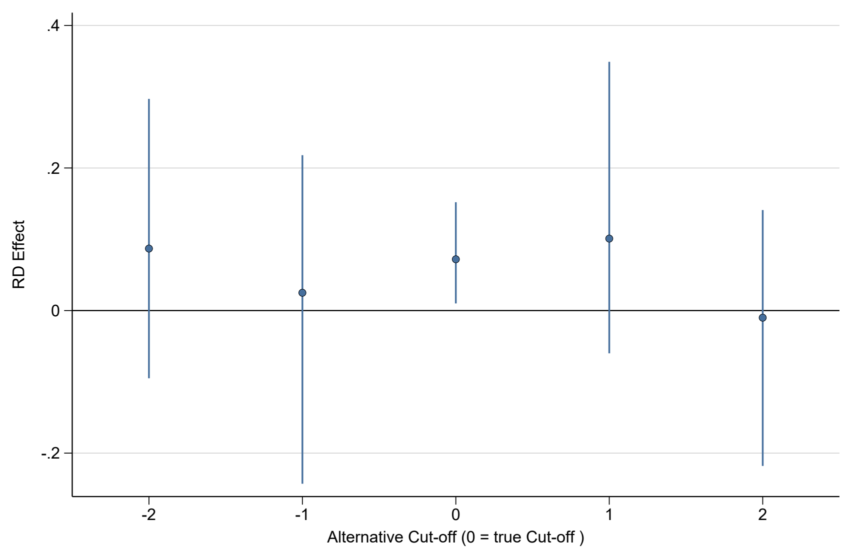
To examine the continuity assumption, I estimate Equation 2 on the outcomes of interest using alternative cutoffs from -2 to 2 spaced by one and including the real cutoff value (0). The results are summarized in Figures C.1, C.2, C.3, C.4, and C.5. The true cutoff is the only point with significant results. All the artificial cutoffs show a coefficient much closer to zero than the true one, and all the effects are null. Hence, there is evidence to conclude that the graduation rate did not change at any other point in the SISBEN Score support.

Figure C.1: RD effects on Graduation for True and Artificial Cutoffs



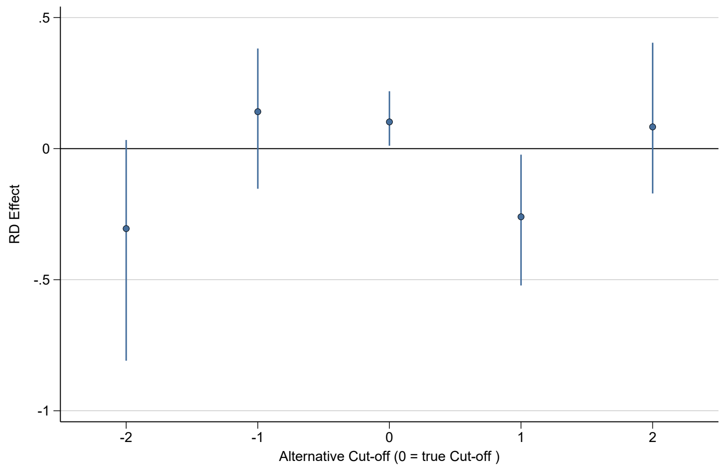
Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Graduation as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.2: RD effects on Graduation on Time for True and Artificial Cutoffs



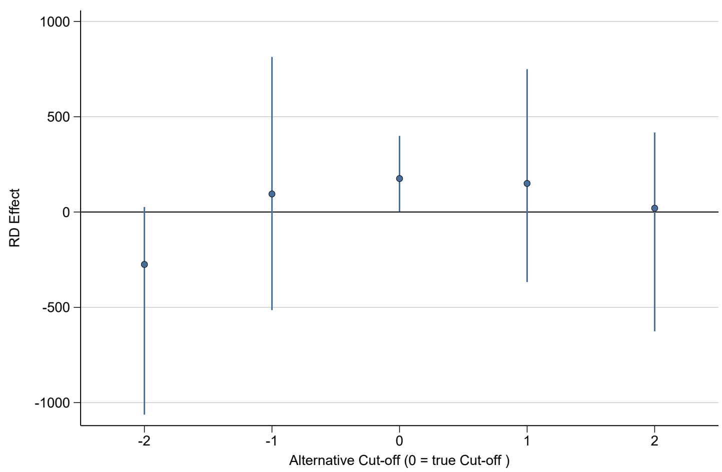
Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Graduation on Time as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.3: RD effects on Employment (eight years after enrollment) for True and Artificial Cutoffs



