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Signaling or better human capital: Evidence from Colombia☆

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ABSTRACT

We use data from the admissions process from a highly selective private university in Colombia to analyze the impact of prestigious university attendance on the education trajectory and labor market outcomes of individuals. The university´s selection process allows the use of a regression discontinuity design. We estimate both intent-to-treatment (offer admissions) and treatment-on-the-treated (enrollment) effects. The results show positive effects of offering admission to the prestigious university on the probability of enrollment, 13.8 percentage point (pp), 1.3 pp increase in academic credits a student need to repeat, and increment in 7 pp in probability of graduation. Despite no significant effects on the standardized university exit exam, we found positive effects on the probability of employment and earnings, 7.4 and 4.6 pp respectively. These results suggest that prestigious universities are more effective source of signaling in the labor market, but they are not more effective than other universities in developing human capital.

1. Introduction

This research aims to test whether the graduate wages bonus from highly prestigious universities is due to these universities having an additional effect on the formation of human capital or whether the bonus is due to university signaling effect. This paper found positive effects on the probability of employment and earnings from attending a private university but no significant effects on performance as measured by a standardized university exit exam. These results suggest that an increase in graduate wages is due to a university signaling effect and not enhanced human capital.

Human capital is defined as the accumulation of skills and knowledge that influence individuals' productivity. In this theory, individuals invest in education until the marginal gain in productivity is equal to the marginal cost (Schultz, 1961). The human capital theory suggests that the labor market recognizes the individual abilities level and determine the salary according whit this level (Schultz, 1972). According to this, people with higher abilities should have a higher salary than those who do not. On the other hand, pioneers in signaling such as Spence (1973), Arrow (1973) and Stiglitz (1975) demonstrate that direct productivity gains are not necessary to explain the observed monetary return to schooling. Signaling suggests that the labor market cannot identify the individual abilities level. This lack of information forces the labor market to determine the salary according to the signal that the individual can give (Hussey, 2012); for example, to hold college diploma or MBA diploma. Our research seeks to show that the university prestige is a signal for the labor market.

Estimating the differences in return between prestigious and non-prestigious university is difficult due to self-selection problems. In the absence of exogenous variation at university entry, the comparison between these kinds of universities in labor outcomes confound individual's characteristics and the education contribution. This paper aims to contribute to a nascent empirical research on causal effects of university attendance. Arteaga (2018) uses data from the Andes University, to estimate the effects of reducing the length of the career in economics and administration. Saavedra (2009) and MacLeod, Riehl, Saavedra, and Urquiola (2017) use similar data and found that college reputation is positively correlated with graduates' earnings, while the

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salaries fixed in their job offer. Additionally, it contributes in analyzing the value added in higher education.[1] We use a discontinuity in the entry exam of a highly selective and prestigious university in Colombia to estimate the effects of offering entrance to those close to the entry cutoff, versus those who did not receive this university's offer, just below the cutoff point.

We aim to advance the empirical evidence on the causal effects of university education in two directions. First, we use several sources of administrative data to estimate effects at different points of the educational process of individuals. We are able to estimate effects on repetition, dropout, graduation, time to graduation, and a standardized university exit exam. Likewise, we are able to estimate the impact of university on probability of employment during the first year in the labor market and on wages. Second, the majority of evidence comes from developed countries; in contrast, our paper sheds light on the trajectory of individuals in a middle-high earning country. An increasing number of individuals are finishing secondary education and demanding tertiary education in several middle earnings countries. Understanding the returns to university education in middle earnings countries is critical.

There is consensus in the literature on the positive effect of years of education on salary (Hoekstra, 2009). There is less agreement on the role that university quality or prestigious university has on returns to education, or its effect on variables such as student retention, graduation, and enrollment, among others (Black & Smith, 2004; Brewer, Eide, & Ehrenberg, 1999; Dale & Krueger, 2002; Hoekstra, 2009). Additionally, evidence for the effect of university quality on salaries is mixed, while at the same time failing to clearly identify whether any positive effect is due to students being more highly educated (value added – human capital), or whether the effect comes from market signaling.[2]

Other evidence shows that low-income individuals who apply for admission to any selective college have educational achievement at levels similar individuals who apply for admission to other less selective colleges (Hoxby & Avery, 2013; Hoxby & Turner, 2013).

An important feature of our data is the availability of Colombian's university exit exam. The literature on returns to education has seen important developments in recent years, generating a wide consensus on the positive impact of years of education on salary. This contrasts with very little evidence on the impact of educational university quality on salary and less evidence about signaling effects (Hoekstra, 2009). The evidence is mixed, as some empirical evidence suggests a positive effect of university quality on salaries (Brewer, Eide, & Ehrenberg, 1999; Hoekstra, 2009; Saavedra, 2009), while other studies suggest that university quality has no impact on graduates' salaries (Dale & Krueger, 2002, 2011).[3] The availability of the specific university exit exam allows us to have a first approximation of the contribution of quality associated with a highly selective university. We advance the estimation of Saavedra (2009) in that our data include a period in which this exam became obligatory for any graduating individual in Colombia. This difference is quite important since the selection problems are exacerbated previous this period.

The admission process of the university is based on the high school exit exam, Saber 11. Applicants have to declare a major; each major has a specific cutoff point. Some majors are more selective (for example, engineering) than others (for example, arts). Individuals above the major-specific cutoff point are offered a place in the university. We use the place offer to estimate intent-to-treat effects for those individual (just) above and (just) below the cutoff point. In turn, we instrument (locally) enrollment in the college with the Saber 11 score to find a treatment-on-the-treated (TOT) estimator. We run a fuzzy design, with the running variable Saber 11 and enrollment as the instrumented variable (Jinyong, Todd, & van derKlaauw, 2001).

Our strategy follows closely Hoekstra (2009) and Saavedra (2009). Hoekstra estimate effects on earnings from attending a flagship state college in US. He uses a RD strategy, based on the entry process of the university. He found positive large impacts on earnings. Our paper extends Hoekstra's paper to a developing country (Colombia) and to different outcomes, including college exit exams. Saavedra (2009) estimates the return to a highly selective college in Colombia, using data similar to our data. He uses an RD design as well, finding positive effects on probability of employment one year after college. In contrast to our data, he uses college exit exams at a moment in which the exam was optional. We extend the period under analysis, with the starting year the moment in which the exam was obligatory. This will dissipate any concerns about self-selection in taking college exit exams. Additionally, and given theoretical considerations of differential market remunerations to different careers, we present estimates by academic major (Dale & Krueger, 2002).

We find that the aggregate impact of offering admission to a high competitive university is significant and positive for enrollment, the percentage of academic credits a student repeats, and graduation rates, with effects of 13.8, 1.3, and 7 percentage points, respectively. We find no effect on dropout risk, the time it takes students to graduate, the time it takes a graduate to find employment, or their scores on the standardized university exit exam. The last result is particularly important in light of a positive effect of 7.4 percentage points on the probability of finding a job one year after graduation and a 4.6 percentage point differential on earnings. Given large differences in returns to education for different majors, we estimate effects by five majors: engineering, health, sciences, economics and administration, and arts and humanities. We found large differential impact across these majors. Moreover, given that the TOT estimators scale up the point estimate by the differential probability of enrollment between the (marginal) students offered and not offered place, these estimators are larger for actual enrollment in university.

We divide this paper into five sections. Section two briefly presents some background on higher education in Colombia. Section three describes the data and the identification strategy, and we present the results in section four. Finally, we discuss our conclusions in section five.

2. Higher education in Colombia

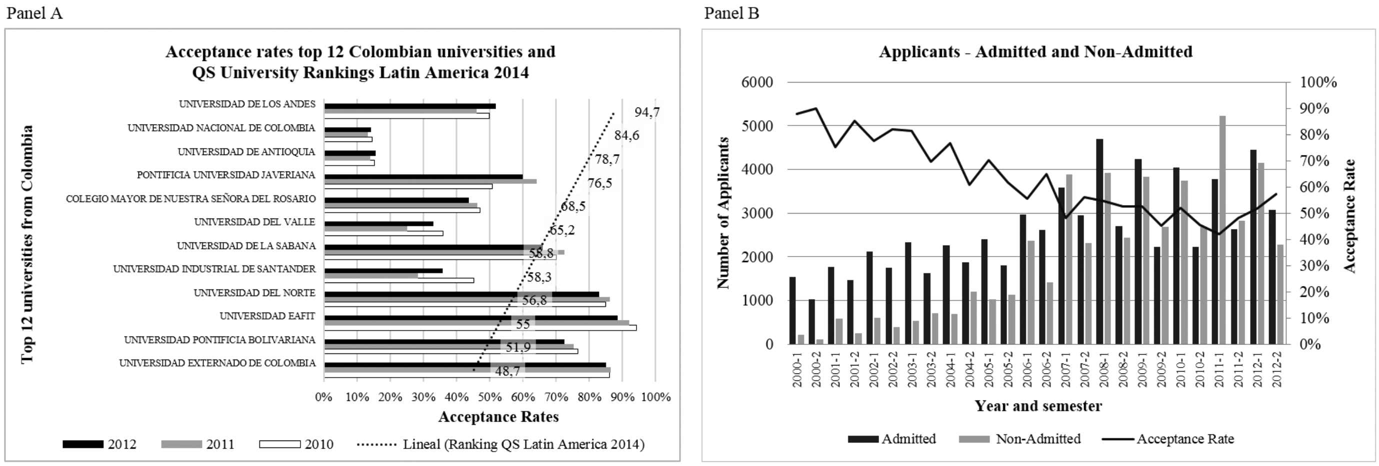
Post-secondary education in Colombia is organized at different levels of preparation: Technician (two-year), Technological (three-year), and professional (four-year or more). The educational institutions are classified by the National Education Ministry (Ministerio de Educación Nacional, MEN), according to the level of education the school offers. This study focuses on educational institutions at the university level. 32% of these institutions are public, although the number of students in these universities represents 54% of the total, suggesting that private universities are smaller on average. Of the total of students who enroll in post-secondary studies in Colombia, 52% are women. That number has been constant in recent years.

