Equality of Opportunity and Human Capital Accumulation: Motivational Effect of a Nationwide Scholarship in Colombia*

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Abstract

We study the ex-ante motivational effect of a nationwide merit and need-based scholarship in Colombia. *Ser Pilo Paga* (SPP) is a program that grants full scholarships at top-quality universities for 10,000 low-income students per cohort. After its introduction in 2014, SPP completely closed the socioeconomic enrollment gap for high-performing students in top universities. Using administrative data on the universe of high-school seniors, we explore whether this unprecedented change in opportunities generated an ex-ante motivational effect on eligible students' performance in the 2015 national high school exit exam. Our results from a Difference in Difference model and a Regression Discontinuity Design indicate that the need-based eligibility to the scholarship had a substantial effect on test scores at the top of the distribution, starting around the 70th percentile. For example, at the 90th percentile of the test score distribution, eligibility to the scholarship reduced the socioeconomic achievement gap by 17 percent. We also find that the motivational effect is concentrated in schools where at least one student received the scholarship in 2014, and that university enrollment rates even increased for eligible students who obtained a test score just below the requirement to obtain the scholarship. Our results highlight the way in which the lack of opportunities for social mobility discourages human capital accumulation by low income students, thus contributing to the persistence of poverty and inequality.

JEL codes: H52, I24, I25, O15

Keywords: equality of opportunity, socioeconomic achievement gap, Colombia

* We wish to thank Prashant Bharadwaj, Alain De Janvry, Leopoldo Fergusson, Karen Macours, Craig McIntosh, Karthik Muralidharan, and Elizabeth Sadoulet for useful comments. We are grateful to seminar participants at Universidad de los Andes, UC Berkeley, UC Davis, UC San Diego, University of San Francisco, MWIEDC 2017, the 4th DIAL Development Conference in Dauphine University, and LAGV 2017 for useful comments and suggestions. We also thank the Colombian Ministry of Education for providing access to the data, and to Felipe Arango who provided excellent research assistance. The usual disclaimers apply. This paper is dedicated to the memory of Miguel Alejandro Rodriguez, one of our *Ser Pilo Paga* students and a role model to us.

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I. Introduction

The relationship between inequality and growth has long been debated by economists. Standard growth theories stress different channels through which wealth inequality spurs economic growth (Kaldor, 1957; Stiglitz, 1969; Mirrlees, 1971; Okun, 1975). Alternative growth theories emphasize that, in the presence of credit market imperfections, inequality hinders investments in human capital accumulation, and growth (Galor and Zeira, 1988 and 1993; Aghion, Caroli, and García-Peñalosa, 1999).[1] Recently, a growing body of work on equality of opportunities highlights how the circumstances at birth and during childhood are key determinants of future socioeconomic success (Heckman, 2008; Chetty, et al., 2011; Chetty, Friedman, and Rockoff, 2014; Chetty, Hendren, and Katz, 2016; Aghion et al., 2017; Bell et al., 2017; Chetty and Hendren, 2018a, 2018b). This research demonstrates how an unequal distribution of opportunities hinders the human capital accumulation of low-income individuals. Hence, it provides evidence on how inequality is established early in life, how it reproduces across generations, and how it hinders innovation and growth.

We contribute to this recent body of work with new evidence on the way in which inequality of opportunity discourages human capital accumulation by low income students. We explore the ex-ante effects on students' learning of Ser Pilo Paga (SPP), a nationwide scholarship that created unprecedented opportunities for social mobility in Colombia. The scholarship is awarded to 10,000 new students per year and funds their entire undergraduate education and living expenses at top quality (accredited) universities.[2] SPP, which translates as *Being a Good Student*

[1] Cross-country evidence in general documents a negative relationship between inequality and growth, although the conclusions vary depending on the data and empirical strategies. See Benabou (1996), Aghion et al. (1999), and Voitchovsky (2009) for reviews of the literature.

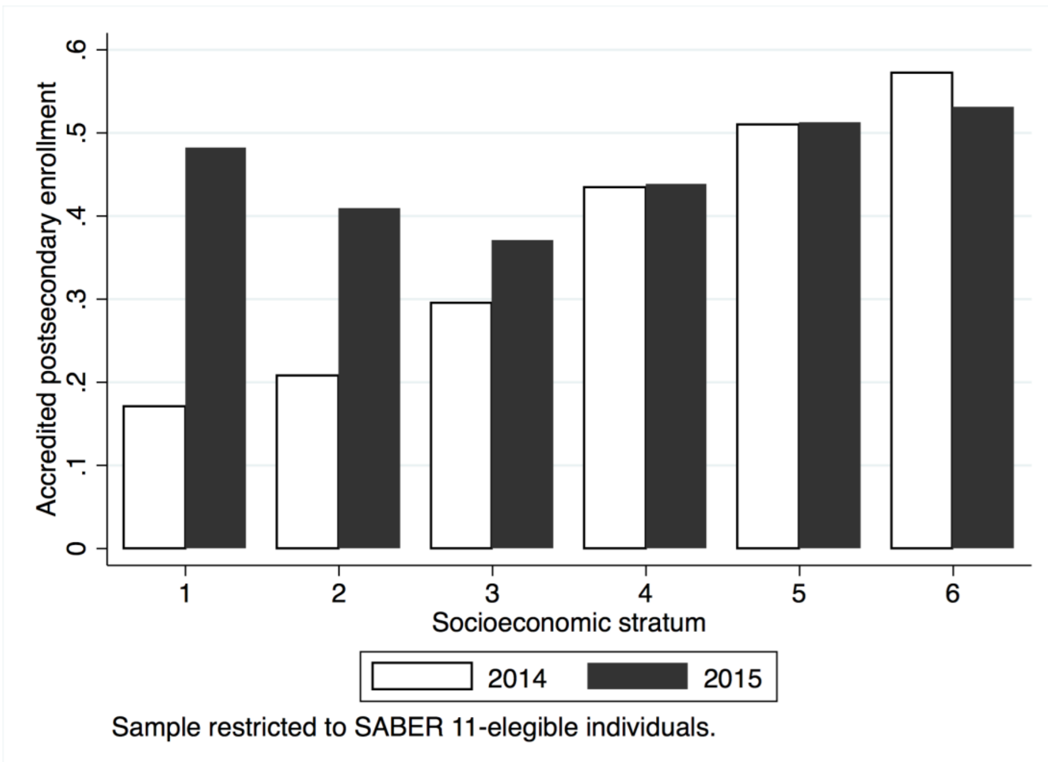
[2] Accreditation is awarded by the Ministry of Education based on an assessment of the institution and program quality. By December 2016, 46 out of approximately 300 higher education institutions in the country had received the quality accreditation.

Pays Off, is awarded to students who fulfill the following need and merit-based criteria: First, students must come from a household scoring below a threshold in the *Sisbén*, the socioeconomic index used to target subsidies and social programs. Second, students must score above a threshold in the *Saber 11*, the national high school exit exam. This threshold approximately corresponds to the 91st percentile. Throughout the analysis, we estimate the effect of the need-based eligibility to analyze the ex-ante motivational effect of SPP on human capital accumulation.

SPP was first announced in October 2014, two months after the national high school exit exam had been administered. Immediately, SPP transformed the opportunities for low-income students to access a high-quality university. Figure 1, taken from Londoño et al. (2017), depicts the enrollment rates at these universities by socioeconomic strata in 2014 and 2015, before and after SPP. The figure sharply illustrates how the socioeconomic enrollment gap for high-skilled students at top private universities almost entirely disappeared at the beginning of the 2015 academic year. Appendix Figures A1 and A2, in turn, illustrate how SPP entirely closed the enrollment gap among all universities and increased the geographic diversity of students at accredited universities. Therefore, SPP made access to quality higher education depend only on students' academic performance rather than on their socioeconomic background. In Colombia, where inequality is above the Latin-American standards and intergenerational mobility is low, SPP brought about a sudden and unprecedented change in the opportunities for social mobility.

We analyze whether the new opportunities to access top quality universities had a positive effect on the performance of the low-income need-based eligible students in the 2015 national high school exit exam. This exam covers 10 different subjects which correspond to the entire high-school curricula. Higher scores at the national end of high school exam would signal that the introduction of SPP motivated eligible students leading to a higher level of effort and human capital accumulation even before the reception of the scholarship. Moreover, we anticipate that such ex-ante motivational effect should have been concentrated at the top of the test-score distribution: for these students, a higher level of effort should have had the strongest effect on the likelihood of obtaining the scholarship.

FIGURE 1—ENROLLMENT RATES AT TOP-PRIVATE UNIVERSITIES BY SOCIOECONOMIC STRATA



Notes: Postsecondary enrollment at top-private universities by socioeconomic stratum for students at the top 10 percentiles of the distribution in the national high school exit exam in 2014 and 2015 - before and after SPP was introduced. Figure taken from, and reproduced with permission of, Londoño et al. (2017).

SPP provides a unique opportunity to estimate the causal ex-ante motivational effect of the new opportunities on students' tests scores for the following reasons: First, SPP is a large-scale, nationwide scholarship that benefits approximately 3% of each cohort of high school graduates. Second, the scholarship was announced two months after the 2014 national high school exit exam and ten months before the 2015 exam. Third, the program's characteristics and eligibility criteria were widely publicized by the Colombian Government, which committed to sustain the scholarship at least until 2018. These three features imply that the 2015 cohort of high-school seniors experienced a drastic change in the incentives to learn; this is, they received a credible signal regarding the scholarship, its benefits, and eligibility criteria and had several months to prepare for their high school exit exams. Finally, rich administrative data and the strict implementation of the eligibility criteria allow us to match students' test-scores with their households' socioeconomic index score and estimate the causal ex-ante effects of the program. We describe these features of the scholarship and the data in more detail in sections II and III.

In section IV, we employ different strategies to estimate the causal ex-ante effects of SPP on human capital accumulation. First, we estimate a Difference in Difference (DD) model where we compare the change in the test scores of the need-based eligible students between 2014 and 2015 to that of non-eligible students. Second, we follow a Regression Discontinuity Design (RDD) around the need-based eligibility threshold to estimate the motivational effect of the scholarships' eligibility on students' test scores in 2015. Finally, we estimate a non-parametric RDD to compare the change in the test scores between 2014 and 2015 around the eligibility threshold. Throughout the analysis, we pay close attention to the effects across different percentiles of the distribution, since we expect that the motivational effect should have emerged at the top of the test-score distribution.

We find that the new opportunities created by the scholarship led to a substantial improvement in eligible students' test scores in the national high school exit exams, occurring only at the top of the distribution. We first observe a sizeable socioeconomic achievement gap at every percentile of the distribution of the 2013 and 2014 high school exit exams, before the introduction of SPP. Then, our DD and RDD results indicate a positive and significant effect of the eligibility to the scholarship on the *Saber 11* test scores, which was concentrated at the top of the test-score distribution, starting around the 70th percentile. For instance, the RDD results indicate that, at the 90th percentile of the test-score distribution, the introduction of SPP led to a 17 percent reduction in the socioeconomic achievement gap between eligible and non-eligible students.

In Section V, we explore two additional results. First, we find that the motivational effect was concentrated in high schools where at least one student received the scholarship in 2014. These results do not seem to be explained by differences in school-quality, and thus suggest a role-model or aspirational effect. Second, we observe that access to higher education and to accredited universities increased even for need-based eligible students who barely missed the test-score required to obtain the scholarship. This indicates that the new opportunities brought by SPP had positive effects on human capital accumulation of eligible students beyond the recipients of the scholarship.

Our research contributes to the literature in three ways. First, it relates to research on the factors that contribute to the socioeconomic gaps in skills, college enrollment, and academic performance (Kane, 1994; Heckman, 2008; Hoxby and Avery, 2013; Schady et al., 2015). Our results demonstrate that students' motivation is a key input in the learning process, and that it contributes to explain this gap. Second, we build upon research that analyzes the effects of scholarships and financial aid mechanisms on enrollment, assistance, drop-out rates, and academic performance. Most this research, however, analyzes ex-post effects of these interventions; this is, the effects on the direct beneficiaries (Cornwell et al., 2006; Filmer and Schady, 2008; Angrist and Levy, 2009; Barrera-Osorio et al., 2011; Scott-Clayton, 2011; Castleman and Long, 2013; Fack and Grenet, 2015; Levitt et al., 2016; Solis 2017). We thus contribute to a smaller body of research on the ex-ante effects of scholarships and financial incentives on students' academic performance and motivation (Angrist and Lavy, 2009; Kremer, Miguel, and Thornton, 2009; Scott-Clayton, 2011; Goodman, 2016; Levitt, List, and Sadoff, 2016). Our study differs from this latter body of work since we evaluate a large-scale, nationwide scholarship that bears life-changing consequences for its beneficiaries.

Finally, we contribute to the literature on equality of opportunity by providing micro-level evidence on the way in which a change in the opportunities for social mobility stimulated the effort, learning, and academic performance of low-income students. Our results further illustrate the way in which inequality of opportunities hampers human capital accumulation. This occurs not only because imperfect credit markets prevent poor but talented students from investing in their education, but also because the recognition of the lack of real opportunities discourages them from exerting effort throughout the schooling process. In doing so, we highlight how inequality of opportunities leaves an untapped potential and hurts low-income individuals who could have otherwise become high achievers and moved out of poverty. Together, we provide evidence for an additional mechanism through which inequality of opportunities affects economic growth, hinders socioeconomic mobility, and reproduces itself over time. In Section VI we conclude discussing these and other implications.