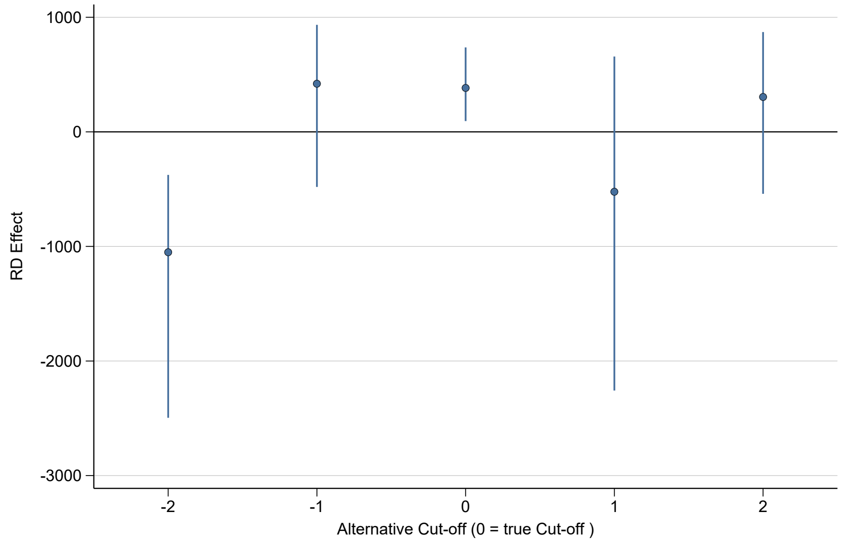
Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Employment (eight years after enrollment) as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.4: RD effects on Earnings (seven years after enrollment) for True and Artificial Cutoffs



Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Earnings (seven years after enrollment) as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.5: RD effects on Earnings (eight years after enrollment) for True and Artificial Cutoffs



Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Earnings (eight years after enrollment) as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

C.3 Donut-Hole Approach

I assess the sensitivity of the results to the influence of the closest observations to the cutoff (given these are the most influential when fitting the local polynomials) using a donut-hole approach (i.e. excluding observations near the cutoff at different score bands) (Cattaneo et al., 2019). Table C.2 presents the results. The donut-hole 0 corresponds to the main specification; from there, each table row shows the exclusion of observations with a SISBEN score lower than the hole in absolute terms. The results show that the conclusions from the analysis are robust to excluding observations near the cutoff with significant results at every donut-hole level. Therefore, the conclusions remain unchanged. It is worth noting that the magnitude of the coefficient is directly related to the margin of extrapolation.

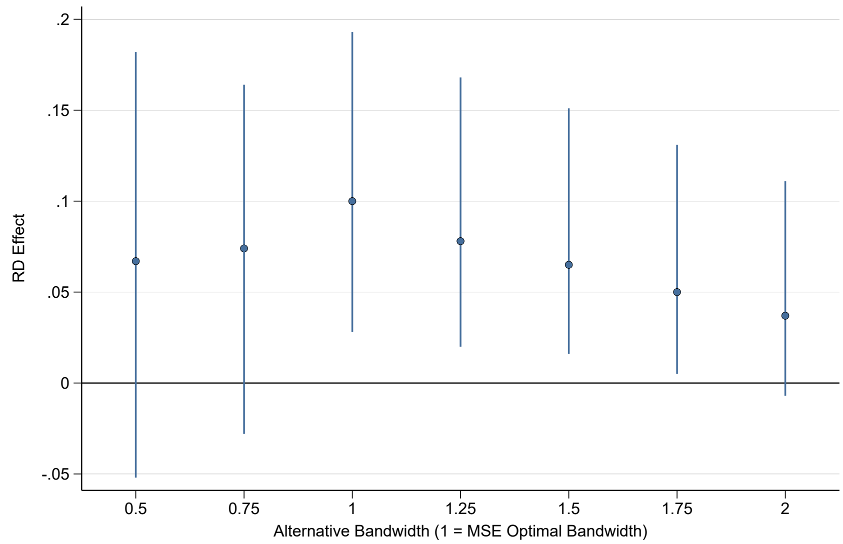
Table C.2: RD effects for the Donut-Hole Approach