Universities, may have high quality accreditation granted by the MEN. Accreditation process is developed through the evaluation of the

[1] de Luna and Lundin (2014), Fletcher and Frisvold (2014) and Black and Smith (2004) uses propensity scores and matching estimations. Close to our paper, Hoekstra (2009) estimates the effect to attend a selective college using an RD design and Saavedra (2009) uses a similar strategy for Colombia.

[2] Two studies fine no effects from (high) quality university education. Dale and Krueger (2002) find that graduates from more selective universities earn very similar salaries to graduates with similar abilities from less selective schools. Altonji and Poerret (2001) find that as firms obtain more information about employees' abilities over the course of their employment, education ceases to be a significant predictor of salary.

[3] These mixed results may be due in part to the enormous problems with identifying causal effects through the identification strategies employed in previous studies, with few studies capable of making causal inference (Black & Smith, 2006; Cohodes & Goodman, 2013)



Graph 1. Acceptance rates. Source MEN, QS University Rankings Latin America 2014.

quality carried out by the university itself (self-evaluation), by external academic peers (hetero-evaluation) and by the National Accreditation Council (final evaluation); the process culminates with the public recognition of quality by the MEN. (CNA, 2013). In addition that, there are several ranking such as QS World University Rankings that allow as to have some measure of university quality. We use both, Accreditation a QS World University Rankings as measure of quality.

In recent years Colombia has seen an increase in the supply of higher education, as the formation of new educational institutions and the expansion of new academic programs in existing institutions has increased access to post-secondary schooling. As an example, the number of undergraduate programs in the country increased from 11,869 in 2006 to 18,266 in 2011. Additionally, the number of students rose from 1,301,728 to 1,819,304 over the same period. However, the number of programs with high quality certification[4] remains small, at only 8.7% of post-secondary education programs. A similar trend is seen at the institutional level, with only 7.7% of higher education institutions carrying a high-quality accreditation[5] from the Colombian government.

Institutions of higher education have different admissions criteria, though results on the Saber 11 national standardized test almost always play a significant role. This exam is administered to students in their final year of secondary school, and is a requirement for acceptance into a higher education program. The Saber 11 is administered by the Colombian Institute for the Development of Higher Education (Instituto Colombiano para el Fomento de la Educación Superior, ICFES), a governmental body under the MEN.[6] However, several universities incorporate other steps into the application process, including interviews and university-specific entrance exams.

The most selective universities use an applicant's Saber 11 results as the principal admissions criteria. The exam is composed of various sections: mathematics, physics, chemistry, biology, language, philosophy, social sciences, and English. In particular, the university analyzed in our study uses a weighted average of the scores from the different exam areas in its admissions criteria. The way this average is weighted depends on the program a candidate applies for, and is not open to the public. Once the college determines the number of applicants it will accept for each program, it determines a cutoff score to be accepted into the program. As such, this cutoff threshold may vary by program and semester.

Our sample includes 80,602 applicants at the university under study, 50.6% of which were admitted. Out of the 40,752 admitted, 13,752 actually enrolled, 33.75% of those accepted. Admission rate in the last 5 years to the university is around 50% (Graph 1 Panel B). In addition, Graph 1 panel A presents the acceptance rates for the top 12 universities in Colombia according with QS ranking in 2014. The university analyzed here is within the top ten ranked universities making it a highly selective.

3. Data and methodology

3.1. Data and outcomes

Data from the MEN and ICFES were merged together; they provided information on individuals before beginning university, during the individual's course of study, and in the first years following graduation. The ICFES dataset provides information about the secondary exit exam, Saber 11, whose objective is to verify the level of development of the competences of the students who finish the high school (MEN 2009). Currently take Saber 11 is obligatory to obtain the high school diploma. The exam is composed of different sections, which we have already described, and also collects socioeconomic and demographic data on students. Independent of whether or not a student's exam score meets a college's acceptance criteria, universities require that all applicants take the exam.

Additionally, the ICFES administers an exam to students who have completed at least 75% of the credits of any post-secondary program (Saber Pro); we denote this test as the university exit exam. Saber Pro has been mandatory for all potential college graduates since 2009. The exam is composed of two broad components, generic and specific.[7] The specific component tests the professional formation of students in areas corresponding to a specific course of academic study. Not all academic programs are subject to the specific component of the exam, and the number of programs to which this component applies has varied over time, from 23 programs in 2003, to 38 programs in 2004, 55 programs in 2008, and 33 programs in 2010. In addition, and more important, the specific component of the exam presents problems for comparability of

[4] The certification of quality for each academic program is awarded by the National Education Ministry (MEN) through a rigorous, peer-reviewed evaluation process.

[5] According to the National Council of Accreditation, this certification is the act by which the State publicly adopts the recognition, awarded by academic peers, of the quality of a university´s academic programs, its organization, and fulfillment of social responsibility.

[6] Several papers have been using Saber 11 either as an outcome variable or as part of the identification strategy; for instance, Angrist, Bettinger, and Kremer (2006), Angrist, Bettinger, Bloom, King, and Kremer (2002), and Bettinger (2010), among others.

[7] Law 1324 of 2009 and Decree 3963 of 2009.

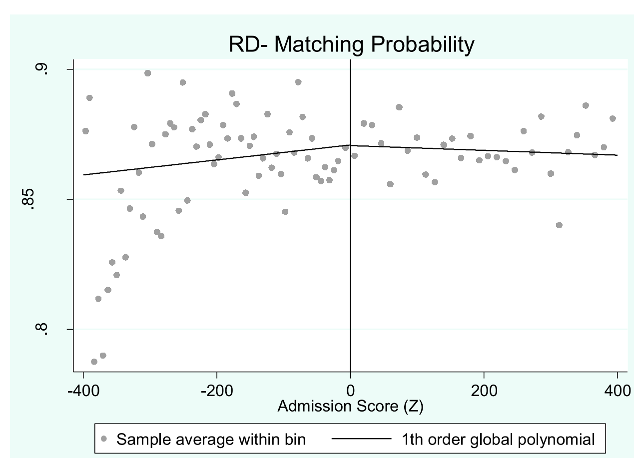
Table 1
Descriptive statistics.

Variable	2007–2009						2010–2012					
	Admitted		Not admitted				Admitted		Not admitted			
	Obs.	Mean or% Pob.	Obs.	Mean or% Pob.	Diff		Obs.	Mean or% Pob.	Obs.	Mean or% Pob.	Diff	
Panel A. Characteristics at baseline												
Ege	20,449	17.84	19,009	17.98	−0.14	***	20,302	17.79	20,839	17.95	−0.16	***
		(1.40)		(1.52)	(0.01)			(1.32)		(1.40)	(0.01)	
Women (*)	20,397	43.8%	18,973	54.0%	−0.10	***	19,103	45.1%	20,149	53.6%	−0.09	***
Economic level (*)												
1	19,501	1.32%	18,038	2.35%	−1.0%	***	20,302	1.41%	20,840	2.84%	−1.4%	***
2	19,501	13.71%	18,038	19.54%	−5.8%		20,302	7.77%	20,840	13.18%	−5.4%	
3	19,501	21.48%	18,038	23.41%	−1.9%		20,302	17.37%	20,840	20.28%	−2.9%	
4	19,501	20.11%	18,038	19.58%	0.5%		20,302	15.23%	20,840	16.43%	−1.2%	
5	19,501	28.28%	18,038	23.23%	5.0%		20,302	40.20%	20,840	33.45%	6.7%	
6	19,501	15.01%	18,038	11.84%	3.2%		20,302	18.02%	20,840	13.81%	4.2%	
Rural	19,501	0.10%	18,038	0.06%	0.0%		20,302	0.00%	20,840	0.00%	0.0%	
Household members	8,173	4.19	7,520	4.24	−0.05	**	14,112	4.22	16,732	4.29	−0.06	***
		(1.21)		(1.32)	(0.02)			(1.31)		(1.39)	(0.02)	
Siblings	19,926	1.34	18,319	1.47	−0.13	***	5,145	1.24	6,128	1.46	−0.22	***
		(0.72)		(0.86)	(0.01)			(0.61)		(0.92)	(0.02)	
Household income (SMMLV)	20,450	6.96	19,010	6.28	0.69	***	20,302	7.54	20,840	6.68	0.86	***
		(2.97)		(3.17)	(0.03)			(3.11)		(3.34)	(0.03)	
Panel B. Outcome variables												
Enrollment	20,450	0.84	19,010	0.74	0.10	***	20,302	0.54	20,840	0.29	0.25	***
		(0.36)		(0.44)	(0.00)			(0.50)		(0.45)	(0.00)	
Repetition rate	18,084	0.07	15,477	0.09	−0.01	***	5,971	0.07	6,184	0.08	−0.01	***
		(0.18)		(0.20)	(0.00)			(0.19)		(0.20)	(0.00)	
Drop out risk	5,254	0.01	4,300	0.03	−0.02	***	4,088	0.02	3,918	0.04	−0.03	***
		(0.02)		(0.04)	(0.00)			(0.02)		(0.05)	(0.00)	
Drop out	18,084	0.20	15,477	0.27	−0.08	***	5,971	0.17	6,184	0.21	−0.04	***
		(0.40)		(0.45)	(0.00)			(0.38)		(0.41)	(0.01)	
Graduate time	9,295	4.90	5,631	4.88	0.02	**	879	4.98	454	4.86	0.12	***
		(0.46)		(0.53)	(0.01)			(0.34)		(0.69)	(0.03)	
Graduate	12,829	0.72	9,878	0.57	0.15	***	1,891	0.46	1,780	0.26	0.21	***
		(0.45)		(0.50)	(0.01)			(0.50)		(0.44)	(0.02)	
Exit score DS	9,953	1.40	6,180	0.61	0.79	***	939	1.51	465	0.52	0.99	***
		(0.99)		(0.87)	(0.02)			(0.99)		(0.94)	(0.06)	
Obtain employment in the first year	9,295	0.29	5,631	0.19	0.09	***	879	0.04	454	0.07	−0.04	***
		(0.45)		(0.39)	(0.01)			(0.19)		(0.26)	(0.01)	
Time to obtain employment	9,295	0.72	5,631	0.81	−0.09	***	879	0.96	454	0.93	0.03	**
		(0.46)		(0.40)	(0.01)			(0.19)		(0.28)	(0.01)	
Income for graduate (SMMLV)	9,295	2.20	5,631	1.84	0.36	***	879	1.50	454	1.69	−0.19	
		(1.71)		(1.41)	(0.03)			(1.21)		(2.02)	(0.09)	

