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Impacto del financiamiento educativo en la movilidad social de graduados universitarios: Un análisis de regresiones discontinuas

Impact of educational financing on the social mobility of university graduates: An analysis using regression discontinuities

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RESUMEN

La investigación evaluó el impacto del programa de ayudas económicas en una universidad privada en Venezuela, sobre las variables de resultado de posgrado o movilidad social, como la remuneración en el momento de la graduación y en la actualidad, y la probabilidad de ingresar al mercado laboral. Se utilizó el diseño de regresión difusa para tratamientos múltiples, dado que el programa consiste en la aplicación de descuentos porcentuales en la matrícula, donde el índice de asignación solo muestra la probabilidad de ser tratado, encontrando así individuos beneficiarios a la derecha y a la izquierda del umbral en cada uno de los puntos de corte. Los resultados muestran que existen diferencias en la inserción laboral entre los individuos tratados y no tratados, a favor de los primeros, pero salarios más altos para los no beneficiarios. En cuanto a las estimaciones de las regresiones de regresión difusa tanto para la remuneración en los diferentes puntos del tiempo como para la inserción en el mercado laboral, no es posible identificar un impacto positivo del tratamiento.

PALABRAS CLAVE

Financiamiento educativo, evaluación impacto, regresiones discontinuas difusas, movilidad social, educación superior.

ABSTRACT

The aim of this research was to evaluate the impact of the financial aid programme at a private university in Venezuela on the outcome variables of post-graduation or social mobility, such as remuneration at the time of graduation and at present, and the probability of entering the labour market. We used the fuzzy regression design for multiple treatments, given that the programme consists of the application of percentage discounts on tuition, where the allocation index only shows the probability of being treated, thus finding beneficiary individuals to the right and to the left of the threshold at each of the cut-off points. The results show that there are differences in labour market insertion between treated and untreated individuals, in favour of the former, but higher wages for non-beneficiaries. As for the estimates of the fuzzy regression regressions for both remuneration at the different points in time and labour market insertion, it is not possible to identify a positive impact of the treatment.

KEYWORDS

Educational funding, impact evaluation, fuzzy regressions, social mobility, higher education.

Clasificación JEL: C14, C21, C52, I22

MSC2010: 62P20

1. INTRODUCTION

Educational funding programmes or exemptions from all or part of the tuition fees in higher education institutions, at least in Latin America, are limited. These affirmative action policies aim, in addition to providing access to the higher education system, to encourage retention and to improve the social mobility conditions of graduates.

This relationship, at least in terms of financial aid programmes and the possibility of labour market insertion, has been explained in the economic literature through models such as human capital (Becker, 1962), signalling theory (Akerlof, 1970; Spence, 1973; Stiglitz, 1975; Laibson, 1997), labour market supply and demand adjustment theory (Mincer, 1974; Freeman, 1976; Becker, 1994) and social mobility theory (Becker, 1962; Wright, 1997).

In the first case, human capital theory suggests that education is an investment that enables students to acquire knowledge and skills that make them more productive and valuable in the labour market. In this way, educational financing programmes for higher education can help students obtain a higher quality education, which increases their chances of getting better paying jobs with better conditions.

In the second case, signalling theory addresses the question of how employers evaluate and select candidates for jobs. This theory suggests that education can serve as a signal to employers about the skills, commitment and ability of candidates to perform a particular job. In this context, educational credit can have a significant impact on job placement, as it can serve as a signal to employers about the quality and commitment of the candidate to his or her education and career.

In the third case, educational credit and the labour market adjust to each other to meet the needs of the economy in terms of human capital formation. This means that, if there is a demand for highly skilled workers, wages for these jobs will increase, which will motivate students to seek higher education to obtain the necessary skills and knowledge to obtain these jobs. In this case, educational credit can play a significant role in providing students with the necessary resources to access higher education.

In this sense, access to educational credit can increase investment in human capital, improving the skills and training of workers and increasing their ability to meet the demands of the labour market (Mincer, 1974; Becker, 1994). However, it must be considered that, if the labour market is oversupplied with highly skilled workers, a fall in wages and an increase in competition for skilled jobs will be experienced. Thus, access to educational credits may have a limited impact on labour market entry if there is an oversupply of highly educated workers, which may make it difficult for the labour market to adapt to labour demand (Freeman, 1976).

Finally, social mobility theory refers to the ability of an individual to change position in the socio-economic hierarchy over the course of his or her lifetime. This theory argues that access to education and training are principal factors in enhancing a person's social mobility. In this sense, educational credits can play a key role in improving people's social mobility by financing higher education, which in turn can improve their employability (Wright, 1997).

To evaluate the impact of financing programmes in higher education, several studies have been developed considering different quasi-experimental methodologies such as the design of discontinuous, sharp or fuzzy regressions, as well as matching or difference-in-difference methods.

Notably, most of the studies that employed the regression discontinuity design have been developed in European countries or for North American universities, such as the traditional studies by Singell (2001), Van Der Klaauw (2002) or Herzog (2008), as well as more recent studies such as those by Chapman (2015), Baker et al. (2017), Bettinger et al. (2019), Scott-Clayton and Zafar (2019), Daniels and Smythe (2019).

Chapman (2015) analysed the relationship between financial support programmes associated with academic merit and labour market outcomes using a regression discontinuity design. Baker et al. (2017), warn about the case of the most vulnerable students in the United States, indicating that the effect will depend on decreasing existing inequalities. While Bettinger et al. (2019) and Scott-Clayton and Zafar (2019) fail to identify a long-term impact.

For Latin America, most studies have been developed in countries such as Chile, Colombia, Peru and Mexico. In the first case, the most recent research includes Beyer et al. (2015), Bucarey et al. (2018), Andrade and Gallegos (2018), Bellei and Cabalin (2018); for Colombia, studies by Forero and Ramírez (2008), Rangel (2016), Duryea and Galiani (2016), Arbeláez, Gallego and Posada (2020) are identified; while in Mexico, Bernal et al. (2018) and Hoyos and Gómez (2019) are mentioned; and in Peru, García (2010) and Blakeslee et al. (2020) are mentioned.

Both Beyer et al. (2015) and Bucarey et al. (2018) fail to identify an impact of funding on mobility. Also, for the Chilean case, Andrade and Gallegos (2018), using regression discontinuities to assess the impact of the Crédito con Aval del Estado (CAE) programme on students' labour market outcomes, find that students who received CAE were more likely to obtain quality, high-paying jobs compared to students who did not receive CAE. Another study conducted in Chile by Bellei and Cabalin (2018) evaluated the impact of the educational credit programme "Beca Nuevo Milenio" on students' social mobility.

