Information Policies and Higher Education Choices

Experimental Evidence from Colombia*

Leonardo Bonilla†[1], Nicolas L. Bottan[1], and Andrés Ham[2]

[1]Department of Economics, University of Illinois
[2]Department of Agricultural and Consumer Economics, University of Illinois

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Abstract

This paper studies how providing information on the returns and financing of college affects higher education decisions. We conducted a randomized controlled trial in Bogotá, Colombia, on a representative sample of 120 urban public high schools, 60 of which received a 35-minute informational talk delivered by local college graduates. We find no effects of the intervention on post-secondary enrollment rates. However, treated students who do enroll chose more selective degrees. Treated students also perform slightly better on the national exit exam. Since most individuals in our sample are from low-income families, and positive effects derive mostly from changes in behavior of students from better socioeconomic backgrounds, we conclude that informational policies to motivate the demand for higher education are less effective in contexts where credit constraints are sizable.

Keywords: information, beliefs, higher education, schooling demand, Colombia
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†lbonill2@illinois.edu (Corresponding author), bottan2@illinois.edu, and hamgonz2@illinois.edu. Mail: 214 David Kinley Hall, 1407 W. Gregory, Urbana, IL 61801. MC-707.

1 Introduction

Since Jensen (2010), the role of information on educational choices has attracted much attention. The core problem is that individuals are often misinformed about the returns to education and their inaccurate beliefs may lead to sub-optimal choices that have lasting implications for lifetime earnings and welfare. For instance, while primary and secondary education usually have low costs, students generally underestimate their returns leading to higher drop-out rates (Attanasio and Kaufmann, 2009, Kaufmann, 2010). Similarly, incorrect beliefs about the costs and benefits of higher education may lower incentives to enroll in post-secondary institutions (Hoxby et al., 2013, Hastings et al., 2015).

There is credible evidence that providing information on the returns of education has significant effects on primary enrollment. Jensen (2010) found that reading a simple paragraph on the earning premiums for completing secondary increases educational attainment by 0.20-0.35 years. Large impacts of information are also reported by Nguyen (2008), who evaluates differential effects when using role models to deliver information. The most attractive aspect of these policies is budgetary. The *Abdul Latif Jameel Poverty Action Lab* (JPAL) estimates that informational interventions are approximately 100 times more cost-effective than conditional cash transfers at increasing enrollment in primary schools.

Are these interventions as effective when it comes to higher education? A growing number of papers have started to focus on this question, particularly in countries that have achieved high enrollment rates in primary and secondary. Most of the evidence, mainly from developed countries, suggests that information treatments are less effective at this level. On the one hand, "pure" information treatments in the spirit of Jensen (2010) have found small or no effects on enrollment (Kerr et al., 2014, Oreopoulos and Dunn, 2013, Fryer, 2013). On the other hand, more comprehensive programs that provide students with personalized assistance report similar results for enrollment but find individuals choose more selective degrees (Hoxby et al., 2013, Hastings et al., 2015).

In this paper, we study how a "pure" information treatment affects school effort and college enrollment in a developing country. We conducted a randomized controlled trial on students in their final year of high school at pubic institutions in Bogotá, Colombia.

Public schools in Bogotá mostly serve low-income students, who have systematically lower college enrollment rates. A representative sample of 120 schools was randomly selected to participate in the study, and half received a 35-minute informational talk delivered by local college graduates. Students were provided with statistics on the monetary returns to college by major-institution pairs and briefed on the availability of funding programs to cover costs. Almost six thousand students responded our baseline and follow-up surveys – the latter timed just before students sat down for the high school exit exam. The survey data were then matched to administrative records containing exit exam scores and college enrollment status. We thus have unique data on the perceptions, aspirations, effort, and higher education enrollment choices for public school students in Bogotá.

Our results indicate the intervention did not affect higher education enrollment rates. However, it had some positive effects on test scores, and treated students that go to college gained admission to more selective institutions and majors. For example, we find an increase of 7.5% of a standard deviation in mathematics scores, and increases of around 1.4 percentage points on the probability of enrolling in a top-10 college, a 4.1 percentage point increase in pursuing an academic (4-year) program, and a 3.2 percentage point increase in selecting a Science, Technology, Engineering, and Mathematics (STEM) degree. These impacts are economically significant and have important implications for future earnings. For instance, graduates from top-10 colleges in Colombia have a higher starting salary compared to other higher education graduates, about 50% on average.

The limited impact of our intervention in increasing the demand for college may be explained by its inability to remove credit constraints. In fact, most of our sample comes from low-income households, whose monthly income is unable to cover the costs of college education and may face barriers to funding programs. Two of our results further support this interpretation. On the one hand, the information treatment increased the knowledge of funding programs but did not update beliefs about the returns to higher education. This is consistent with the fact that students in our sample see costs as the main barrier to attend college. On the other hand, we find larger effects of the intervention on individuals from better socioeconomic status, for whom the likelihood of attending college is higher.

Our analysis also suggests that the improvements in test scores and enrollment choices are mostly driven by motivation, rather than information itself. In fact, most of the positive effects are concentrated in students who already knew about funding programs and did not update their beliefs about the returns to education. Consistent with this, we find particularly large impacts among students who highly believe in their ability to achieve their goals. The effects are also significantly larger effects for males, which could be reflecting gender-specific traits or preferences.

This study contributes to two strands of literature. First, it relates to research on extending access to higher education. Returns to post-secondary education tend to be high, but enrollment remains low (McMahon, 2009). Studying how low-income students make decisions at the end of high school will shed further light on why so few apply to and ultimately enroll in college. Second, we add to the debate on the effectiveness of information policies to motivate post-secondary enrollment among low-income students from developing countries, which has received relatively less attention in the literature. There are a few exceptions. In Chile, Dinkelman and Martínez (2014) study the effect of providing funding information on student absenteeism and effort in high school, but do not study subsequent college enrollment decisions. Also in Chile, Hastings et al. (2015) disclose information on the net benefits of higher education to college loan applicants. However, extrapolating these findings may be problematic for various reasons. First, Chile's education system is an outlier in the region.[1] Second, the latter study focuses on students already applying for a college loan, therefore already far down the application process. In Mexico, Avitabile and De Hoyos Navarro (2015) perform a similar intervention to ours on students in technological schools and evaluate whether it influenced the probability of taking the national exit exam and their performance, although they do not estimate effects on college enrollment.

The remainder of this paper is organized as follows. Section 2 reviews the literature on information and college choices. Section 3 describes Colombia's higher education system.

[1]The Chilean education system is much closer to the US than to the rest of Latin America in terms of degree of privatization, tuition fees in public universities, and access to state-guaranteed higher education loans. A detailed description of the higher education systems of Chile and Colombia can be found in González-Velosa et al. (2015).

Section 4 details the experimental framework and intervention. Section 5 characterizes the data and sample. Section 6 presents the effects of the informational intervention on higher education decisions. Section 7 analyzes what drives our findings by testing several mechanisms suggested by the literature, including credit constraints, intergenerational factors, and other channels. We conclude in Section 8 by discussing our findings and outlining directions for future research.

2 Related Literature

Beliefs play a crucial role in educational decisions. Assuming that individuals are rational decision-makers, they will choose their optimal schooling level based on the net gains from investment (benefits minus costs). However, these decisions are often made using *perceived* instead of actual net benefits (Manski, 1993, 2004), which makes expectations key to understand student behavior. The consensus in the literature is that most individuals have incorrect beliefs about the benefits and costs of education. However, the direction of these errors could go either way. While most papers that study primary education find that net benefits are underestimated (Nguyen, 2008, Attanasio and Kaufmann, 2009, Jensen, 2010, Kaufmann, 2010), those that deal with college often encounter that students are overestimating (Kerr et al., 2014, McGuigan et al., 2014, Hastings et al., 2015).

The influence of incorrect beliefs on schooling choices has attracted significant attention because it has a simple solution: providing accurate information. One of the first studies to analyze such a policy was Jensen (2010), who conducted a randomized controlled trial in the Dominican Republic. Treatment was simple: surveyors in treated schools read a paragraph explaining the wage premium for completing secondary education (difference in mean earnings). Students who heard this completed on average 0.20 to 0.35 more years of schooling over the next four years. In terms of cost-effectiveness, this "pure" information policy achieves 3.1 additional years of schooling per US$100.[2] Compared to other programs that allocate scholarships or financial aid, the impact on

[2]These cost-effectiveness calculations are taken from the Abdul Latif Jameel Poverty Action Lab website, http://www.povertyactionlab.org/policy-lessons/education/student-participation.

enrollment and further schooling is substantial despite its relatively low cost.

Due to the success of this intervention, ensuing experimental papers have tested variations in how information is disclosed. For instance, Nguyen (2008) provides average returns to students and their parents in Madagascar but is more concerned with who provides the talk. Results indicate that using role models, especially those who come from a poor background, is more effective than just providing statistics. Moreover, this design has wider effects, since it also improves student effort measured by test scores.