II. Context

Colombia has long been characterized by high levels of inequality, even by Latin American standards. Although the country sustained growth rates above the regional average and almost cut extreme poverty by half between 2002 and 2014––from 49.7 to 27.8 percent of the population—inequality is still high. A Gini coefficient of 53.5 places Colombia as the 11th most unequal country in the world (World Bank, 2013). In addition, opportunity for socioeconomic mobility are scarce, especially for the most disadvantaged individuals. According to García et al., (2015), there is an average 0.72 correlation between parent's and children's educational attainments, which increases to 0.83 for poor and vulnerable households.[3]

Access to higher education can play a significant role to promote social mobility and reduce inequality. Colombia made progress in this dimension during the last decade as enrollment rates at higher education increased from 31.6 to 49.4 percent between 2007 and 2015 (Gonzalez-Velosa et al., 2015). However, in a context of limited credit and financial aid, low-income students could at most aspire to attend low-cost and low-quality institutions (Sánchez and Velasco, 2012). In fact, due to prohibitive tuitions at top-quality universities, the abovementioned increase in enrollment rates was driven by the expansion of low-quality programs in non-accredited institutions, which have low or even negative rates of return (Camacho, Messina, and Uribe, 2017).

In October 1st, 2014, the Colombian Government launched SPP, a nation-wide merit and need-based scholarship program to benefit 10,000 new low-income students per year. Beneficiaries can choose any university among the 46 accredited, top-quality universities of the country. SPP covers their entire tuition and provides a stipend, which ranges between one and four minimum monthly salaries per semester (US $263 – US $1,054).[4]

Eligibility for SPP is based on two criteria: First, students must come from a household scoring below a threshold in the *Sisbén* socioeconomic index. The Sisbén threshold varies according to the households' geographical location: 57.21 for the 14 main cities, 56.32 for other urban areas, and 40.75 for rural areas (see Figure 2, Panel A). The *Sisbén* is calculated by the *National Planning Department*

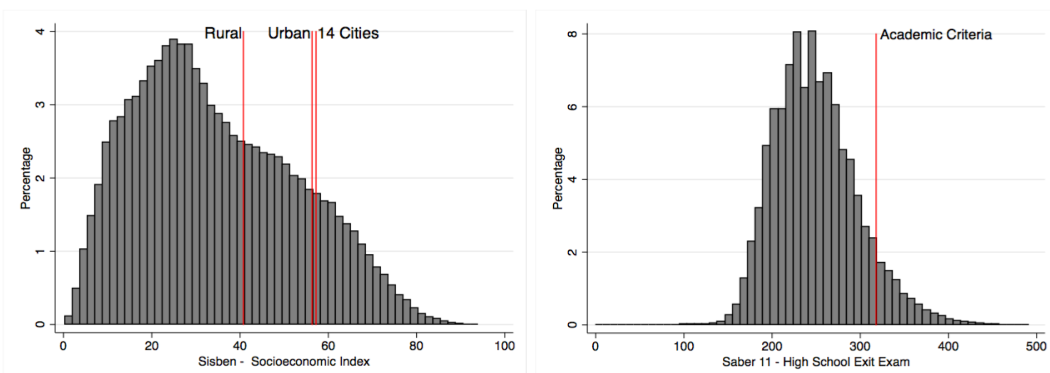
[3] These figures have been stagnant over the last two decades and are considerably higher than in other countries of the region (Behrman, Gaviria, and Szekely, 2001).

[4] The stipend varies according to whether the student chose a program in different city and migrated for this purpose. In addition, students may receive an additional semester subsidy of around US $320, conditional on completing the academic semester, an additional US $80 per semester if their GPA is at least 3.5 over a 5-point scale, and in-kind subsidies and transfers from the universities to support daily expenses in photocopies, transport, and food, among others (Londoño, Rodríguez, and Sánchez, 2017).

(DNP, for its Spanish acronym), using information from a household survey administered for this purpose. Contrary to prior versions, the more recent version of the index is based on a formula that is unknown to the public and cannot be modified by local authorities or program administrators.[5] To fulfill the second criteria, students must score above a given threshold in the *Saber 11* national high school exit exams.[6] In 2014, when the program was announced, the *Saber 11* threshold was set at 310 (over a 500-scale), corresponding to the 91st percentile of all scores in that year. Students who fulfill both conditions, and are accepted at an accredited university, are offered the scholarship. Figure 2 illustrates the distributions of the *Sisbén* index and *Saber 11* scores and the thresholds that jointly determine eligibility.

FIGURE 2—NEED-BASED AND ACADEMIC ELIGIBILITY CRITERIA

SISBÉN —SOCIOECONOMIC CRITERIA   *SABER 11*—ACADEMIC CRITERIA



Notes: The figures above illustrate the distribution of Saber 11 test scores (left-hand panel) and the *Sisbén* index (right-hand panel) and the specific need-based and academic thresholds that determine eligibility. The distribution for the *Sisbén* index omits information for wealthier households who do not have a score.

The ex-ante motivational effect should occur because of the recognition of the new opportunities brought forth by SPP. These include an immediate increase in

[5] The new method of the *Sisbén* index addresses previous limitations, which allowed manipulation around the cutoffs by local officials (Camacho and Conover, 2011). It also shifted from a categorical to a continuous score, allowing each program to choose its own threshold. Since this version has been in place, there has been no evidence of manipulation.

[6] By contrast with to what occurs in the U.S. with the SAT, over 90 percent of seniors take the *Saber 11*, regardless of whether they intend to apply to post-secondary education.

enrollment of 32.6 percentage points for eligible (need and merit-based) students, a shift in students' choice towards top-quality accredited universities, and the complete reduction of the socioeconomic enrollment gap among top students at top private universities (Londoño, Rodríguez, and Sánchez, 2017). These new opportunities constitute a vehicle for socioeconomic progress and bear life-changing consequences for low-income students. For instance, Gonzalez-Velosa et al. (2015) found that a degree in a top institution (top 90^{th} percentile) has a net rate of return of 78%, whereas a degree at a low-quality institution (bottom 10^{th} percentile) yields a negative return of 23%.

As discussed previously, SPP was announced in October 2014, two months after the *Saber 11* test was administered. Since the 2014 cohort was not aware of the scholarship when taking the high school exit exam, the need-based eligibility to SPP should not have had any effect on the socioeconomic achievement gap in that year. Instead, we expect that the motivational effect emerged for the cohort of eligible students who took the test in 2015, knowing that the program created an unprecedented opportunity for enrollment into top universities.[7] The ex-ante motivational effect was enhanced by the fact that the Colombian government widely publicized the program in the press, TV, radio, internet, and social media, depicting the attributes, requirements, and benefits of the program, as well as success stories of the 2014 recipients. Finally, 35% of the schools in the country had at least one recipient in 2014, which may have induced an aspirational effect, a question that we investigate in section V.

[7] There are two overlapping high-school academic calendars in Colombia. Calendar A applies to most high schools in the country, including the universe of public schools, and runs through the calendar year: high school seniors take the national exam in August of each year, and then start their university studies in January of the following year. Calendar B in turn, runs in parallel with the U.S calendar year and applies to a small subset of private high schools. As a result, higher education institutions receive students in January and August.

III. Data

We combine rich administrative data from two different sources. First, we use data from the *Instituto Colombiano para el Fomento de la Educación Superior* (ICFES), the state institution that administers standardized tests in Colombia. This database contains information for all *Saber 11* test takers from 2013 to 2015, including test-scores, school characteristics, and self-reported demographic and socioeconomic characteristics, such as the parents' education, the household's assets and income levels. Overall, the ICFES database contains information on approximately 550,000 test takers per year from 2013 to 2015. Second, we matched the ICFES data with data from the DNP that provides the *Sisbén* score, which is used to determine the socio-economic eligibility, for the entire Colombian population.

In Appendix Table A1 we compare eligible and non-eligible students across a range of socioeconomic characteristics. The data in the table reveals a sharp difference in academic achievement by socio-economic stratum, which is more accentuated at the top percentiles of the test score distribution. In 2014, 55% of students in Colombia fulfilled the need-based criteria, while 8.5% of those who took the *Saber 11* obtained a score above the minimum threshold. However, among the need-based eligible students, only 5% achieved the required test score and fulfilled the merit-based criteria. This figure is considerably lower than those for non-eligible students with a *Sisbén* score (11.2%), and for students without a *Sisbén* score (13.2%), who typically come from wealthy households and are excluded from all government need-based programs.[8]

[8] Table A2 provides descriptive statistics between eligible and non-eligible students on the Saber 11 test-scores and on key characteristics such as the household's *Sisbén* score, a range of socioeconomic indicators, and the student's demographic characteristics and area of residence. Unsurprisingly, the two groups differ in every domain.

IV. Results - Motivational Effects of the SPP Scholarship

In this section, we first estimate a difference-in-difference model, comparing the change in the performance in the *Saber 11* of eligible students versus non-eligible students between 2014 and 2015. Second, we follow an RDD to estimate the effect when comparing similar students around the *Sisbén* eligibility threshold. Finally, we follow a non-parametric RDD which allows us to compare the change in test scores between 2014 and 2015 around the *Sisbén* eligibility threshold.

Before we proceed with the empirical analysis, we discuss the theoretical argument that guides our hypothesis regarding the distributional effects of the eligibility to the scholarship. We assume that each student has a belled curved distribution of expected test scores in the *Saber 11* that is, on average, centered at the test score predicted by the student's underlying academic skills. We also assume that a higher level of effort shifts the expected distribution of the students to the right. For some students, the distribution of their expected test scores is centered exactly at the merit-based eligibility threshold, which corresponds to the 91st percentile of the *Saber 11* distribution. Hence, the mode of their distribution coincides with the test score required to obtain the SPP. In this simple framework, this group of students perceive the highest marginal effect of effort on the probability of surpassing the merit-based eligibility threshold. These students should thus be the ones who become most motivated by the introduction of SPP: the incentive provided by the eligibility to SPP should have the strongest effect for students with test scores at the 91st percentile of the distribution.

However, there are reasons to expect that the motivational effect will not be restricted to the 91st percentile but will broadly affect the top of the test score distribution. First, a more dispersed distribution of expected test scores implies that the motivational effect will increase the performance of students in the vicinity of the 91st percentile, who will also perceive a high marginal return of effort. Second, students' expectations may be systematically biased, for example due to overconfidence (Pallier et al., 2002). In such case, the strongest effect would affect those students who believe that their most likely test score will place them at the 91st percentile of the distribution of realized test scores. While this may occur to some extent, it is unlikely that such bias will be substantial; for instance, that students below the median will incorrectly perceive that they will be at the top of the *Saber 11* distribution with a high likelihood.

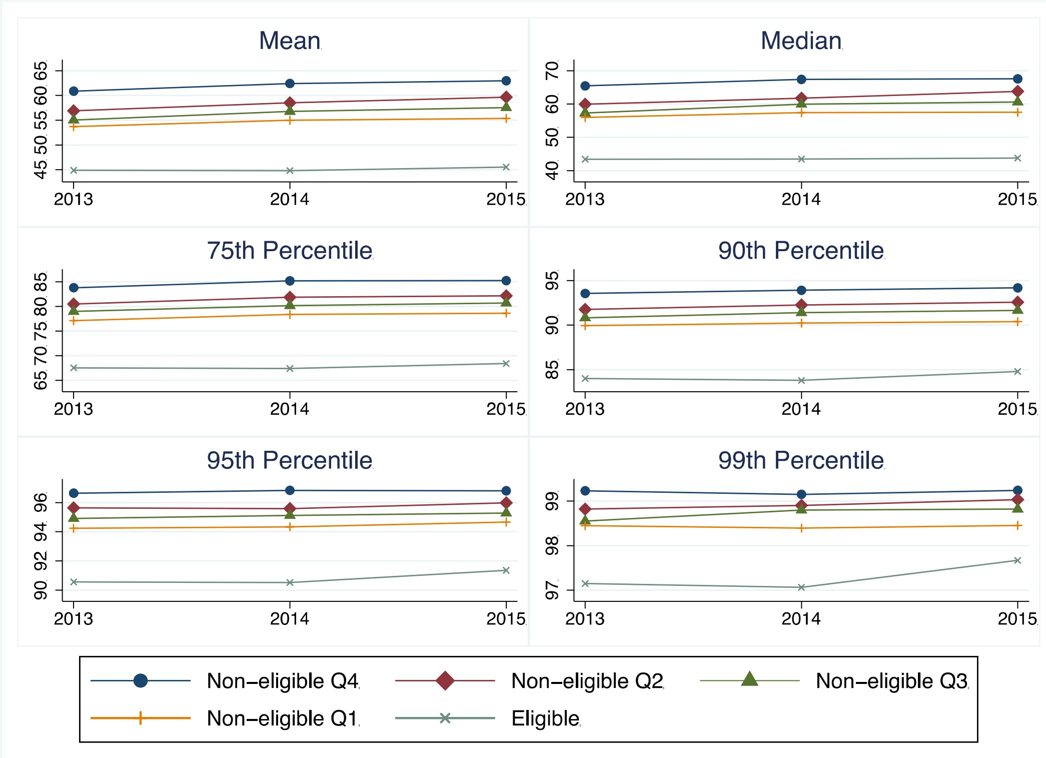
A. Difference in Difference between Eligible and Non-Eligible Students

The DD approach compares the change in the academic performance among eligible and non-eligible students from 2014 to 2015. Our outcome variable is the relative ranking in the *Saber 11* test among all students who took the test in the same cohort, normalized from 0 for the lowest score to 100 for the best score in each year. We use the relative ranking to avoid variations in test scores (in average and variance) due to changes in the difficulty of the exam from year to year.[9]

Figure 3 provides a preview of the difference-in-difference results. The figure illustrates the evolution in the year-specific ranking between eligible and non-eligible students. The latter are stratified by quartiles of the *Sisbén* index to illustrate the socioeconomic achievement gap. In addition, the figure illustrates the evolution in the relative ranking at different percentile in the distribution to examine whether the motivational effects of SPP affects the top of the distribution.