Note: variables with (*) using the chi square test. SMMLV = Legal Monthly Minimum Wage.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

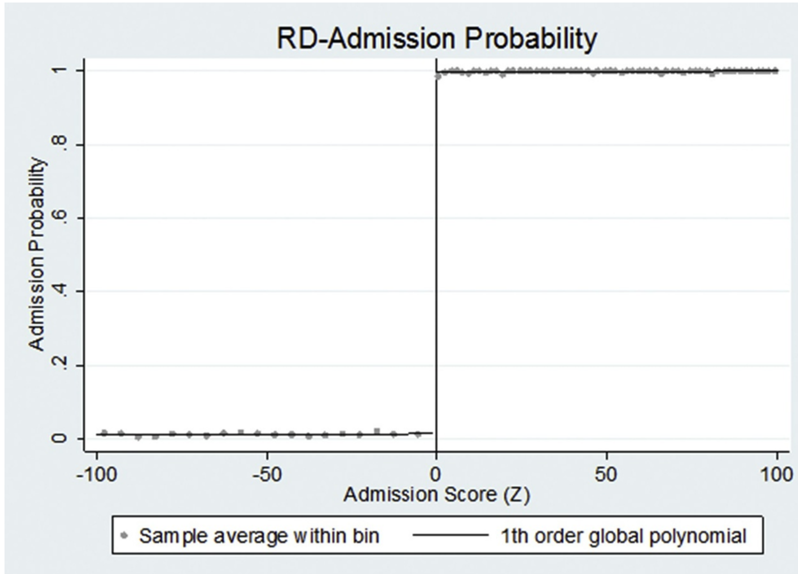
results across time and program of study. The generic component, on the other hand, broadly evaluates the general professional and academic skills of post-secondary graduates. This section of the exam has applied for all post-secondary academic programs since 2009. The specific competences evaluated are defined by the Ministry of National Education, with the participation of the academic, professional and productive sector (regulated by decree 3963 of 2009). Given that the generic component evaluates a broad spectrum of the abilities that the labor market expects from post-secondary graduates, and that the data for this component is available for graduates from all academic programs and has been administered with regularity since its implementation, this study uses this component of the exam for analysis. It is emphasized that the ICFES is a highly recognized entity for the quality of its processes and tests and methodological rigor, all its tests are technically supported.

The MEN collects information through its System for the Prevention of Desertion in Higher Education (Sistema para la Prevención de la Deserción de la Educación Superior, SPADIES). The system consolidates information with the purpose of conducting follow-up on the academic and socioeconomic conditions of students in the post-secondary education system. Additionally, The MEN created the Labor Market Observatory for Education (known in Spanish as OLE), whose purpose is to conduct follow-up on post-secondary graduates, maintaining



Graph 2. Probability of matching observations between databases.

information on their labor market conditions. The information comes from the higher education institutions, the National Civil Registry, the Ministry of Social Protection, and the Ministry of the Finance and Public Credit. The information of labor market is collected by the social



Graph 3. Probability of being accepted.

Table 2
Discontinuity in observable variables.

	Admitted (1)	Women rate (2)	Age (3)	Economic level (4)	Household income (5)	Siblings (6)	Household members (7)
Conventional	0.983***	−0.012	−0.020	−0.034	−0.025	0.002	0.029
	(0.002)	(0.011)	(0.026)	(0.027)	(0.061)	(0.019)	(0.032)
Bias-corrected	0.983***	−0.010	−0.000	−0.038	−0.027	0.002	0.036
	(0.002)	(0.011)	(0.026)	(0.027)	(0.061)	(0.019)	(0.032)
Robust	0.983***	−0.010	−0.000	−0.038	−0.027	0.002	0.036
	(0.003)	(0.016)	(0.048)	(0.035)	(0.081)	(0.036)	(0.039)
Observations	38,531	35,209	47,294	44,189	48,038	27,542	28,752
Bandwidth	131.4	121.8	169.6	160.9	172.4	152.3	178
Control	0.530	0.529	17.94	4.020	6.671	1.416	4.255

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular.Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

security system directly from employers, which support the quality of the data.[8]

For this study, the information from the MEN and ICFES was combined using the unique database identification keys developed by these entities. As part of the Saber 11 exam, students report general sociodemographic data such as gender, age, socioeconomic strata, number of siblings, number of household members, and monthly earnings. This information, available for the years 2000–2013, provides the characterization of students before college application (hereafter “baseline” information).

The university in our study classified each candidate's application according to a points system during the period 1997–2012, using Saber 11 test scores. The university designed a weighted average of the different components evaluated by the Saber 11, and determined the cutoff threshold for acceptance into each academic program for each application period. We do not have access to the details about the weight the university uses because it's confidential. Given that the cutoff score depends on the program applied for and the semester of application, each student´s score was standardized by subtracting the cutoff score defined by the university from the student's actual weighted score on the exam:

$$Z_{ij} = Score_{ij} - Cutoff_j$$

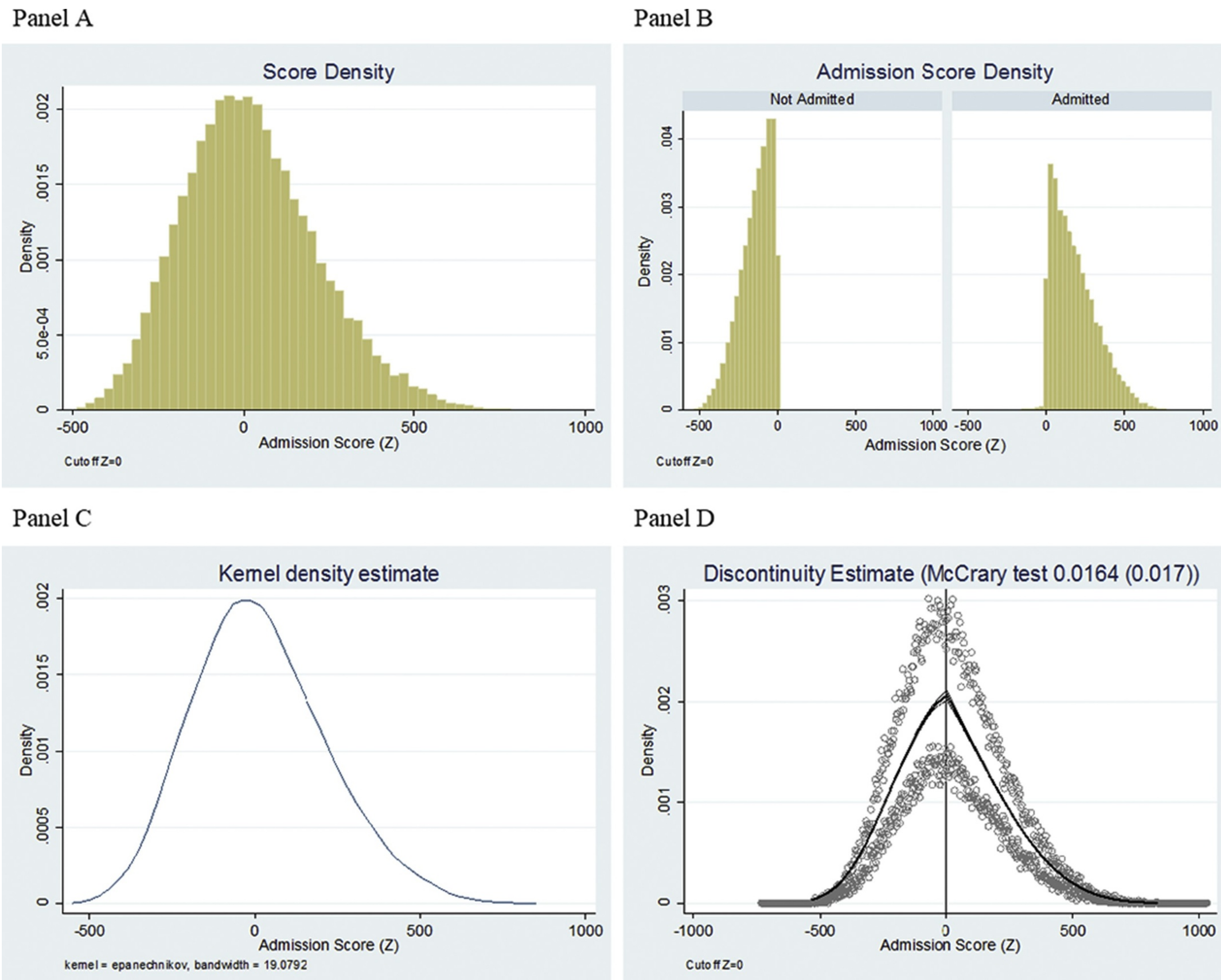
where Z_{ij} is the standardized score of the individual, i, in program, j, $Score_{ij}$ is the score of the individual, i, applying to the program, j, and $Cutoff_j$ is the minimum score required for admission into program, j. As such, applicants with scores below the cutoff threshold will have a negative standardized score.