For the Colombian case, Forero and Ramírez (2008) and Rangel (2016) identify a relationship, but with the social and human capital of the parents who determine the labour market insertion of graduates, but not with the educational funding they were able to access. While Duryea and Galiani (2016) did evaluate the impact of the educational credit programme "Ser Pilo Paga" on the social mobility of students, finding that students who received the credit were more likely to access higher education and, once graduated, to obtain better paid jobs with greater job stability. A more recent study conducted in Colombia by Arbeláez et al. (2020) evaluated the impact of the "Generation E" educational credit programme on students' social mobility.

In Mexico, Bernal et al. (2018) studied the education credit programme "Crédito Joven", concluding that students who received the Crédito Joven were more likely to enter the labour market with better working conditions.

In the case of Peru, Blakeslee et al. (2020) analysed the education credit programme "Beca 18", also finding a positive impact of the programme, i.e., students who received the scholarship had access to better jobs with higher salaries.

A series of variables must also be considered, such as the human capital of parents, social capital and a series of factors not directly associated with formal education, as well as the continuity of this process after graduation (Van Belle et al, 2019; Tomlinson, 2008; Finnegan et al, 2019).

In the particular case of a country like Venezuela, this type of impact analysis has been little explored for two reasons: firstly, most higher education institutions do not have affirmative action policies that employ credit or educational financing as a mechanism for access to the system; and secondly, impact evaluation has been little studied to analyse this type of programme, especially in terms of social mobility, given that most research analyses variables related to academic performance, such as dropout, continuation or graduation.

As reflected in the literature, the studies are based on variables that are part of academic performance, given the availability of data, since the complexity of analysing variables related to social mobility such as labour market insertion and wages is related to the follow-up of graduates and the availability of information that allows the study to be carried out.

Although research has been carried out on the fuzzy regression design in which the treatment has different cut-off points, the pioneer being that of Van Der Klaauw (2002), research with this methodology and for the analysis of variables related to the social mobility of graduates is limited and, in the case of Venezuela, non-existent.

In this sense, this research aimed to analyse the impact of a financial support programme of the Universidad Católica Andrés Bello, a higher education institution entrusted to a religious congregation (Compañía de Jesús), which is among the best positioned universities in Venezuela according to different specialised rankings.

For more than thirty years, this university has had an aid programme that consists of the exemption of different percentages of tuition fees (treatment with multiple cut-off points), which depends on the socio-economic condition of the student and not on academic aspects.

The relevance of the analysis is therefore associated with the use of a methodology that avoids selection biases and guarantees the causality of the treatment based on the definition of a strategy of identification or assignment to the intervention, allowing the evaluation and identification of opportunities for improvement in terms of the social mobility of graduates benefiting from the programme.

2. METHODOLOGY

To assess the impact of the treatment on post-graduation variables (employment and salaries) or social mobility, it was necessary to apply an instrument to follow up graduates and to define the identification strategy to determine the most suitable methodology: sharp or fuzzy regressions.

In this way, the social mobility variables on which the impact was assessed were associated with salary, at three points in time: during the degree, at the time of graduation and at least two years after obtaining the degree, in addition to employment status, employed or unemployed.

2.1 Graduate monitoring instrument

The starting point was the application of a graduate follow-up instrument for the cohort admitted in 2013-2014. This cohort was used given that most of the institution's programmes were designed for 10 semesters and, in addition, salary was considered at various points in time, which required the graduation of the largest number of students.

As proposed in various graduate follow-up manuals (Columbus, 2006), questions associated with three basic aspects were used: graduate profile, relationship with the labour market and relationship with the institution (Table 1).

TABLE 1. STRUCTURE OF THE INSTRUMENT APPLIED TO GRADUATES.

Section	Questions
Academic information	Knowledge of foreign languages, computer science, other undergraduate degrees obtained.
Work experience during the degree	Work, relationship with the degree, salary, dedication, duration.
Characteristics of first job	Relationship between job and profession, salary, economic activity, dedication, duration, aspects valued by the employer.
Characteristics of current job	Experience, salary, type of employment relationship, training for the job, type of position.
Unemployed status	Time spent unemployed, reasons for unemployment.
Self-employment status	Economic activity, entrepreneurial nature of the activity, training to become an entrepreneur.
Further studies	Studies completed, place of study, relation to your profession.
Evaluation of your undergraduate studies	If you studied the same, at another university, abroad.

The instrument was applied to 2,292 graduates through electronic means, obtaining a response rate of 41.8%, which represented 958 graduates, so the margin of error is estimated at 2.4% for 95% confidence, lower than the 5% established for sample estimates, therefore, the data are cross-sectional.

The population that enrolled in the first year consisted of 5,613 students, of whom only 2,292 graduated, which constitutes the population on which the study was conducted, and the graduate follow-up instrument was applied. Of the total number of graduates, 395 were beneficiaries of the tuition waiver programme in its various percentages, so that 541 treated students did not complete their degree at the time of the study, although the graduation rate of the treated group was higher (42%) than that of the untreated (40%).

2.1 Characterisation of the financial aid programme

The analysed programme consists of a percentage discount of the tuition fee depending on the student's socio-economic status. It is not associated, therefore, with academic or merit conditions, but only with economic need and availability of resources from the institution. Each discount percentage corresponds to different cut-off points.

For the allocation to treatment and the different cut-off points, an interview and the review of documentation is used, which allows the construction of an assignment index, which is estimated considering variables of the student and the family, such as: average monthly family income, type of housing, housing condition, family burdens and place of residence of the student.

In each cut-off, students who apply for the benefit of the exemption programme, according to the allocation variable, will receive treatment if they have an index equal to or higher than 100 points, in which case the higher the need, the higher the percentage discount will be. If it is between 100 and 199 points it is 25%, between 200 and 299 it will be 30%, between 300 and 399 it will be 45% and above 400 it will be 50%. In this way, the index has four cut-off points, which generates a multiple treatment (Vásquez, 2019).

When analysing the results of the treatment allocation index and the percentages of discounts received, there are beneficiaries who were entitled to another exemption or did not receive the aid at all. This is because it is the interviewer who makes the final decision through the interview, with the support of the index.

To determine whether the index could predict each of the treatments (discount rates) and to corroborate the existence of the four cut-off points or allocation of different waivers, an ordered probit of the waiver rates in relation to the aid index was estimated (Table 2).

TABLE 2. ORDERED PROBIT MODEL FOR EACH TREATMENT TYPE.

	Coefficients
Assignment index	0.0048***
	(0.0001)
Cut-off point 1	1.8737
	(0.0411)
Cut-off point 2	1.9423
	(0.0416)
Cut-off point 3	2.1011
	(0.0431)
Cut-off point 4	3.0057
	(0.0565)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

The results show that the four cut-off points of the index associated with discounts are indeed corroborated and contribute to the explanation of the exoneration by 11%. The difference is explained by the interviewer's decision, as suggested by the literature.