[9] The scale for the Saber 11 test scores in 2013 is not strictly comparable to that of 2014 and 2015. Therefore, we rely on differences in the relative ranking across time to make the results in each comparable. However, results are robust if we instead use a standardized score as the outcome variable.

FIGURE 3—EVOLUTION OF STUDENTS' RANKING IN THE SABER 11 BETWEEN 2013 & 2014



Notes: Evolution of the ranking in the *Saber 11* national high school exit exam for need-based eligible students (those below the *Sisbén* threshold) and non-eligible students, stratified by quartiles (according to their *Sisbén* score). The figure illustrates the evolution of the rankings at the mean and median, and for different percentiles of the distribution. The data used to compute the figures excludes information from the wealthier students who do not have a *Sisbén* score.

We estimate the following Difference in Difference model to assess how SPP altered the evolution in the *Saber 11* ranking of eligible and non-eligible students:

$$Ranking_{it} = \beta_0 + \beta_1 \mathbb{I}\{Eligible\}_i + \beta_2 \mathbb{I}\{2015\}_t +$$

$$\beta_3 \mathbb{I}\{Eligible\} \times \mathbb{I}\{2015\}_{it} + \varepsilon_{it}, \qquad (1)$$

where $Ranking_{it}$ corresponds to student's i relative ranking in the *Saber 11* national test in year t, $\mathbb{I}\{Eligible\}_i$ is an indicator variable that denotes whether student i fulfilled the need-based eligibility criteria, $\mathbb{I}\{2015\}_t$ is an indicator variable that takes the value of 1 if $t = 2015$ and 0 if $t = 2014$, and ε_{it} is the

White-robust error term. β_1 provides a measure of the initial achievement gap between (poorer) eligible students and non-eligible students. In turn, β_3 captures the difference-in-difference motivational effect, measuring the change in the ranking of eligible students between 2014 and 2015, relative to the change of non-eligible students over the same period. The DD model has the advantage of offering a bare look at the data, through a simple and transparent functional form and without controlling for any characteristic.

We first estimate the motivational effect through ordinary least squares to assess how the introduction of SPP affected the average ranking of eligible students and estimate quantile regressions to assess the effect on different points of the distribution. For a better comparability, we restrict the sample to the Sisbén eligible students and the non-eligible students at the first quartile of the socioeconomic distribution as in Figure 3.

TABLE 1— DIFFERENCE-IN-DIFFERENCE EFFECT OF SPP ELIGIBILITY ON *SABER 11* RANKING:

	OLS	Quantile Regressions					
		(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	(1)	0.25	0.50	0.75	0.90	0.95	0.99
$\mathbb{I}(Eligible)$	-10.19***	-11.72***	-13.95***	-10.98***	-6.436***	-3.82***	-1.33***
	(0.23)	(0.44)	(0.31)	(0.27)	(0.21)	(0.14)	(0.14)
$\mathbb{I}(2015)$	0.36	0.54	0.10	0.26	0.15	0.32*	0.06
	(0.32)	(0.59)	(0.41)	(0.35)	(0.27)	(0.19)	(0.16)
$\mathbb{I}(Eligible) \times \mathbb{I}(2015)$	0.35	-0.34	0.19	0.74**	0.85***	0.51**	0.55***
	(0.33)	(0.59)	(0.43)	(0.37)	(0.28)	(0.20)	(0.16)
Observations	612,815	612,815	612,815	612,815	612,815	612,815	612,815
Gap Reduction	0.03	-0.03	0.01	0.07**	0.13***	0.14***	0.41***
	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)	(0.05)	(0.09)

Notes: The sample is restricted to the *Sisbén* eligible group and the first quartile of the distribution of the non-eligible according to the *Sisbén* index. The gap reduction is the ratio between the coefficient of eligible *Sisbén* × year and the gap in the *Saber 11* in 2014 between eligible *Sisbén* students and the entire group of non-eligible students. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1 reports the results of the difference-in-difference model above, which are consistent with the patterns observed in Figure 3. The results of the first row of the table, which correspond to the coefficient β_1, indicate that, on average and at every point of the distribution, eligible students rank below the non-eligible students, thus depicting the socioeconomic achievement gap. In turn, the results of the third row of the table, which correspond to the estimated DD coefficient β_3, indicate that the introduction of SPP did not generate a statistically significant change on the average ranking of eligible students between 2014 and 2015, relative to that of non-eligible students. However, we find a significant and sizeable change at the top percentiles, starting around the 75^{th} percentile and increasing for the 90^{th}, 95^{th}, and 99^{th} percentiles. For example, between 2014 and 2015, the 90^{th} percentile of the distribution of eligible students increased by 0.85 percentage points in the *Saber 11* ranking relative to that of non-eligible students in the lowest socioeconomic quartile.

To provide a more intuitive interpretation of the magnitude of the effects, the bottom line of Table 1 reports the estimated effect as a fraction of the 2014 socioeconomic achievement gap between eligible students and the entire set of non-eligible students. The above-mentioned effect of 0.85 percentage points in the ranking of the 90^{th} percentile of the eligible students represents a reduction of 13% in the initial gap between eligible students and non-eligible students. This figure increases as we move towards the top of the distribution: at the 99^{th} percentile, for example, the estimated coefficient of 0.55 percentage points corresponds to a significant reduction of 41% in the socioeconomic achievement gap.[10]

Appendix Table A4 reports the results of a placebo test of the DD model, comparing the change in the *Saber 11* ranking between 2013 to 2014 for eligible students relative to the one of non-eligible students in the first quartile of the

[10] The results are robust if we instead use the students' test-scores as the variable of interest in the DD estimation (see Table A3). Appendix Figure A3 illustrates the reduction in the initial gap in ranking between eligible and non-eligible students across the test-score distribution and highlights a significant gap reduction starting at the 70th percentile of the distribution.

socioeconomic *Sisbén* index. Here we should not observe positive effects since the 2014 cohort only became aware of the scholarship after the exam was administered. Indeed, we do not observe evidence of a motivational effect on the average ranking or at the top of the distribution. Quite the opposite, we observe a negative and significant effect concentrated at the bottom of the distribution.

Taken together, the results above are consistent with our hypothesis of an ex-ante motivational effect that emerged in 2015 at the top of the distribution. The attribution of causality of these findings rests on the assumption that no other policy or event occurred in 2015 and affected the top of the test score distribution of eligible students differently than the one of non-eligible students. Two features lend credence to the notion that the results above capture causal ex-ante motivational effects of SPP: First, SPP is by far perceived as the major change in education that occurred in Colombia around this period. In fact, as we will discuss in the following section, there were no other programs that were introduced prior to 2014 in which eligibility was determined by the same *Sisbén* threshold. Second, it is hard to imagine any alternative major event that took place in 2015 and that affected exactly the top students of low-income (eligible) households but not the rest of the distribution nor the wealthier students. Hence, the results above appear as a credible estimate of the ex-ante motivational effect of the scholarship. To provide additional evidence of a causal motivational effect of SPP, in the next section we estimate an RDD based on the student's *Sisbén* score.

B. RDD Estimates of the Motivational effect of SPP

We now use an RDD to compare test-scores of students above and below the *Sisbén* eligibility threshold. Since we compare students who are very similar in all aspects except in their eligibility to the scholarship, a significant difference in the test scores of the two groups can be attributed to the motivational effect of the scholarship.

We discuss the RDD model and results below, and then report the standard specification tests.

For the cohort of students who took the Saber 11 in 2015, we estimate the following model:

$$Score_i = \beta_0 + \beta_1 \mathbb{I}\{Eligible\}_i + \beta_2 Sisben_i + \beta_3 Sisben_i^2 + \beta_4 Sisben \times \mathbb{I}\{Eligible\}_i + \beta_4 Sisben^2 \times \mathbb{I}\{Eligible\}_i + X_i' \gamma + \varepsilon_i, \quad (2)$$

where $Score_i$ is student i's test-score in the *Saber 11* exam in 2015, $\mathbb{I}\{Eligible\}_i$ is an indicator variable for whether student i fulfills SPP's need-based eligibility criteria, $Sisben_i$ is the continuous *Sisbén* score of the student's household, X_i' is a matrix of individual and school level characteristics, and ε_i is the White-robust error term.[11] Hereafter, our variable of interest is the test score rather than the ranking, to avoid overestimating the impact of SPP, which would occur if the ranking of the control group is negatively affected by the fact that eligible students perform better.[12] We use a quadratic polynomial and allow the quadratic relationship to differ on both sides of the cutoff. Following Gelman and Imbens (2017), we do not control for higher order polynomials of the forcing variable, whereas in the following section we use an RDD using a smoothed local polynomial. Finally, we use the optimal bandwidths recommended by Calonico, Cattaneo, and Titiunik (2014) to assess the robustness of the results across different bandwidths.[13]

TABLE 2— RDD EFFECT OF ELIGIBILITY ON *SABER 11* SCORE

Bandwidth	OLS	Quantile						Obs.
	MCO	0.25	0.5	0.75	0.9	0.95	0.99	

[11] In matrix X_i' we control for the students' area of residence (14 main cities, other cities, or rural area), parents' level of education, gender, age, school ranking in the 2014 *Saber 11*, and dummies for state of residency of the student.

[12] The results using the relative ranking as the outcome variable instead of the score lead to a similar conclusion; that the positive effects of the eligibility on *Saber 11* score are concentrated in the top of the distribution (see Appendix Table A5).

[13] The bandwidths are organized in the following order: MSERD, MSESUM, CERRD and, finally, CERSUM. The first two are constructed with the mean square error, while the latter two with the coverage error rate. The first and third are constructed for the optimal RD, while the other two are designed with the sum of the regression estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	0.41	-0.49	-0.04	1.48	4.22**	1.05	4.03	61,474
[7.51]	(0.92)	(0.95)	(1.11)	(1.20)	(2.04)	(2.17)	(4.90)	
MSESUM	0.86	-0.55	0.44	1.98	3.85*	1.56	2.52	53,203
[6.50]	(0.97)	(1.30)	(0.99)	(1.32)	(2.27)	(2.77)	(4.47)	
CERRD	1.79	0.59	1.54	3.31*	5.28**	5.48*	6.82	32,032
[3.97]	(1.25)	(1.57)	(1.47)	(1.85)	(2.62)	(3.00)	(6.83)	
CERSUM	2.34*	0.56	1.98	3.85*	5.13*	6.03*	11.44	27,674
[3.43]	(1.34)	(1.56)	(1.71)	(2.19)	(2.76)	(3.11)	(7.73)	

Notes: The table reports the coefficients of the eligibility dummy on *Saber 11* scores following model (2). The model is constructed with the *Sisbén* and its quadratic term, both interacted with the eligibility dummy. The first column in the table reports the LATE of the scholarship at the need-based eligibility threshold, whereas Columns 2-7 report the results from estimating model 2 through quantile regressions to assess the distributional effects of the scholarship. Each row in the table reports the results of estimating model 2 for different optimal bandwidths following Calonico, Cattaneo and Titiunik (2014). All specifications use the following controls: students' age, gender, and area of residence (14 main cities, other cities, or rural area), parents' level of education, high school ranking in the 2014 *Saber 11*, and fixed effects for student's state of residency. Robust standard errors in parentheses. Standard errors of the quantile regressions are bootstrapped with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

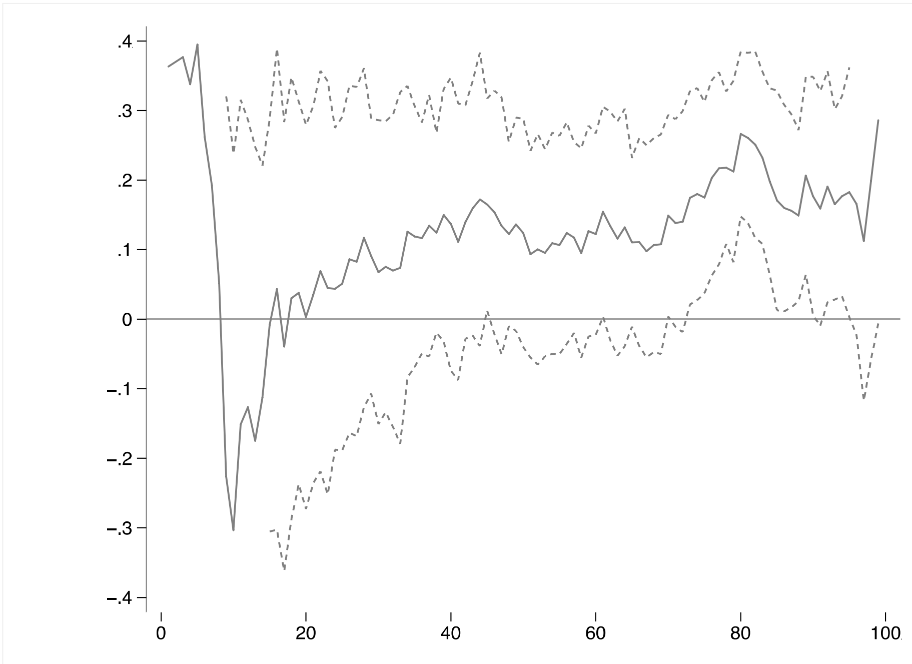
In Table 2, we report the results from the RDD estimates of the effect of the need-based eligibility for the scholarship on students' test scores in the *Saber 11*. For conciseness, we only report the estimated coefficient of interest β_1 and its standard error. In Column 1, we report the result from estimating model 2 through ordinary least squares, which corresponds to the Local Average Treatment Effect (LATE) of the eligibility to the scholarship estimated at the eligibility threshold. We find that eligibility to the scholarship only had a positive and significant effect on average test scores when we use the smallest optimal bandwidth. This result, however, is not robust across other bandwidths.

