Information Policies and Higher Education Choices

Experimental Evidence from Colombia*

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Abstract

This paper studies whether providing information on funding opportunities and college premiums by degree-college pairs affects higher education decisions in a developing country. 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. Using survey data linked to administrative records, we analyze student beliefs and evaluate the intervention. Findings show that most students overestimate true college premiums and are generally unaware of funding options. The talk does not affect earning beliefs but improves knowledge of financing programs, especially among the poor. There is no evidence that information disclosure affects post-secondary enrollment. However, students in treated schools who do enroll choose more selective colleges. These positive effects are mostly driven by students from better socioeconomic backgrounds. We conclude that information policies are ineffective to raise college enrollment in contexts with significant academic and financial barriers to entry, but may potentially affect certain students' choice of college.

Key words: information, beliefs, higher education, schooling demand, Colombia
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1 Introduction

Many developing countries have taken steps to reduce inequality in attendance rates for primary and secondary education. However, enrollment at post-secondary levels remains relatively low among the poor, despite its significant returns (McMahon, 2009). While credit constraints are often cited as the main barrier to attend higher education[1], recent research argues that information also plays a key role. In fact, college attendance decisions are usually based on *perceived* rather than actual net benefits (Manski, 1993). Therefore, inaccurate beliefs may lead to sub-optimal schooling choices that have lasting consequences for lifetime earnings and welfare.

The influence of incorrect beliefs on educational choices has attracted significant attention because it has a simple and cost-effective solution: providing accurate information. At basic educational levels, the main concern is low perceived benefits of schooling. Most papers studying basic education find that students and families tend to underestimate the returns to education (Nguyen, 2008, Attanasio and Kaufmann, 2009, Jensen, 2010, Kaufmann, 2014). "Pure" information policies have proven successful in updating these beliefs. For instance, Jensen (2010) found that reading a short paragraph on the earning premiums for completing secondary increased educational attainment in the Dominican Republic by 0.20-0.35 years. Nguyen (2008) finds larger effects in Madagascar when using role models to deliver information. These treatments may achieve up to 0.24 additional years of basic schooling per US$100, which is more cost-effective than cash transfers.[2]

Higher education schooling decisions are more complex, and so is the associated information problem. On one hand, college represents a major financial investment, and students usually have limited information regarding its costs and available funding options (Booij et al., 2012, Loyalka et al., 2013, Dinkelman and Martínez, 2014, McGuigan et al., 2014, Hoxby and Turner, 2015, Hastings et al., 2015). On the other, higher education premiums vary dramatically by college and degree, information only recently made avail-

[1]Previous studies suggests that liquidity constraints not only discourage potential applicants from enrolling (Manski, 1992, Solis, 2013), but also from applying for and receiving student loans (Kane, 1994, Ellwood and Kane, 2000).

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

able to the wider public (Oreopoulos and Petronijevic, 2013, Hastings et al., 2013). While a number of countries have created websites for this purpose and encouraged students to visit them[3], evidence suggests that they remain largely uninformed. Interestingly, many studies find that students tend to overestimate the returns to college (Pekkala-Kerr et al., 2015, McGuigan et al., 2014, Hastings et al., 2015).

This paper conducts a randomized controlled trial (RCT) in which senior high school students receive information about available funding programs and the premiums to higher education. We evaluate how providing this information affects their test scores and enrollment decisions. Our experiment takes place in public schools in Bogotá, Colombia. These schools gather students from low and middle-income families who face severe financial constraints to attend college and a very small likelihood of admission to affordable public universities. In addition, since college loans are not backed by the state, funding institutions require a co-debtor to approve any request for financial assistance. Most of the students in our sample are unable to fulfill this binding condition.

We randomly selected a citywide representative sample of 120 public schools to participate in the study. Half of these schools were given a 35-minute informational talk delivered by local college graduates. Students were first provided with an overview of the average premiums associated to attending college compared to finishing high school (and not finishing). We then introduced the Government website where they could search for the average starting salaries of college graduates by degree-college pairs, as well as the probability of finding formal employment by degree. After this, students were briefed on the admission process and 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. Survey respondents were later matched with government administrative records that contain standardized exit exam scores and college enrollment data (degree and institution of attendance).

Our results indicate the intervention did not affect college enrollment rates. However,

[3]Some examples are the *Observatorio Laboral* in Colombia: http://www.graduadoscolombia.edu.co, *Mi Futuro* in Chile: http://www.mifuturo.cl, and the *Observatorio Laboral* in Mexico: http://www.observatoriolaboral.gob.mx.

students in treated schools that go to college gained admission to more selective institutions. We find that these individuals increase the likelihood of enrolling in a top-10 college by almost 50% of the mean. This effect is economically significant and potentially has fairly large implications for future earnings (assuming students' graduate, of course). For instance, graduates from top-10 institutions in Colombia have a higher starting salary compared to other college graduates, about 50% on average.

The limited impact of information in increasing the demand for college may be explained by its inability to remove financial and academic barriers to entry. Most of our sample comes from low-income households, whose monthly income is unable to cover the costs of college education, has below average grades, and cannot fulfill loan requirements. In fact, students report that the most important obstacles to attend higher education are that it is unaffordable (64.5%) or difficult to gain admission (32%). 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 earning beliefs. 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 because these barriers are less binding.