Information from the SPADIES database allows us to identify whether the applicant actually enrolled in the university, repetition rate, dropout, whether or not the student graduated, and the time students took to graduate. SPADIES contains this information for students since 2004 until today. Failing rate is the number of not-approved academic credits, divided by the total number of academic credits. Dropout is a dummy variable that takes the value of 1 if the student drops out of college and 0 otherwise.

The standardized university exit exam administered by the ICFES, Saber Pro, measures the academic achievement of graduates from post-secondary programs, and has been obligatory for graduation from such a program since 2009. Students can take exams only after having passed 75% of their academic credits. We restrict our sample to university applicants since 2007 in order to guarantee that all students we analyze were required to take the exam. We standardize the results in terms of standard deviations for better interpretation and comparison. Finally, the Labor Market Observatory for Education provides information on graduates’ earnings and whether or not they found employment. This information is used as our outcome variable.

Table 1, Panel A, presents basic sociodemographic characteristics of applicants to prestigious university based on Saber 11 information,

[8] http://www.mineducacion.gov.co.



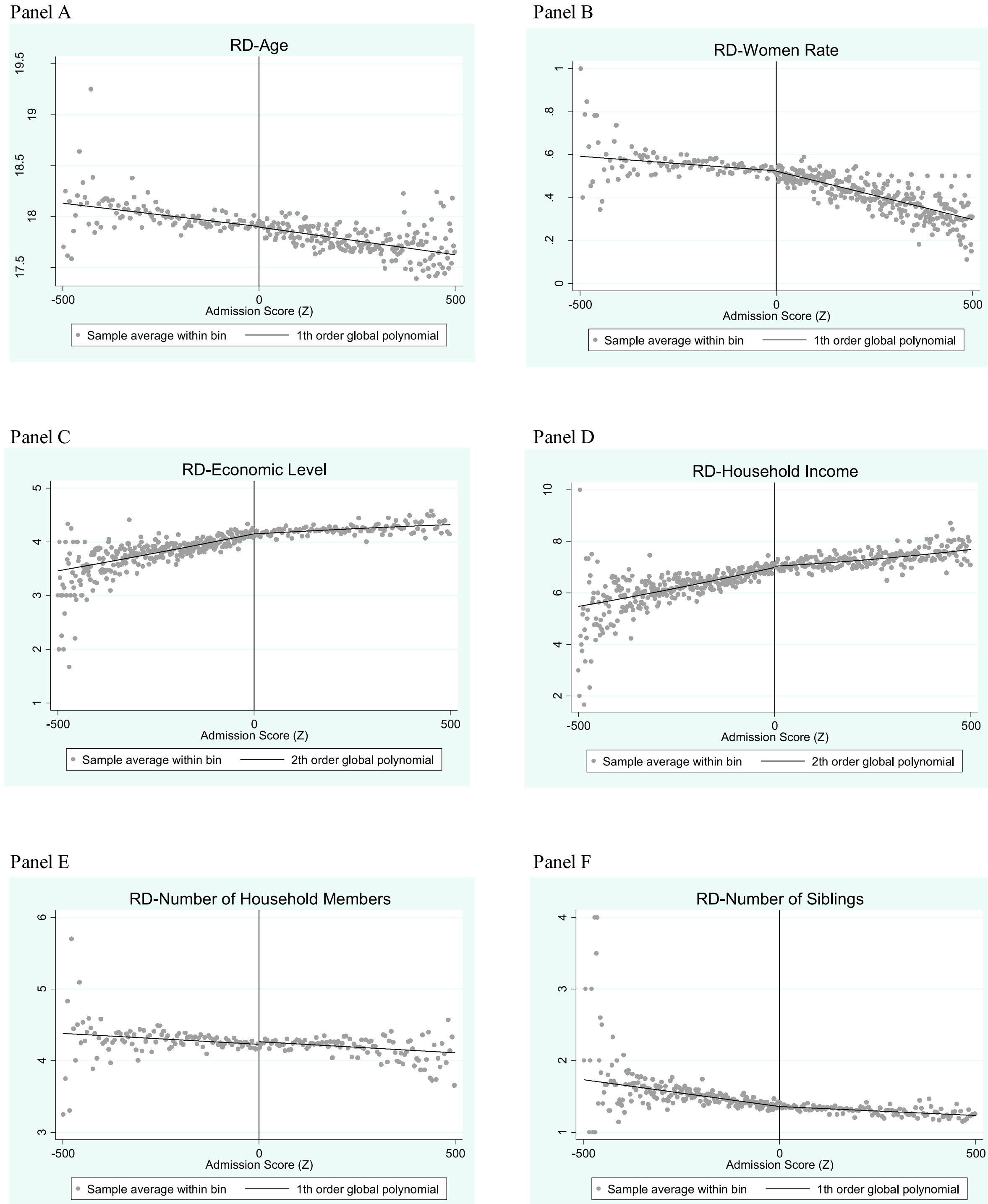
Graph 4. Panel A. Distribution of admissions scores, Panel B. Distribution of admissions scores, by Admissions Decision. Panel C. Kernel distribution. Panel D. McCrary test.

comparing accepted and non-accepted for the period 2007–2012. Instead of presenting information for each year, we take three years' average of the early period (2007–2009) versus the late period (2010–2012) to show evolution over time.[9] While 54.1% of non-admitted applicants are women, women represent only 45.2% of admitted applicants. Although age shows a significant difference between admitted and non-admitted applicants, this difference is small, at about 0.16 years. The socioeconomic stratum is a proxy for household earnings. It is a classification that depends on the area in which an applicant resides, as every residential area in Colombia is assigned a socioeconomic classification for the purpose of pricing domestic utility bills. The table shows that the socioeconomic composition of accepted applicants has changed over the period 2007–2012. While during the years 2007–2009 37.95% of accepted applicants reported living in neighborhoods classified as strata 4, 5, or 6, between 2010 from 2012 this percentage rose to 59.22%. Additionally, average socioeconomic status is significantly higher for accepted population than for non-accepted applicants. On average, family earnings is consistently higher for admitted applicants than non-admitted applicants, with a difference of 0.99 SMMLV[10] (USD $350) in 2007–2009, and 0.85 SMMLV for 2010–2012. According to the MEN, the average salary for recent college graduates is 2.8 SMMLV (USD $969). All in all, there are statistically significant differences between accepted and non-accepted applicants.

Panel B, Table 1, presents information for the main outcome variables. The enrollment rate has diminished over time: in the period 2007–2008 the enrollment rate was 84% for the admitted, but between 2010 and 2012 it was 54%. Similarly, the enrollment rate for the non-admitted falls from 74% to 29%. One plausible explanation to this phenomenon is the financial crisis of 2008–2009, which probably led households to defer entry to the University. In contrast, the failing rate and the time to graduate has been relatively constant for the admitted and non-admitted, approximately 9% and 4,9 years, respectively. The standardized exam score (in standard deviations) has raised for the admitted and has declined for the non-admitted. In 2007–2009 the

[9] The information is similar to individual year data and any other grouping of the data.

[10] For the purposes of this study, monthly earnings is measured in terms of Colombia´s Legal Monthly Minimum Wage (Salarios Minimos Mensuales Legales Vigentes, SMMLV). The SMMLV is established by the Colombian government and is a common unit of measurement in the country.



Graph 5. Discontinuity in observable variables.

average score for the admitted was 1.40SD, for the non-admitted it was 0.61SD; between 2010 and 2012 the score for the admitted augmented to 1.51DS in contrast with the 0.52SD of the non-admitted. With respect to earnings, the gap between the admitted and non-admitted students came from 0.36 SMMLV in 2007–2009 to -0.19 SMMLV in 2010–2012. Accordingly, with MEN, the average earning of the just-graduate students is 2.8 SMMLV (969 USD)

3.2. Merge

An important challenge was crossing information from different sources. Crossing information generally presents loss of information that might reduce the validity of the results. For example, crossing information would generate results biased towards admitted students if information on these students is successfully crossed between databases at a higher proportion than non-admitted students, confounding the effect of being admitted with other effects that explain successfully crossing observations, such as attending university that keeps better records on its students. This means it is important to validate that the loss of data that occurs through information crossing equally affects admitted and non-admitted applicants, especially around the cutoff. This research makes two big dataset matching, the first is between our

Table 3
Contrafactual characteristics.