In columns 2 to 7, we estimate model 2 by quantile regressions at the 25^{th}, 50^{th}, 75^{th}, 90^{th}, 95^{th}, and 99^{th} percentiles, to explore the distributional effects. We observe that the motivational effect of SPP is concentrated at the top of the distribution, just as we had observed with the DD model. For instance, the effect of the eligibility at the 90th percentile ranges from 4.22 to 5.28 points in the *Saber 11* and is statistically robust regardless of the optimal bandwidth that we use. For example, when we use the smallest optimal bandwidth, results indicate that the 90^{th} percentile of the *Saber 11* score for eligible students was 5.13 points higher than that for non-eligible students (Table 2, Column 5). This effect is more than twice as high as the average effect obtained by OLS.

We also find positive and significant effects at other points of the distribution. For instance, when we use the smallest optimal bandwidth, we find that eligibility to SPP brought forth an increase of 3.85 and 6.03 points in the *Saber 11* at the 75th and 95th percentiles of the distribution, respectively. These effects, however, are not robust to the use of all optimal bandwidths.

To provide a more intuitive picture of the magnitude and heterogeneity of the motivational effect of SPP, in Figure 4 we illustrate the gap reduction resulting from the eligibility to the scholarship, across the distribution of test scores. At each percentile of the quantile RDD and using the CERSUM bandwidth, the gap reduction corresponds to the estimated β_1 coefficient divided by the gap between all eligible students and all non-eligible students. The figure indicates that the reduction in the socioeconomic achievement gap, which stems from the motivational effect of SPP, emerges around the 70th percentile. Between the 90 and 95th percentiles of the test-score distribution, the motivational effect of SPP leads to a reduction of approximately 17 percent. This result is of similar magnitude to the 14% gap reduction that we observed by the DD estimate at the 90th percentile. In addition, we observe that the gap reduction peaks at the 80th percentile, reaching a sizeable and strongly significant reduction of 26 percent in the socioeconomic achievement gap.

FIGURE 4—RDD ESTIMATIONS OF GAP REDUCTION IN SABER 11 TEST SCORE BY PERCENTILE



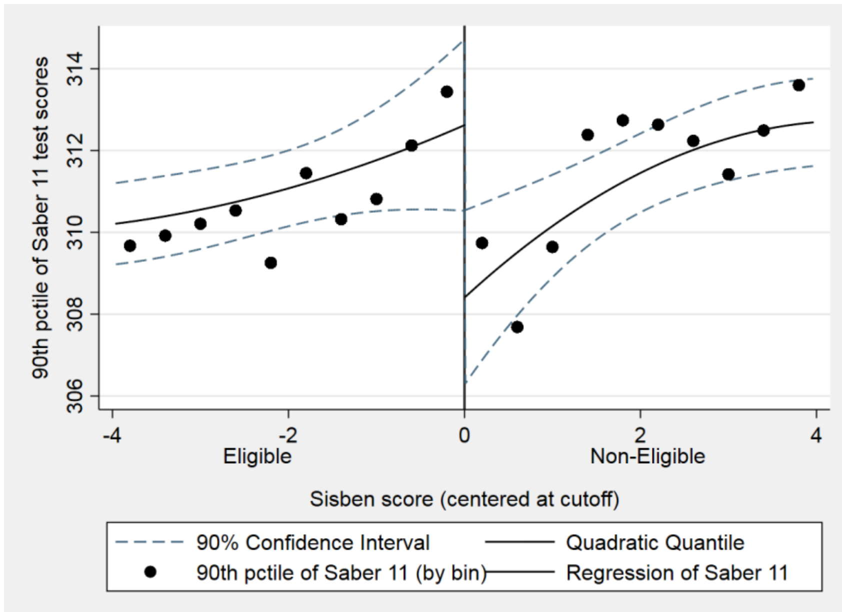
Notes: At each percentile, the gap reduction is calculated as the estimated motivational effect at that percentile p using table 2's RDD quantile estimation for the smallest optimal bandwidth (CERSUM), divided by the gap in percentile p in 2014. The latter, is the difference between the percentile p in the Saber 11 of all non-eligible students to percentile p of Saber 11 of all eligible students.

Below we report the standard specification and robustness tests for the RDD model. We conduct this analysis at the 90th percentile of the distribution, to be consistent with our initial hypothesis and to avoid endogenously selecting the percentile where observed the strongest effect. Figure 5 illustrates the quadratic quantile regression at the 90th percentile, around the socio-economic cutoff. The curve illustrates the prediction resulting from the estimation of model (2) and its 90% confidence intervals. The dots in the figure represent the 90th percentile calculated within each bin, corresponding to intervals of 0.4 units of the *Sisbén* score.[14] Figure 5 highlights the sharp and statistically significant discontinuity in test scores at the need-eligibility threshold. Consistent with the results of Table 2, Column 5, which correspond to the quadratic quantile RDD regression at the 90th

[14] The high frequency of bins leaves on average 85 observations per bin.

percentile, we find an effect of eligibility of *Saber 11* test scores of approximately 5 points.

FIGURE 5—QUANTILE REGRESSION DISCONTINUITY: 90TH PERCENTILE, SECOND ORDER POLYNOMIAL



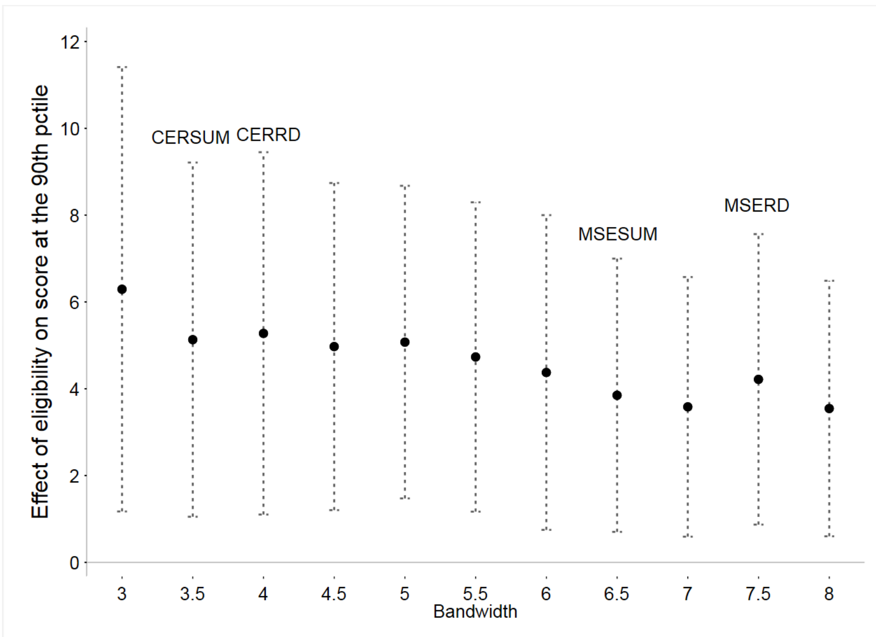
Notes: The projection and 90% confidence intervals correspond to the estimation of regression (2) and the results of table 2, column 5 (the RDD quadratic quantile regression at the 90th percentile). The dots represent the 90th percentile calculated within each bin (intervals of .4 units of Sisbén).

In Figure 6 we test for the sensitivity of the results at the 90th percentile across different bandwidths. We illustrate the point estimate and confidence intervals for a set of bandwidths that encompass the four optimal bandwidths recommended by Calonico, Cattaneo and Titiunik (2014). The figure demonstrates that our main conclusion is not sensitive to the choice of bandwidth, lending further credence to the motivational effect of SPP at the top of the distribution.

The validity of the RDD specification relies on the assumption of conditional unconfoundedness. This is, that in the absence of SPP, the test score distributions of eligible students and non-eligible students would have been the same at the vicinity of the need-based threshold, conditional on the forcing variable and other controls. Below we address three concerns that can affect the validity of the RDD:

whether the forcing variable was subject to manipulation, whether students below and above the threshold are comparable, and the possibility that other social programs used the same cutoff and could thus partially explain the results above.

FIGURE 6—QUANTILE REGRESSION EFFECTS AT THE 90TH PERCENTILE FOR DIFFERENT BANDWIDTHS



Notes: The RDD estimate of the Local Average Treatment Effect of being eligible to receive the scholarship on the 90th percentile of Saber 11 score (coefficient β_1 of equation 2), is estimated for various bandwidths.

First, we argue that it is unlikely that the *Sisbén* score was manipulated specifically around the eligibility threshold. Since its third version, which started being used in 2009, the *Sisbén* cannot be modified by any local authority and is directly calculated by an online application, using a formula unknown to the public.[15] To confirm this, we test for discontinuity in the density of observations at the cutoff. A bunching below the cutoff would suggest that households were able

[15] The Sisbén index may be subject to "manipulation" in the sense that some respondents try to appear poorer to be more likely to benefit from social programs; for example, by failing to disclose asset ownership. However, this is not an issue for identification if this does not happen differentially above and below the eligibility threshold of SPP. Since the formula is unknown to the public, it is unlikely that at the time of the survey, respondent can manipulate answers in a way that affects whether their *Sisbén* will be just above or below the cutoff.

to manipulate the *Sisbén* score to become eligible for the program, thus creating selection effects and raising concerns about non-observable differences between students below and above the eligibility cutoff. A visual inspection of the *Sisbén* distribution in Figure 2 and in Appendix Figure A5, in which we zoom-in at the vicinity of the need-based threshold, shows no evidence of bunching around the threshold. Furthermore, the Cattaneo, Jansson, and Ma (2017) test confirms the absence of any significant discontinuity in the density of the *Sisbén* score at the cutoff (p-value=0.303).[16]

Second, we analyze whether students just below and above the cutoff are similar across a range of individual and household characteristics. For this purpose, we first run model (2) using as the outcome variables also the set of controls used in the RDD. We report the results of this analysis in Table 3. We find that only four out of 44 estimated coefficients are significant at the 10 percent level. This is not beyond what should be expected due to random variation. Hence, we do not find evidence of systematic differences between students just below and above the cutoff.

[16] Compared to the McCrary test (2007), this local polynomial density estimation technique improves size properties because it avoids pre-binning of the data and is constructed in an intuitive way based on easy-to-interpret kernel functions.