Overall findings are consistent with existing evidence on the effectiveness of "pure" information policies for higher education. These studies provide information on costs and funding programs, college premiums, or both. Interventions focusing exclusively on costs and funding yield mixed results. For instance, Dinkelman and Martínez (2014) increase high school attendance but have no effect on academic performance in Chile. Loyalka et al. (2013) increase college enrollment despite not affecting specific college choices in China. Booij et al. (2012) find no detectable effects on loan take-up in Netherlands. Papers that only provide information about earning premiums, more in the spirit of Jensen (2010), tend to be less effective. This is the case of Pekkala-Kerr et al. (2015), who find Finnish students update their college aspirations but do not change their enrollment choices.

There are three studies similar to ours, where students receive information on premiums as well as cost and funding options. Oreopoulos and Dunn (2013) find that Canadian students raise their college earning expectations. In Avitabile and De Hoyos Navarro (2015), Mexican students improve their exit exam scores but not their dropout behavior. However, the main limitation of these two papers is that they do not assess effects on actual enrollment choices. Hastings et al. (2015) focus on a sample of students who are applying for financial aid in Chile, finding that information on costs and earnings has no effect on overall enrollment, but does encourage low-income students to choose higher-earning degrees. It is important to note that our work is different from Hastings et al. (2015) because we provide information to all students, not only those who apply for financial aid. This may be a more relevant intervention to Governments considering mass advertising of different tools to aid students in acquiring more information on college.

This study contributes to two strands of literature. First, it relates to research on unequal access to higher education. 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 burgeoning literature that evaluates information policies at the post-secondary level, focusing on low-income students from developing countries. The findings may help understand whether an extensive low-cost information campaign is useful to attract students to college and if not, why. While our intervention is one of many possible designs, its implementation and results can potentially inform researchers and policymakers on what, how, and when information should be provided.

The remainder of this paper is organized as follows. Section 2 provides background on Colombia's higher education system. Section 3 describes the experimental framework and intervention. Section 4 characterizes our data and sample. Section 5 presents the effects of the information treatment on higher education decisions. Section 6 analyzes what drives our findings by testing several mechanisms suggested by the literature, including credit constraints, gender differences, non-cognitive factors, and aspirations. We conclude in Section 7 by discussing our findings and outlining directions for future research.

2 Higher Education in Colombia

There are 327 colleges in Colombia, with 132 located in the Bogotá region.[4] Of these 132 colleges, 40 are Universities, 23 are public, and 6 are ranked top-10 in the country.[5] Degrees are classified in two levels, vocational (2-year) and academic (4-year), that encompass 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 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 at top-ranked public universities, the average tuition fee for private universities in the top-10 is 13.2 minimum wages.[6] 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.

There are two main funding programs. At the national level, there is the Colombian Public Student Loans Institution (ICETEX), an agency that handles student loans for vocational, academic, and postgraduate education in Colombia and abroad. This is the largest student loan program, with 22% of enrolled students during 2013 funded by this source, and is also the most widely known. Recent reforms, that introduced zero-interest loans for low-income students, have had large impacts on enrollment and retention (Melguizo et al., 2016). The Secretary of Education of Bogotá offers a less-known funding option for low-income students from the city's public schools through the Fund for Higher Education of Bogotá (FESBO). The fund has two financing options. The first targets high achieving students and offers loans for any college or degree choice. The

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

[5]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.

[6]Hereafter, all monetary variables will be expressed in monthly minimum wages, a commonly used measure in Colombia. The 2013 monthly minimum wage was 535,600 Colombian Pesos (roughly 288 US Dollars). The average excludes medicine, which is usually more expensive than other degrees in private universities.

second only provides loans for vocational education. In both cases a fraction of the debt can be condoned if students complete the degree.

In order to obtain a loan from either funding program, students must fulfill standard application requirements. However, all credits must be backed by an approved co-debtor, a restriction that is particularly binding for low-income families. Proposed co-debtors must pass a credit check and have financial capacity to repay the full debt. In this sense, Colombia is different from Chile, which provides state-backing for college loans.[7]

There are significant differences in starting salaries for college graduates between institutions 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 earnings by college, degree, and field.[8] Figure 1 shows the distribution of earnings for different categories. Notice that the choice of college matters. In fact, we observe median premiums for private and top-ranked colleges of 0.33 and 1.05 minimum wages, respectively. Degrees are at least as important. While median earnings for recent graduates with an academic degree are 2.9 minimum wages, individuals with vocational degrees make a median 1.9 minimum wages. Salaries for academic degree graduates 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.[9]

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, 72.6% of private school students come from middle or high income families (>2 minimum wages), and 58% 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

[7]A more detailed description and comparison of the higher education systems of Chile and Colombia can be found in González-Velosa et al. (2015).

[8]We use the 2011 monthly salary for college graduates from 2008-2011 that report non-negative earnings.

[9]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.

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 institutions and degrees.

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 application process is completely decentralized (each institution 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 common to retake if necessary.[10] Over the last few years, Bogotá's private schools have consistently scored 0.76 SD above the city's public schools as Table 1 shows.

Less than half the students who 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 during 2013 enrolled in higher education during 2014. Moreover, private schools perform much better, since their students have consistently higher probabilities of enrolling (57.1%) and doing so in a private (42.4%) or a top-10 (16%) college. They are also more likely to choose academic and STEM degrees as Table 2 denotes.

In summary, Bogotá has a very heterogeneous higher education system that translates into large wage premiums for selective colleges and degrees. However, there are significant financial and academic barriers to entry for low-income and low-achieving students. 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.

[10]The exam fee is roughly equivalent to US$17 for students taking the SABER 11 for the first time and $21 otherwise.