Panel A: Enrollment in the analyzed university	Enrolled		Total
	Yes	No	
Admitted	13,752	27,000	40,752
Non-admitted		39,850	39,850
	13,752	66,850	80,602

Panel B: Enrollment statistics for non-enrolled applicants at the university analyzed	Enrolled at other universities		Total
	Yes	No	
Admitted	14,434	12,566	27,000
Non-admitted	20,069	19,781	39,850
	34,503	32,347	66,850

Panel C: Characteristics of the institutions attended by applicants not enrolled at the analyzed					
Type of institution	Public institution		Private institution		Total
	High quality accreditation		High quality accreditation		
	No	Yes	No	Yes	
Trade school	16		305		321
Two-year college	43	1	248		292
College/two-year college	218		3,794	14	4,026
University	6,592	1,527	15,552	6,193	29,864
	6,869	1,528	19,899	6,207	34,503

analyzed university database and ICFES. The second is between the final data of the first match and MEN database.

We lost a small proportion of the information during the first merge. The number of shared observations between the database of applicants at our analyzed university and the Saber 11 database was 111,993 students for the period of 2000–2012. This represents 92.8% of the applicants over this period (86.68% between 2009–2012). Keeping in mind that the Saber Pro university exit exam has been obligatory for graduation from all post-secondary programs since 2009, and that taking the exam means students must have completed at least 75% of the credits of a post-secondary program, the database restricts the sample to those who have applied since 2007, allowing us to guarantee that all students we observe were required to take the Saber Pro exam. This restricts our database of university applicants to 80,602 students, of which 50.6% were accepted into a program at the university under analysis.

In contrast, in the second merge we lost 43% of original data. In order to validate the robustness of our estimations despite the loss of data, we checked that the probability of appearing in the second matching is continuous at the cutoff threshold. Graph 2 shows that this probability is continuous at Z = 0, corroborating the estimations from the three methods conventional, bias-corrected, and robust (Calonico et al., 2014a; Calonico et al., 2014b).

3.3. Identification

The probability of admission into the university is a function of the weighted score of the high school exit exam, the Saber 11 test. Applicants above the threshold are admitted, while those below it are not. We exploit this discontinuity in the probability of being accepted to identify the causal effect of attending a highly selective college on the educational trajectory of students (including enrollment, the percentage of academic credits a student repeat, dropout rate, probability of graduating, time taken to graduate, scores on the standardized post-secondary exit exam) and short term labor outcomes (employment during the first year after graduation and earnings.)

The condition necessary for identification is:

$$\lim_{z\uparrow\bar{Z}} \Pr(D = 1|Z = z) \neq \lim_{z\downarrow\bar{Z}} \Pr(D = 1|Z = z) \tag{1}$$

where z is the weighted application score, $\bar{z}$ is the admission cutoff threshold, $\lim_{z\uparrow\bar{Z}}\Pr(\cdot)$ is the lower limit of the probability of attending when z approaches $\bar{z}$. D is a dummy variable that is one if the individual receive the treatment and zero otherwise. Identification requires that the probability of being accepted is discontinuous in $\bar{z}$. The average causal effect of being admitted is given as

$$\tau_{RDB}(\bar{Z}) = \frac{\lim_{z\uparrow\bar{Z}} E(Y_i|Z_i = z) - \lim_{z\downarrow\bar{Z}} \Pr(Y_i|Z_i = z)}{\lim_{z\uparrow\bar{Z}} \Pr(D = 1|Z = z) - \lim_{z\downarrow\bar{Z}} \Pr(D = 1|Z = z)} \tag{2}$$

where $E(Y_i|Z_i{=}z)$ is the conditional expectation of the outcome variable given the baseline application score (Imbens & Lemieux, 2008; Lee & Lemieux, 2010). The estimated effect is the change in the outcome variable, Y, at the point of discontinuity, $\bar{z}$ divided by the discontinuous change in the probability of admission, also at $\bar{z}$. For the empirical implementation of this strategy, we use the construction of local polynomials based on the Kernel function:

$$\hat{\beta}_{+,p} = \arg\min_{\beta\in\mathbb{R}^{p+1}} \sum_{i=1}^{n} 1(Z_i \geq \bar{z})(Y_i - r_p(Z_i - \bar{z})'\beta)^2 K_{h_n}(Z_i - \bar{z}) \tag{3}$$

$$\hat{\beta}_{-,p} = \arg\min_{\beta\in\mathbb{R}^{p+1}} \sum_{i=1}^{n} 1(Z_i < \bar{z})(Y_i - r_p(Z_i - \bar{z})'\beta)^2 K_{h_n}(Z_i - \bar{z}) \tag{4}$$

where $r_p(x) = (1,\ x,\ \ldots,\ x^p)$, $K_{h_n}(u) = K(u/h)/h$ with $K(\cdot)$ is a Kernel function; h_n is a positive sucession of bandwidths and $1(\cdot)$ an indicator function. We also define:

$$\hat{\mu}_{+,p}(h_n) = e'_0\hat{\beta}_{+,p} \tag{5}$$

$$\hat{\mu}_{-,p}(h_n) = e'_0\hat{\beta}_{-,p} \tag{6}$$

as the intercepts of the polynomials of conditional expectation at the admissions cutoff threshold for admitted and non-admitted students, respectively, where $e_0 = (1,\ \ldots,0) \in \mathbb{R}^{p+1}$.

We estimate the effects of offering a place in the university (intention-to-treatment, ITT) and the effect of enrollment in the university

Table 4
Program transition matrix for applicants enrolled in other universities.

	Agronomy, Veterinary Studies, and related programs	Arts	Education	Health Sciences	Humanities and Social Sciences	Economics, Administration, Accounting and related programs	Engineering, Architecture, Urban Studies and Related Programs	Mathematics y Natural Sciences
Arts	1.1%	44.1%	2.1%	1.6%	14.2%	9.6%	26.6%	0.7%
Health Sciences	1.2%	1.1%	3.1%	65.9%	7.5%	7.2%	10.9%	3.0%
Humanities and Social Sciences	1.7%	2.5%	5.2%	2.6%	67.7%	14.1%	5.5%	0.7%
Economics, Administration, Accounting and related programs	0.7%	1.8%	0.8%	1.3%	7.2%	79.2%	8.1%	0.9%
Engineering, Architecture, Urban Studies and Related Programs	1.0%	2.6%	1.4%	2.2%	3.5%	11.1%	75.8%	2.4%
Mathematics y Natural Sciences	3.7%	1.5%	6.9%	13.3%	5.7%	8.5%	26.0%	34.3%

Table 5
QS university rankings: Latin America 2014.

Percentage of enrolled	Accumulated	QS ranking	Score
		5	94.7
16.49%	16.49%	31	76.5
10.30%	26.79%	14	84.6
8.53%	35.32%	42	68.5
5.49%	40.81%	171	
4.89%	45.70%	67	58.8
4.53%	50.23%	102	48.7
3.46%	53.69%	119	43.1
2.65%	56.34%	201	
2.23%	58.57%	151	
2.15%	60.71%		
1.97%	62.68%	191	
1.95%	64.64%		
1.90%	66.54%	201	
1.55%	68.09%		
1.28%	69.37%		
1.27%	70.64%	75	56.8
1.19%	71.84%	251	
1.17%	73.01%		
1.09%	74.10%	69	58.3
0.97%	75.08%		
0.87%	75.94%		
0.78%	76.73%		
0.71%	77.44%		
0.67%	78.11%		
0.64%	78.75%	151	
0.64%	79.38%	89	51.9
0.60%	79.98%		
0.60%	80.58%		
0.60%	81.17%		
0.59%	81.76%		
0.57%	82.33%		
0.57%	82.91%		
0.56%	83.46%		

(treatment-on-the-treatment, TOT). Since enrollment is a function of the Saber 11, and, from the point of view of the students, the cutoff is as good as a lottery, we can instrument enrollment with the test score, and then estimate the effect on the other outcomes. The ITT is akin to estimate a sharp regression discontinuity design, with the test as the running variable; the TOT is akin to a fuzzy discontinuity (FD) design, with enrollment instrumented with the test (Jinyong et al., 2001).

The estimated FD model is then given by:

$$\hat{\tau}_{RDB}(h_n) = \frac{\hat{\mu}_{+,p}(h_n) - \hat{\mu}_{-,p}(h_n)}{\hat{pr}_{+,p}(h_n) - \hat{pr}_{-,p}(h_n)} \tag{7}$$

where $\hat{pr}_{+,p}(h_n)$ and $\hat{pr}_{-,p}(h_n)$ denote the intercepts of the polynomials of the probability of enrollment, which are defined similarly to those in Eqs. (3) and (4). The letter p denotes the weighting of the polynomials (Calonico et al., 2014b).

For the actual estimation, we use a non-parametric estimation, given that this requires no functional assumptions about the variables of interest (Lee & Lemieux, 2010). We report bias-corrected estimates, as described in Calonico et al., 2014a.[11] These authors proposed robust biased correct intervals. We use a triangular kernel that gives more importance, in terms of weight, to observations close to the cut-off point. Finally, we use the bandwidth selector proposed by Imbens and Kalyanaraman (2012).

[11] We also estimate conventional and robust estimates; estimations are robust to the three specifications (conventional, bias-corrected and robust). Results are available upon request.

Table 6
Effects on educational trajectory.