TABLE 3—RDD ON CONTROLS

Bandwidth	Area		Father's education			Mother's education			Age	Sex	2014 High School Ranking	Obs.
	14 cities	Urban	Primary	High School	Tech.	Primary	High School	Tech.				
MSERD	0.01	-0.02***	-0.01	0.00	-0.00	0.00	0.00	-0.01*	-0.015	-0.01	0.07	61,474
[7.62]	(0.008)	(0.008)	(0.008)	(0.008)	(0.004)	(0.007)	(0.008)	(0.005)	(0.033)	(0.008)	0.239	
MSESUM	0.01	-0.02**	-0.01*	0.00	-0.00	0.00	0.00	-0.01	-0.04	-0.004	0.20	53,203
[6.11]	(0.009)	(0.009)	(0.008)	(0.009)	(0.005)	(0.008)	(0.009)	(0.005)	(0.035)	(0.009)	0.256	
CERRD	-0.01	0.01	-0.02	0.01	0.00	0.00	-0.01	-0.01	-0.03	0.00	-0.20	32,032
[4.02]	(0.011)	(0.011)	(0.010)	(0.011)	(0.006)	(0.010)	(0.011)	(0.007)	(0.046)	(0.011)	0.328	
CERSUM	-0.01	0.00	-0.02	0.01	-0.00	0.01	-0.01	-0.00	-0.03	-0.008	-0.29	27,674
[3.22]	(0.012)	(0.012)	(0.011)	(0.012)	(0.006)	(0.011)	(0.012)	(0.007)	(0.051)	(0.012)	0.359	

Notes: The table reports the coefficients of the eligibility dummy on the outcome variables, which are the set of controls used in the main regression (model 2). Each row in the table reports the results of estimating model 2 for different optimal bandwidths following Calonico, Cattaneo and Titiunik (2014). The model is constructed with the Sisbén and its quadratic term, both interacted with the eligibility dummy. Robust standard errors in parentheses. Standard errors of the quantile regressions are bootstrapped with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

Perhaps the main threat to the RDD validity relates to the existence of other governmental programs that use the same *Sisbén* threshold to determine eligibility. In Table A5 we report an exhaustive list of social programs that were active in 2015 and used the *Sisbén* to determine eligibility. We observe that 6 programs used the same cutoff as SPP for at least part of the population.[17] However, these programs do not relate to education, but rather focus on early childhood development, housing, pensions, and humanitarian aid for victims of violence. While it is possible that these programs had spillovers through reallocation of resources within the household, it is hard to conceive why the spillovers would only affect the top of the test-score distribution. A notable exception is the ICETEX program, which provides credit at a subsidized interest rate to college students.[18] However, 5 out of the 6 programs, including ICETEX, started before 2014.[19] We conduct a placebo test of the RDD in 2014, before students were aware of SPP. Results in Appendix Table A6 indicate that being below the *Sisbén* eligibility threshold had no effect on the *Saber 11* test scores at the top of the distribution.[20] This result rules out that other programs partially explain the effects that we attribute to the motivational effect of SPP in 2015.

Finally, in principle an RDD requires that the treatment does not affect the control group. In our analysis, it is likely that SPP affected the non-eligible students through an increase in competition. To illustrate this, we can break up the impacts of the scholarship into two effects: the motivational effects on eligible students and the competition effect. To the extent that the latter affects all students, our

[17] Different cutoffs are applied for 14 largest cities, other cities, and rural areas. Programs can share the same cutoff for only one, two, or the 3 types of residence.

[18] Even if ICETEX contributed to the motivational effect through access to university, this would be consistent with the channel that we propose. Nevertheless, a credit is likely to generate a smaller motivational effect than a full scholarship.

[19] The only program that started in 2015 is a savings program for the elderly who do not have a pension, and it is unlikely that it had any effect on tests scores concentrated on students at the top of the distribution.

[20] If anything, we find a negative effect of eligibility on test scores at the top of the distribution in 2014, yet these effects are not robust to the use of the four optimal bandwidths.

empirical approach provides an estimation of the motivational effect, which drives the difference between eligible and non-eligible students.[21] If one expects a heterogeneous competition effect based on the *Sisbén*, this would invalidate the difference in difference approach. Yet, this would not invalidate the RDD since there is no reason to expect that the competition effect would differ around the Sisbén eligibility threshold.

C. Non-parametric analysis of the discontinuity at the eligibility cutoff and in the change in Saber 11 test scores between 2014 and 2015

An additional concern regarding the validity of our RDD analysis refers to the robustness of the results to changes in the functional form. For this purpose, we conduct a non-parametric RDD quantile estimation of the effect of eligibility on the *Saber 11* score and on the change in *Saber 11* scores from 2014 to 2015.

Following Gelman and Imbens (2017), we use a smoothed local polynomial, in which each observation is implicitly weighted by a function that is decreasing in its distance to the cutoff. The combination of local polynomial and quantile regressions introduces challenges, which we address in the following way: First, we group the observations within a small bin of 0.02 units of the forcing variable (the *Sisbén* index). Second, within each bin we calculate the 90th percentile of the *Saber 11* score. Finally, for each side of the eligibility cutoff, we run a first order local polynomial on the estimated 90th percentile of each bin. This provides an estimation of the way in which the 90th percentile moves as a function of the forcing variable and the eligibility status.

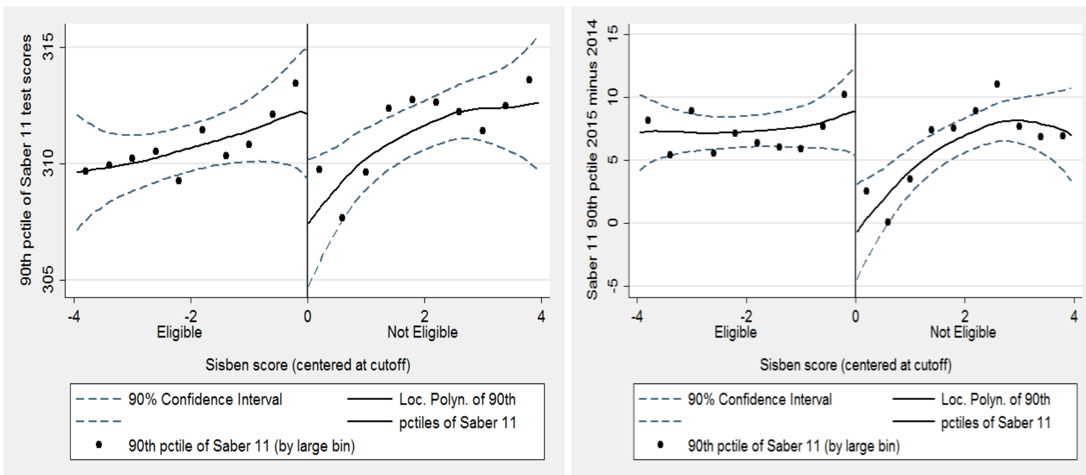
In figure 7, Panel A illustrates the discontinuity at the eligibility cutoff for the 2015 scores. We find that the discontinuity is significant and of a magnitude of 5

[21] We assume that students can be affected differently depending on their percentile of the score distribution, but not on their eligibility status. The competition can either push students to work harder, or sometimes discourage them if it raises the bar too high compared to the level that the student believes she can achieve.

points in the *Saber 11* score, in line with the results of table 2. Moreover, we observe that the shape of the non-parametric estimation on both sides of the cutoff, is similar to the one of the quadratic estimation observed in figure 5. This provides reassurance about the fit of the functional form used in the parametric estimation.

FIGURE 7— QUANTILE REGRESSION DISCONTINUITY USING LOCAL POLYNOMIAL

A. 90TH PCT OF SCORES IN 2015 B. CHANGE IN 90TH PCT OF SCORES (2014 & 2015)



Notes: In Panel A, we calculated the 90th percentile of the *Saber 11* score by bin of 0.02 units of the *Sisbén* index, and present, separately on each side of the eligibility threshold, a local polynomial of the estimated 90th percentile of each bin and its 90% Confidence Interval. The dots represent the 90th percentile calculated within each larger bin (of .4 units of Sisbén). In Panel B, we apply the same method except that for each bin we use the difference between the 90th percentile of the *Saber 11* scores in 2015 and the 90th percentile of the *Saber 11* scores in 2014.

The non-parametric analysis also allows us to assess how the change in the 90th percentile of *Saber 11* from 2014 to 2015 differs around the eligibility threshold. This presents the advantage of isolating the effect of other programs that benefited the eligible population both in 2014 and 2015. [22] We apply the same methodology described above, except that we now calculate, within each bin, the difference between the 90th percentile of the *Saber 11* score in 2015 and in 2014.

[22] This assumes that the number of beneficiaries of other programs did not vary considerably from 2014 to 2015. However, the fact that the significance increases when looking at the variation from 2014 to 2015 largely reduces any concern that other programs had any clear positive effect on their beneficiaries at the 90th percentile of *Saber 11*.

In figure 7 Panel B, we observe that both the magnitude and significance of the discontinuity in test scores at the eligibility cutoff are greater than when we estimated the effects in 2015. Hence a look at the change from 2014 to 2015 reinforces our previous conclusions. Moreover, it provides additional evidence that the effects in Table 2 are not due to other social programs that use the same *Sisbén* cutoff.

Taken together, the results from this section highlights a sizeable motivational effect of the eligibility to SPP on student's test scores that emerges at the top of the test score distribution; an effect that is robust to the choice of bandwidth, to the standard RDD tests and to different specifications of the model.

IV. Additional Results

A. Aspirational Effect

In this section, we investigate whether there is an aspirational effect for eligible students who attend a high school in which a student received a SPP scholarship in the previous year. The observation of peers who succeeded and obtained the scholarship in 2014 may have increased the aspirations of eligible students and thus reinforce the motivation of eligible students in 2015 through the following channels: first, by making more likely that students became aware of the scholarship and the rules for eligibility and believed in its proper implementation; second, by raising the salience of the opportunities brought forth by the scholarship; and third, through a role-model effect that enhanced the perception that the scholarship is attainable for students who would otherwise have perceived it as an unachievable goal.

To explore the aspirational effect, we follow an RDD strategy as in model (2), except that we now stratify the sample into two groups based on whether at least one student of the same school received the SPP scholarship in 2014.[23] The results in Table 4, Panel A indicate that the motivational effect that we documented in Table 2 is driven by students who attended high schools in which at least one student was awarded the SPP scholarship in 2014. For instance, we observe strong and robust effects at the 90th percentile, which range between 4.3 and 7.4 points in the *Saber 11*. In general, these effects are larger in magnitude than those observed with the full sample in Table 2. In addition, for the two smallest optimal bandwidths we again observe positive and significant effects at the 75th and 95th percentiles, just as we had observed with the full sample. By contrast, for students coming from high schools without any SPP recipient in 2014, the motivational effect is not significantly different from zero at any percentile of the distribution and has a smaller or even a negative point estimate (Table 4, Panel B).

The results in Table 4 are suggestive of an aspiration effect, broadly encompassing a pure information effect, an increased salience of the program, and a perception that the scholarship is accessible through a role model effect. Yet, this interpretation relies on the underlying assumption that high schools with and without at least one recipient of the SPP scholarship in 2014 did not differ systematically. However, it is likely that the high schools that had at least one recipient of the scholarship in 2014 were also of better quality, had better teachers or students, and hence to be better able to respond to the opportunity created by the scholarship. In that case, the results above would be driven by differences in high school-level characteristics, rather than being suggestive of an aspirational effect.

[23] In 2015, 61% of students were enrolled in a high-school in which there was at least 1 student who received the scholarship in the previous year.

TABLE 4—ASPIRATIONAL EFFECT

A—STUDENTS IN HIGH SCHOOLS WHERE AT LEAST ONE STUDENT RECEIVED SPP IN 2014

	OLS	Quantile						
Bandwidth	MCO	0.25	0.5	0.75	0.9	0.95	0.99	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	-0.22	-1.31	-1.00	1.47	4.27**	1.98	4.74	45,755
[7.981]	(1.050)	(1.399)	(1.124)	(1.496)	(2.147)	(2.834)	(5.332)	
MSESUM	-0.092	-1.02	-1.29	2.09	4.46**	2.21	3.11	40,873
[7.147]	(1.118)	(1.537)	(1.356)	(1.405)	(2.128)	(2.816)	(5.557)	
CERRD	1.37	-0.28	0.34	3.78*	7.38***	6.55**	3.41	24,600
[4.329]	(1.436)	(1.812)	(1.949)	(1.990)	(2.729)	(3.234)	(6.599)	
CERSUM	1.14	-0.73	0.27	3.61*	5.79**	6.52*	4.61	21,999
[3.877]	(1.506)	(1.653)	(1.671)	(1.943)	(2.765)	(3.490)	(6.694)	

B—STUDENTS IN HIGH SCHOOLS WHERE NO STUDENT RECEIVED SPP IN 2014

	OLS	Quantile						
Bandwidth	MCO	0.25	0.5	0.75	0.9	0.95	0.99	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	-0.28	-0.88	1.16	0.54	-0.11	-3.67	-3.39	21,819
[8.875]	(1.511)	(1.687)	(1.824)	(2.085)	(3.143)	(4.067)	(8.444)	
MSESUM	0.96	0.15	2.67	0.89	0.82	-3.47	1.34	19,201
[7.846]	(1.596)	(1.786)	(2.031)	(2.322)	(3.638)	(4.730)	(7.091)	
CERRD	2.50	2.21	4.04	3.25	1.90	0.78	0.40	11,749
[4.915]	(2.035)	(1.937)	(2.469)	(3.380)	(4.456)	(6.083)	(10.760)	
CERSUM	2.21	2.55	3.88	2.21	-0.61	1.32	-0.94	10,342
[4.346]	(2.167)	(2.167)	(2.545)	(3.394)	(5.083)	(6.249)	(13.130)	

Notes: Estimates from the heterogeneity analysis following model 2: Panel A reports the coefficients of the eligibility dummy on *Saber 11* scores for the subsample of students who attended high schools in which at least one student was awarded the SPP scholarship in 2014. Panel B reports the coefficients of the eligibility dummy for the subsample of students who attended high schools in which no student was awarded the SPP scholarship in 2014. As in Table 2, the first column in each panel reports the LATE, whereas Columns 2-7 report quantile effects. Likewise, each row in the table reports the results for different optimal bandwidths following Calonico, Cattaneo and Titiunik (2014). All specifications use the same controls as in Table 2, including the high school's ranking in the 2014 Saber 11. Robust standard errors in parentheses. Standard errors of the quantile regressions are bootstrapped with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

While the previous argument cannot be fully ruled out, we provide evidence that the results above are not explained by high school-level characteristics. In particular, we explore whether higher-quality schools were better able to respond to the opportunity brought forth by SPP. For each high school, we calculate the average test score among eligible students and then conduct the RDD stratifying the sample according to whether students were in a high school above or below the median of all high schools. The average score of eligible students should be a better proxy for school quality than the dummy for whether at least one student obtained the SPP scholarship because the latter is driven by the test scores of a few students and thus bears a stronger idiosyncratic component. Hence, if the results in Table 4 are explained by the ability of high-quality schools to react to SPP, this additional analysis should yield at least as much heterogeneity between the two groups. However, in Table A6 we find no systematic difference between the motivational effects estimated in high quality schools compared to low quality schools.