3 Experimental Setting

3.1 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 were public high school students enrolled in their senior year. 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-shifts were randomly selected out of the 570 that offer an academic track.[11] These institutions are all mixed-sex, urban, high schools with at least 20 senior high school students enrolled in the 2012 academic year. Half of the 120 high schools were randomly assigned to receive an informational talk detailing college premiums by degree-college pairs 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 surveyed all students in attendance that day. In Colombia, the public school year often begins in February and ends in December. The timing of our intervention is summarized in Figure 2. Fieldwork for the baseline survey and the intervention took place during March 2013. The follow-up survey was conducted in August 2013, just 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 as Figure 3 shows.

3.2 The Intervention

During our baseline visits in March we first collected self-administered surveys. After all surveys were collected, students in treatment schools were given a 35-minute presen-

[11]Most public high schools in Bogotá have two 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. In what follows, we refer to school-shifts as schools.

tation delivered by young local Colombian college graduates.[12] The talk described the relationship between higher education and earnings, 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 by describing statistics on the average monthly earnings of individuals with incomplete and complete secondary, then comparing these values to the expected salaries of individuals who completed a higher education degree (differentiating by vocational and academic).[13] We then introduced students to two websites where they could find very detailed information on the labor market outcomes of recent higher education graduates, including average earnings by degree-college pairs and the probability of obtaining formal employment by career.[14] 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.[15]

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[12] We opted for local college graduates based on findings in Nguyen (2008), where information provided by local role models yielded higher effects.

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

[14] 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 of individuals who graduated from higher education in a user-friendly way.

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

4 Data and Estimation Strategy

4.1 Data

The baseline survey collected information on 6,636 students in 116 schools.[16] 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.[17] 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 *Bogotá Higher Education and Labor Perspectives Survey* (BHELPS).

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 records contain scores 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 they are missing in the BHELPS survey. 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 to the baseline sample are quite high: 95.3% and 95%. There are no significant differences between matched and unmatched students and the rates are similar across treatment and control groups.[18] We present results for three samples: i) all students observed in the follow-up BHELPS, ii) students observed in the baseline BHELPS successfully matched to the administrative data, and iii) individuals observed in the baseline and follow-up rounds of the BHELPS that are matched to each source of administrative data.

[16]Despite numerous attempts, we were unable to visit four schools. These corresponded to 3 treatment schools and 1 control school. However, the inability to interview these students does not seem to generate issues that affect randomization nor representativity as our descriptive statistics and balance tests presented below reveal.

[17]Attrition between baseline and follow-up waves was 7.5%, mainly due to absences on survey days.

[18]See Table A.1 in the Appendix for attrition diagnostics.

4.2 Sample Representativity and Characteristics

Our sample, which includes approximately 20% of the city's public high schools, is representative of the target population though slightly over-sampled morning-shift schools. Table 1 summarizes individual and school-level characteristics for all private and public schools, as well as surveyed students in the BHELPS. In Table 3, we present baseline characteristics for students in control and treatment groups, as well as the p-value for the differences (clustering standard errors at the school level). Both groups look very similar on their observable characteristics, suggesting that our randomization was successful.

On average, students are almost 18 years old when they graduate (measured in December 31, 2013) and most were born in Bogotá (84.7%). Almost a quarter of students have repeated at least one grade. Around 15% of students in the treatment group have at least one parent that completed college, around 2 points lower than the control group, though not statistically different. Students in treatment and control groups look almost identical in terms of family income, where 31% report income over 2 minimum wages. Since most 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 and the difference is barely statistically significant at the 10% level.

We asked students in the follow-up survey what they believed to be the most significant barriers 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 affordable public universities are very selective. While only 31% of our sample reports monthly family income above 2 minimum wages, college 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 progressively-priced public universities (that may cost as little as 0.1 minimum wages) 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 bureaucratic barriers from funding institutions. As mentioned before, most available programs require a co-debtor to back college loans.

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 different games in the baseline.[19] The resulting classification indicated that 85% of our sample was risk averse. 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 (from 1 to 10, where 1 is never and 10 is always). Individuals above the median response are classified as high academic self-concept and self-efficacy, while those below constitute the low group. We also asked their perceived probability of enrollment in college the following year. Almost 85% reported in the baseline survey that they were likely to enroll but only 19.4% were certain of attending some post-secondary institution.

Treatment and control groups look very similar in school characteristics. Using administrative data from 2010-2012, we find on average that over 90 students per school sit for the SABER 11 exam each year. Additionally, previous cohorts performed similarly across groups. 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 attributes explain the likelihood of attending a treatment school, with a p-value of 0.680.

4.3 Estimation Strategy

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

$$y_{is,t=1} = \alpha + \beta T_s + \theta X_{is,t=0} + u_{is,t=1} \tag{1}$$

[19]Students face the following hypothetical scenario: They were just hired for a new short-term job and can choose between a fixed salary or a lottery in which earnings are determined by a coin flip. By varying the optimistic scenario payment, 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.

where $y_{is,t=1}$ is the studied outcome for student i attending school s at the follow-up, $t = 1$. We include an intercept, α, and control for baseline student-level attributes (male, age, age squared, family income, and parental education) and school characteristics (average score on exit exam in previous years, has computer lab, shift indicators, and school size) with $X_{is,t=0}$. Our coefficient of interest is β, which captures the average effect of the informational treatment. $u_{is,t+1}$ is a mean-zero error term assumed to be uncorrelated with the treatment indicator since it was randomly assigned. Equation (1) is estimated by Ordinary Least Squares (OLS)[20], 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 on degree-college premiums and funding options.