Donut-Hole	RD Effect	Robust p-val	Conf. Int. L	Conf. Int. R	MSE Bandwidth	Excluded Observations
Panel A: Graduation						
0	0.100	0.009	0.028	0.193	11.666	0
0.1	0.120	0.004	0.044	0.222	10.927	534
0.2	0.121	0.007	0.037	0.232	10.293	992
0.3	0.122	0.010	0.033	0.240	10.158	1,129
0.4	0.156	0.002	0.062	0.285	9.480	1,583
0.5	0.187	0.001	0.082	0.334	8.685	2,173
Panel B: Graduation on Time						
0	0.072	0.025	0.01	0.152	12.455	0
0.1	0.081	0.017	0.016	0.166	11.941	421
0.2	0.085	0.019	0.015	0.175	11.445	809
0.3	0.075	0.045	0.002	0.169	11.470	860
0.4	0.116	0.005	0.038	0.222	10.351	1,673
0.5	0.112	0.012	0.028	0.224	10.032	1,933
Panel C: Employment (eight years after enrollment)						
0	0.020	0.502	-0.047	0.096	17.181	0
0.1	0.009	0.764	-0.060	0.082	18.409	-522
0.2	0.014	0.670	-0.059	0.092	17.324	2
0.3	0.020	0.571	-0.059	0.106	16.309	497
0.4	0.015	0.676	-0.065	0.100	16.646	396
0.5	0.003	0.910	-0.075	0.084	18.203	-288
Panel D: Earnings (seven years after enrollment)						
0	175.592	0.047	2.233	399.591	13.016	0
0.1	191.255	0.041	9.370	426.467	12.592	218
0.2	230.621	0.023	36.000	483.806	11.999	514
0.3	252.610	0.022	41.835	528.321	11.626	714
0.4	209.716	0.063	-13.120	498.448	11.961	601
0.5	235.225	0.053	-3.624	547.602	11.725	743
Panel E: Earnings (eight years after enrollment)						
0	383.204	0.011	94.072	737.039	13.828	0
0.1	464.395	0.004	159.455	836.705	12.6	267
0.2	525.169	0.002	201.865	933.128	12.269	333
0.3	537.603	0.003	194.715	971.825	12.038	402
0.4	523.733	0.007	160.404	989.514	12.249	376
0.5	530.332	0.008	151.007	1020.358	12.188	406

Notes: This table presents the effect of debt forgiveness eligibility on Graduation, Graduation on time, Employment (eight years after enrollment) and Earnings (seven and eight years after enrollment) using a regression discontinuity donut-hole approach. The Centered and Reversed SISBEN Score is used as the running variable. Hence, a positive effect would be described as a positive coefficient in the outcome variable

Source: Author's calculation based on ICETEX, MEN and DNP information

Figure C.6: Sensititvity to Bandwidht for the RD Effect on Graduation

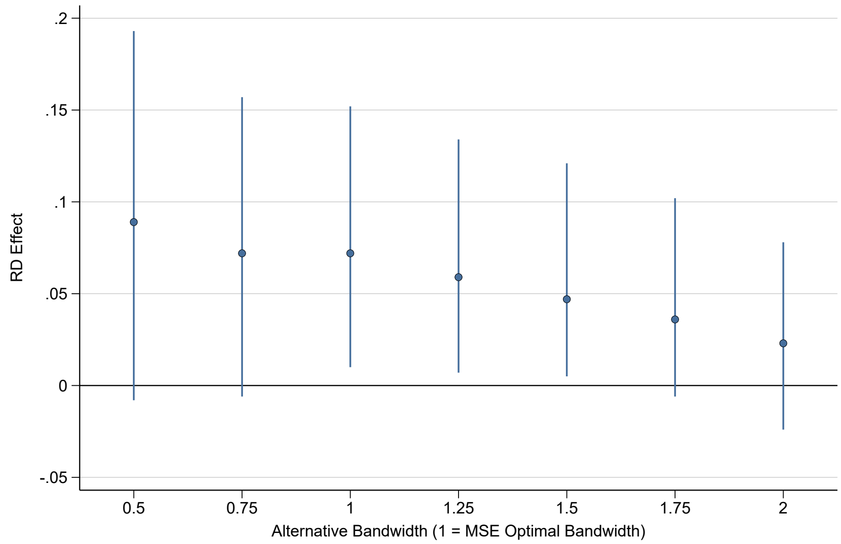


Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Graduation as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017). Source: Author's calculations based on ICETEX, ICFES and DNP data.