The decision rule is complex and contains objective elements, but also considerable subjective factors that depend on the evaluator (Van Der Klaauw, 2002), trying to establish simple assignment criteria that are complemented by the information obtained in the interview and the interviewer's perception.

It is for this reason that the index does not effectively determine whether the student receives the treatment or the percentage discount; it could only indicate the probability of being treated, thus finding beneficiary individuals to the right and to the left of the threshold, which is why we propose the fuzzy regression discontinuity design.

2.3 Fuzzy regression discontinuous regression methodology

Methods such as propensity score matching, while matching each student with the most similar student based on the probability of receiving the treatment, do not take into consideration how students are assigned to the treatment, which needs to be reflected in the methodology applied to assess the causal effect.

This causal effect demands that the process of programme assignment is understood and used in the design of the model and the methodology to be used, which determines whether the design is sharp or fuzzy. In this case, the regression discontinuity design was fuzzy, since it allows estimating the causal effect eliminating the bias in unobservables by using instrumental variables, starting from the index or treatment assignment criterion that only allows ordering the students, since the final decision to participate or not depends on each one of them (Angrist and Lavy, 1999; Bernal and Peña, 2011).

If around each of the cut-off points there is a discontinuity in the probability of receiving the treatment, Angrist and Pischkle (2009) point out that a causal effect could be expected to exist, which would be given by the difference on either side of the threshold of the expected value of the outcome variable, and the conclusions obtained can be extended only around that cut-off point because the validity is not average but local.

In order to determine whether the index could predict each of the treatments (percentage of exonerations), an ordered probit was estimated, the results of which indicate the existence of the four cut-off points, with an explanatory power of 11% and, as stated in the literature, the decision rule is complex and contains objective elements, but also considerable subjective factors that depend on the evaluator or staff in charge of analysing the case, as pointed out by Van Der Klaauw (2002).

It is for this reason that the index effectively does not determine whether the student receives treatment or the percentage of discount. It could only indicate the probability of being treated, thus finding beneficiary individuals to the right and to the left of the threshold.

In addition to the existence of an assignment criterion or identification strategy, the implementation of this regression discontinuity design, according to Lee and Lemieux (2009), requires ensuring internal validity through the continuity of the density function of the treatment assignment variable and the non-existence of significant differences in the observable characteristics of treated and untreated individuals.

This check showed that there is no jump or discontinuity in the Kernel density function for the treatment assignment variable or "forcing variable" and furthermore, tests of differences in means or proportions indicate that the differences between the two groups stem from socio-economic conditions, which is correct if they are associated with the selection criterion.

Having validated the two basic assumptions of the regression discontinuity design, it is necessary to identify whether the design is sharp or fuzzy. To verify that the study fits a fuzzy regression discontinuity design, it is necessary to determine the existence of differences between the observed treated and untreated, versus those estimated through the assignment criterion, if there is no such difference it would be a sharp design.

Comparisons reveal that unlike the acute estimate, there are treated and untreated students on either side of the threshold, which shows that the allocation rate only

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determines the probability of receiving the treatment and not actually receiving it. An increase in the estimated waiver as the allowance rate rises indicates that the higher the degree of student financial need, the higher the percentage of waiver allocated should be, and there is a jump or discontinuity at least at the higher levels of waiver.

The model with the outcome variables salary and probability of employment was estimated parametrically and non-parametrically (Wald estimator), for multiple treatments including each of the allocation index cut-off points. The parametric estimates of the impact of the cash transfer programme were estimated using two-stage least squares as proposed by Van Der Klaauw (2002) and developed in the following equations:

(2.1)

$$Y_i = \beta + \alpha E\left(exon_i \middle| aid\_index_i\right) + k\left(aid\_index_i\right) + \varepsilon_i$$

Where the first stage is given by:

(2.2)

$$\begin{aligned} E(exon_i|aid\_index_i) \\ &= f(aid\_index_i) + \gamma_1 1\{aid\_index_i \geq \overline{aid\_index_1}\} \\ &+ \gamma_2 1\{aid\_index_i \geq \overline{aid\_index_2}\} + \gamma_3 1\{aid\_index_i \geq \overline{aid\_index_3}\} \\ &+ \gamma_4 1\{aid\_index_i \geq \overline{aid\_index_4}\} \end{aligned}$$

These parametric two-stage least squares (2SLS) estimates were performed for the different functional forms of the assignment index (piecewise cubic, piecewise quadratic and piecewise linear), for the whole population and the different bandwidths of +/- 20 points, +/- 15 points, +/- 10 points, except +/- 5 points because there were not enough observations.

To complement the parametric analysis of each of the outcome variables (wages at different points in time and probability of employment), non-parametric estimations were conducted using the Wald estimator. The Wald estimator is the quotient of the difference in the averages of the outcome variable on each side of the threshold and the average probability of receiving the treatment in the same interval as reported by Bernal and Peña (2011), estimated in turn, as developed by Van Der Klaauw (2002) in the following expression:

(2.3)

$$\tau_{RDB}(\bar{Z}) = \frac{\bar{Y}(\overline{Z^-}) - \bar{Y}(\overline{Z^+})}{\widehat{Pr}(D = 1|\overline{Z^-}) - \widehat{Pr}(D = 1|\overline{Z^+})}$$

The Wald estimate could be obtained for the 15- and 20-point bands, as for the rest exogeneity is not guaranteed (that the instrument is not correlated with the error term, $(Cov(u_i, Z_i) = 0)$, and it could not be estimated for the 30% exemption treatment because there are not enough observations to guarantee validity.

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3. RESULTS AND DISCUSSION

3.1 Characteristics of graduate: Result variables

About the result variables, we asked about labour market insertion, during the degree, upon graduation and at the time the instrument was applied. In the first moment, 48.9% report having worked during their studies, of which 79.6% did so in some career-related responsibility, receiving an average monthly income of 2.5 times the salary and with a length of service of 26.4 months. Secondly, upon graduation, the average waiting time for employment is 2.21 months and the average monthly income is 1.95 times the wage.

The behaviour of the performance variables on which we will measure the impact of the treatment seems to indicate at least that the level of average monthly income rises as training is completed and experience is acquired in the labour market. However, when analysing the results by degree, the gap expands with experience, with certain degrees being better remunerated, while in others the very characteristics of the labour market (e.g., Education) do not allow for compensating for learning and knowledge acquired on the job.

Degrees such as Economics, Law, Computer Engineering, Telecommunications and Industrial Engineering report the highest earnings, while Arts and Education report the lowest wages. While the results show differences in terms of study programmes, employability and wages, there are also statistically significant differences in terms of participation or not in the financial aid programme, distinguishing between treated and untreated (Table 3).