When studying the potential mechanisms driving our main results, we take advantage that some outcomes are available for both the baseline and follow-up BHELPS surveys. In these cases, we employ two additional specifications. First, we estimate Equation (1), but include the outcome at the baseline as an additional explanatory variable. This approach could potentially provide additional power. Second, we estimate a difference-in-differences specification; defining a binary variable, *Post*, that equals one after information exposure and zero otherwise:

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

where α estimates the change in the outcome over time and μ_i is a student-specific effect that controls for all time-invariant characteristics (observed and unobserved) in our sample. Again, β is our coefficient of interest, which measures the average effect of the information treatment on the studied outcome. Standard errors are also clustered at the school-level. Note that the modified Equation (1) and Equation (2) can only be estimated for outcomes obtained in the BHELPS surveys and not from administrative data (i.e. test scores and enrollment outcomes).

[20] We also estimate Probit regressions but the main results are largely unchanged. We therefore choose to report only OLS estimates.

5 Results

This section studies the effect of information disclosure on higher education outcomes. Since information should first affect beliefs, then decisions in high school, and ultimately college enrollment, the findings are presented in that order.

5.1 Beliefs

Our measures of student perceptions include knowledge about funding programs and beliefs about labor market premiums. Knowledge is measured using binary variables that denote awareness of funding institutions (ICETEX and FESBO).[21] Earning beliefs are measured by the error between perceived and actual premiums for vocational and academic degrees relative to completing high school.[22]

Baseline statistics for knowledge and beliefs are presented in Table 4. Almost 70% of students express familiarity with ICETEX and 18% know FESBO, with both treatment and control groups reflecting similar baseline knowledge. These patterns illustrate that students remain largely unaware of the existence of certain funding programs. On average, public high school students in Bogotá overestimate college premiums. Approximately 87.6% overestimate the premiums to vocational degrees and 89.1% for academic degrees. Reported errors for vocational and academic degrees are 69.6% and 118% larger on average. These results are consistent with findings for the same population in Colombia (Gamboa and Rodríguez, 2014) and other countries (Pekkala-Kerr et al., 2015, McGuigan et al., 2014, Hastings et al., 2015).

In addition to overestimating the average premiums to college education, students show sizable variation in their beliefs. Figure 4 plots the distribution of errors for vocational and academic premiums. Individuals overestimate the associated benefits of vocational degrees, but most of them are not far from the correct belief. 76.3% are within

[21] While desirable, we were unable to collect a measure that captures the degree of knowledge about funding programs.

[22] Similar to Hastings et al. (2015), 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 $(\pi^{perceived} - \pi^{actual})/\pi^{actual}$. Results are similar when using different measures.

one standard deviation of the true premiums. Earning beliefs for academic degrees are more disperse: 60.1% of surveyed students have errors of one standard deviation, 29.2% between one and three standard deviations, and 10.7% more than three standard deviations. Students are therefore more misinformed about the average premiums for academic degrees than vocational careers.[23]

Are students who overestimate different than those who underestimate? Table 5 presents student and school characteristics based on the direction of their baseline beliefs: below the true premium or above it. There are no differences across students in treatment and control schools, as expected. Younger students seem to overestimate college premiums for both vocational and academic degrees. Interestingly, low income students tend to underestimate the monetary benefits to college education while higher income individuals overestimate. There is also evidence that repeaters, risk averse, and more confident students are more likely to overestimate college premiums relative to their counterparts.

The effects of information on knowledge and beliefs are presented in Table 6. Panels A and B report cross-section estimates on two samples: all students observed in the follow-up BHELPS and students observed in both BHELPS rounds. Panel C presents difference-in-differences results with individual fixed-effects for the second sample. We find that the treatment increases knowledge of the largest funding program, ICETEX. Students in treated schools increase their average awareness of this institution by 3.8 percentage points, or 6.6% of the mean. The impact is larger for students observed in both rounds, with cross-section and difference-in-difference effects of 4.7 and 4.6 percentage points, respectively. There are no statistically significant effects on knowledge of FESBO or perceived premiums.

We find that students are acquiring more information over time, independently from our intervention. The coefficient for the follow-up period ($Post$) in Panel C is positive and significant for both funding programs. Likewise, all individuals significantly reduce the degree to which they were overestimating college premiums. This reflects that students

[23] 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. These students have slightly more accurate beliefs for vocational degrees, but not for academic degrees compared to those whose parents have not completed higher education.

in our sample gain further knowledge about higher education during their senior year.

One potential reason we do not find that students in treated schools corrected their beliefs at a faster rate than control students could be due to opposing effects: students who were initially 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 baseline in Table 7. 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 earning premiums.

As an additional robustness test, we change the reference values for earning beliefs. In all previous estimates, we compared students' perceptions to the average vocational and academic premiums with respect to high school. Perhaps students used their own expectations as a reference instead of those for an average individual. In the baseline BHELPS, we asked students to tell us the degree, college, and field they aspired. Using the records from the Labor Observatory on starting salaries for college graduates, we calculated two measures of expected earnings for each student: i) by degree and field, and ii) by degree and college. The same analysis from Tables 6 and 7 confirms that the treatment did not affect premium beliefs (results are shown in Table A.2 in the Appendix).

5.2 Test scores

As previously mentioned, 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. We measure student performance using test scores from the national high school exit exams (SABER 11) that was taken approximately five months after our intervention. In particular, we focus on the overall score and the two most important subjects: mathematics and language.[24] All scores are standardized with mean zero and standard deviation of one with respect to the control group for ease of comparison.

[24]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).