A number of papers disseminate information on both returns and costs, finding that while individuals update their beliefs, behavior is unaffected. Some recent studies that estimate the effects of information in developed countries include Booij et al. (2012), Wiswall and Zafar (2012), Fryer (2013), Oreopoulos and Dunn (2013), Kerr et al. (2014), and McGuigan et al. (2014). While the interventions and contexts differ, this research largely concludes that "pure" information is less effective to motivate the demand for higher education.

In developing countries, two studies have evaluated how providing "pure" information affects higher education decisions. The first, Dinkelman and Martínez (2014), randomly distributed DVDs to eighth grade students in Chile with information on funding sources for college and the importance of effort to gain admission. This increased exposure to information improves financial aid knowledge and lowers absenteeism, but is insufficient to affect effort or ninth grade enrollment. The second, Avitabile and De Hoyos Navarro (2015), provided information on the returns to upper secondary and tertiary education in Mexico to tenth grade students in technological schools. They evaluate whether the treatment influenced the probability of taking the national exit exam and students' performance, finding no effect for the former but large gains in test scores. However, the effect on college enrollment is not explored.

Given the small responses to "pure" information, recent interventions have been augmented with personal assistance components. While helping low-income individuals prepare US tax returns, Bettinger et al. (2012) also guide beneficiaries in completing financial aid applications. Compared to pure information disclosure, which has no effect on behavior, providing assistance leads to increased aid requests and a higher probability of enrollment in higher education. Hoxby et al. (2013) are even more comprehensive. They randomize low-income high-achieving students into a program that provides semi-customized college application guidance, information on net benefits, and fee waivers. This intervention significantly increases applications and enrollment in selective colleges in the US. Hastings et al. (2015) disclose information on the net benefits of higher education to loan applicants in Chile. This information is tailored to their field of interest. Even while overall enrollment rates do not increase, they find evidence that low-income students become more selective and enroll in better-paid careers.

In summary, previous research provides us with three main findings. First, information matters. Evidence shows that students have incorrect beliefs about the net benefits of higher education. Second, it seems that providing information is less effective at raising college enrollment rates compared to primary and secondary. However, it does induce individuals who enroll to choose more selective colleges and degrees. Last, informational policies may range between "pure" exposure and interventions tailored to each beneficiary. Determining which combination works best to encourage higher education enrollment is an empirical question whose answer will provide important policy implications.

3 Higher Education in Colombia

There are 327 colleges in Colombia, with 132 located in the Bogotá region.[3] Of these 132 colleges, 40 are Universities, 23 are public, and 6 are ranked top-10 in the country.[4] Degrees are classified in two levels, vocational (2-year) and academic (4-year), and 55 fields. Universities supply most of the academic programs, while vocational degrees are offered at Technical/Technological Institutes. *Servicio Nacional de Aprendizaje* -SENA- is the biggest such institute in Colombia, which is public and completely free. Universities

[3]The Bogotá region includes the city and the following municipalities: Cajicá, Chía, Facatativá, Madrid, Mosquera, and Soacha.

[4]According to the 2012 Higher education exit exams (SABER PRO), the top-10 colleges in Colombia are (in order): *Universidad de los Andes*, *Universidad Nacional* (Bogotá), *Universidad del Rosario*, *Universidad Externado*, *Universidad Icesi* (Cali), *Universidad Eafit* (Medellín), *Universidad de la Sabana*, *Universidad Javeriana*, *Universidad Nacional* (Medellín), and *Universidad del Norte* (Barranquilla). *Universidad Nacional* (Bogotá and Medellín) are the only public Universities ranked top-10.

are not free, but students attending public universities pay tuition under a progressive system based on family income. While low income households pay between 0.1 and 1.8 minimum wages per semester in top-ranked public universities, the average tuition fee for private universities in the top-10 is 13.2 minimum wages.[5] Scholarships for low-income students are scarce and only those who achieve the highest scores on the national exit exam have access to such opportunities.

Funding programs for higher education require in most cases a co-debtor to back the credit, a restriction that can be binding for low-income families. At the national level, there is the Colombian Public Student Loans Institution (ICETEX), an agency that handles student loans for public, private, vocational, academic, and postgraduate education in Colombia and abroad. Recent reforms, that introduced zero-interest loans for low-income students, have had large impacts on enrollment and retention (Melguizo et al., 2015). This is the largest student loan program in Colombia, with 22% of enrolled students during 2013 funded by this source, and is also the most widely known. The Secretary of Education of Bogotá offers complementary funding options for low-income students from the city's public schools through the Fund for Higher Education of Bogotá (FESBO). The fund has two main programs. The first one targets high achieving students offering schools loans for any college or degree. The second one offers school loans for vocational education only. In both cases a fraction of the debt is condoned when students complete the degree.

[FIGURE 1 ABOUT HERE]

There are significant differences in wages between colleges and degrees. Using official records from the Ministry of Education's Labor Observatory, which links individual-level social security records to higher education graduates, we calculate average wages by college, degree, and field.[6] Figure 1 shows the distribution of wages for different categories of colleges and degrees. Notice that the choice of college matters. In fact,

[5]Hereafter, all monetary variables will be expressed in monthly minimum wages (MW), a commonly used measure in Colombia. The 2013 monthly MW was 535,600 Colombian Pesos (roughly 288 US Dollars). The average excludes medicine, which is usually more expensive than other degrees in private universities.
[6]We use the 2011 wages of individuals who graduated between 2008 and 2011 and that report non-negative labor income.

we observe average wage premiums for private and top-ranked colleges of 0.33 and 1.05 minimum wages, respectively. Degrees are at least as important. While the average wage for recent graduates with an academic degree is 2.9 minimum wages, individuals with vocational degrees make on average 1.9 minimum wages. Interestingly, the wages of academic degrees are also much more disperse, reflecting large heterogeneity both within and between fields. This is partially confirmed by the 0.83 minimum wages premium for Science, Technology, Engineering, and Mathematics (STEM) degrees.[7] We also rank the college-degree choices by average pay, and classify those above the median monthly wage (2.49 minimum wages) as high-earning.

In order to characterize the demand for higher education it is worth noting that Colombia has a large share of private high schools, particularly in urban areas. Private schools account for 28% of the class of 2013, and 51.4% in Bogotá, where higher income households opt for private education. As shown in the top-left panel of Table 1, 72.4% of private school students come from middle or high income families ($\geq$2 minimum wages), and 57.8% have at least one parent who completed higher education. In public schools, which are completely free, the share of students satisfying these two characteristics drops to 29.7% and 15.6%, respectively. One of the reasons why this happens is that private schools tend to perform better on high school exit exams and have higher college enrollment rates, particularly in selective colleges and degrees.

[TABLE 1 ABOUT HERE]

Test scores reflect significant differences between public and private schools. The national exit exam, SABER 11, administered by the Colombian Institute for the Promotion of Higher Education -ICFES- is taken by almost every 11th-grader in public and private schools, and is required for college admission. Although the college application process is completely decentralized (each college has its own admission criteria), SABER 11 scores are heavily weighted by most universities and funding programs. Students are allowed to take the SABER 11 exam more than once, and it is relatively affordable so it is quite

[7]Academic degrees from the following fields are classified as STEM: Agronomy, animal sciences, veterinary medicine, medicine, bacteriology, biology, physics, mathematics, chemistry, geology, business, accounting, economics, and all engineering.

common to retake if necessary.[8] Over the last few years, Bogotá's private schools have consistently scored 0.65 SD above the city's public schools as Table 1 shows.

Less than half the students that graduate from high school enroll in college, and the odds are significantly smaller for public school students. The National Information System for Higher Education -SNIES- matches SABER 11 information to higher education administrative records for all institutions, allowing to track how many students enroll. Our estimates based on SNIES indicate that only 46.9% of the students that graduated in Bogotá in 2013 enrolled in higher education in 2014. Moreover, private schools perform much better in this respect, since their students have consistently higher probabilities of enrolling (57.2%) and doing so in a private (42.4%) or a top-10 (16%) college. They also have higher chances of enrolling in academic, STEM, and high-earning degrees (See bottom-left panel of Table 5).

In summary, Bogotá has a very heterogeneous higher education system that translates into large wage premiums for selective colleges and degrees, with sizable variation in costs that price some students out. On the demand side, Bogotá's higher income families opt for private schools that have significantly higher exit exam scores and better placement in selective colleges and degrees. This paper studies public schools in order to focus on the group that is most disadvantaged in terms of access to higher education.

4 Experimental Setting

4.1 Randomization

In order to study the effects of information on higher education decisions, we conducted a randomized control trial in Bogotá, Colombia. Our population of interest was public high school students deciding whether to pursue higher education. We focused on public schools since they have significantly lower college enrollment rates, particularly when it comes to selective institutions and degrees. A representative sample of 120 public school-

[8] The exam fees are 1.7 daily minimum wage for first takers public school students, and 2.3 otherwise (equivalent to approximately 17 and 21 US dollars, respectively)

shifts out of the 571 that offer an academic track was selected for participation.[9] These institutions are all mixed-sex, urban, public high schools with at least 20 senior high school students enrolled in the 2012 academic year. We randomly assigned 60 schools to receive an informational talk detailing the returns to higher education and discussing funding opportunities, while the remaining institutions served as our comparison group.