TABLE 3. DIFFERENCES IN EMPLOYMENT AND WAGES BETWEEN TREATED AND NON-TREATED BY FINANCIAL ASSISTANCE PROGRAMME.

Variable	Untreated	Treated	Difference	
Worked during studies (proportion of graduates)	0.4765	0.5373	-0.0607	*
Work duration during the degree (months)	24.4567	30.6496	-6.1929	***
Current job (proportion of graduates)	0.8151	0.8667	-0.0516	*
Self-employed (proportion of graduates)	0.00610	0.0632	-0.0023	
Currently unemployed (proportion of graduates)	0.1821	0.1333	0.0487	*
Monthly salary during the degree (number of minimum wages)	2.0544	1.56996	0.3547	**
Monthly salary after graduation (number of minimum wages)	2.2226	1.9496	0.2729	***
Current monthly salary (number of minimum wages)	2.7446	2.0884	0.6562	***

Note: Significant at: 1% (***), 5% (**), 10% (*).

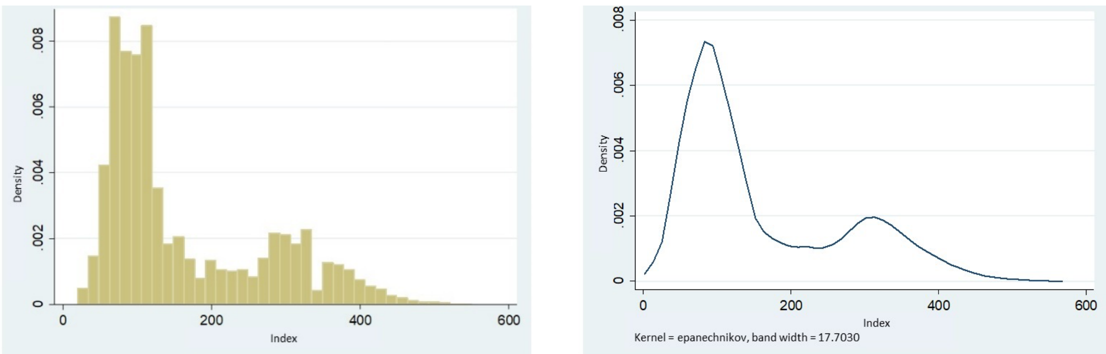
As can be seen, there are statistically significant differences in terms of employment, with the proportion of treated employees being higher than those who did not receive treatment, both during the training period and at the time of applying the instrument, but despite this, the salaries of the untreated are higher than those treated and these differences are statistically significant at the three points in time evaluated, during training, at the time of graduation and at the time of applying the instrument.

Moreover, it is evident that not only the monthly remuneration measured as the number of minimum wages is higher in the untreated, but that this difference widens as the years of graduation go by.

3.2 Treated and untreated analyses: Sharp or fuzzy regression discontinuous design

In addition to the existence of an assignment criterion or identification strategy, the implementation of the fuzzy regression discontinuity design requires ensuring internal validity (Lee & Lemieux, 2009), through the continuity of the density function of the treatment assignment variable and no significant differences in the observable characteristics of treated and untreated individuals (Figure 1).

FIGURE 1. DENSITY FUNCTION OF THE TREATMENT ASSIGNMENT VARIABLE

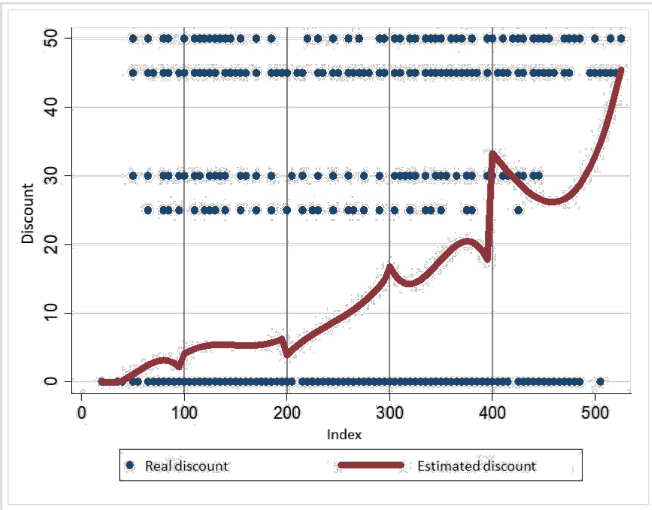


It was found that there is no jump or discontinuity in the Kernel density function for the forcing variable, and furthermore, the tests of differences in means or proportions seem to indicate that the differences between the two groups come from the socio-economic conditions, which is correct if one considers that they are associated with the selection criterion.

Having validated the two basic assumptions of the regression discontinuity design, it is necessary to identify whether the design is sharp or fuzzy. To verify that our study fits a fuzzy regression discontinuity design, it is necessary to determine the existence of differences between the observed treated and untreated versus those estimated through the assignment criterion; if there were no such difference, we would be in the presence of a sharp design.

As shown in Figure 2, the blue points represent the students who are grouped in each category, the untreated, and the treated with exemptions of 25%, 30%, 45% and 50%, while the red line represents the estimation of the cubic (spline) piecewise function, The illustration shows that, unlike the acute estimation, there are treated and untreated individuals on either side of the threshold, which shows that the allocation index only determines the probability of receiving the treatment and not actually receiving it, since it is the evaluator's criterion that will establish the benefit.

FIGURE 2. DENSITY FUNCTION OF THE TREATMENT ASSIGNMENT VARIABLE



Second, the graph reveals an increase in the estimated discount as the aid index rises, indicating that the higher the student's degree of financial need, the higher the percentage discount assigned should be.

Thirdly, the graphical analysis should show a jump or discontinuity at each of the cut-off points, so that the difference in the probability of receiving discounts at that threshold is evident, being greater to the right of the threshold than to the left. This jump is considerable at the last level of treatment where the index is above 400 points, assigning a 50% discount exemption.

At the lower levels of assignment there does not seem to be any jump or discontinuity for the cut-off points of 100, 200 or 300 points in the aid index, so that, if true, the index would not be the best predictor of the probability of receiving the treatment, but on the contrary the leakages could be so high that in the end it is the evaluator's criteria that determines whether or not the student receives the benefit.

To check if indeed, the discontinuity exists at each cut-off point, it is necessary to analyse the expected value of exemption given the aid index. This consists of estimating the expected value of the discount for each student given the aid index that was constructed, explained by a function of the index and by the theoretical participation of the student in a discount percentage depending on the value obtained in that index.

Additionally, for the aid index function ($f(aid\_index_i)$), the diverse types of cubic, quadratic and linear piecewise functions were included in each estimation (appendices).