Table 8 presents the average effects of information on test scores for all students matched to administrative records (Panel A), and two more restricted samples of students: those observed in the baseline BHELPS that were successfully matched and individuals observed in both baseline and follow-up who were matched (Panels B and C). While the estimated coefficients are consistently larger for mathematics, we do not find statistically significant effects of the treatment on test scores for any sample.

We test for differential effects along the score distribution using quantile regressions. Figure 5 presents quantile treatment effects and their corresponding 90% confidence interval for test scores on mathematics and language. There is suggestive evidence of some positive and significant effects on students at the lower end of the distribution in math. The treatment induced students in the lower 20th percentile to perform nearly a tenth of a standard deviation better in mathematics. In turn, only students at the highest percentiles performed better on language. Nevertheless, the average estimates suggest that information had no overall effect on test scores, and small quantile effects.

5.3 College Enrollment

We are able to track students who enrolled in higher education after graduation, and may further characterize their college and degree of choice. 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%).

Table 9 presents treatment effect estimates on higher education enrollment for the same three samples used in Table 8. We find that the effect of information on the probability of enrolling in any post-secondary program is not statistically distinguishable from zero. However, there is a significant increase in the probability of enrolling in a top-10 college. Effects range from 0.4 to 0.6 percentage points depending on the sample. This impact, though small in magnitude, is also economically significant. In fact, it represents an increase of approximately 50% with respect to the control group average. Estimated effects on the other three intensive margin outcomes are also positive but not statistically significant.

Our results are consistent with previous literature. Among "pure" information treatments, most studies find no effect of disclosing information on higher education enrollment (Booij et al., 2012, Fryer, 2013, Oreopoulos and Dunn, 2013, Pekkala-Kerr et al., 2015, McGuigan et al., 2014, Dinkelman and Martínez, 2014, Wiswall and Zafar, 2015). Our intensive margin effects are consistent with those of interventions focusing on students who are already applying to college and have a high probability of enrollment (Hoxby and Turner, 2013, Hastings et al., 2015). In the long run, opting for a top-10 college may have important implications on future earnings (conditional on graduating). Recall from Figure 1 that students who graduate from a top-10 college in Colombia earn approximately 50% more than non-top college students (1 minimum wage more on average). Therefore, while providing information may not lead more individuals to attend college, it does seem to affect what colleges are chosen by those who do enroll.

6 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 their earning beliefs. On the other hand, we observe no improvement on college enrollment but a higher likelihood of admission to top-10 colleges. In this section we explore potential mechanisms that help interpret these results.

Our analysis highlights the role of credit constraints, gender differences, non-cognitive factors, and aspirations. We have already discussed that the main barrier to college attendance for low income students in Colombia are its high costs. Additionally, there remain considerable gender differences in higher education choices and labor market outcomes (Goldin et al., 2006). In part, this may reflect gender-specific traits or preferences that affect boys and girls differentially.[25] Non-cognitive factors also play an important role in determining human capital accumulation and academic success (Heckman and Rubin-

[25] 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).

stein, 2001). We assess potential heterogeneity by two non-cognitive dimensions: risk aversion (Belzil and Hansen, 2004, Belzil and Leonardi, 2007, Heckman, 2007), as well as self-concept and self-efficacy (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 them (Appadurai, 2004, Ray, 2006, Heifetz and Minelli, 2014, Genicot and Ray, 2014, Dalton et al., 2016).

6.1 Credit Constraints

To evaluate the extent to which credit constraints could explain our results, we explore the heterogeneity of treatment effects by estimating fully interacted versions of Equation (1) by income groups. Table 10 presents separate coefficients for each grouping (low and middle) for our main outcomes. It also includes the p-value for a Wald test that these coefficients are equal. For parsimony, we focus on the sample of students observed in the baseline that are matched to the later rounds of survey data and administrative records.[26]

In column (1) we find that only students from low-income families learn about ICETEX – the main funding institute. While the estimated effect on middle-income students is not statistically significant, low-income students increased their knowledge of ICETEX by about 5.4 percentage points. This effect is statistically different from the effect on middle-income students. This likely reflects a catching-up: students from higher income families report significantly higher knowledge of funding programs in the baseline survey. We do not find any statistically relevant effects or differences between income levels for all other knowledge or belief outcomes. Overall, students appear to have valued information on financing more than that of earnings, suggesting that credit constraints are indeed a primary concern for most of the students in our sample.

Columns (2) to (4) present heterogeneous effects of the intervention by income level on test scores. Unlike knowledge of ICETEX, positive effects are driven by students from middle-income families, with an increase in mathematics and language scores of 8.2% and 7.1% standard deviations, respectively.

[26]Appendix Table A.3 presents results using individuals observed in both rounds of the BHELPS and matched to each source of administrative data. Those findings are unchanged from those discussed here.

Heterogeneous effects by family income on enrollment outcomes are presented in columns (5) to (9). As with the average estimates, we find no significant effects. However, students' intensive margin decisions respond differently to information depending on their income category. First, entry to top-10 colleges is dominated by middle-income students. The estimated effect is 1.2 percentage points and statistically different from that of low-income students. Second, poorer students increase their probability of enrolling in a private college, with an estimated coefficient of 2.1 percentage points. However, the difference with respect to middle-income students is not statistically significant.