	All (1)	Arts (2)	Health (3)	Humanities (4)	Administration and Economics (5)	Engineering (6)	Science (7)
Efect on enrollment							
ITT effect	0.138***	0.243***	0.060**	0.117***	0.234***	0.147***	0.098**
	(0.009)	(0.036)	(0.026)	(0.017)	(0.027)	(0.015)	(0.049)
Observations	53,447	3455	6388	12,507	5459	18,046	1789
Bandwidth	198	139.6	224.7	238.2	124.5	161	152.9
Control	0.522	0.496	0.542	0.529	0.521	0.526	0.500
Failing grades							
ITT effect	0.013**	−0.062***	0.065***	0.079***	0.025*	0.002	−0.021
	(0.005)	(0.016)	(0.018)	(0.010)	(0.014)	(0.011)	(0.036)
TOT effect	0.038**	−0.160***	0.256***	0.254***	0.071*	0.007	−0.089
	(0.016)	(0.039)	(0.079)	(0.031)	(0.040)	(0.030)	(0.147)
Observations	25,120	2368	1931	6344	2654	7855	947
Bandwidth	181.4	218.1	118	247	122.3	131.6	168.7
Control	0.0929	0.0700	0.0762	0.0854	0.0702	0.111	0.143
Drop out							
ITT effect	−0.019	−0.057	0.036	−0.042	−0.045*	0.000	−0.006
	(0.012)	(0.041)	(0.028)	(0.029)	(0.027)	(0.021)	(0.063)
TOT effect	−0.056	−0.107	0.160	−0.137	−0.126*	0.001	−0.019
	(0.036)	(0.099)	(0.132)	(0.095)	(0.073)	(0.061)	(0.251)
Observations	22,668	2023	3640	3671	4118	7410	956
Bandwidth	131.4	142.8	219.4	92.06	161.4	105.5	144.7
Control	0.222	0.212	0.217	0.240	0.213	0.207	0.261
Graduation							
ITT effect	0.070***	0.027	0.008	0.192***	0.007	0.037*	0.043
	(0.016)	(0.051)	(0.033)	(0.041)	(0.029)	(0.022)	(0.061)
TOT effect	0.213***	0.061	0.037	0.625***	0.021	0.106	0.173
	(0.048)	(0.122)	(0.151)	(0.139)	(0.077)	(0.065)	(0.247)
Observations	16,757	1881	2320	2582	5216	8492	907
Bandwidth	93.71	128.2	127.7	62.27	214.9	123.7	134.1
Control	0.315	0.440	0.154	0.322	0.408	0.290	0.258
Graduate time							
ITT effect	0.003	0.027	0.082	0.039	−0.219***	0.010	−0.211
	(0.020)	(0.092)	(0.104)	(0.046)	(0.026)	(0.034)	(0.160)
TOT effect	0.010	0.057	0.325	0.096	−0.475***	0.036	−1.043
	(0.048)	(0.185)	(0.409)	(0.113)	(0.057)	(0.087)	(0.740)
Observations	9600	734	556	1813	3165	3458	368
Bandwidth	169.1	103.6	191.8	138.8	481.8	162.7	230.9
Control	4.895	4.838	4.947	4.928	4.884	4.893	4.867
Exit score							
ITT effect	−0.050	−0.172	0.323	−0.241***	0.105	−0.081	0.171
	(0.034)	(0.127)	(0.210)	(0.071)	(0.096)	(0.061)	(0.211)
TOT effect	−0.119	−0.335	1.252	−0.616***	0.224	−0.193	0.605
	(0.080)	(0.260)	(0.895)	(0.180)	(0.203)	(0.148)	(0.807)
Observations	11,302	882	393	2118	1544	3213	281
Bandwidth	190.9	119.2	127.8	152	114.2	136.7	153.1
Control	0.907	0.657	0.923	0.831	1.293	0.853	0.634

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular.
We report only Bias-Corrected; we state that results are very stable to three methods: "conventional, bias-corrected and robust".
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

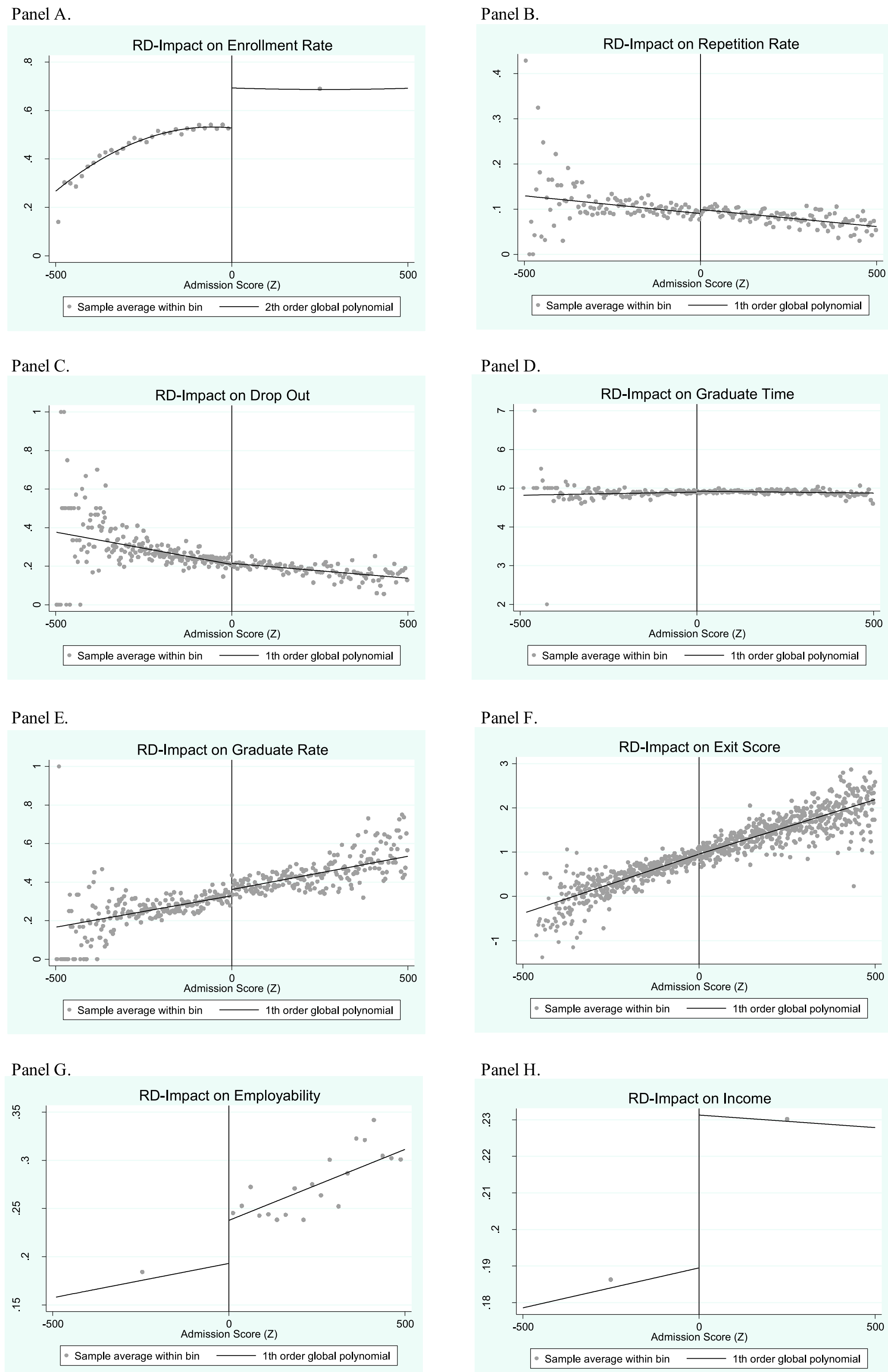
4. Results

4.1. Methodological validity

We present evidence that the main assumptions for an RD design holds in our data: (i) the probability of admission is discontinuous at the cutoff threshold; (ii) the applicants' scores cannot be adjusted in response to the admissions criteria (the scores are non-manipulable); (iii) and the observable variables in the baseline are continuous at the cutoff threshold (Imbens & Lemieux, 2008; Lee & Lemieux, 2010).

Graph 3 shows the horizontal axis of the standardized admissions scores, while the vertical axis shows the probability of being admitted. The graph shows a clear discontinuity at the cutoff threshold. A visual inspection corroborates the estimation presented in the first column of Table 2, which indicates that the probability of admission jumps by 1 at the cutoff. This jump in probability is explained by two factors. First, the number of applicants for whom the admissions decision does not fulfill the admissions rule is quite small; 1.9% of students with a score higher than the cutoff were not accepted, and 0.7% of students with scores below the cutoff were accepted. Secondly, there are no observations of applicants for whom the admissions decision does not fulfill the rule within the optimum bandwidth of the estimation. Both Graph 3. and the estimation (first column of Table 2) indicate this first criterion is fulfilled.

A critical assumption for internal validity of RD is non-manipulation of the forcing variable. In this case, it would be violated if the applicants can manipulate their scores and the admission status. We expected that non-manipulation test holds for two main reasons. First, the



Graph 6. Discontrinuity in outcomes.

college's weighting process for scores and the score cutoff threshold for admission are unknown to the applicants. Before applying to the college, applicants do not know the minimum score for admission. Moreover, the score is not public information, making highly unlikely anticipation of the exact cut-off point. Second, admission depends on the Saber 11 exam, which is applied by ICFES, an independent governmental entity with high level of technical expertise.

Non-smoothness in the number of applicants around the cutoff threshold is a serious indicator of potential manipulation. Graph 4 Panel A shows the distribution of scores. The distribution shows no

Table 7
Effect on short run labor outcomes.