A priori, a better way to isolate the motivational effect of having a student in 2014 receiving the scholarship is to use an RDD in which the forcing variable is the test score of the best eligible student in the high-school in 2014, and the cutoff is the *Saber 11* score required to obtain the SPP scholarship in 2014.[24] However, we do not find any significant effects using this method.[25] A plausible explanation for this null result is that this RDD focuses on high-schools in which the best student was in the vicinity of the *Saber 11* eligibility cutoff in 2014. However, most top universities apply an admission cutoff above the one used by SPP, meaning that the students whose *Saber 11* was barely above the threshold most likely did not access one of these universities.[26] It is then conceivable that the aspirational effect is particularly strong when a peer accessed one of the most renowned universities in

[24] The test score of the best eligible student of the school in 2014 is the forcing variable that triggers whether or not there is at least one student in the school that is offered the SPP scholarship.

[25] Results available upon request

[26] In Figure A4 we can observe that students who in 2014 obtained a *Saber 11* score between 310 and 315 are largely under-represented in the top accredited universities and are over-represented in the middle to lower quality accredited universities.

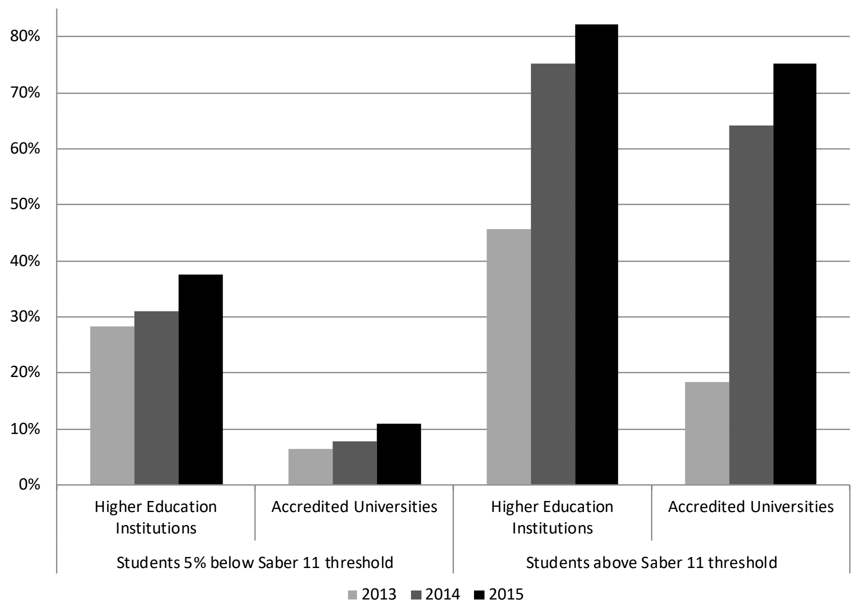
the country, but this is not captured by an RDD that estimates the local effect around the *Saber 11* eligibility cutoff of SPP.

B. Changes in Enrollment Rates for Low-Income Students

Our results indicate that eligibility to the scholarship motivated students, and possibly their parents and teachers, to exert a higher level of effort to obtain the required *Saber 11* test score. However, it is not straightforward that this positive effect on learning made eligible students better off. Many of the students who exerted a higher level of effort will not reach the required test score to obtain the scholarship. In fact, plausibly because of the increased motivation, the merit-based threshold increased from 310 in 2014 to 318 in 2015 and to 340 in 2016, implying that obtaining the scholarship became more challenging over time. Hence, since the number of scholarship is fixed to 10,000 per year, the increase in competition may bring additional costs in terms of effort without improving the economic prospects for the non-recipients and induce frustration. Nevertheless, we find evidence suggesting that the motivational effect had positive effects on post-secondary enrollment, even for eligible students who did not reach the *Saber 11* merit-based threshold.

In Figure 8, we illustrate the evolution of enrollment rates in post-secondary institutions between in 2013 and 2015 for low-income students with a *Sisbén* index below the threshold that in the latter two years was used to define the need-based eligibility. In the right-hand panel of Figure 8, we illustrate the enrollment rates for students in the top 5 percentiles of the *Saber 11* in each year. In 2014 and 2015, these students are almost exactly those who scored above the *Saber 11* merit-based threshold (see Appendix Table A1). Unsurprisingly, enrollment rates at accredited universities dramatically increased for this group of students from 18 to 64 percent between 2013 and 2014 as a result of the unexpected introduction of the scholarship. From 2014 to 2015, enrollment rates further increased by 11 percentage points, even though the number of beneficiaries of the scholarship remained identical. The last results is consistent with our hypothesis, according to which the improvement in *Saber 11 test* scores in 2015, resulting from the motivational effect, contributed to this additional increase in enrollment at accredited universities.

FIGURE 8—HIGHER EDUCATION ENROLLMENT OF NEED-BASED ELIGIBLE STUDENTS ABOVE AND BELOW THE ACADEMIC CUTOFF OF SPP



Notes: Figure 8 illustrates enrollment rates at higher education institutions and at accredited universities. The sample is restricted to students with a *Sisbén* score that satisfies the need-based eligibility criteria. Students above the *Saber 11* threshold are: (1) the top 5% of eligible students in the 2013 *Saber 11*; (2) 4.9% of eligible students with a score above 310 in the 2013 *Saber 11*; and (3) 4.9% of eligible students with a score above 318 in the 2015 *Saber 11*. Students below the *Saber 11* threshold are the 5% of eligible students just below those who scored above the threshold in each year.

More important for the discussion of possible frustration effects, the left-hand of Figure 8 illustrates enrollment rates for the need-based students who scored between the 5^{th} and the 10^{th} percentile in the *Saber 11* in 2013, 2014, and 2015. In 2014 and 2015, this corresponds to the 5% of eligible students just below the *Saber 11* merit-based threshold. Although these students did not receive the SPP scholarship, they also experienced a sizeable increase of 7 percentage points in the enrollment rate in all higher education institutions and of 3 percentage points in accredited universities. These figures correspond to sizeable 18 and 42 percent changes in the enrollment rates respectively. It is plausible that, by exerting more effort, these students improved their Saber 11 test scores, which in itself opened new opportunities. Hence the findings of figure 8 provide evidence suggestive of a motivational effect that had positive effects on enrollment to university, even among students who did not obtain the scholarship.

V. Discussion

In this article, we assess the ex-ante, motivational effect of SPP, a nationwide merit and need-based scholarship program in Colombia that allows low-income students to attend top quality universities. We separately implement a DD an RDD based on the need-based eligibility criteria and find a substantial motivational effect that raised the performance of eligible students at the top distribution in the *Saber 11* national high school exit exam. At the 90^{th} percentile of the distribution, the ex-ante, motivational effect of SPP led to a remarkable reduction of about 14 to 17% in the socioeconomic achievement gap between eligible and non-eligible students. In addition, we find that the motivational effect is concentrated in schools where at least one student received the scholarship in 2014, suggesting an aspiration effect. Furthermore, in 2015 the enrollment rates increased substantially among eligible students who obtained a *Sisbén* score slightly below the merit-based criteria of the scholarship.

The ex-ante motivational effects of SPP can be interpreted from two different perspectives. On the one hand, the fact that the motivational effect of SPP only emerged among students with the highest potential is a strong limitation of this policy, highlighting that the program may be a complement rather than a substitute to other education policies. On the other hand, the reduction in the socioeconomic achievement gap among top students is a remarkable result, especially when considering that eligible students had ten months to respond to the new opportunities brought forth by the scholarship. Over time, the motivational effect may influence students from early-on in their curriculum, become stronger, and span across a broader segment of low-income students. Molano, Rodríguez, and Bayona (2017) document an unprecedented reduction in the socioeconomic achievement gap in the national exams for grades 3, 5, and 9. While their data do not allow causal evidence of a motivational effect of SPP on younger cohorts, it is consistent with a higher level of effort among low-income students in primary and secondary schools.[27]

A common concern with incentives to study is the possibility that the extrinsic motivation to obtain the reward replaces students' intrinsic motivation. In this context, this means that students may redirect their effort to mastering the *Saber 11* without a positive effect on their human capital accumulation. We cannot fully rule out that students redirected their effort towards the *Saber 11* at the expense of other forms of learning. However, it is worth noting that SPP provides an incentive to allow top-performing low-income students to pursue a higher education degree at a top university, which may in fact reinforce their intrinsic motivation. Furthermore, since the *Saber 11* is a general knowledge exam that covers the entire high-school curricula and 10 different subjects, it is difficult to imagine that students could substantially increase their test scores without improving their skills and knowledge. Finally, the reduction in the socioeconomic achievement gap in the national exams for grades 3, 5, and 9 documented by Molano *et al.* (2017)

[27] Unfortunately, administrative data on younger cohorts is less complete and cannot be linked to the households *Sisbén* index. This forbids us from exploring the causal ex-ante effects of SPP on test scores during primary and secondary education. Likewise, we cannot explore the motivational effects of SPP beyond 2015, since the micro-data for the 2016 and 2017 *Saber 11* exams has not been shared by the Ministry of Education.

suggests an intrinsic motivation for human capital accumulation since these exams have low, if any, incentives for the students.

Taken together, our results should contribute to the debates on the costs and benefits of merit-based scholarships, which by and large have focused on the ex-post effects for actual recipients. For instance, SPP has been contested among policy and academic circles in Colombia, especially regarding the program's cost, which will represent nearly 20% of the Ministry of Education's budget for higher education in 2018. The program's costs are substantial considering that only 3% of students per cohort receive the scholarship. As such, current proposals lean towards shutting down the program and using the available resources to increase the enrollment of low-income students in public universities.

Unfortunately, these discussions fail to consider the positive and substantial ex-ante benefits that reach beyond the scholarship's beneficiaries. Our paper does not aim to be normative and a full cost-benefit analysis of SPP goes well beyond our reach. However, we find that SPP brought about a considerable reduction in the socioeconomic achievement gap, an increase in higher education enrollment rates even for eligible students who failed to obtain the scholarship, and a mechanism that promotes socioeconomic mobility and contributes to reduce the intergenerational reproduction of poverty and inequality. Therefore, it is an open question how to weight the program's substantial costs against the ex-ante and ex-post effects and especially against the equity gains that it brings about.

Our analysis highlights important lessons on the extent to which the lack of meritocracy discourages effort and human capital accumulation. The results suggest that an unequal distribution of opportunities harms the human capital accumulation of low-income students. The loss in human capital occurs not only because good students from vulnerable households cannot afford to enroll at a top university, but also because being a good student is endogenous to prior effort, which is conditional on whether students perceive that such effort will pay off.

Hence, a lack of real opportunities discourages low-income students from exerting effort throughout the schooling process, which hinders their capacity to move out of poverty and becomes a different mechanism through which inequality reproduces over time. On the contrary, when low income students perceive attainable and meritocratic opportunities for social mobility, their effort, motivation, and human capital accumulation increase and pave the way for actual transitions out of poverty.