In general, we find that most of the positive effects of the intervention were on the students from middle-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 main barriers to entry. In the Colombian case these are twofold: sizable credit constraints and low probabilities of admission to affordable institutions. Since most of the higher-income students are already aware of available funding options, it seems plausible that information provides them with additional motivation to perform better on the exit exam and therefore attend more selective colleges.[27]

6.2 Gender differences

In Panel C of Table 10, we present heterogeneous effects by gender. At baseline, boys had significantly lower knowledge of ICETEX than girls. The treatment appears to have bridged this gap as suggested by the positive and statistically significant effect on males and no statistically distinguishable effect for females. At the same time, there is suggestive evidence that males increased their performance on mathematics by 0.07 of a standard deviation. However, this effect is not statistically different to the effect for females.

Evaluating the heterogeneous effects on enrollment outcomes in columns (5) to (9), we find suggestive evidence that the information treatment increased college enrollment,

[27] In the Appendix, we also consider heterogeneous effects by the direction of errors in baseline earning expectations. Our results showed that poorer students underestimate college premiums while richer children overestimate. Findings are shown in Table A.4 and are similar to those using income groups. While information has slightly larger positive effects on those who underestimate, these differences are not statistically significant.

private, and top-10 college admission for boys, but no statistically significant effects for girls. Nevertheless, we cannot reject the null hypothesis that the effects between males and females are the same (although overall enrollment is borderline insignificant at the 10% level). Even though each effect in itself is at best suggestive, these results are largely consistent with existing studies that find that males are encouraged (maybe driven by overconfidence) to pursue more competitive degrees (Buser et al., 2014).

6.3 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 and student aspirations.[28]

Panel A of Table 11 explores differences by risk aversion. Risk loving students increase their probability of enrolling in academic and STEM degrees, with estimated effects of 3.1 and 3.8 percentage points. Differences with respect to risk averse students are significant for STEM degrees but not academic. This suggests that information may resonate more with students who take more risks. It is important to note that one shortcoming of this measure is that pursuing higher education is likely an intra-household decision taken by a student and his/her parents. Unfortunately, we do not count with measures of parental risk aversion but this would be an interesting avenue for future studies to address.

We also assess the role of self-confidence and self-efficacy using three proxies. The first, academic self-concept, measures whether a student believes they are above average in academic terms (Panel B of Table 11). We find no significant differences by this classification. The second, student self-efficacy, measures whether students are more likely to achieve their goals (Panel C of Table 11). We find that highly self-efficacious students improve both mathematics and language test scores, and increase their probabilities of enrolling in academic and STEM degrees. Nevertheless, only the difference in language scores are statistically significant. The third, perceived likelihood of enrollment, reflects not only students' self-concept and self-efficacy, but also accounts for the financial constraints they

[28] Appendix Table A.5 presents largely similar results for the sample of individuals observed in both rounds of the BHELPS and matched to each source of administrative data.

foresee (Panel D of 11). Students with low probabilities of enrollment learn more about financial programs, with an estimated effect of 10.2 percentage points. However, this does not lead to higher enrollment rates or more selective choices. On the contrary, enrollment effects are concentrated on students with higher perceived probability of enrolling. For top-10 colleges, the difference between groups is statistically significant.

Finally, we examine whether information affects student aspirations. We exploit a question in both BHELPS waves that asks students what college and degree they would like to attend.[29] Because students absorb the information about financing institutions, this could affect their aspirations (whether they want to enroll in a post-secondary program or what type of degree they desire). Results for these outcomes are presented in Table 12. Findings show no effect of information on any of the aspiration measures. This suggests that intensive margin effects on enrollment are not driven by changes in student aspirations.

7 Conclusion

This paper analyzes whether providing information on funding opportunities and college premiums by degree-college pairs affects higher education decisions in Bogotá, Colombia. We conduct a randomized controlled trial on a representative sample of 120 urban public high schools, half of which received an informational talk. Using survey data linked to administrative records, we analyze student beliefs and evaluate the intervention. We find that most students overestimate true college premiums and are generally unaware of funding options. The talk does not affect earning beliefs but improves knowledge of financing programs, especially among the poor. There is no evidence that our treatment affects post-secondary enrollment. However, students in treated schools who do enroll choose more selective colleges. These positive effects are mostly driven by students from better socioeconomic backgrounds.

Our findings confirm that misinformation is a problem among potential college entrants since they tend to overestimate its benefits and are mostly unaware of its costs.

[29] Descriptive and balance statistics for the aspiration outcomes may be found in Appendix Table A.6.

However, this is not the main deterrent for attending college. The existence of significant academic and financial barriers to college entry in Colombia might limit the influence of better information because low-income students believe the system limits upward mobility. In fact, we find larger effects of the intervention on middle-income individuals, for whom the likelihood of attending college is higher since constraints are less binding. Moreover, our treatment increased the knowledge of funding programs but did not update earning beliefs. This is consistent with most students in our sample believing that costs are the main barriers to higher education. We conclude that providing information cannot single-handedly increase higher education enrollment among low-income students in this context. It takes more comprehensive measures, such as zero-interest rates loans (Melguizo et al., 2016), to achieve substantial improvements in this respect.

Despite the inability to attract more low-income students into college, providing information has some positive effects on college choices for those who enrolled. These results are particularly interesting since we targeted a wider population than other papers, such as Hastings et al. (2015) and Hoxby and Turner (2013), and yet found similar results in the intensive margin. Given the low-cost of "pure" information interventions, policymakers may therefore consider less targeted policies to orient students in their college choices, even if only a fraction of them is expected to benefit from the additional information.

How and when to provide information is an interesting direction for future research. Our intervention is one of many possible designs in this respect. For instance, while we provided average college premiums, future studies could present the entire distribution of earnings in a simple and intuitive manner. Likewise, disclosing more detailed cost data may be useful. The timing of information policies, especially for higher education choices, is also highly relevant. Additionally, whether these interventions should target students, parents, or both is an open-ended question. Our results indicate that providing information to students in the final year of high school is mostly ineffective since it does not eliminate existing barriers to entry. However, earlier interventions of the benefits and costs of education to students and their parents may affect household behavior so that by the time children apply to college, both academic and financial barriers are less binding.