The results of these estimations confirm the findings of the graph; in all cases, the treatment equivalent to the 50% waiver (T4_real) is significant at 1%, both for the cubic, quadratic and linear piecewise function, and only the first level of the treatment (25% waiver) is significant in the cases of the quadratic and linear piecewise function.

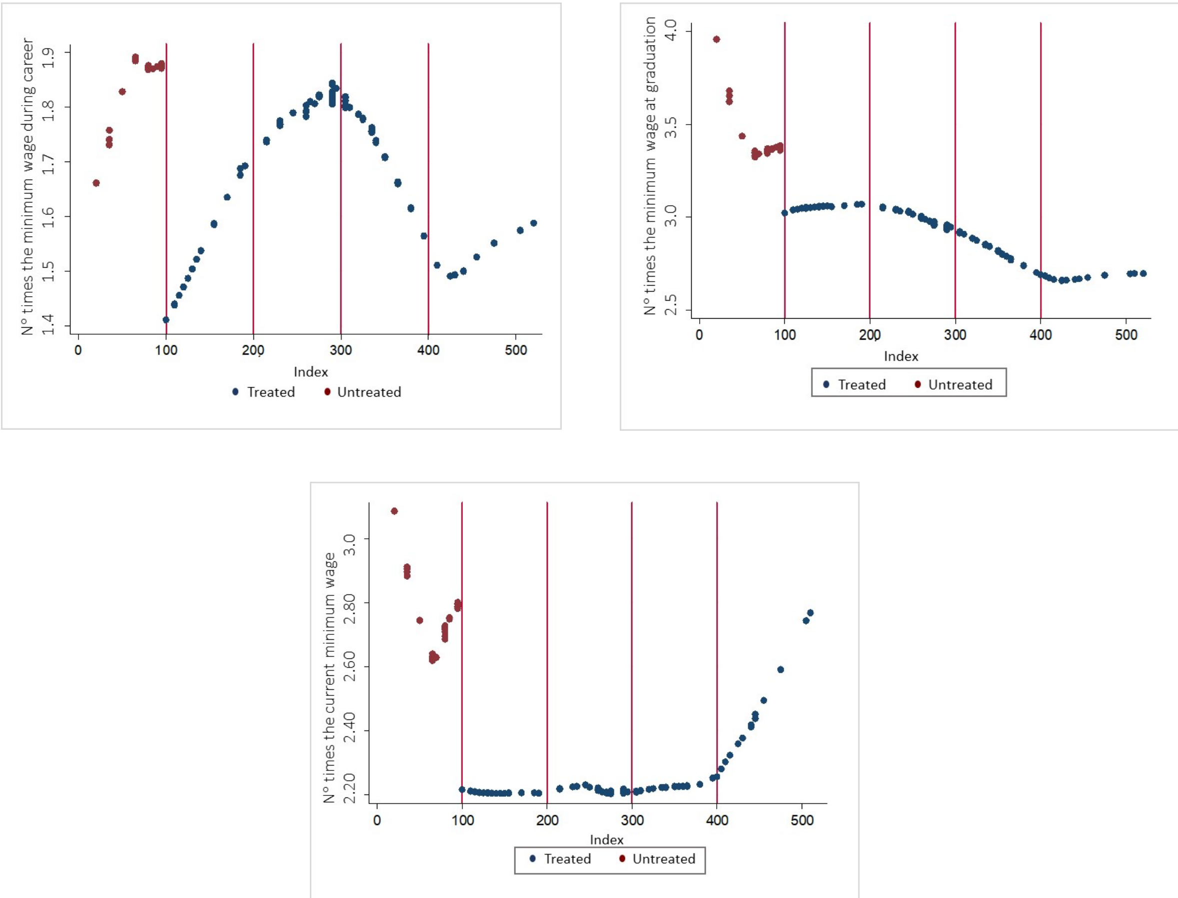
In light of these considerations it would appear, firstly, that the difference between the observed and estimated exonerations merits the use of the fuzzy regression discontinuity design as the final award decision is subject to subjective considerations of the evaluator (the index only explains 11% of the assignment); Secondly, not all treatment levels present a jump or discontinuity around the cut-off point, so we will first analyse the impact considering all exemption levels, then we will contrast the results by grouping all treatment levels and finally we will analyse the impact obtained with the 50% exemption level.

3.3 Discontinuity at different cut-off points

In contrast to the acute estimate there are treated and untreated on either side of the threshold, which shows that the allocation rate only determines the probability of receiving the treatment and not actually receiving it; an increase in the estimated waiver as the aid rate rises indicates that the higher the student's degree of financial need, the higher the percentage of waiver assigned should be; and there is a jump or discontinuity at least at the higher levels of waiver.

The presence of these discontinuities at each of the cut-off points of the assignment variable can be analysed at least initially by plotting the outcome variable with the selection criterion. Thus, the relationship between the salaries at the different points in time (during the course, at graduation and at present) and the rate of support is shown in the figure below.

FIGURE 3. DISCONTINUITY OF SALARY DURING THE CAREER, AT GRADUATION AND AT PRESENT



In general terms, there seems to be a discontinuity at least at the first level of treatment (25% exemption, allocation index equals to 100 points), the expected value of all wages is higher to the left of the first cut-off point and significantly lower to the right of it, so that the expected value of the wage of the untreated is higher than that of those who received the benefit.

If we take the time of graduation, the salary of those treated systematically decreases as the allowance index increases, therefore, students with more need receive worse salaries, stabilising from an index of 400 points onwards. The last moment reveals a different behaviour from the previous ones, the salary currently remains extremely low at the levels of least need but rises from the cut-off point of 400 (higher level of aid) onwards.

From the graphical analysis it can be seen, therefore, that a discontinuity exists at the first cut-off point in favour of higher wages for the untreated and, in turn, that the behaviour of the wages of the treated with respect to the allocation criterion differs depending on the moment at which the wage is assessed.

With respect to the probability of being employed at the time of graduation, which is the second outcome variable, a jump or discontinuity is evident between the untreated and the treated at least at the first level or cut-off point (treatment assignment index equal to

100 points), with the probability of employment being lower on the left of this threshold representing the untreated group and higher on the right or treated group.

This preliminary analysis of the discontinuity provides some indications of the presence of the discontinuity in the different wages and in the probability of employment at least at the first cut-off point, which distinguishes between treated and untreated (100-point threshold), but not at the different levels of support, which needs to be corroborated by the econometric estimations of the proposed model.

3.4 Estimation of fuzzy regression discontinuities

Table 4 shows the exemption coefficients for each impact variable (wages and probability of employment), obtained from the second stage of estimation with a quadratic piecewise function of the aid index (the first stage can be found in the appendices).