While conducting our surveys at schools, we only interviewed students from two classrooms. These were selected at random if there were more than two classrooms at the senior level. Otherwise, we interviewed all students attending that day. In Colombia, the public school year often begins in February and ends in December. Fieldwork for the baseline survey and the intervention took place during March 2013. The follow-up survey was conducted in August 2013, one week before students took the SABER 11 exam. Our sample of schools covers a large extent of the city and most urban neighborhoods in Bogotá, with treatment and control schools being relatively spread out (the Online Appendix shows the geographic distribution of schools in our study).

4.2 The Intervention

During our baseline visits in March we first collected the self-administered surveys. After all surveys were collected, students in treatment schools were given a 35-minute presentation delivered by young local Colombian college graduates. The talk described the relationship between higher education and wages, presented the most relevant funding programs to finance post-secondary studies, and emphasized the importance of exit exam scores for admission committees.

The talk began describing statistics on the average wages of individuals with incomplete and complete secondary, and then compared them to the expected wages of individuals who completed a higher education degree (differentiating by vocational and academic).[10] We then introduced students to two websites where they could find very de-

[9]Most public high schools in Bogotá have two independent shifts: morning and afternoon. Each shift has different students and most importantly, different teachers and staff. Hence, each school-shift may be considered as an independent educational institution. Henceforth, we refer to these school-shifts as schools.

[10]Reference wages for incomplete and complete secondary are 0.85 and 1.07 minimum wages, respectively and were estimated using 2011 household surveys.

tailed information on labor market outcomes of recent graduates, including average wages by major-institution pairs.[11] Additionally, we showed how the different search tools on the websites worked using some examples.

The second part of the talk focused on two funding programs: ICETEX and FESBO. For each program, we provided basic information regarding benefits, application requirements, and deadlines. Students were encouraged to visit the websites of each program for more information. We emphasized the fact that college education can be affordable, even if they choose a relatively expensive university.

The last portion of the talk focused on the importance of the high school exit exam (SABER 11). We insisted on the fact that this test is a determinant factor for admission decisions in most colleges, and that higher scores also increase the possibility of receiving funding. Students were allowed some time for questions and we gave out a one-page handout summarizing the main points of the talk and containing all the relevant links to the websites described during the talk.[12]

5 Data and Estimation Strategy

5.1 Data

The baseline survey collected information on 6,636 students in 116 schools.[13] The questionnaire inquired about individual demographic characteristics, family background, socioeconomic status, educational background, aspirations, current employment, future work perspectives, and attitudes towards risk. The follow up survey was completed by 6,141 students in the same 116 schools. The questionnaire followed up on some baseline questions, mainly educational and employment aspirations. It also added modules on students' household environment. In what follows, we refer to the survey data as the

[11] The websites are: http://www.graduadoscolombia.edu.co/ and http://www.finanzaspersonales.com.co/calculadoras/articulo/salarios-profesion-para-graduados/45541. They present Labor Observatory information on average wages of individuals who graduated from higher education in a user-friendly way.

[12] The original and translated copy of this handout may be found in the Online Appendix.

[13] Despite numerous attempts, we were unable to visit 4 schools. These corresponded to 2 treatment schools and 2 control schools. However, the inability to interview these students does not seem to generate issues that affect randomization as our balance tests and Online Appendix reveal.

Bogotá Higher Education and Labor Perspectives Survey (BHELPS).

For our analysis, we focus on the sample of 5,503 students observed both at baseline and follow-up for 115 schools[14] The attrition rate for the selected sample was 17.1%, mainly due to absences on the days of the survey. Nevertheless, we find evidence that this attrition was unrelated to treatment status.[15]

The survey data are further augmented by matching students in our sample to two administrative sources: the ICFES (Colombian Institute for the Promotion of Higher Education) and SNIES (National Information System for Higher Education). ICFES administrative records contain data for the high school exit exam (for the 8 different subjects and the overall score), as well as information on date of birth, gender, parents' education, and family income. We use the administrative records for these variables when available since we believe they are measured more precisely than in the BHELPS (though the correlation is very high). The SNIES higher education enrollment records for 2014 provide evidence on whether students in our sample enrolled in a higher education program, identifying both the institution and degree. The matching rates for ICFES and SNIES on the balanced sample are quite high: 98.6% and 98.4%. There are no significant differences between matched and unmatched students and the rates are similar across treatment and control groups.[16]

5.2 Sample Representativity and Characteristics

Our sample, which includes approximately 20% of the city's public high schools, is representative and well balanced. The right panel of Table 1 summarizes individual and school-level baseline characteristics of the sample. The last two columns present differences across treatment and control groups along with their p-value (clustering standard errors at the school-level). Overall, the sample is representative of the universe of public schools in the city, though slightly oversampling morning-shift schools. Moreover, we do not find any statistically relevant differences across characteristics between treatment and

[14]Our final sample consists of 115 rather than 116 schools because during the follow up, the wrong classrooms were interviewed at one of the schools.

[15]See the Online Appendix for a detailed analysis of attrition in our data.

[16]Attrition diagnostics for the matched samples may be found in the Online Appendix.

control groups. This suggests that our randomization was indeed successful.

On average, students are almost 18 years old when they graduate (measured in December 31, 2013) and most were born in Bogotá (84.9%). Around 14.6% of students in the treatment group have at least one parent that completed college, around 3 points lower than the control group (the difference is borderline insignificant at the 10% level, p-value=0.115). Students in treatment and control groups look almost identical in terms of family income, where less than 15% report incomes below 1 minimum wage, around 54% between 1 and 2 minimum wages and 31% over 2 minimum wages. Since most of the high-income families opt for private education, we will classify students in public schools with a family income higher than 2 minimum wages as middle-income. Approximately 71% of students in the control group have internet at home, while internet access is almost 4 points lower for treatment students. Again, the difference is borderline statistically insignificant at the 10% level (p-value=0.105).

It is worth noting that to most of the students in our sample, cost is the major barrier to college. We asked students in the follow up survey what they believed to be the most significant limitation to enroll in college. The majority responded that college was unaffordable (64.5%), followed by 32% who claimed that obtaining admission was the largest obstacle. This is consistent with the fact that private education is expensive and top-ranked public universities are very competitive. While only 31% of our sample reports monthly family income above 2 minimum wages, Section 3 mentioned that tuition for a semester may rise to 13.2 minimum wages at private top-10 institutions, which is equivalent to 2.2 minimum wages per month. As for top-ranked public universities (that may cost as little as 0.1 MWs) admission rates are fairly low. While 40% of the students in our sample wanted to enroll in the *National University* in the baseline survey, less than 1% made it. These students might also face barriers to access funding programs. As mentioned before, in most cases the available programs still require a co-debtor to back the loans.

In terms of self-reported academic performance, almost a quarter of students have repeated at least one grade. To measure academic self-concept, we ask students to rank themselves relative to the rest of the class on a Likert-scale from 1-10 where the latter is the highest value. As a measure of self-efficacy, students rated how often they achieved their proposed goals (on a scale of 1 to 10, where 1 is never and 10 is always). Students above the median response are classified as high academic self-concept and self-efficacy, while those below constitute the low group. Given that risk aversion has been found to play an important role for human capital accumulation decisions (Heckman, 2007), students were asked to play two games intended to measure attitudes towards risk in the baseline survey.[17] On average, 85% of our sample was classified as risk averse. We also asked the perceived probability of enrollment in college after graduation. 85% of the students reported in the baseline survey that they were likely to enroll.

Both treatment and control groups look very similar in school characteristics. Using administrative data from 2010-2012, we find that over 90 students sit for the exam each year, on average. Additionally, previous cohorts in both groups performed similarly on the exam. More than half the schools are morning shift and over 95% of them have a computer lab. A joint-test for balance rejects that individual and school-level characteristics explain the likelihood of attending a treatment school, with a p-value of 0.680.

5.3 Estimation Strategy

Given the random assignment of the treatment, we quantify the effect of providing information on our main outcomes: college enrollment and SABER 11 exam scores, by estimating a cross-sectional regression where outcomes in period $t+1$ are explained by baseline treatment status and attributes:

$$y_{is,t+1} = \beta T_{s,t} + \theta X_{is,t} + u_{is,t+1} \tag{1}$$

where $y_{is,t+1}$ is the studied outcome for student i attending school s at the follow up, $t+1$. X_{ist} is a matrix containing individual, family, and school characteristics at baseline, and

[17] Students face the following hypothetical scenario: They were just hired for a new short-term job and can chose between a fixed wage or a lottery in which the wage is determined by a coin flip. By varying the optimistic scenario wage, we classify students in a scale from 1 to 4 where 1 is extremely risk averse and 4 is risk loving. We consider a student risk averse if they are classified 1 or 2.

includes all the attributes in Table 1. Our coefficient of interest is β, which captures the effect of the informational treatment. $u_{is,t+1}$ is a mean-zero error term assumed to be uncorrelated with the treatment indicator. Equation (1) is estimated by Ordinary Least Squares (OLS), clustering standard errors at the school-level. Given that the actual take up of the information depends on the level of attention placed by students, β would capture the intent-to-treat rather than the average treatment effect of acquiring new information.