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Table 1. Descriptive Statistics: Private, Public, and BHELPS schools

	Bogotá				BHELPS	
	Private schools		Public schools			
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Panel A: Students						
Males	0.492	(0.500)	0.458	(0.498)	0.474	(0.499)
Age	17.648	(0.907)	17.641	(0.873)	17.662	(1.065)
Born in Bogotá					0.847	(0.360)
Parent completed secondary	0.288	(0.453)	0.395	(0.489)	0.394	(0.489)
Parent completed higher education	0.580	(0.494)	0.156	(0.363)	0.160	(0.367)
Family income (<1 MW)	0.028	(0.165)	0.144	(0.351)	0.144	(0.352)
Family income (1-2 MWs)	0.246	(0.431)	0.559	(0.497)	0.541	(0.498)
Family income (>2 MWs)	0.726	(0.446)	0.297	(0.457)	0.315	(0.464)
Internet at home					0.691	(0.462)
Victim of violence					0.035	(0.183)
Student works					0.170	(0.375)
Has repeated at least one grade					0.251	(0.434)
Risk averse					0.851	(0.357)
Perceived high academic ranking					0.410	(0.492)
Perceived high self-efficacy					0.352	(0.478)
Perceived high likelihood of enrollment					0.843	(0.364)
Panel B: Schools						
Number of students (2010-2012)	111.2	(168.5)	99.7	(48.1)	93.7	(40.7)
SABER 11 score (2010-2012)	0.874	(0.809)	0.117	(0.254)	0.139	(0.248)
Morning shift	0.191	(0.393)	0.547	(0.498)	0.633	(0.482)
Afternoon shift	0.019	(0.137)	0.390	(0.488)	0.348	(0.476)
Single shift	0.790	(0.407)	0.063	(0.243)	0.019	(0.138)
School has computer lab					0.964	(0.187)
Total number of students	37,068		37,787		6,636	
Total number of schools	790		570		116	

Source: Authors' calculations from ICFES and BHELPS survey.
Notes: Statistics for Bogotá are based on ICFES, which includes the universe of schools offering an academic track. Using date of birth, we compute each student's age on December 31, 2013. The number of students is the average number of individuals who sat for the SABER 11 exam in each year from 2010-2012. SABER 11 scores are standardized with respect to each year's national average.

Table 2. Descriptive Statistics for the 2013 Cohort of Public School Students

	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)

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.
Notes: Statistics for Bogotá are based on 2013 ICFES and 2014 SNIES data, which includes the universe of schools offering an academic track. SABER 11 scores are standardized with respect to the 2013 national average.

Table 3. Balance in Baseline Student and School Characteristics by Treatment

	Control		Treatment		Difference
	Mean	(SD)	Mean	(SD)	P-value
Panel A: Students					
Male	0.477	(0.500)	0.472	(0.499)	0.735
Age	17.655	(1.117)	17.669	(1.013)	0.704
Born in Bogotá	0.851	(0.357)	0.843	(0.364)	0.539
Parent completed higher education	0.171	(0.377)	0.150	(0.357)	0.245
Family income (>2 MWs)	0.322	(0.467)	0.308	(0.462)	0.571
Internet at home	0.711	(0.453)	0.672	(0.470)	0.090
Victim of violence	0.034	(0.181)	0.035	(0.184)	0.816
Student works	0.163	(0.370)	0.176	(0.381)	0.329
Has repeated at least one grade	0.247	(0.431)	0.255	(0.436)	0.648
Risk averse	0.856	(0.351)	0.845	(0.362)	0.400
Perceived high academic ranking	0.425	(0.494)	0.395	(0.489)	0.111
Perceived high self-efficacy	0.349	(0.477)	0.355	(0.479)	0.714
Perceived high likelihood of enrollment	0.841	(0.365)	0.844	(0.363)	0.862
Panel B: Schools					
Number of students (2010-2012)	95.007	(48.106)	92.349	(31.826)	0.740
SABER 11 score (2010-2012)	0.160	(0.215)	0.118	(0.275)	0.379
Morning shift	0.641	(0.480)	0.625	(0.484)	0.867
Afternoon shift	0.337	(0.473)	0.359	(0.480)	0.807
Single shift	0.023	(0.149)	0.016	(0.125)	0.808
School has computer lab	0.970	(0.172)	0.958	(0.201)	0.741
Total number of students	3,259		3,377		
Total number of schools	59		57		

Source: Authors' calculations from ICFES and baseline BHELPS survey.
Notes: Using date of birth, we compute each student's age on December 31, 2013. The number of students is the average number of individuals who sat for the SABER 11 exam in each year from 2010-2012. SABER 11 scores are standardized with respect to each year's national average. The last column presents the p-value of the difference in the attribute between treatment and control groups calculated by regression with clustered standard errors at the school-level. 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.

Table 4. Balance in Baseline Student Knowledge and Beliefs by Treatment

	Control		Treatment		Difference
	Mean	(SD)	Mean	(SD)	P-value
Knows ICETEX	0.700	(0.458)	0.688	(0.463)	0.612
Knows FESBO	0.180	(0.384)	0.168	(0.374)	0.295
Premium Error: Vocational	0.696	(1.539)	0.615	(1.475)	0.105
Premium Error: Academic	1.184	(1.259)	1.100	(1.234)	0.091

Source: Authors' calculations from baseline BHELPS survey.
Notes: The last column presents the p-value of the difference in the attribute between treatment and control groups calculated by regression with clustered standard errors at the school-level.