C.4 Bandwidth Sensitivity

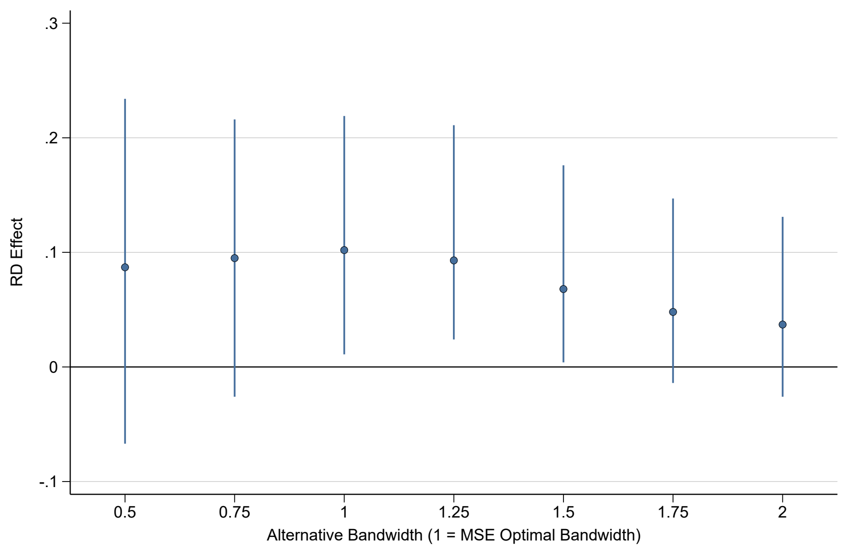
Last, I evaluate the sensitivity to the bandwidth selection. I normalize the MSE optimal bandwidth (from the main specification) to one and estimate new RD models for different bandwidth sizes. According to Cattaneo et al. (2019), it is natural to expect that, as the bandwidth increases, the confidence intervals will decrease in length but also be displaced (because of the bias induced by the deviation from the optimal bandwidth). Figures C.6, C.7, C.8, C.9, and C.10 show the results. Consistent with the priors from the literature, the point estimation is biased towards zero, and the confidence intervals are smaller as the bandwidth increases. The effect on Graduation remains significant at traditional statistical levels from 1 to 1.75 transformations of the MSE optimal bandwidth. Thus providing additional evidence of the reliability of the point estimation presented in this paper.

Figure C.7: Sensititvity to Bandwidht for the RD Effect on Graduation on Time



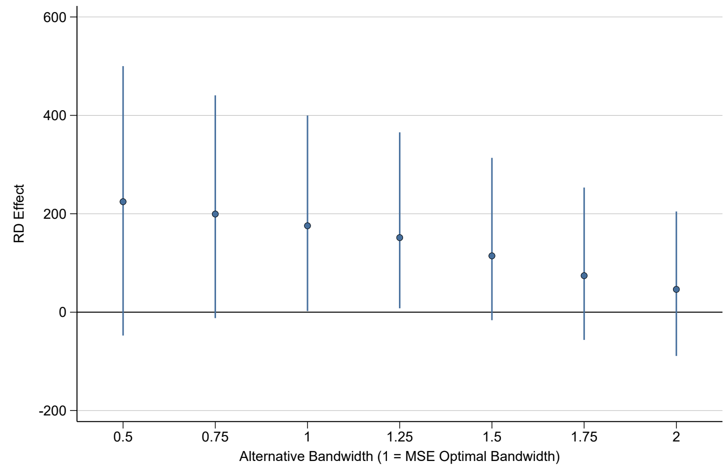
Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Graduation on Time as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.8: Sensititvity to Bandwidht for the RD Effect on Employment (eight years after enrollment)



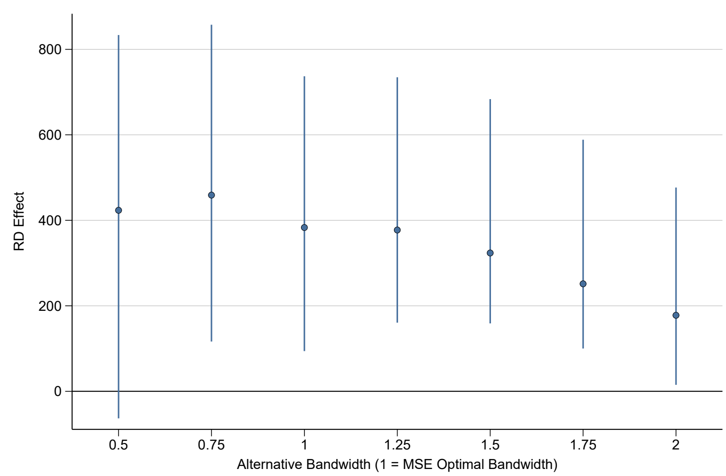
Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Employment (eight years after enrollment) as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.9: Sensititvity to Bandwidht for the RD Effect on Earnings (seven years after enrollment)



Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Earnings (seven years after enrollment) as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

Figure C.10: Sensititvity to Bandwidht for the RD Effect on Earnings (eight years after enrollment)



Notes: This plot presents the coefficients and robust confidence intervals from a RD specification using Earnings (eight years after enrollment) as the outcome and the Centered and Reversed SISBEN Score as the running variable. Thus, if there were a positive effect, it would be above the threshold (at the top of the solid line). The sample comprises cohorts from 2011 to 2013. All results are estimated with package rdrobust (Calonico et al., 2017).
Source: Author's calculations based on ICETEX, ICFES and DNP data.

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