TABLE 4. SECOND STAGE OF 2SLS ESTIMATION FOR MULTIPLE TREATMENTS AND QUADRATIC PIECEWISE FUNCTION

	Total sample	+/- 20 points	+/- 15 points	+/- 10 points
N	472	251	181	153
Nº times the minimum wage during career	-0.0377	-0.0027	-0.0058	0,0089
	(0.0302)	(0.0168)	(0.0166)	(0,0189)
N	954	478	341	291
Nº times the minimum wage at graduation	-0.0145	-0.0121	-0.0186	-0,0154
	(0.0177)	(0.0129)	(0.0131)	(0,0145)
N	738	375	268	229
Nº times the current minimum wage	-0.0287	-0.0188	-0.0212	-0,0111
	(0.0194)	(0.0164)	-0.0166	(0,0111)
N	958	480	343	293
Probability of employment	-0.007	-0.005	-0.004	-0.0001
	(0.005)	(0.004)	(0.003)	(0.004)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

As can be seen, in none of the cases is the exemption coefficient significant in explaining average earnings, nor in the probability of employment, and the signs do not correspond to those expected. Looking at career earnings, for all bandwidths except +/- 10 points, the relationship is inverse, whereby a higher level of aid (lower socio-economic status) leads to lower earnings. At the lowest bandwidth the relationship, although showing the expected sign, is not significant.

If we consider the results for the probability of being employed, similar conclusions are obtained, as the exemption coefficient is not significant and shows an inverse relationship (lower probability of being employed the worse the socio-economic status), although the interpretation of these values in terms of probability has its limitations, so that a probit model for instrumental variables must be estimated, whose second stage results for all bands and a piecewise quadratic function of the allocation index are shown in Table 6.

TABLE 6. SECOND STAGE OF INSTRUMENTAL VARIABLES PROBIT FOR MULTIPLE TREATMENTS AND PIECEWISE QUADRATIC FUNCTION OF THE PROBABILITY OF USE

	Total sample		**+/- 20 points**		**+/- 15 points**		**+/- 10 points**	
N	958		48		343		293	
Discount coefficient	-0.0445	***	-0.0291	**	-0.0264	**	-0.0205	
	(0.0115)		(0.0133)		(0.0125)		(0.0190)	
Marginal effect discount	-0.0121	***	-0.0077	**	-0.0073	**	-0.0057	
	(0.0031)		(0.0036)		(0.0035)		(0.0055)	
Constant marginal effect	0.6985	***	0.7735	***	0.7675	***	0.7815	***
	(0.0632)		(0.0492)		(0.0494)		(0.0611)	

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

These instrumental variables probit estimates corroborate the inverse relationship between treatment exemption and the probability of employment when comparing graduates around each of the cut-off points. The coefficients of the exemption as well as the marginal effects turn out to be significant at least at 5%, making it appear that the treatment negatively impacts the probability of employment: more aid derived from lower socio-economic status reduces the probability of employment at least around each of the cut-off points.

The results obtained from the Wald estimator show that exemption in none of the financial support brackets seems to have an impact on average earnings and the probability of employment, as shown in Table 7.

TABLE 7. WALD ESTIMATOR FOR MULTIPLE TREATMENTS

	25% discount	45% discount	50% discount
Monthly income during career (No. times minimum wage)			
N	150	60	20
Discount for	0.0354	0.0581	0.0794
Band +/-20 points	(0.1553)	(0.1190)	(0.0749)
N	102	46	13
Discount for	-0.4143	0.0791	0.0432
Band +/-15 points	(0.8778)	(0.1584)	(0.0279)
Monthly income at graduation (No. times minimum wage)			
N	294	104	37
Discount for	-0.1071	0.2007	-0.1648
Band +/-20 points	(0.1117)	(0.1354)	(0.2057)
N	197	78	24
Discount for	-0.2187	0.3300	-0.0769
Band +/-15 points	(0.2147)	(0.3284)	(0.0349)
Current monthly income (Nº times minimum wage)			
N	225	84	29
Discount for	-0.0236	-0.3869	-0.1735
Band +/-20 points	(0.0438)	(0.1833)	0.1675
N	151	62	19
Discount for	-0.0133	-0.7418	-0.1608
Band +/-15 points	(0.0320)	(0.0698)	(0.0877)
Probability of graduation			
N	295	105	37
Discount for	0.0171	0.0682	0.0330
Band +/-20 points	(0.0328)	(0.3815)	(0.0668)
N	195	79	24
Discount for	-0.0718	0.1089	0.000
Band +/-15 points	(0.0699)	(0.8643)	(0.0108)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

If we analyse in detail the impact of different levels of exemption on first degree entry, for the +/-15 point and +/-20 point bandwidths, we find that, although the Wald estimator is not significant, its values are positive, except for the 25% exemption on tuition and the +/-15 point bandwidth. The sign is therefore as expected in the sense that there is a (non-significant) discontinuity around each threshold in favour of the treated compared to the untreated, or among the treated for those with a higher percentage discount.

Likewise, when looking at the values of the Wald estimator for income at graduation and at present, as well as during the degree, they are not significant, and the signs do not correspond to the expected ones either, in all cases except for the estimator for the 45% exemption, and income at graduation where the value is positive, raising the graduate's remuneration around this cut-off point, if they receive a 45% tuition fee discount compared to those who receive a 30% tuition fee discount. The rest of the estimates indicate a decrease in salary at the threshold for treated compared to untreated graduates.

Third, looking at the Wald estimator for the probability of employment, while not significant in any of the cases, the values correspond to those expected, without considering the scenario of a +/-15 point bandwidth and 25% exemption. This positive sign in most cases of the Wald estimator shows that at least around each cut-off point the probability of being employed rises with treatment or with an increase in the level of exoneration.

3.5 Estimates for grouped treatment.

To confirm whether indeed, considering the treated as a particular group without distinguishing between the different discount levels when compared to the untreated, any discontinuity is generated, parametric and non-parametric estimations like those used in the multiple cut-off treatment were performed.

We start the analysis with the results of the two-stage parametric least squares estimation using the quadratic piecewise function for the treatment assignment index, and then complement it with the instrumental variables probit estimation for the probability of employment, and finally the Wald estimator or non-parametric estimation.

As shown in the table below, the treatment coefficients for each of the bandwidths used (+/-20, +/-15 and +/-10 points) were not significant, and only for the cases of current income level and probability of employment are the signs related to the initial hypothesis. For these variables, the treatment improves, comparing treated and untreated, around the cut-off point for the first level of 25% discount on tuition.