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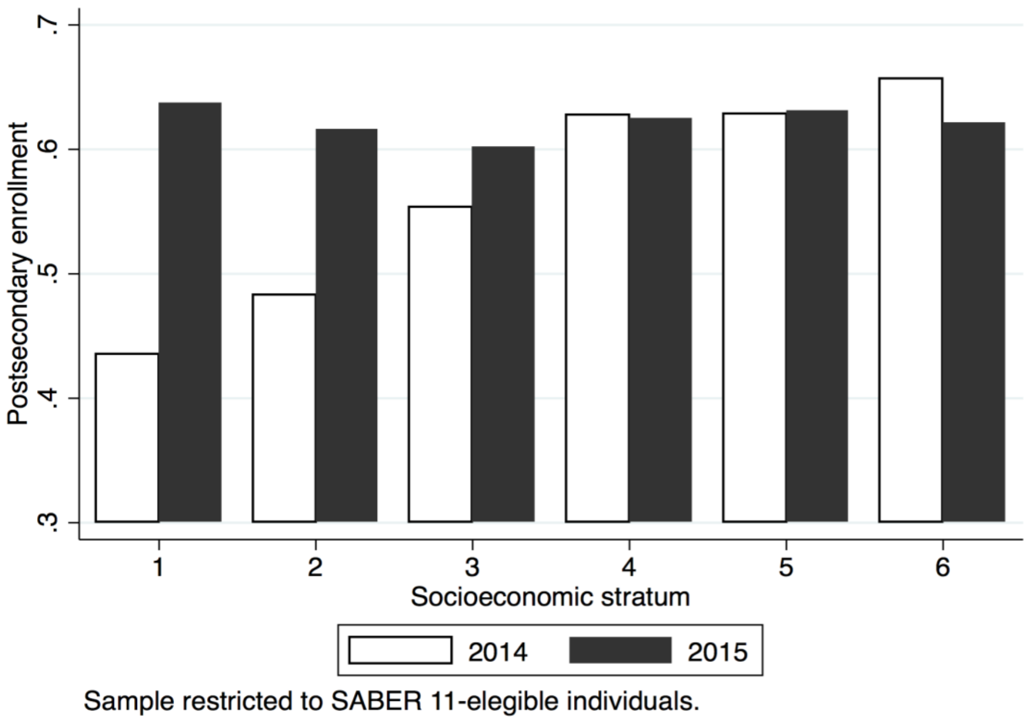
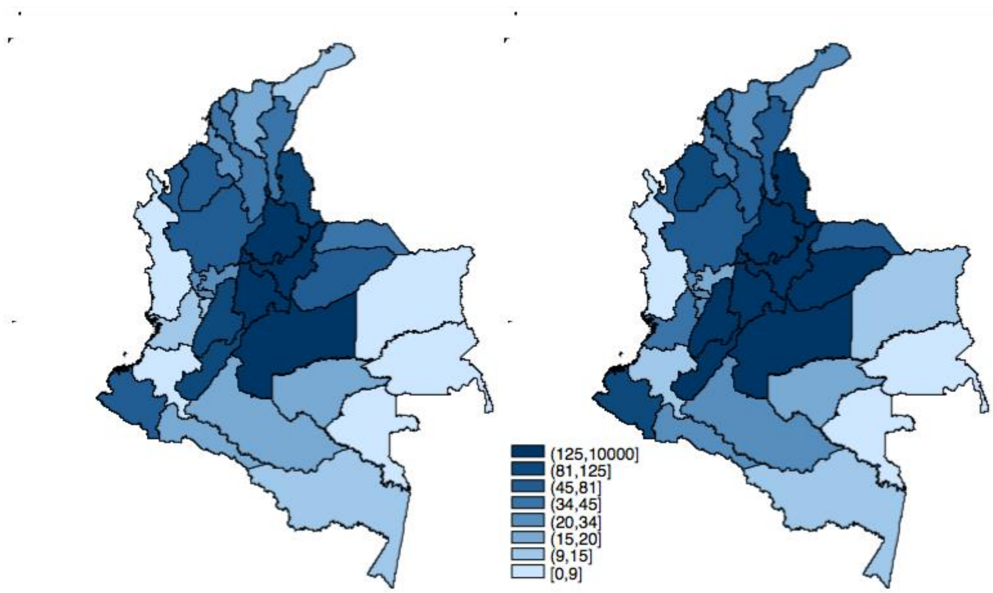
APPENDIX – ADDITIONAL FIGURES & RESULTS

FIGURE A1. ENROLLMENT RATES AT ALL UNIVERSITIES
BY SOCIOECONOMIC STRATA



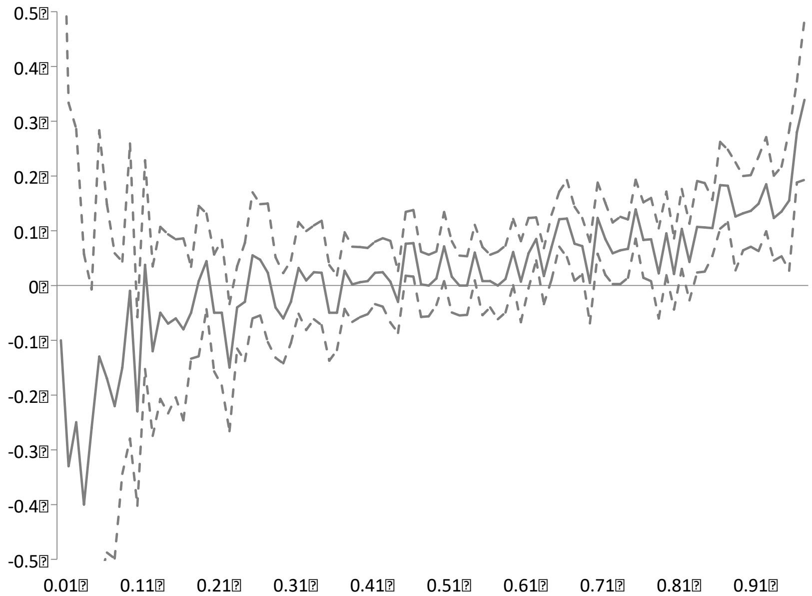
Notes: Rates of postsecondary enrollment across socioeconomic stratum in 2014 and 2015 (before and after the program was introduced) for students at the top 10 percentiles of the distribution in the national high school exit exam. Figure taken from, and reproduced with permission of, Londoño et al. (2017).

FIGURE A2. ACCESS TO ACCREDITED UNIVERSITIES IN BOGOTÁ BY DEPARTMENT OF ORIGIN, ENTRY IN 2014 COMPARED TO 2015



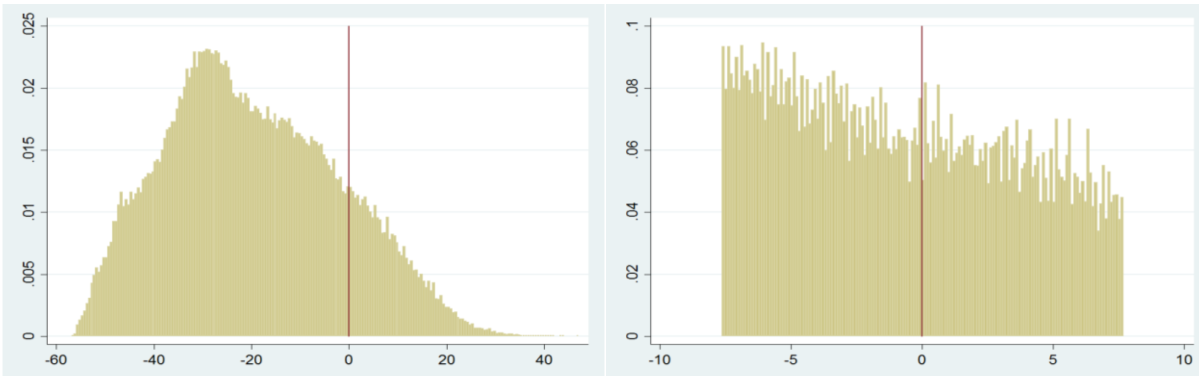
Notes: Number of students enrolled at accredited (and top) universities in Bogotá in 2014 and 2015, by department (state) of origin. Students who enter in 2015 passed their Saber 11 test in 2014 and are the first cohort of beneficiaries of SPP.

Figure A3. Difference in Difference Gap Reduction by Percentile



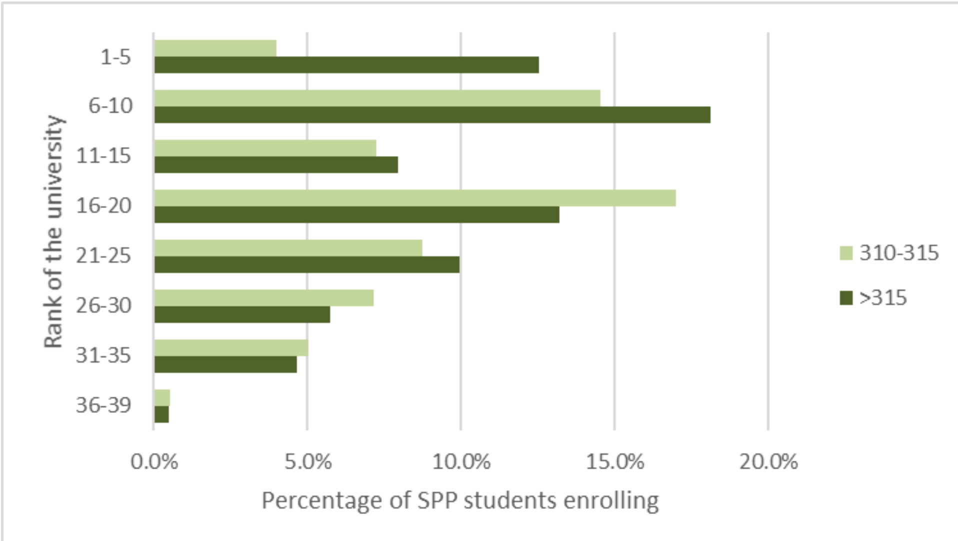
Notes: At each percentile, the gap reduction is calculated as the estimated motivational effect at that percentile p (using table 1's DD quantile estimation) divided by the gap in percentile p in 2014. The gap in percentile p, is the difference between the percentile p in the Saber 11 of all non-eligible students to percentile p of Saber 11 of all eligible students.

FIGURE A4—DENSITY OF SISBÉN INDEX AROUND SOCIO-ECONOMIC ELIGIBILITY THRESHOLD



Notes: The variable in the x-axis corresponds to the Sisbén Index centered on the socio-economic eligibility (which varies by area). To center it, the eligibility criteria in the area was subtracted to the Sisbén Index of the household.

FIGURE A5—RELATIONSHIP BETWEEN THE SABER 11 SCORE OF THE SPP BENEFICIARY AND THE QUALITY OF THE UNIVERSITIES IN WHICH THEY ENROLL



Notes: Universities were ranked by categories based on the average Saber 11 score of their entering students. The graph indicates the proportion of SPP students who entered each category of accredited universities separating SPP recipients with a Saber 11 score below 315 and above 315.

TABLE A1. DESCRIPTIVE STATISTICS OF SCORE DISTRIBUTION WITH RESPECT TO ELIGIBILITY CRITERIA

	Observations	Share of students eligible according to: Sisbén	Saber 11	Sisbén & Saber 11	Share of students with Saber 11 above the: 75th pctile	90th pctile	95th pctile	99th pctile
Full Sample	546,654	54.9%	8.5%	2.7%	25.0%	10.0%	5.0%	1.0%
Sisbén Eligible	300,241	100%	5.0%	5.0%	19.0%	6.2%	2.7%	0.4%
Non-Eligible with Sisbén	56,235	0%	11.2%	0.0%	34.8%	13.6%	6.3%	1.0%
Non-Eligible without Sisbén	190,178	0%	13.2%	0.0%	32.3%	15.3%	8.6%	2.0%

Notes: Percentage of students in 2015 who are eligible for a SPP scholarship according to the socioeconomic (Sisbén) and academic (Saber 11) thresholds. The sample of "Non-Eligible without Sisbén" is excluded from the empirical analysis, which requires having a Sisbén score. "Non-Eligible without Sisbén Index", students without a Sisbén index, who typically come from wealthy household that are excluded from all government need-based programs

TABLE A2. OTHER DESCRIPTIVE STATISTICS

A. Student Characteristics	**Full Sample**		
	Non-Eligible	Eligible	Difference
Saber 11 score	259.3	242.1	17.21***
	[50.34]	[42.38]	(137.20)
Age	17.22	17.29	-0.0677***
	[1.974]	[2.549]	(-10.73)
Male (dummy)	0.483	0.427	0.0560***
	[0.500]	[0.495]	(41.29)
Sisben	63.97	29.08	34.89***
	[8.310]	[13.74]	(582.58)
14 Cities (dummy)	0.409	0.299	0.110***
	[0.492]	[0.458]	(49.16)
Other Urban Area (dummy)	0.483	0.536	-0.0522***
	[0.500]	[0.499]	(-22.74)
Rural (dummy)	0.108	0.165	-0.0577***
	[0.310]	[0.371]	(-39.18)
Observations	546,654		

Statistics of the cohort that passed the Saber 11 test in 2015. Standard deviation in brackets, t-statistic of test of difference in parenthesis.

B. Household Characteristics	Full Sample		
	Non-Eligible	Eligible	Difference
Father's Education - Elementary (dummy)	0.269	0.424	-0.155***
	[0.443]	[0.494]	(-121.99)
Father's Education - Junior High School (dummy)	0.389	0.379	0.0107***
	[0.488]	[0.485]	(8.09)
Father's Education - Technical or Technological (dummy)	0.0931	0.0529	0.0402***
	[0.291]	[0.224]	(56.26)
Father's Education - University (dummy)	0.171	0.0501	0.121***
	[0.376]	[0.218]	(140.96)
Mother's Education - Elementary (dummy)	0.240	0.389	-0.149***
	[0.427]	[0.488]	(-120.46)
Mother's Education - Junior High School (dummy)	0.429	0.448	-0.0190***
	[0.495]	[0.497]	(-14.12)
Mother's Education - Technical or Technological (dummy)	0.115	0.0697	0.0457***
	[0.320]	[0.255]	(57.58)
Mother's Education - University (dummy)	0.180	0.0520	0.128***
	[0.384]	[0.222]	(146.74)
Observations 2015	546,654		

Statistics of the cohort that passed the Saber 11 test in 2015. Standard deviation in brackets, t-statistic of test of difference in parenthesis.