When studying the potential mechanisms driving our main results, given available information for the baseline and follow-up, we use a difference-in-differences specification. We define a binary variable, $Post$, that equals one after information exposure and zero otherwise:

$$y_{ist} = \alpha Post + \beta(T_{st} \times Post) + \gamma T_{st} + \mu_i + u_{ist} \tag{2}$$

where α estimates the change in the outcome over time, γ captures any pre-existing differences between treatment and control groups, and μ_i is a student-specific effect that controls for all time-invariant characteristics (observed and unobserved) in our sample. Again, our coefficient of interest is β, which measures the average effect of the information-based treatment on the studied outcome. Standard errors are clustered at the school-level.

6 Results

This section studies the effect of information disclosure. Since information affects beliefs, then decisions in high school, and ultimately college enrollment, our findings are presented in that order. First, we examine whether the treatment influenced students' beliefs about higher education returns and funding knowledge. Second, we test whether effort increases as a result of being exposed to the information by estimating the impact on test scores. Finally, we quantify whether the treatment affected post-secondary enrollment decisions of students by examining both overall enrollment and the types of colleges and degrees that enrolled students were admitted to.

6.1 Beliefs

Our measures of student perceptions include knowledge about funding programs and beliefs about labor market returns. Knowledge is measured using binary variables that denote awareness of funding institutions (ICETEX and FESBO). Beliefs on labor market returns are measured by the error between perceived and actual wage premiums for vocational and academic degrees.[18]

[TABLE 2 ABOUT HERE]

Baseline statistics for knowledge and beliefs are presented in Table 2. Almost 70% of students express familiarity with ICETEX and 17% know FESBO, with both treatment and control groups reflecting similar baseline knowledge. These patterns reflect that students are mostly aware of the existence of funding programs, but imperfectly so.

On average, public high school students in Bogotá overestimate the returns to higher education. Reported errors in premiums for vocational and academic degrees are 70% and 119% larger on average, respectively. These results contradict the usual assumption that students underestimate the returns to education, but are consistent with findings for the same population in Colombia (Gamboa and Rodríguez, 2014) and other countries (Kerr et al., 2014, McGuigan et al., 2014, Hastings et al., 2015).

[FIGURE 2 ABOUT HERE]

In addition to overestimating the average returns to post-secondary studies at the baseline, students show sizable variation in their beliefs. Figure 2 plots the distribution of errors for vocational and academic premiums. Students overestimate the associated benefits of 2-year vocational degrees, but most of them are not far from the correct belief. 76.3% are within one standard deviation of the true premiums. Perceptions are less accurate for 4-year academic degrees. Furthermore, these beliefs are more disperse.

[18] We calculate errors by estimating the difference between perceived and actual premiums and then dividing by the actual premium. That is, if π^j denotes the wage premium and $j = \{\text{actual, perceived}\}$, then our measures are $(\pi^{perceived} - \pi^{actual})/\pi^{actual}$. Using other measures yields similar results.

43.1% have errors of one standard deviation, 46.4% between one and three standard deviations, and 10.5% more than three times the standard deviation. Students are therefore substantially more misinformed about higher education than other schooling levels.[19]

[TABLE 3 ABOUT HERE]

Difference-in-difference estimates of the effect of the information treatment on knowledge and beliefs are presented in Table 3. We find a positive impact on knowledge of the largest funding program, ICETEX. In particular, average awareness of this institution increases by 4.6 percentage points (or 6.6% of the mean). There are no statistically significant effects of the treatment on knowledge of FESBO or perceived returns.

However, students appear to be acquiring more information over time – independently from our intervention. Notice that the coefficient for the follow up period ($Post$) is positive and significant for both funding programs. Likewise, students significantly reduce the degree to which they were overestimating the returns to higher education on average.

[TABLE 4 ABOUT HERE]

One potential reason we do not find that treated students corrected their beliefs at a faster rate than control students could be due to opposing effects: students who were overestimating before the intervention update downwards and those that were underestimating update upwards. We test for this possibility by estimating separate regressions for each group defined at the baseline in Table 4. Similar to the average effects, individuals do correct their beliefs in the appropriate direction, but not because of the information treatment. Once again, students acquire information over time on their own, pushing them closer to the actual wage premiums.

Overall, treated students learned about funding programs but did not update their beliefs about the returns to college. This is probably due to the fact that most of our students are credit constrained. In fact, our sample consists of mostly low-income students and this is a binding restriction when it comes to paying for college, or even applying for funding programs (see Section 5.2).

[19] Jensen (2010) suggests that noisier beliefs for higher education may be due to college being a rare outcome. In our sample, less than 18% of the students have parents who completed higher education.

6.2 Test scores

Academic performance plays a central role in college admissions in Colombia. The informational talk could have affected effort in high school by increasing the desirability or attainability of a post-secondary degree. Student performance is measured using test scores from the national high school exit exams (SABER11) that was taken months after our intervention. In particular, we focus on the overall score and the two most important subjects: mathematics and language.[20] Descriptive statistics are reported in Panel A of Table 5. All scores are standardized with mean zero and standard deviation of one with respect to the control group for ease of comparison.

[TABLE 5 ABOUT HERE]

Table 6 presents the effects of information on test scores. In column 1, we do not find any statistically significant effects of the treatment on the overall score. However, the aggregate score masks some heterogeneity across exam topics. The treatment induced students to perform better on mathematics (column 2). On average, math scores increased by 7.5% of a standard deviation, statistically relevant at the 10% level. Given that most universities weigh mathematics performance higher than scores for other topics, it is not surprising that a student would invest the marginal unit of effort on the subject that yields the largest potential return. No effects are found on language scores (column 3).

[TABLE 6 ABOUT HERE]

To put the magnitude of the effects on math scores into perspective, they are smaller than those obtained by Nguyen (2008) for primary students (0.2 SD) and Avitabile and De Hoyos Navarro (2015) for technological high schools (0.3 SD), but comparable to a number of far more expensive programs.[21] Using data from our follow-up survey, we found that the treatment had no statistically significant effects on student preparation

[20]The overall score is computed using the official weights: mathematics (3), language (3), social sciences (2), biology (1), physics (1), chemistry (1) and philosophy (1).

[21]See for instance the JPAL analysis of education programs that target student learning: http://www.povertyactionlab.org/policy-lessons/education/student-learning.

for the exit exam.[22] We cannot reject the possibility that the increase in mathematics score is due to either more hours studied or expending more effort at the time of the actual exam given that the perceived stakes are higher due to the information treatment.

6.3 College Enrollment

We are able to track students who enrolled in higher education after graduation, and further characterize their college and degree of choice with the set of categories described in Section 3. Descriptive statistics are reported in Panel B of Table 5. The enrollment rate for a post-secondary degree (academic or vocational) in our sample is 44.4%, with around 34.8% enrolled in a vocational program. Less than 10% of the students enroll in academic degrees, very few in top-ranked colleges (1%), and STEM degrees (4.9%). Overall, only 9% opt for a high-earning college-degree combination.

[TABLE 7 ABOUT HERE]

Table 7 presents treatment effect estimates on higher education enrollment. We find that the information treatment had no statistically significant effect on the probability of enrolling in any post-secondary program. However, this is not true for intensive margin outcomes, related to the choice of college, degree, and field. There is a statistically significant increase of around 1.5 percentage points on the probability of enrolling in a top-10 college, a 4.1 percentage point increase in pursuing a academic program, a 3.2 percentage point increase in choosing a STEM degree. The combined effect leads to an increase of 3.5 percentage point in the probability of choosing a high-earning college-degree. These impacts, though small in magnitude, are economically significant. Effects range from 75% of the mean for top-10 college, 30.1% of the mean for pursuing a STEM degree, 20.7% for academic degrees, and 15.6% for high-earning college-degree.

Compared to existing estimates, our results are consistent with previous literature. Among "pure" information treatments, most studies find no effect of disclosing informa-

[22] Around 88.9% reported to have studied at home, while 81.1% of the students took a preparation course for the exam. It is important to note that in many cases preparation courses were provided by the schools as part of the course load. We did ask about time spent studying, however the non-response rate for that question was 40% even though the vast majority reported that they studied at home.

tion on higher education enrollment (Booij et al., 2012, Wiswall and Zafar, 2012, Fryer, 2013, Oreopoulos and Dunn, 2013, Kerr et al., 2014, McGuigan et al., 2014, Dinkelman and Martínez, 2014). Our intensive margin effects are similar to more comprehensive interventions that provide information and personalized assistance (Hoxby et al., 2013, Hastings et al., 2015), which conclude that individuals choose more selective degrees.