TABLE 8. SECOND STAGE OF MC2E ESTIMATION FOR POOLED TREATMENTS AND QUADRATIC PIECEWISE FUNCTION

	Total sample	**+/- 20 points**	**+/- 15 points**	**+/- 10 points**
N	472	251	183	153
Nº times the minimum wage during career	1.9253	-2.8910	0.7392	-2.6753
	(2.0646)	(1.9779)	(2.3641)	(2.3849)
N	954	478	341	291
Nº times the minimum wage at graduation	-2.7839	-0.9911	-0.4424	-1.6462
	(2.6198)	(1.3355)	(1.4330)	(1.9789)
N	738	375	268	229
Nº times the current minimum wage	2.6431	1.3853	0.8878	2.1727
	(2.4736)	(1.5212)	(1.7604)	(2.6143)
N	958	480	343	293
Probability of employment	0.4586	0.3464	0.6289	0.8200
	(0.6457)	(0.4120)	(0.4682)	(0.7233)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

To corroborate these results on a possible favourable, though not significant, impact of the programme on the probability of employment, an instrumental variables probit model was estimated for the pooled treatments, using a quadratic piecewise function of the support index. The estimates presented in the following table confirm that the probability of being employed on the right of the threshold (treated) is higher than that found on the left (untreated).

TABLE 9. SECOND STAGE INSTRUMENTAL VARIABLES PROBIT FOR POOLED TREATMENTS AND QUADRATIC PIECEWISE FUNCTION OF THE PROBABILITY OF EMPLOYMENT

	Total sample	**+/- 20 points**	**+/- 15 points**	**+/- 10 points**
N	958	480	343	293
Discount coefficient	1.6976	1.3133	1.5683	2.5332***
	-1.3036	-1.0929	-0.9911	-0.1074
Marginal effect discount	0.4927	0.371	0.4512	0.7283***
	-0.4509	-0.3644	-0.3347	-0.044
Constant marginal effect	0.7256***	0.7615***	0.7333***	0.4993***
	-0.181	-0.1203	-0.1329	-0.1094

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

Despite showing the expected signs, only the coefficient of the treatment effect is significant (at 1%) for the narrowest bandwidth, for individuals more similar at least in the modelled characteristics, thus corroborating that in the +/- 10 point band, programme beneficiaries are more likely to be employed than the untreated.

These results are not possible to validate using the non-parametric estimation (Wald estimator) shown in the table below, as none of the values found for the Wald estimator are significant and the signs are ambiguous.

TABLE 10. WALD ESTIMATOR FOR MULTIPLE TREATMENTS

	+/- 20 points	+/-15points
N	150	102
Nº times the minimum wage during career	1.2589	-9.9821
	(4.9791)	(17.4382)
N	294	104
Nº times the minimum wage at graduation	-4.5742	8.7224
	(4.9290)	(9.1160)
N	225	ND
Nº times the current minimum wage	-1.0504	
	(1.9619)	
N	295	195
Probability of employment	0.7313	-2.8632
	(1.4000)	(2.8933)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

Thus, the parametric (two-stage least squares and probit) and non-parametric (Wald estimator) estimates do not allow us to accept the hypothesis of a significant impact of each of the levels of treatment (exoneration) on the performance variables used: average earnings during the course, at graduation and at present, and the probability of being employed. When the data are grouped into treated and untreated, there is an impact with the expected signs and significant (at 1%) of the treatment on the probability of employment at least in the +/- 10 point bandwidth, but not on the rest of the impact variables.

As indicated in the descriptive analysis of the survey results, at least in the current average income there seem to be significant differences by career, which could cause the results obtained not to measure the impact of the programme; to try to assess whether the existing differences generate any bias in the results, the design of fuzzy regressions was estimated for each career both parametrically and non-parametrically.

The results obtained by degree programme show that the previous estimates are not modified by degree programme; indeed, the treatment has no impact on the current average income for any of the degree programmes that had enough observations to perform the estimation.

4. DISCUSSION AND CONCLUSIONS

The affirmative action policies applied by higher education institutions have among their objectives not only access to the system through university initiation courses, but also continuation and graduation, and even successful insertion into the labour market. Universities in this context also employ educational funding policies to reduce access gaps, favouring the inclusion of students who represent minorities or belong to low socio-economic levels, thus contributing to social mobility (Becker, 1962; Wright, 1997).

The results with respect to the post-graduation variables are ambiguous. The literature indicates in general terms that education broadens opportunities for insertion, through the signalling generated by the university degree, which facilitates the processes of social mobility, but when the behaviour is analysed by differentiating between graduates who have benefited from economic aid programmes and those who have not, the impact is not usually equal or positive.

This is evident in the results obtained in this study for the financial aid programme (percentage of tuition fee exemption) at the Universidad Católica Andrés Bello. Given that this treatment is received by analysing only the socio-economic conditions of the student, the beneficiaries come from low economic strata, which, in most cases, conditions their social capital.

The analysis of differences in means and proportions between treated and untreated indicates, as stated by Daniels and Smythe (2019) and Vélez et al. (2018), that the employment rate of beneficiaries is higher due to the need to repay the debt, being employed in lower paying jobs (Chapman, 2015). In this case, the employment rate of trainees is not only higher at the time of the study, but throughout the career and upon graduation, which could be explained by the need for additional income for the beneficiaries.

At this point, it is important to reflect on the amount of tuition assistance or exemption, which is a maximum of 50%, which implies that students from low socio-economic levels must not only cover the remaining 50%, but also the costs associated with the rest of the training process, which requires them to enter the labour market, so that the exemption is not sufficient for an exclusive dedication to study.

Given that the criterion of assignment to treatment only indicates the probability of receiving it, since it depends on the judgement of the evaluator, students can be identified as beneficiaries on either side of the threshold, fuzzy regression regressions were estimated for both the probability of employment and the salary received at the three points in time analysed. These results do not allow us to identify a positive impact of the treatment on social mobility variables, like the studies by Beyer et al. (2015) and Bucarey et al. (2018).

The reasons, as stated in the theory of human capital, can be linked to pressure from graduates to work, given that they have to pay their commitments acquired with financing, thus accepting lower quality jobs and lower salaries, even more so if the labour market presents an oversupply of professionals that tends to reduce remuneration (Freeman, 1976), in these conditions social capital takes on special relevance (Bourdieu, 1979), differentiating the opportunities for labour market insertion between treated and untreated, in favour of the latter.

In short, the opportunities for labour market insertion are a multifactorial analysis, where, in addition to social capital, the human capital of parents, acquired skills and experience, among other factors, are relevant, showing in most cases better starting conditions for the untreated, due to their higher socio-economic level (Van Belle et al., 2019; Tomlinson, 2008; Finnegan et al., 2019).

The Universidad Católica Andrés Bello, UCAB, makes efforts to try to keep students with fewer resources in the educational system, and furthermore, stimulates the graduation of those who do not have the necessary resources to pay their tuition fees through the financial aid programme. This support is not sufficient to reduce the gap that might exist between treated and untreated students.