	All (1)	Arts (2)	Health (3)	Humanities (4)	Administration and Economics (5)	Engineering (6)	Science (7)
Obtaining employment in the first year after graduation							
ITT effect	0.069***	−0.166***	−0.152*	0.016	0.135***	0.109***	0.289***
	(0.020)	(0.055)	(0.079)	(0.047)	(0.046)	(0.031)	(0.098)
TOT effect	0.166***	−0.340***	−0.604*	0.042	0.280***	0.275***	1.301**
	(0.048)	(0.115)	(0.323)	(0.118)	(0.093)	(0.078)	(0.515)
Observations	7579	1030	483	1295	1525	3119	315
Bandwidth	126.4	158.3	165.9	92.68	123.5	144.5	187.4
Control	0.181	0.170	0.191	0.169	0.211	0.169	0.146
(ln) Income							
ITT effect	0.039***	−0.051	−0.019	0.087***	0.107***	0.030*	0.032
	(0.008)	(0.034)	(0.020)	(0.025)	(0.026)	(0.016)	(0.036)
TOT effect	0.124***	−0.135	−0.105	0.310***	0.288***	0.094*	0.124
	(0.026)	(0.088)	(0.107)	(0.088)	(0.069)	(0.050)	(0.138)
Observations	53,156	2961	5218	6281	7581	13,358	1768
Bandwidth	197.8	116.8	174.2	94.79	180.8	112.7	149.7
Control	0.180	0.186	0.120	0.193	0.242	0.171	0.166

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Non-parametric RD results for Merge Probability by different cut-off.

	cut off = 100 (1)	cut off = 175 (2)	cut off = −100 (3)	cut off = −175 (4)
Conventional	0	0.018	−0.001	−0.006
	(0.012)	(0.014)	(0.013)	(0.015)
Bias-corrected	0.003	0.024	0.003	−0.008
	(0.012)	(0.014)	(0.013)	(0.015)
Robust	0.003	0.024	0.003	−0.008
	(0.014)	(0.016)	(0.016)	(0.018)
Observations	79,412	79,412	79,412	79,412
Bandwidth	203.9	218.6	152.3	142.3
Control	0.504	0.504	0.504	0.504

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9
Non-parametric RD results for Merge Probability.

	2007 (1)	2008 (2)	2009 (3)	2010 (4)	2011 (5)	2012 (6)
Conventional	0.003	−0.017	0.021	0.041	−0.019	−0.01
	(0.021)	(0.021)	(0.023)	(0.032)	(0.027)	(0.015)
Bias-corrected	0.002	−0.02	0.024	0.049	−0.026	−0.014
	(0.021)	(0.021)	(0.023)	(0.032)	(0.027)	(0.015)
Robust	0.002	−0.02	0.024	0.049	−0.026	−0.014
	(0.025)	(0.026)	(0.027)	(0.038)	(0.031)	(0.018)
Observations	7363	8506	7944	7694	8875	8489
Bandwidth	243.9	213.7	214.6	136.5	119.9	230.9
Control	0.692	0.692	0.692	0.692	0.692	0.692

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

jump or accumulation in the density of scores around Z, the admissions cutoff point which has been standardized to zero. The McCrary test (McCrary, 2008) test shows a (small) value of 0.0164 at the cutoff, non-statistically significant. As such, we take this as further evidence of non-manipulation for the period under study (Graph 4 Panel D). This result are very similar by majors.

We examined possible discontinuities in the baseline variables: age, sex, socioeconomic level, family earnings, number of household

Table 10
Non-parametric RD: interacting socio-demographic characteristics with match.

	Match x Age (1)	Match x Women rate (2)	Match x Economic level (3)	Match x Siblings (4)	Match x Household income (5)
Conventional	0.238	0.008	0.06	0.024	0.127
	(0.206)	(0.009)	(0.048)	(0.022)	(0.084)
Bias-corrected	0.202	0.007	0.049	0.021	0.11
	(0.206)	(0.009)	(0.048)	(0.022)	(0.084)
Robust	0.202	0.007	0.049	0.021	0.11
	(0.236)	(0.011)	(0.055)	(0.026)	(0.096)
Observations	79,409	77,459	77,534	48,742	79,412
Bandwidth	116.8	159.8	137.4	138.6	147.5
Control	10.35	0.313	2.232	1.135	3.73

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

members, and number of siblings. We conducted a visual inspection of the density graphs for each variable at the cutoff threshold for each academic program (Graph 4). Additionally, we ran the model described in Eq. (7), using the baseline characteristics as the dependent variable. The results (Table 2) (Graph 5) indicate that the baseline characteristics are smooth around the cutoff point.

All in all, the three test present strong evidence that the data fits the assumptions for estimating an RD design.

4.2. Conterfactual

Before we discuss main results, it is important to characterize the people who applied to the highly selective prestigious university but didn't get accepted (control group or conterfactual). It provides a characterization of the conterfactual. Our sample includes 80,602 applicants at the university under study, 50%, approximately, of which were admitted. Of the 66,850 applicants who did not enroll in this university, 51.5% (34,503 individuals) enrolled in another institution of higher education, while the remaining 48.4% (32,347) did not continue on to post-secondary education (Table 3 Panel B). Of the 34,503 who enrolled in other institutions, 98.2% chose university education, while 1.8% enrolled in trade school or two-year colleges. Additionally, 24.4% of these individuals enrolled in a state-run, public educational institution, and 22.4% chose an institution with high

Table 11

Robustness exercise by different bandwidths (increase and decrease of 1, 5 and 10%).

	−1% (1)	1% (2)	−5% (3)	5% (4)	−10% (5)	10% (6)
Effect on enrollment						
ITT effect	0.152***	0.152***	0.152***	0.152***	0.152***	0.152***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)
Bandwith	196	200	188.1	207.9	178.2	217.8
Failing rates						
ITT effect	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
OTT effect	0.042***	0.041***	0.042***	0.041***	0.042***	0.041***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.013)
Bandwith	179.6	183.2	172.3	190.5	163.3	199.5
Drop out						
ITT effect	−0.012	−0.012	−0.012	−0.012	−0.013	−0.012
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
OTT effect	−0.038	−0.037	−0.038	−0.036	−0.039	−0.035
	(0.036)	(0.036)	(0.037)	(0.035)	(0.038)	(0.034)
Bandwith	130.1	132.7	124.8	138	118.3	144.5
Graduation						
ITT effect	0.055**	0.055**	0.056**	0.053**	0.056**	0.051**
	(0.022)	(0.022)	(0.022)	(0.021)	(0.023)	(0.021)
OTT effect	0.140**	0.139**	0.142**	0.135**	0.142**	0.130**
	(0.055)	(0.055)	(0.056)	(0.054)	(0.057)	(0.052)
Bandwith	92.77	94.65	89.02	98.4	84.34	103.1
Graduate time						
ITT effect	−0.014	−0.013	−0.015	−0.012	−0.015	−0.011
	(0.02)	(0.02)	(0.021)	(0.02)	(0.021)	(0.019)
OTT effect	−0.034	−0.032	−0.036	−0.03	−0.037	−0.027
	(0.049)	(0.048)	(0.05)	(0.047)	(0.051)	(0.046)
Bandwith	167.4	170.8	160.6	177.6	152.2	186
Exit score						
ITT effect	−0.03	−0.03	−0.029	−0.03	−0.029	−0.029
	(0.034)	(0.034)	(0.035)	(0.033)	(0.035)	(0.032)
OTT effect	−0.071	−0.071	−0.069	−0.071	−0.07	−0.07
	−0.08	−0.08	−0.082	−0.078	−0.084	−0.077
Bandwith	189	192.8	181.4	200.4	171.8	210
Obtaining employment in the first year after graduation						
ITT effect	0.073***	0.073***	0.073***	0.072***	0.073***	0.072***
	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)	(0.017)
OTT effect	0.179***	0.179***	0.178***	0.177***	0.178***	0.176***
	(0.049)	(0.048)	(0.05)	(0.047)	(0.051)	(0.046)
Bandwith	125.1	127.7	120.1	132.7	113.8	139
(ln) Salary						
ITT effect	0.113***	0.114***	0.112***	0.115***	0.111***	0.117***
	−0.024	−0.024	−0.025	−0.024	−0.025	−0.023
OTT effect	0.271***	0.272***	0.269***	0.276***	0.265***	0.279***
	−0.057	−0.057	−0.058	−0.056	−0.06	−0.054
Bandwith	195.8	199.8	187.9	207.7	178	217.6

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular.

We report only Bias-Corrected; we state that results are very stable to three methods: "conventional, bias-corrected and robust". Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

quality accreditation[12] (Table 3 Panel C). Therefore, in order to estimate the impact of prestigious university attendance on the education trajectory and labor market outcomes, this research uses two approaches, the intention to treat (ITT) and the Treatment-on-the-Treated (TOT). For the ITT approach, treatment group is composed of individuals who applied and was admitted to the highly selective prestigious university and the control group is composed of all the people who applied, but who was not admitted. For the TOT approach, treatment group is composed of individuals who applied, was admitted and enrolled to the highly selective university. The control group is composed by all the individuals who applied to the highly selective prestigious university but enrolled in other university. We compare the individuals in the same careers, and presents the results by areas: arts, health, humanities, administration and economics, engineering and sciences.

Table 4 shows the transition matrix between academic programs for applicants who enrolled in another institution. We observe that for students who applied to natural sciences and mathematics, health, humanities, economics and administration, and engineering academic programs, but decided to enroll in another academic institution, the probability of enrolling in the same academic program was 34.4%, 65.8%, 67.6%, 79.4%, and 75.6%, respectively. For the particular case of natural sciences and mathematics, which has a much higher transition rate than other programs (65.6%), applicants that initially applied to this program and enrolled in another institution most often changed to programs in engineering (25.9%), heath (13.2%), and economics and administration (8.4%).