In the long run, these intensive margin enrollment effects may have important implications on future earnings. Recall from Figure 1 that students enrolling in a top-10 college earn approximately 50% more than non-top college students (1 minimum wage more), on average. There is a similar difference in expected earnings for pursuing academic rather than vocational degrees. Therefore, while information may not lead more individuals to attend college, it does affect what colleges and degrees are chosen by those who do enroll.

7 Mechanisms

The effects of providing "pure" information appear to have been modest overall. On the one hand, students update their knowledge on funding programs but not on the returns to education. On the other hand, we observe no improvement on enrollment rates, but some positive effects on math scores and enrollment in selective colleges and degrees. In this section we discuss potential mechanisms that help interpret our results.

A sizable body of literature has explored why low-income individuals do not enroll in post-secondary education. The most widely discussed determinants are related to credit constraints and family background. Empirical evidence suggests that liquidity constraints discourage potential applicants not only from enrolling (Manski, 1992, Solis, 2013) but also from applying for and receiving student loans (Kane, 1994, Ellwood and Kane, 2000). Additionally, parents' education tends to account for a large share of the variation in higher education enrollment (Cameron and Heckman, 2001, Keane and Wolpin, 2001, Carneiro and Heckman, 2002).

Non-cognitive factors also play an important role in determining human capital accumulation and academic success (Heckman and Rubinstein, 2001). Heterogeneity across different non-cognitive dimensions might attenuate the overall impact of our information treatment. Furthermore, we may learn more about the mechanisms mediating the effects of the information treatment on the intensive margin of post-secondary enrollment. This paper explores four different dimensions of non-cognitive factors. First, there still is a considerable gender gap in major choice and labor market outcomes (Goldin et al., 2006). In part, this can be explained by what appear to be gender-specific traits or preferences.[23] Second, low-income families tend to be more risk averse and thus have lower incentives to invest in college where success is not guaranteed (Belzil and Hansen, 2004, Belzil and Leonardi, 2007, Heckman, 2007). Third, the role of self-confidence is often cited as an important non-cognitive measure influencing schooling decisions of individuals (Bénabou and Tirole, 2002, Heckman et al., 2006). Last, aspirations may keep poor children from pursuing more ambitious goals or induce frustration because of the difficulties in achieving their objectives (Appadurai, 2004, Ray, 2006, Heifetz and Minelli, 2006, Genicot and Ray, 2009, Dalton et al., 2014).

7.1 Credit Constraints and Parents' Education

To evaluate the extent to which credit constraints and parental education could dampen the potential effects of providing more accurate information on the returns and financing of higher education, we explore the heterogeneity of treatment effects by these factors. In particular, we classify students into three income and parental education categories. Tables 8 to 10 present the estimated treatment effect on our main outcomes for each group, as well as differences between coefficients with their corresponding standard error.

[TABLE 8 ABOUT HERE]

In Table 8 we find that only students from low-income families and/or low-educated parents learn about ICETEX – the main funding institute. On average, students from a very low and low income family increased their knowledge of ICETEX by about 7 and 4.5

[23] For instance, there is evidence that, when given the option, women shy away from competition (Niederle and Vesterlund, 2007), perform less well in competitive environments (Gneezy et al., 2003), and self-select into less competitive or lower earning careers (Buser et al., 2014).

percentage points, respectively. Similarly, students whose parents completed primary or less increased their knowledge by 8.5 percentage points. Differences between coefficients are significant for parents' education levels but not for family income. This likely reflects a catching-up: students from higher income families and more educated parents report significantly higher knowledge of funding programs in the baseline survey. We do not find any statistically relevant effects or differences between groups for all other knowledge or belief outcomes. Overall, students appear to have valued information on financing more than that of returns, suggesting that credit constraints are indeed a primary concern for most of the students in our sample.

[TABLE 9 ABOUT HERE]

Table 9 presents heterogeneous effects of the intervention by family income and parents' education on test scores. Unlike knowledge of ICETEX, most of the effect found for mathematics seems to be driven by students from middle income families, with an increase in the mathematics score of 13.1% of a standard deviation. There is also a positive and significant effect of 8.5% of a standard deviation for students with low-educated parents, however, the difference with respect to other groups is not significant.

Heterogeneous estimates by family income and parental education on enrollment are presented in Table 10. As with the average estimates, we find no differential effects on higher education enrollment. However, students' intensive margin decisions respond differently to information depending on both of these factors. First, most of the students who move to private colleges come from low-income families and/or low-educated parents, with estimated effects of 6.3 and 7.7 percentage points, respectively. In both cases we find significant differences with respect to at least one other group. When it comes to top-10 colleges, we see some significant effects for middle-income students, but the effect is not statistically different from the estimate for lower income groups. Second, students from very-low income families are not significantly changing their college choice, although they are 7 percentage points more likely to opt for STEM degrees. Something similar happens with students whose parents completed higher education, although in both cases the differences with respect to other groups are not significant. The students that significantly increased their chances of enrolling in a high-earning college-degree have college-educated parents, and come from middle-income, and to lesser extent, very-low income families, with estimated effects that oscillate between 4.8 and 8.9 percentage points. However, the difference with respect to other groups are never significant.

[TABLE 10 ABOUT HERE]

In general, we find that most of the positive effects of the intervention were on the students coming from the higher-income families in our sample. This further supports that providing information may have limited effects on higher education demand when such interventions do not eliminate the sizable credit constraints associated with college.

7.2 Other factors

We now explore additional factors that might influence the impact of the information treatment. We focus on non-cognitive factors that have been identified as key determinants of education choices: gender, risk aversion, self-confidence, and aspirations.

[TABLE 11 ABOUT HERE]

First, in Panel A of Tables 11, 12 and 13 we find that the intervention only had significant effects on males. Not only they learned about funding programs, but they also improved all scores at the exit exam, and enrolled in more selective colleges and majors. In particular, we find a 4.4 percentage point increase in the overall enrollment rate for boys that is significantly larger than the estimate for girls. The difference in coefficients between genders is also significant for the overall and language test scores. Hence, it appears that gender-specific traits or preferences for post-secondary education are playing a role in determining the effectiveness of the intervention.

[TABLE 12 ABOUT HERE]

Second, we classify students in our sample with low and high risk aversion using baseline variables. Panel B of Tables 11, 12 and 13 present results for this classification. We only find a statistically significant differences between low and high risk averse students for knowledge of the Bogotá funding program, FESBO. This suggests that the information did not resonate more with students who may have been more or less cautious about making the decision to enroll in higher education. It is important to note that one shortcoming of using this measure is that pursuing higher education is likely a joint decision between the student and his/her parents. Unfortunately, we do not count with measures of parental risk aversion but this would certainly be an interesting avenue for future studies to address.

[TABLE 13 ABOUT HERE]

Third, we assess the role of self-confidence using two classifications. The first, academic self-concept, measures whether a student believes they are above average in academic terms. Heterogeneous estimates of information by high and low academic self-concept groups are presented in Panel C of Tables 11, 12 and 13. Similar to the previous cases, we do not find statistically relevant differences in the effects for both groups.

The second, student self-efficacy, measures whether students are more likely to achieve their goals. Results for this non-cognitive attribute are presented in Panel D of Tables 11, 12 and 13. Here, we do find some interesting differences. Highly self-efficacious students gained significantly more knowledge of ICETEX than those students with low self-efficacy. These students also increased their overall score on the exit exam by 12.3% of a standard deviation. This effect is statistically different to that found for low self-efficacious students. Similar effects are found for mathematics and language test scores. Finally, these same students are those that increased their probability of selecting a high earning or STEM degree, and are more likely to enroll in a academic degree or a top-10 college. However, note that the differences are not statistically significant with respect to the reference group.

Finally, we examine whether the information treatment affected student aspirations. In order to do so, we asked students about their educational aspirations in the baseline and follow-up survey.[24] Even though we do not find significant effects on beliefs about

[24] Specifically, we ask the students to report their college and degree of preference. Descriptive statistics

returns to post-secondary education, students do learn about financing institutions. This could affect student's aspirations on whether they want to enroll in a post-secondary program or what type of degree to pursue. Results for aspiration outcomes are presented in Table 14. Findings show no effect of information on any of the aspiration indicators. This suggests that the intensive margin effects on enrollment found are not driven by changes in student aspirations.

[TABLE 14 ABOUT HERE]

Overall, we find that our information treatment had larger effects on boys, which may reflect gender-specific traits or preferences. Moreover, students with high self-efficacy, i.e. belief in one's ability to achieve goals, benefited more from the intervention. This is consistent with the hypothesis that motivation, rather than information itself, is driving most of the positive effects. More precise measurements of non-cognitive skills may provide further insights on both these results.

8 Conclusion

This paper studies the effectiveness of providing information on the returns and financing of college on higher education decisions in a developing country. We conducted a randomized controlled trial on students in their final year of high school at pubic institutions in Bogotá, Colombia. Public schools in Bogotá mostly serve low-income students, who have systematically lower college enrollment rates than their peers. A representative sample of 120 schools was randomly selected to participate in the study, and half received a 35-minute informational talk delivered by local college graduates.