In any case, what does seem to be clear, and what the literature suggests, is that a financial aid programme alone does not correct the existing differences between treated and untreated students, which is why it is necessary to incorporate, for the most disadvantaged students, mechanisms for insertion in the labour market, designing employment exchanges that remedy the deficiencies in terms of relationships and networking, in conjunction, for example, with the Alumni Association, which has experience in this area.

To improve the study, interaction with other programmes could be considered, which although not of a monetary nature, correspond to university access initiatives such as the university initiation course or the academic accompaniment programme that can contribute to the graduation rate, also improving social capital. These improvements in terms of social capital could generate more and better relationships that translate into employment opportunities and higher salaries.

The estimates from the fuzzy regression discontinuity design show that it is not possible to identify an impact, due to the sample size, which would require further studies to expand it by degrees. From the graphical analysis and the parametric and non-parametric estimates considering all treatment levels, there is no empirical evidence to confirm the hypothesis of the positive impact of different treatment levels on wages at the different points in time at which they were assessed and the probability of employment.

With respect to the probability of employment variable, a different analysis emerges for the impact of treatment on it. The graphical analysis reveals the apparent existence of a discontinuity, at least around the cut-off point of the assignment index, for the first level of treatment (25% exemption), without considering the multiple treatment, as there the graphical evidence does not reveal discontinuities in the rest of the critical points.

The results of the non-parametric estimations for the multiple treatments, although not significant, indicate at least a positive value for the treatment coefficient considering as impact variable the probability of being employed, which, although it does not allow accepting the initial hypothesis of positive impact, does not generate evidence to reject it either.

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APPENDICES

A1. TWO-STAGE LEAST-SQUARES FIRST-STAGE ESTIMATES FOR THE WHOLE SAMPLE AND DIFFERENT BANDWIDTHS WITH QUADRATIC PIECEWISE FUNCTION.

	Total sample	+/- 20 points	+/- 15 points	+/- 10 points	+/- 5 points
Assignment index	0.2014**	14.7826**	-33.082	-0.1558	-5.0184*
	(0.0985)	(6.0647)	(43.272)	(1.2504)	(2.9902)
Index squared.	-0.0001*	-0.0846**	0.1809	0.0031	0.0170*
	(0.0007)	(0.0346)	(0.2402)	(0.0023)	(0.0101)
Treatment 1	2.2635*	- 4.0467***	-8.0851	2.7119	13.9289**
	(1.1652)	(3.5708)	(18.074)	(6.2499)	(6.2335)
Treatment 2	-1.0730	0.5141	-5.3923	-3.6797	-13.802
	(2.6812)	(2.5158)	(3.6933)	(4.6586)	(8.5731)
Treatment 3	-0.6734	-2.6860	3.5430	6.5942	-14.2187
	(1.9352)	(4.9365)	(3.1953)	(7.0972)	(10.861)
Treatment 4	13.6260***	2.1913	-3.5950	2.4031	17.503*
	(3.0256)	(0.8832)	(5.5973)	(5.8600)	(9.4157)
Index treatment 1	0.0811	2.1913***	-3.1346	-0.7836	omitted
	(0.0779)	(0.8832)	(4.7905)	(1.2026)	
Treatment 1 squared index	0.0010	0.0846	-0.1802	omitted	omitted
	(0.0010)	(0.0346)	(0.2402)		
Treatment 2 index	0.1078	0.0169	-0.0004	0.4688	-1.5594
	(0.1083)	(0.2570)	(0.2780)	(0.6372)	(1.6155)
Index treatment 2 squared	0.0004	0.0005	-0.0007	-0.0105	-0.0184
	(0.0009)	(0.0025)	(0.0027)	(0.0068)	(0.0163)
Treatment 3 index	-0.0733	-0.3453	-0.6811	0.8556	3.4593
	(0.0975)	(0.2145)	(0.4276)	(0.9212)	(2.1536)
Treatment 3 squared index	-0.00001	0.0017	0.0058	0.0062	-0.0324
	(0.0009)	(0.0021)	(0.0042)	(0.0087)	(0.0211)
Index treatment 4	-0.4168***	3.1951***	4.7263***	-1.2584	3.8203*
	(0.1339)	(1.0506)	(1.2757)	(2.5142)	(2.1995)
Index treatment 4 squared	0.0031***	-0.1835***	-0.3404***	0.3297	omitted
	(0.0011)	(0.0638)	(0.0818)	(0.2266)	
Constant	-5.3263*	-638.01**	1512.02	-11.4731	324.903*
	(3.2275)	(263.71)	(1942.49)	(113.14)	(192.77)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.

A2. TWO-STAGE LEAST-SQUARES FIRST STAGE ESTIMATES FOR THE WHOLE SAMPLE AND DIFFERENT BANDWIDTHS WITH LINEAR PIECEWISE FUNCTION

	Total sample	+/- 20 points	+/- 15 points	+/- 10 points	+/- 5 points
Assignment index	0.0328**	-0.0463	-0.4969***	0.4264	0.0214
	(0.0160)	(0.0578)	(0.1861)	(1.1732)	(0.0678)
Treatment 1	1.5790**	2.4706**	4.8253***	0.3680	3.9888**
	(0.7970)	(1.0544)	(1.4359)	(6.0032)	(2.0243)
Treatment 2	-1.9509	-4.3520*	-4.4366*	-0.0449	-4.5356
	(1.5477)	(2.3219)	(2.3826)	(3.9154)	(6.6028)
Treatment 3	-0.5850	-0.9483	0.3403	0.1960	0.7885
	(1.3049)	(1.5200)	(1.6692)	(1.6447)	(3.8034)
Treatment 4	8.4821***	6.5662	9.2082**	-0.8123	1.3362
	(2.0964)	(4.0735)	(4.4445)	(4.7410)	(4.8910)
Index treatment 1	-0.0206	0.0842	0.5367***	-0.4304	omitted
	(0.0225)	(0.0624)	(0.1876)	(1.1739)	
Index treatment 2	0.0952***	0.0718**	0.0730***	0.1165***	0.0895
	(0.0228)	(0.0294)	(0.0301)	(0.0523)	(0.0783)
Index treatment 3	-0.0425	-0.0591**	-0.0992***	-0.0769**	-0.0717
	(0.0244)	(0.0268)	(0.0312)	(0.0334)	(0.0471)
Index treatment 4	-0.0388*	0.6942*	0.6457	2.0939***	0.2606
	(0.0410)	(0.3842)	(0.4085)	(0.4967)	(1.3046)
Constant	-0.1217	6.7066	49.3161***	-38.384	0.0947
	(1.1922)	(5.0742)	(17.477)	(111.396)	(6.4765)

Note: Significant at: 1% ***, 5% **, 10% *. Values in parentheses represent standard errors.