C. School Characteristics	Full Sample		
	Non-Eligible	Eligible	Difference
0 to 10 Books (dummy)	0.395	0.567	-0.171***
	[0.489]	[0.496]	(-128.21)
11 to 25 Books (dummy)	0.285	0.272	0.0127***
	[0.451]	[0.445]	(10.45)
26 to 100 Books (dummy)	0.236	0.133	0.103***
	[0.424]	[0.339]	(97.62)
More than a 100 books (dummy)	0.0813	0.0263	0.0550***
	[0.273]	[0.160]	(88.20)
School Schedule - Full day (dummy)	0.268	0.142	0.126***
	[0.443]	[0.349]	(114.77)
School Schedule - Morning (dummy)	0.473	0.556	-0.0826***
	[0.499]	[0.497]	(-61.01)
School Schedule - Night (dummy)	0.0636	0.0693	-0.00579***
	[0.244]	[0.254]	(-8.57)
School Schedule - Afternoon (dummy)	0.140	0.161	-0.0206***
	[0.347]	[0.367]	(-21.26)
School Schedule - Saturday (dummy)	0.0551	0.0719	-0.0168***
	[0.228]	[0.258]	(-25.54)
Public School (dummy)	0.627	0.842	-0.214***
	[0.483]	[0.365]	(-181.59)
School Ranking (2014)	55.89	46.09	9.797***
	[19.20]	[15.76]	(202.91)
Observations 2015	546,654		

Statistics of the cohort that passed the Saber 11 test in 2015. Standard deviation in brackets, t-statistic of test of difference in parenthesis.

TABLE A3— DIFFERENCE-IN-DIFFERENCE EFFECT OF SPP ELIGIBILITY ON *SABER 11* SCORE:

	OLS	Quantile Regression					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES		0.25	0.50	0.75	0.90	0.95	0.99
$\mathbb{I}(Eligible)$	-0.670***	-0.619***	-0.627***	-0.781***	-0.929***	-0.738***	-0.794***
	(0.062)	(0.073)	(0.069)	(0.095)	(0.115)	(0.135)	(0.221)
$\mathbb{I}(2015)$	-1.281***	-1.527***	-1.244***	-1.180***	-1.007***	-0.509*	0.844**
	(0.088)	(0.104)	(0.102)	(0.121)	(0.166)	(0.262)	(0.358)
$\mathbb{I}(Eligible) \times \mathbb{I}(2015)$	0.202**	0.146	0.0584	0.240*	0.403**	0.0877	-0.516
	(0.090)	(0.107)	(0.104)	(0.124)	(0.170)	(0.266)	(0.367)
Observations	612,815	612,815	612,815	612,815	612,815	612,815	612,815

Notes: The sample is restricted to the *Sisbén* eligible group and the first quartile of the distribution of the non-eligible according to the *Sisbén* index. The gap reduction is the ratio between the coefficient of eligible *Sisbén* × year and the gap in the *Saber 11* in 2014 between eligible *Sisbén* students and the entire group of non-eligible students. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A4— PLACEBO: DIFFERENCE-IN-DIFFERENCE

	OLS	Quantile Regression					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	-	0.25	0.50	0.75	0.90	0.95	0.99
Elegible Sisbén * Yr2014	-1.38***	-2.21***	-1.36***	-1.40***	-0.51	-0.15	-0.03
	(0.32)	(0.56)	(0.50)	(0.40)	(0.33)	(0.20)	(0.17)
Elegible Sisbén	-8.80***	-9.51***	-12.59***	-9.57***	-5.93***	-3.67***	-1.30***
	(0.22)	(0.35)	(0.40)	(0.30)	(0.26)	(0.14)	(0.10)
Yr2014	1.32***	2.32***	1.44***	1.26***	0.30	0.11	-0.06
	(0.31)	(0.55)	(0.49)	(0.39)	(0.32)	(0.18)	(0.16)
Observations	581,330	581,330	581,330	581,330	581,330	581,330	581,330

Notes: The sample is restricted to the Sisbén eligible group and the first quartile of the distribution of the non-eligible according to the Sisbén. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. This placebo test looks at the change from 2013 to 2014 (the year before the announcement of the SPP scholarship).

TABLE A5— RDD EFFECT OF ELIGIBILITY ON *SABER 11* RANKING

Bandwidth	OLS	Quantile						Obs.
	MCO	0.25	0.5	0.75	0.9	0.95	0.99	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	0.0203	-0.214	0.197	0.801	1.149**	0.870*	0.138	62,476
[7.51]	(0.574)	(0.835)	(0.904)	(0.725)	(0.576)	(0.478)	(0.420)	
MSESUM	0.404	-0.341	0.497	1.104	1.341**	0.766	0.123	49,968
[6.50]	(0.637)	(0.904)	(0.823)	(0.699)	(0.611)	(0.562)	(0.547)	
CERRD	1.095	0.553	1.205	1.729*	1.606**	1.349*	0.52	32,641
[3.97]	(0.780)	(1.006)	(1.013)	(0.917)	(0.813)	(0.719)	(0.560)	
CERSUM	1.629*	1.06	1.579	1.940*	1.358	1.358*	1.173*	25,928
[3.43]	(0.870)	(1.435)	(1.082)	(1.010)	(0.868)	(0.758)	(0.654)	

Notes: The table reports the coefficients of the eligibility dummy on *Saber 11* scores following model (2). The model is constructed with the *Sisbén* and its quadratic term, both interacted with the eligibility dummy. The first column in the table reports the LATE of the scholarship at the need-based eligibility threshold, whereas Columns 2-7 report the results from estimating model 2 through quantile regressions to assess the distributional effects of the scholarship. Each row in the table reports the results of estimating model 2 for different optimal bandwidths following Calonico, Cattaneo and Titiunik (2014). All specifications use the following controls: students' age, gender, and area of residence (14 main cities, other cities, or rural area), parents' level of education, high school ranking in the 2014 *Saber 11*, and fixed effects for student's state of residency. Robust standard errors in parentheses. Standard errors of the quantile regressions are bootstrapped with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A6— PLACEBO: REGRESSION DISCONTINUITY DESIGN

	OLS	Quantile						Obs.
	MCO	0.25	0.5	0.75	0.90	0.95	0.99	
Bandwidth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	-0.65	-0.69	-0.93	-1.32	-2.41	-2.41	-2.49	73,365
[8.532]	(0.76)	(0.92)	(0.78)	(1.24)	(1.52)	(1.88)	(3.47)	
MSESUM	-0.44	-0.55	-0.57	-1.22	-1.52	-1.92	-1.91	74,928
[8.71]	(0.76)	(0.83)	(0.85)	(1.12)	(1.40)	(1.70)	(3.38)	
CERRD	-1.76*	-1.61	-1.80	-1.86	-4.41**	-5.31*	-4.06	38,712
[4.511]	(1.05)	(1.22)	(1.15)	(1.67)	(2.09)	(3.07)	(4.89)	
CERSUM	-1.38	-1.25	-1.51	-1.17	-4.46**	-5.09*	-3.50	39,372
[4.605]	(1.05)	(1.23)	(1.28)	(1.59)	(1.84)	(2.75)	(4.29)	

Notes: Standard errors in parentheses for OLS model clustered by school. The estimation of the standard errors for the all the specifications of the quantile regression was calculated through bootstrapping (100 repetitions). The optimal bandwidth is presented in the following order: mserd, msesum, cerrd and cersum. All specifications use the following controls: Sisbén area, father's education level, mother's education level, sex, age, school ranking in 2013 and state of residency of the student. The model is constructed with the Sisbén, its quadratic term, and its interaction with eligibility criteria. The full sample is used in this estimation. *** p<0.01, ** p<0.05, * p<0.1. This placebo test looks at the discontinuity in Saber 11 scores in 2014 (the year before the announcement of the SPP scholarship).

TABLE A7. SISBÉN CUTOFF OF OTHER PROGRAMS

Program name	Sisben Cut-off			Starting year	What it provides
	14 Cities	Other Urban	Rural		
SPP	**57.21**	**56.32**	**40.75**	**2014**	**Merit and need-base college scholarship**
ICBF Primera Infancia	57.21†	56.32†	40.75†	2007	Education and nutrition of young children (0-5 years old)
Vivienda Rural	NA	56.32†	40.75†	2013	Rural housing building or improvement
BEPS	57.21†	56.32†	40.75†	2015	Saving program for the elderly without a pension
Susbsidio de sostenimiento (Icetex)	57.21†	56.22	40.75†	2013	Credits for college students' life expenditures.
Subsidio de tasa de interés (Icetex)	57.21†	56.32†	40.75†	2013	Credits for college students at a subsidized interest rate
Atención Humanitaria	57.21†	56.32†	56.32	2011	Financial aid, food, housing and health services for victims of the armed conflict
Más Familias en Acción	30.56	32.2	29.03	2012	Nutrition (0-6 years old) and Education (4-18 years old)
Jóvenes en Acción	54.86	51.57	37.8	2012	Conditional money transfers used to keep young adults (16-24 years old) in tertiary education.
Acces (Icetex)	30.39	30.73	22.19	2002	Long-run credit for tertiary education
Exención en el pago de la cuota de compensación militar	61.91	61.91	61.91	1993	Exemption of the compensation fee for avoiding mandatory military service
Implementación generación de ingresos y desarrollo de capacidades productivas	NA	NA	40.79	2014	Technical assistance for agricultural projects
Colombia Mayor	43.63	43.63	35.26	2010	Subsidies for third age population
Red Unidos	23.4	32.2	26.12	2016	Support for poor displaced families and preferential access to social services of the state
SENA Emprende Rural		56.32	40.75†	2016	Agricultural trainings
Tú Eliges (Icetex)	58.12	58.16	40.75†	2016	Credits for college students at a subsidized interest rate
Regimen Subsidiado	54.86	51.57	37.8	1993	Subsidies to access the national health system

† means that the cutoff is the same as the one used by SPP for this part of the population.
Programs on the upper part share at least one cutoff with the Sisbén eligibility criteria of SPP.
Source: https://www.sisben.gov.co/Paginas/Noticias/Puntos-de-corte.aspx , completed with information from websites of the different programs

Table 8. RDD Splitting the Sample by School Quality

A. Students in Schools with High-performing Eligible Students in 2014

	OLS	Quantile						Obs.
	MCO	0.25	0.5	0.75	0.9	0.95	0.99	
Bandwidth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	-0.68	-0.32	-0.61	0.23	2.16	-0.05	0.19	43,032
8.624	(1.08)	(1.29)	(1.20)	(1.59)	(1.86)	(2.29)	(4.80)	
MSESUM	-0.15	-0.12	0.14	0.98	3.08	1.47	-1.86	45,391
9.118	(1.05)	(1.36)	(1.29)	(1.30)	(2.27)	(2.70)	(5.34)	
CERRD	1.08	0.32	1.71	3.16*	5.15*	1.17	5.46	23,657
4.719	(1.47)	(1.76)	(2.12)	(1.90)	(2.83)	(3.05)	(6.87)	
CERSUM	0.38	0.15	0.67	2.25	4.19	1.20	2.49	24,987
4.989	(1.43)	(1.58)	(1.78)	(1.98)	(2.62)	(3.22)	(6.54)	

B. Students in Schools with Low-performing Eligible Students in 2014

	OLS	Quantile						Obs.
	MCO	0.25	0.5	0.75	0.9	0.95	0.99	
Bandwidth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
MSERD	0.82	-0.39	0.60	1.92	4.01*	1.08	3.80	31,149
9.708	(1.27)	(1.61)	(1.61)	(1.72)	(2.36)	(3.36)	(5.98)	
MSESUM	1.01	-0.83	0.93	1.97	3.57	0.11	1.76	26,752
8.362	(1.35)	(1.97)	(1.75)	(1.98)	(2.70)	(3.64)	(6.71)	
CERRD	2.48	0.91	3.23	4.82*	4.36	1.91	-0.56	16,356
5.295	(1.70)	(1.96)	(2.06)	(2.69)	(3.39)	(4.46)	(8.01)	
CERSUM	2.24	1.68	3.02	4.22*	2.10	2.75	3.22	14,029
4.561	(1.83)	(2.05)	(2.51)	(2.42)	(3.78)	(5.20)	(11.48)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The table only presents the coefficients of the eligibility dummy on Saber 11 scores. The standard errors in parentheses are clustered by school for the OLS model, and bootstrapped for the quantile regressions (100 repetitions). The optimal bandwidths (mserd, msesum, cerrd and cersum) are the ones recommended by Calonico, Cattaneo and Titiunik (2014). All specifications use the following controls: Sisbén area, father's education level, mother's education level, sex, age, school ranking in 2014 and state of residency of the student. The model is constructed with the Sisbén and its quadratic term, both interacted with the eligibility dummy. The sample of Panel A is restricted to students from schools that are above median in the sense that the average of the score of all eligible students in this school is above the median of these averages calculated in all schools. The sample of Panel B is restricted to students from schools that are below median.