We find that providing students with information on post-secondary funding opportunities and returns by major-institution pairs did not significantly induce higher enrollment in post-secondary education. However, it does have a positive effect on the national exit exam, which is a determining factor for admission in most colleges. Moreover, treated students who enrolled chose more selective colleges and majors. These estimated effects

and baseline balance for the aspiration outcomes may be found in the Online Appendix.

are economically significant and may have important implications for future earnings of college students.

Evidence indicates that credit constraints might be seriously limiting the impact of our intervention in increasing the demand for college. First, most of our sample comes from low-income households, who are unable to cover the costs of college education and may face barriers to funding programs. Second, the information treatment increased the knowledge of funding programs but did not update beliefs about the returns to higher education. This is consistent with the fact that students in our sample see costs as the main barrier to attend college. Third, we find larger effects of the intervention on individuals from better socioeconomic status, for whom the likelihood of attending college is higher.

Results also suggest that the most of the positive effects of the intervention are driven by motivation, rather than information itself. In fact, the students who benefited the most from the intervention already knew about funding programs and did not update their beliefs about the returns to education. Consistent with this, the estimated effects are significantly larger for students who highly believe in their ability to achieve their goals. We also find significantly larger effects on boys, which could be reflecting gender-specific traits or preferences. Such patterns may lead to further research on the role of non-cognitive skills in education choices.

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Table 1. Student and School Characteristics

	Bogotá				BHELPS					
	Private schools		Public schools		Control		Treatment		Difference	
	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	p-value
Panel A: Students										
Males	0.492	(0.500)	0.458	(0.498)	0.465	(0.499)	0.474	(0.499)	0.009	0.589
Age	17.648	(0.907)	17.641	(0.873)	17.653	(1.144)	17.644	(1.017)	-0.010	0.806
Born in Bogotá					0.849	(0.358)	0.846	(0.361)	-0.003	0.803
Parent completed primary or less	0.132	(0.339)	0.449	(0.497)	0.430	(0.495)	0.462	(0.499)	0.032	0.291
Parent completed secondary	0.288	(0.453)	0.395	(0.489)	0.394	(0.489)	0.393	(0.488)	-0.001	0.933
Parent completed higher education	0.580	(0.494)	0.156	(0.363)	0.176	(0.381)	0.146	(0.353)	-0.031	0.115
Very low income (<1 MW)	0.028	(0.165)	0.144	(0.351)	0.136	(0.343)	0.147	(0.354)	0.011	0.434
Low income (1-2 MWs)	0.246	(0.431)	0.559	(0.497)	0.546	(0.498)	0.544	(0.498)	-0.002	0.940
Middle-high income (>2 MWs)	0.726	(0.446)	0.297	(0.457)	0.319	(0.466)	0.309	(0.462)	-0.010	0.717
Internet at home					0.717	(0.451)	0.677	(0.468)	-0.039	0.105
Victim of violence					0.033	(0.177)	0.033	(0.180)	0.001	0.869
Student is employed					0.163	(0.370)	0.168	(0.374)	0.005	0.701
Has repeated at least one grade					0.243	(0.429)	0.244	(0.430)	0.002	0.918
Academic self-concept					0.424	(0.494)	0.388	(0.487)	-0.036	0.075
High self-confidence					0.347	(0.476)	0.347	(0.476)	-0.001	0.971
Risk averse					0.857	(0.350)	0.842	(0.364)	-0.015	0.286
Likely to enroll					0.842	(0.364)	0.842	(0.365)	-0.001	0.971
Panel B: Schools										
Number of students (2010-2012)	111.152	(168.483)	99.655	(48.081)	94.147	(48.067)	90.719	(31.450)	-3.428	0.667
SABER 11 score (2010-2012)	0.874	(0.809)	0.117	(0.254)	0.166	(0.216)	0.123	(0.281)	-0.042	0.394
Morning shift	0.191	(0.393)	0.547	(0.498)	0.646	(0.478)	0.611	(0.488)	-0.036	0.700
Afternoon shift	0.019	(0.137)	0.390	(0.488)	0.331	(0.471)	0.372	(0.483)	0.041	0.652
Single shift	0.790	(0.407)	0.063	(0.243)	0.023	(0.149)	0.018	(0.131)	-0.005	0.853
School has computer lab					0.968	(0.175)	0.956	(0.205)	-0.012	0.747
Total students	37,286		37,891		2,712		2,791			
Total schools	790		571		58		57			

Source: Authors' calculations from ICFES and BHELPS survey on balanced sample.
Notes: The Bogotá statistics are based on ICFES, and includes the universe of schools offering an academic track. Using date of birth, we compute the age of each student on December 31, 2013. The number of students is the average number of individuals who sat for the SABER 11 exam in 2010-2012. Likewise, the SABER 11 score is the average of the 2010-2012 standardized scores (with respect to each year national population). The last two columns present the difference in means and p-values between treatment and control groups calculated by regression with clustered standard errors at the school-level.

Table 2. Baseline Balance in Student Knowledge and Beliefs

	Control		Treatment		Difference	
	Mean	(SD)	Mean	(SD)	Mean	p-value
Knows ICETEX	0.697	(0.460)	0.690	(0.463)	-0.007	0.784
Knows FESBO	0.173	(0.379)	0.165	(0.371)	-0.008	0.451
Premium Error: Vocational	0.699	(1.559)	0.626	(1.461)	-0.073	0.181
Premium Error: Academic	1.192	(1.259)	1.120	(1.229)	-0.072	0.169

Source: Authors' calculations from BHELPS survey on balanced sample.
Notes: The last two columns present the difference in means and p-values between treatment and control groups calculated by regression with clustered standard errors at the school-level.

Table 3. Treatment Effects on Knowledge and Beliefs

	Knows ICETEX (1)	Knows FESBO (2)	Premium Error: *Vocational* (3)	Premium Error: *Academic* (4)
Treat × Post	0.046**	0.007	0.077	0.043
	(0.018)	(0.014)	(0.062)	(0.054)
Post	0.125***	0.025**	-0.097**	-0.110***
	(0.011)	(0.010)	(0.049)	(0.042)
Mean(y)	0.695	0.169	0.670	1.164
N	10730	10224	10140	10126

Source: Authors' calculations from BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 4. Treatment Effects on Beliefs by Baseline Error

	Premium error: *Vocational*		Premium error: *Academic*	
	Under (1)	Over (2)	Under (3)	Over (4)
Treat × Post	0.107	0.131	-0.007	0.041
	(0.189)	(0.083)	(0.168)	(0.069)
Post	1.732***	-1.056***	1.475***	-0.659***
	(0.145)	(0.065)	(0.121)	(0.056)
Mean(y)	-1.614	1.866	-0.833	1.668
N	1,236	4,494	1,145	6,022

Source: Authors' calculations from BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate diffenrence-in-difference regression that controls for individual fixed-effects. Regressions (1) and (3) only include students who underestimate the respective premium wage in the baseline survey. Regressions (2) and (4) only include students who overestimate the respective premium wage in the baseline survey. Standard errors are clustered at the school-level.

Table 5. Descriptive Statistics, Test Scores and College Enrollment

	Bogotá				BHELPS	
	Private schools		Public schools			
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Panel A: Exit Exam						
Overall Score	0.864	(1.192)	0.138	(0.841)	0.129	(0.825)
Math	0.708	(1.231)	0.046	(0.884)	0.023	(0.870)
Language	0.702	(1.060)	0.156	(0.870)	0.175	(0.868)
Panel B: College Enrollment						
Enrolled	0.571	(0.495)	0.426	(0.495)	0.443	(0.497)
Public College	0.147	(0.354)	0.278	(0.448)	0.290	(0.454)
Private College	0.424	(0.494)	0.148	(0.355)	0.153	(0.360)
Top-10 College	0.160	(0.366)	0.011	(0.106)	0.011	(0.102)
Academic degree (4-year)	0.370	(0.483)	0.098	(0.298)	0.095	(0.293)
Vocational degree (2-year)	0.201	(0.400)	0.328	(0.469)	0.349	(0.477)
STEM degree	0.211	(0.408)	0.054	(0.227)	0.050	(0.217)
High-earning college-degree	0.335	(0.472)	0.093	(0.290)	0.091	(0.288)

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey on balanced sample.
Notes: The Bogotá statistics are based ICFES and SNIES, and includes the universe of school offering an academic track. Test scores are standardized with mean zero and variance one with respect to the national population.

Table 6. Treatment Effects on Test Scores

	Overall (1)	Math (2)	Language (3)
Treat	0.031	0.075*	0.018
	(0.033)	(0.040)	(0.031)
Mean(y)	-0.023	0.008	-0.019
N	4481	4481	4481

Source: Authors' calculations from ICFES and BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate OLS regression that control for individual and school characteristics in Table 1. Standard errors are clustered at school-level.