Finally, according to the QS World University Rankings 2014, In Colombia there is great heterogeneity among universities. Table 5 shows the percentage of people enrolled in another university. The second university in the preference (16.49%) is ranked 31st and the score is 76.7, followed by the preference (10.3%) the university in 14th place and the rest is over 42nd place and lower scores of 68.5. this means that about 73% of students in the control group enroll in not prestigious university.

4.3. Effects on the educational trajectory

In Table 6, we present estimates of Eq. (7) for five variables that comprise the educational trajectory of individuals: enrollment, class failure rate, risk of dropout, time taken to graduate, and scores on a standardized university exit exam (Saber Pro) (Graph 6 Panel A to Panel F), which are conditioned to enrollment in a higher education institution. We present the effect of offering admission (ITT estimates) and the effect of enrolling in the highly selective and prestigious university, after instrumenting enrollment with the score in high school exit exam (TOT estimate). The first column of Table 6 presents the effect for all students, independent of major. The subsequent columns present the effect for six major areas: arts, health, humanities, administration and economics, engineering and sciences.

The aggregate effect of offering a place on highly selective and prestigious university enrollment for people close to the cutoff point is 13.8 percentage points (pp), with differential effects for all academic programs. We find a significant, positive impact on applicant enrollment in the majority of the academic programs we studied; these effects range from 24.3 pp for arts to 6 pp for health majors. Taking into account that the enrollment rate for post-secondary education in Colombia is close to 37%[13] over the period of study, an aggregate impact of 13.8 pp is an important effect. This effect is the first stage for the TOT estimations.

The overall ITT effect on the repetition rate (calculated in percentage of credits) is positive and statistically significant. On average, (marginal) students admitted in the highly selective university have an additional 1.3 pp in their repetition rate than (marginal) non-admitted students. However, this effect is not homogenous across majors: the impact for arts is −0.063; for health is 0.065; for humanities is 0.079 and for administration and economics is 0.025; all these coefficients statistically significant. The impacts for engineering and science are statistically non-significant. The size of the TOT effects is scale up by

[12] The accreditation status of the university is determined according to the date in which a student enrolled, not the university´s current status.

[13] These statistics come from the MEN.

Table 12
Robustness exercise.

	Graduation (1)	Graduate time (2)	Exit score (3)	Obtaining employment in the first year after graduation (4)	(ln) Income (5)	(ln) Income for graduate (6)
All sample						
ITT effect	0.070***	0.003	−0.050	0.069***	0.039***	0.090***
	(0.016)	(0.020)	(0.034)	(0.020)	(0.008)	(0.030)
TOT effect	0.213***	0.010	−0.119	0.166***	0.124***	0.218***
	(0.048)	(0.048)	(0.080)	(0.048)	(0.026)	(0.071)
Observations	16,757	9600	11,302	7579	53,156	7635
Bandwidth	93.71	169.1	190.9	126.4	197.8	127.9
Control	0.315	4.895	0.907	0.181	0.180	0.406
Restricting the sample to years 2007 and 2008						
ITT effect	0.046**	0.131***	−0.024	0.123***	0.117***	0.166***
	(0.021)	(0.020)	(0.045)	(0.023)	(0.017)	(0.029)
TOT effect	0.123**	0.331***	−0.063	0.335***	0.379***	0.460***
	(0.056)	(0.051)	(0.115)	(0.061)	(0.053)	(0.072)
Observations	8865	9413	6911	6357	18,776	8193
Bandwidth	143.2	273.3	154.6	153.3	218.6	214.2
Control	0.480	4.894	0.890	0.217	0.297	0.420

We use "rdrobust" command on STATA. IK: Imbens and Kalyanaraman optimal bandwidth Kernels: Triangular. We report only Bias-Corrected; we state that results are very stable to three methods: “conventional, bias-corrected and robust”.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the probability of university enrollment. In this case, the overall effect is a differential of 3.8 pp.

We find no evidence that the estimated effect on dropout rates of offering a place —or actual enrollment— on a highly selective university is significantly different from zero. The annual post-secondary education dropout rate in Colombia is 11.8%[14]; comparisons of the number of students who enroll with the number who graduate, nearly half of the students who begin a post-secondary program abandon their studies at some point, particularly in the first few semesters of the program (Guzmán et al., 2009). The only major in which the estimation is statistically significant is administration and economics, with an effect size of −0.045 (ITT) and −0.126 (TOT).

Offering a place in this highly selective university has a positive, significant effect on the aggregate graduation rate in all programs of 7 pp, driven by humanities (0.192) and engineering (0.037). The overall TOT effect is a difference of 21.3 pp in graduation rates of (marginal) accepted, vis-à-vis (marginal) non-accepted students. Keeping in mind that the graduation rates for humanities and engineering in Colombia are 34.1% and 27.8% (MEN, 2013), the effect of college quality is equivalent to 13.5% of the average graduation rate for humanities programs, and 11.5% for engineering. The effects for other programs are positive, but not statistically significant. Finally, regarding the time it takes students to graduate, we find no significant effects, both overall and by particular majors, in line with findings from Herrera (2013). The only exception is on administration and economics, in which the effects are a reduction of 0.219 years.

The aggregate effect of offering admission (and actual enrollment) on Saber Pro scores is statistically insignificant. Differentiating by program, the effect is only significant for humanities programs, with a negative impact of −0.241 standard deviations. We find no evidence of significant effects for other academic programs. These results suggest that students close to the cutoff point of admission will graduate with the same abilities and general skills required for their chosen professions as students non-admitted close to the cutoff who enrolled in other university. This results suggest that students are gaining same knowledge and skills regardless if they attend to a prestigious university or not prestigious university.

Summarizing, students who were offer a place in this highly selective university, in comparison to students who were not offer a place but were close to the admission cutoff, tend to enroll more in different institutions and repeat more credits. However, we do not find effects on dropout rates, graduation and time for graduation.

4.4. Short run labor market outcomes

We measure short run effects on probability of having an employment in the first year after graduation and (ln) earnings, Table 12 (Graph 6 panel G and panel H). The aggregate impact of offering a place on obtaining an employment, one year after graduation, is close to 7 pp and statistically significant. The corresponding TOT effect is 16.6 pp. This effect, however, differ markedly across majors. In contrasts, the ITT effects are negative for arts (−0.166) and health (−0.152). TOT effects are larger. The ITT and TOT effects on (ln) earnings are positive. A (marginal) admitted student earns 3.9 pp more than a (marginal) non-admitted student. The TOT effect is 12.4 pp. The unemployment rate for the typical young individual, graduated in 2012, entering the labor market in 2013 is 19.2%.[15] Moreover, we know that a person that recently enter the market would tend to have (initially) lower wages than a person with more experience (given the typical concave shape of individual earnings). As such, the effects that we report are large.

Three major drive the ITT and TOT aggregate positive effects. ITT effects are found in administration and economics (point estimate of 0.135), engineering (0.109) and science (0.289). TOT estimates scale up these effects: positive effects on humanities (0.087, ITT effects), administration and economics (0.107) and engineering (0.03). These effects are in line with the general point of Dale and Krueger (2002) and Dale and Krueger (2011), who find that graduates from more selective universities have better salaries to graduates with similar abilities from less selective schools.

4.5. Robustness exercises

It is plausible that the matched probability to be correlated with socioeconomic variables, which could generate endogeneity problems, we made several robustness exercises. First, we run the regression on matched probability by different cut-off (100, 175, −100 and −175), Table 8. Second, we run the regression on matched probability by cohorts, Table 9. Third, we are interacting socio-demographic characteristics with match to show that whether there is endogenous sample

[14] MEN.

[15] http://www.graduadoscolombia.edu.co/html/1732/w3-article-344801.html

selection by some socio-demographic characteristics, Table 10. We found the matched probability is smooth across of cut-off, cohort and interacting with socio-demographic characteristics.

Regarding the robustness of the results, we re-estimated Table 6 and Table 7 for different bandwidths (increasing and decreasing in 1, 5 and 10% of original bandwidths), Table 11. In addition, we restricted the sample to the years 2007 and 2008 to know if the results change over time or cohorts, Table 7. We found that all the results maintain the sign and statistical significance.

5. Conclusions

Summing up, we find positive effects of offering place in a highly competitive and prestigious university on enrollment and credit repetition rate. We don't find effects on the probability of dropping out, graduation, or timing of graduation. More important, we don't find effects on university exit exam. In contrast, we find large, significant effects on two short run labor markets: probability of employment one year after graduation and earnings. These effects are concentrated in three majors: humanities, administration and economics and engineering.

A potential explanation of the lack of results during the educational trajectory (conditional on enrollment), especially on the exit exam, and positive results in the labor market is compatible with a signaling model,[16] suggesting that in situations where the labor market has incomplete information on the abilities of job candidates, employers assign salaries based on information that is observable, which in this case could be a diploma from a well-recognized, competitive university. It seems that the labor market places higher value on graduates from a highly prestigious university, even though we find no evidence that their abilities are different from graduates at less prestigious universities, with ability measured through scores on a standardized exit exam taken at graduation.

Another potential explanation is that the university provides students with other skills not measured with the Saber Pro. For instance, most prestigious universities can be developing in their students' soft skill such as team work, assertive communication, etc. In addition, it is possible that prestigious universities create environments in with students developed better networks or social capital. In those cases, the market rewards those skills or the social capital or networks, above the skills that the exam actually measure. We cannot disentangle these to hypothesis with the data at hand.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econedurev.2019.02.006.

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[16] Weiss (1995) presents an early overview of the literature.