Table 7. Treatment Effects on Enrollment Choices

	Enrolled College (1)	Private College (2)	Top-10 College (3)	Academic Degree (4)	STEM Degree (5)	High Earning (6)
Treat	0.009	0.021	0.014**	0.041**	0.032**	0.035*
	(0.021)	(0.026)	(0.006)	(0.020)	(0.014)	(0.021)
Mean(y)	0.446	0.342	0.019	0.212	0.106	0.226
N	4470	2028	2028	2028	2028	1820

Source: Authors' calculations from ICFES, SNIES and BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 8. Treatment Effects on Knowledge and Beliefs by Income and Parental Education

	Knows ICETEX (1)	Knows FESBO (2)	Premium Error: *Vocational* (3)	Premium Error: *Academic* (4)
Panel A: Family income				
Very low income (<1 MW)	0.070*	0.028	0.111	0.092
	(0.036)	(0.038)	(0.158)	(0.115)
Low income (1-2 MWs)	0.045**	-0.002	0.129	0.075
	(0.022)	(0.017)	(0.078)	(0.062)
Middle income (>2 MWs)	0.035	0.013	-0.026	-0.033
	(0.024)	(0.025)	(0.089)	(0.074)
(Low - Very low)	-0.025	-0.030	0.018	-0.017
	(0.039)	(0.039)	(0.166)	(0.116)
(Middle - Very low)	-0.036	-0.015	-0.137	-0.125
	(0.042)	(0.044)	(0.174)	(0.121)
(Middle - Low)	-0.011	0.015	-0.154	-0.108
	(0.025)	(0.030)	(0.111)	(0.079)
Panel B: Parents education				
Primary or less	0.085***	0.016	0.026	0.060
	(0.024)	(0.022)	(0.093)	(0.072)
Secondary	0.014	0.005	0.132	0.040
	(0.023)	(0.025)	(0.091)	(0.082)
Higher education	0.002	0.017	0.048	-0.009
	(0.027)	(0.030)	(0.105)	(0.090)
(Secondary - Primary)	-0.072***	-0.011	0.106	-0.020
	(0.027)	(0.034)	(0.113)	(0.093)
(Higher - Primary)	-0.084**	0.001	0.022	-0.069
	(0.032)	(0.034)	(0.139)	(0.117)
(Higher - Secondary)	-0.012	0.012	-0.084	-0.049
	(0.032)	(0.037)	(0.130)	(0.115)
Mean(y)	0.695	0.169	0.670	1.164
N	10730	10224	10140	10126

Source: Authors' calculations from BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 9. Treatment Effects on Test Scores by Income and Parental Education

	Overall (1)	Math (2)	Language (3)
Panel A: Family income			
Very low income (<=1 MW)	0.006	-0.054	0.004
	(0.067)	(0.072)	(0.072)
Low income (2 MWs)	0.010	0.074	-0.004
	(0.045)	(0.048)	(0.043)
Middle income (>2 MWs)	0.077	0.131**	0.063
	(0.048)	(0.055)	(0.052)
(Low - Very low)	0.004	0.129	-0.008
	(0.075)	(0.081)	(0.081)
(Middle - Very low)	0.071	0.185**	0.059
	(0.081)	(0.085)	(0.094)
(Middle - Low)	0.067	0.057	0.067
	(0.063)	(0.059)	(0.066)
Panel B: Parents education			
Primary or less	0.041	0.085*	-0.012
	(0.044)	(0.047)	(0.046)
Secondary	0.005	0.059	0.033
	(0.045)	(0.054)	(0.049)
Higher education	0.063	0.089	0.064
	(0.070)	(0.071)	(0.070)
(Secondary - Primary)	-0.037	-0.025	0.045
	(0.059)	(0.059)	(0.070)
(Higher - Primary)	0.022	0.004	0.076
	(0.075)	(0.075)	(0.080)
(Higher - Secondary)	0.058	0.029	0.031
	(0.076)	(0.075)	(0.078)
Mean(y)	-0.023	0.008	-0.019
N	4481	4481	4481

Source: Authors' calculations from ICFES and BHELPS survey on balanced sample. Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate OLS regression that control for individual and school characteristics in Table 1. Standard errors are clustered at school-level.

Table 10. Treatment Effects on Enrollment Choices by Income and Parental Education

	Enrolled College (1)	Private College (2)	Top-10 College (3)	Academic Degree (4)	STEM Degree (5)	High Earning (6)
Panel A: Family income						
Very low income (<=1 MW)	0.033	-0.057	0.018	0.024	0.070**	0.057
	(0.045)	(0.057)	(0.015)	(0.046)	(0.031)	(0.044)
Low income (2 MWs)	0.012	0.063*	0.005	0.041*	0.013	0.006
	(0.028)	(0.032)	(0.007)	(0.025)	(0.019)	(0.026)
Middle income (>2 MWs)	-0.008	-0.015	0.027*	0.045	0.048	0.069*
	(0.027)	(0.042)	(0.014)	(0.035)	(0.030)	(0.035)
(Low - Very low)	-0.020	0.121*	-0.013	0.018	-0.057	-0.051
	(0.051)	(0.067)	(0.016)	(0.049)	(0.037)	(0.051)
(Middle - Very low)	-0.041	0.043	0.009	0.021	-0.022	0.012
	(0.048)	(0.068)	(0.021)	(0.059)	(0.044)	(0.051)
(Middle - Low)	-0.020	-0.078*	0.022	0.004	0.035	0.063
	(0.032)	(0.046)	(0.016)	(0.039)	(0.036)	(0.042)
Panel B: Parents education						
Primary or less	-0.001	0.077**	0.008	0.033	0.017	0.048*
	(0.027)	(0.037)	(0.006)	(0.026)	(0.019)	(0.028)
Secondary	0.002	-0.021	0.015	0.028	0.032	-0.003
	(0.028)	(0.037)	(0.011)	(0.032)	(0.024)	(0.032)
Higher education	0.048	0.001	0.025	0.082	0.062*	0.089*
	(0.037)	(0.054)	(0.020)	(0.054)	(0.036)	(0.050)
(Secondary - Primary)	0.003	-0.098**	0.008	-0.005	0.015	-0.050
	(0.031)	(0.047)	(0.012)	(0.041)	(0.031)	(0.041)
(Higher - Primary)	0.049	-0.077	0.018	0.049	0.045	0.042
	(0.040)	(0.062)	(0.022)	(0.061)	(0.041)	(0.054)
(Higher - Secondary)	0.046	0.021	0.010	0.054	0.029	0.092
	(0.042)	(0.061)	(0.023)	(0.061)	(0.042)	(0.059)
Mean(y)	0.446	0.342	0.019	0.212	0.106	0.226
N	4470	2028	2028	2028	2028	1820

Source: Authors' calculations from ICFES, SNIES and BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 11. Treatment Effects on Knowledge and Beliefs by Non-Cognitive Factors

	Knows ICETEX (1)	Knows FESBO (2)	Prem. Error: Vocational (3)	Prem. Error: Academic (4)
Panel A: Gender				
Female	0.033	-0.005	0.069	0.063
	(0.023)	(0.019)	(0.088)	(0.070)
Male	0.060**	0.021	0.086	0.018
	(0.024)	(0.019)	(0.079)	(0.065)
(Male - Female)	0.027	0.026	0.017	-0.045
	(0.028)	(0.026)	(0.114)	(0.082)
Panel B: Risk aversion				
Low	0.047	0.085**	0.093	-0.106
	(0.042)	(0.037)	(0.184)	(0.127)
High	0.046**	-0.006	0.073	0.066
	(0.019)	(0.015)	(0.063)	(0.054)
(High - Low)	0.001	-0.087**	-0.032	0.164
	(0.043)	(0.039)	(0.189)	(0.123)
Panel C: Academic self-concept				
Low	0.065***	0.008	0.063	-0.021
	(0.022)	(0.019)	(0.079)	(0.063)
High	0.015	0.006	0.091	0.124
	(0.024)	(0.021)	(0.085)	(0.076)
(High - Low)	-0.048*	-0.006	0.019	0.145*
	(0.028)	(0.028)	(0.106)	(0.086)
Panel D: Self-efficacy				
Low	0.024	0.015	0.084	-0.002
	(0.022)	(0.017)	(0.064)	(0.062)
High	0.086***	-0.008	0.066	0.127
	(0.024)	(0.024)	(0.101)	(0.082)
(High - Low)	0.059**	-0.028	-0.012	0.121
	(0.027)	(0.029)	(0.106)	(0.092)
Mean(y)	0.695	0.169	0.670	1.164
N	10730	10224	10140	10126

Source: Authors' calculations from BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 12. Treatment Effects on Exit Exam by Non-Cognitive Factors

	Overall (1)	Math (2)	Language (3)
Panel A: Gender			
Female	-0.010	0.045	-0.027
	(0.038)	(0.045)	(0.042)
Male	0.079*	0.111**	0.072*
	(0.047)	(0.053)	(0.043)
(Male - Female)	0.090*	0.066	0.099*
	(0.054)	(0.057)	(0.058)
Panel B: Risk aversion			
Low	0.042	0.121	0.019
	(0.089)	(0.094)	(0.085)
High	0.029	0.068*	0.018
	(0.034)	(0.040)	(0.034)
(High - Low)	-0.013	-0.053	-0.001
	(0.093)	(0.094)	(0.092)
Panel C: Academic self-concept			
Low	0.024	0.072	-0.008
	(0.040)	(0.046)	(0.043)
High	0.039	0.080	0.054
	(0.046)	(0.055)	(0.042)
(High - Low)	0.015	0.009	0.061
	(0.056)	(0.061)	(0.058)
Panel D: Self-efficacy			
Low	-0.018	0.063	-0.047
	(0.040)	(0.047)	(0.041)
High	0.123**	0.100*	0.141***
	(0.047)	(0.050)	(0.052)
(High - Low)	0.141**	0.037	0.187***
	(0.059)	(0.057)	(0.067)
Mean(y)	-0.023	0.008	-0.019
N	4481	4481	4481

Source: Authors' calculations from ICFES and BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate OLS regression that control for individual and school characteristics in Table 1. Standard errors are clustered at school-level.

Table 13. Treatment Effects on Enrollment Choices by Non-Cognitive Factors

	Enrolled College (1)	Private College (2)	Top-10 College (3)	Academic Degree (4)	STEM Degree (5)	High Earning (6)
Panel A: Gender						
Female	-0.021	0.033	0.011	0.042	0.022	0.032
	(0.027)	(0.034)	(0.007)	(0.026)	(0.017)	(0.022)
Male	0.044*	0.007	0.019*	0.039	0.044*	0.038
	(0.024)	(0.034)	(0.011)	(0.030)	(0.025)	(0.034)
(Male - Female)	0.064**	-0.026	0.008	-0.003	0.022	0.005
	(0.030)	(0.041)	(0.014)	(0.038)	(0.031)	(0.039)
Panel B: Risk aversion						
Low	0.064	-0.027	0.039*	0.027	0.050	-0.024
	(0.042)	(0.061)	(0.020)	(0.041)	(0.033)	(0.050)
High	-0.001	0.029	0.010	0.043**	0.029*	0.044*
	(0.021)	(0.030)	(0.007)	(0.022)	(0.015)	(0.023)
(High - Low)	-0.064	0.056	-0.029	0.016	-0.021	0.069
	(0.039)	(0.069)	(0.022)	(0.043)	(0.034)	(0.055)
Panel C: Academic self-concept						
Low	0.010	0.045	0.015*	0.034	0.027*	0.053**
	(0.026)	(0.031)	(0.008)	(0.026)	(0.016)	(0.027)
High	0.007	-0.006	0.014	0.049*	0.038*	0.015
	(0.029)	(0.035)	(0.012)	(0.028)	(0.022)	(0.029)
(High - Low)	-0.003	-0.051	-0.001	0.015	0.011	-0.038
	(0.035)	(0.039)	(0.017)	(0.035)	(0.025)	(0.037)
Panel D: Self-efficacy						
Low	0.016	0.017	0.009	0.032	0.025	0.015
	(0.022)	(0.030)	(0.008)	(0.026)	(0.017)	(0.024)
High	-0.006	0.028	0.024*	0.057*	0.045**	0.071**
	(0.031)	(0.038)	(0.012)	(0.031)	(0.023)	(0.034)
(High - Low)	-0.022	0.010	0.014	0.025	0.019	0.056
	(0.029)	(0.041)	(0.016)	(0.040)	(0.026)	(0.039)
Mean(y)	0.446	0.342	0.019	0.212	0.106	0.226
N	4470	2028	2028	2028	2028	1820

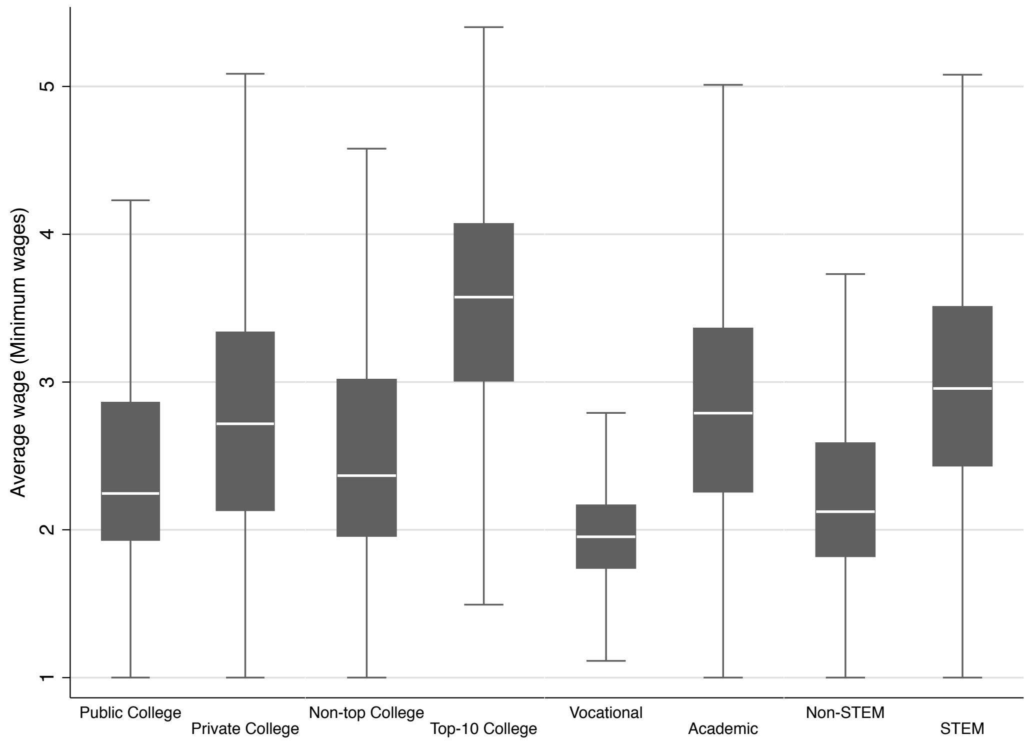
Source: Authors' calculations from ICFES, SNIES and BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 14. Treatment Effects on Aspirations

	Enroll College (1)	Private College (2)	Top-10 College (3)	Academic Degree (4)	STEM Degree (5)	High Earning (6)
Treat × Post	-0.001	0.004	-0.007	0.002	0.007	-0.002
	(0.004)	(0.016)	(0.023)	(0.013)	(0.015)	(0.016)
Post	0.004	0.009	0.000	-0.028***	-0.006	-0.011
	(0.003)	(0.012)	(0.018)	(0.009)	(0.010)	(0.013)
Mean(y)	0.985	0.227	0.462	0.893	0.417	0.796
N	11006	10758	10758	10758	10758	4216

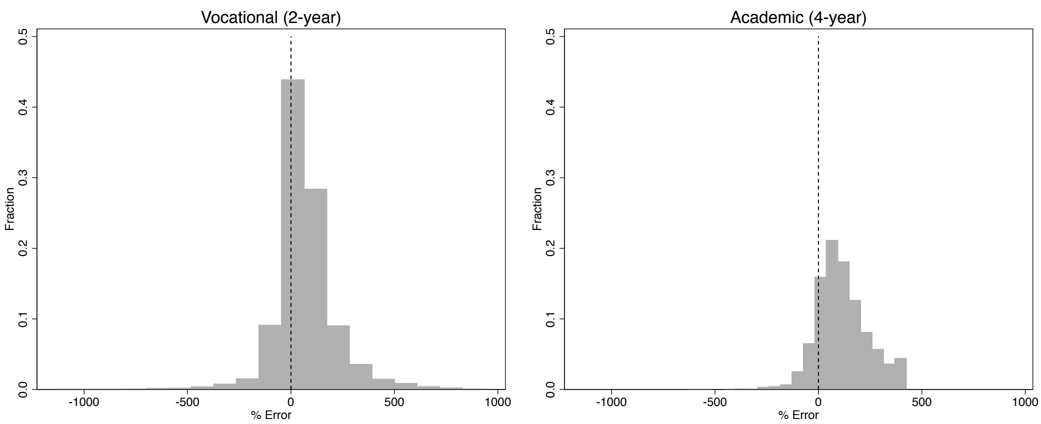
Source: Authors' calculations from ICFES, SNIES and BHELPS survey on balanced sample.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column corresponds to a separate difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Figure 1. Average Wages of Recent Graduates



Source: Authors' elaboration from the Labor Observatory.
Notes: The figure shows the distribution of expected wages for different categories of college and degree. Expected wages as expressed in minimum wages, and correspond to the average wage of recent graduates by college, level and field as defined in Section 3.

Figure 2. Distribution of Wage Premium Beliefs at Baseline



Source: Authors' elaboration from BHELPS on the balanced sample.
Notes: We calculate the error percentage as the difference between perceived and actual premiums divided by the actual premium. Let π^j denote the wage premium, with $j = \{\text{actual,perceived}\}$. Errors are calculated as $(\pi^{perceived} - \pi^{actual})/\pi^{actual}$.