Table 5. Baseline Characteristics by Direction of Belief Error

	Premium Error: Vocational			Premium Error: Academic		
	Under	Over	Difference P-value	Under	Over	Difference P-value
Panel A: Students						
Treatment group	0.529	0.505	0.332	0.542	0.504	0.132
Males	0.471	0.484	0.590	0.475	0.484	0.691
Age	17.765	17.624	0.001	17.800	17.621	0.000
Born in Bogotá	0.829	0.852	0.130	0.838	0.850	0.446
Parent completed secondary	0.380	0.397	0.415	0.381	0.397	0.437
Parent completed higher education	0.179	0.183	0.769	0.170	0.185	0.343
Family income (<1 MW)	0.229	0.160	0.000	0.211	0.164	0.006
Family income (1-2 MWs)	0.458	0.467	0.601	0.498	0.463	0.103
Family income (>2 MWs)	0.314	0.373	0.002	0.291	0.373	0.000
Internet at home	0.665	0.699	0.076	0.670	0.697	0.143
Victim of violence	0.040	0.034	0.445	0.033	0.034	0.837
Student works	0.194	0.168	0.092	0.186	0.169	0.298
Has repeated at least one grade	0.280	0.243	0.065	0.288	0.244	0.036
Risk averse	0.826	0.858	0.043	0.821	0.858	0.024
Perceived high academic ranking	0.357	0.421	0.003	0.321	0.422	0.000
Perceived high self-efficacy	0.370	0.347	0.242	0.337	0.350	0.533
Perceived high likelihood of enrollment	0.788	0.852	0.000	0.770	0.854	0.000
Panel B: Schools						
Number of students (2010-2012)	91.602	94.118	0.123	91.216	94.145	0.101
SABER 11 score (2010-2012)	0.133	0.143	0.408	0.119	0.145	0.038
Morning shift	0.620	0.637	0.417	0.634	0.635	0.971
Afternoon shift	0.359	0.343	0.441	0.355	0.344	0.615
Single shift	0.021	0.020	0.723	0.010	0.021	0.000
School has computer lab	0.971	0.964	0.260	0.961	0.965	0.374

Source: Authors' calculations from ICFES and baseline BHELPS survey.
Notes: The difference column presents the p-value of the difference in the attribute between students who over and under estimate earning premiums and are calculated by regression with clustered standard errors at the school-level.

Table 6. Treatment Effects on Knowledge and Beliefs

	Knows ICETEX (1)	Knows FESBO (2)	Premium Error: Vocational (3)	Premium Error: Academic (4)
Panel A: After, All students in follow-up				
Treat	0.038***	-0.003	0.014	-0.031
	(0.014)	(0.011)	(0.045)	(0.040)
Observations	5,909	5,706	5,826	5,820
Panel B: After, Matched with baseline				
Treat	0.047***	-0.003	0.009	-0.027
	(0.015)	(0.012)	(0.045)	(0.041)
Observations	5,333	5,149	5,267	5,262
Panel C: Difference-in-differences				
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)
Observations	10,861	10,591	10,538	10,532
Mean(y) at baseline	0.694	0.169	0.662	1.155

Source: Authors' calculations from BHELPS survey.
Notes: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel correspond to a separate OLS regression. Panels A and B control for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Panel C presents coefficients for difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 7. Treatment Effects on Beliefs by Direction of Belief Error

	Premium error: Vocational		Premium error: Academic	
	Under (1)	Over (2)	Under (3)	Over (4)
Panel A: After, Matched with baseline				
Treat	0.105	-0.013	0.028	-0.035
	(0.122)	(0.046)	(0.121)	(0.043)
Observations	589	4,378	506	4,454
Panel B: Difference-in-differences				
Treat × Post	0.107	0.052	-0.056	0.047
	(0.189)	(0.058)	(0.131)	(0.050)
Post	1.732***	-0.334***	1.498***	-0.289***
	(0.145)	(0.044)	(0.100)	(0.040)
Observations	1,236	8,993	1,060	9,162
Mean(y) at baseline	-1.604	0.974	-0.837	1.382

Source: Authors' calculations from BHELPS survey.
Notes: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel correspond to a separate OLS regression. Panels A controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Panel B presents coefficients for difference-in-difference regressions that control for individual fixed-effects. Standard errors are clustered at school-level.

Table 8. Treatment Effects on Test Scores

	Overall (1)	Math (2)	Language (3)
Panel A: All matched administrative			
Treat	-0.009	0.035	-0.008
	(0.029)	(0.034)	(0.027)
Observations	6,692	6,692	6,692
Panel B: Matched with baseline			
Treat	-0.005	0.043	-0.005
	(0.030)	(0.034)	(0.029)
Observations	6,105	6,105	6,105
Panel C: Matched with baseline and follow-up			
Treat	0.007	0.054	0.003
	(0.032)	(0.037)	(0.031)
Observations	5,238	5,238	5,238

Source: Authors' calculations from ICFES and BHELPS survey.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table 9. Treatment Effects on Enrollment Choices

	Enrolled College (1)	Private College (2)	Top-10 College (3)	Academic Degree (4)	STEM Degree (5)
Panel A: All matched administrative					
Treat	0.015	0.011	0.004*	0.010	0.007
	(0.019)	(0.010)	(0.002)	(0.008)	(0.006)
Observations	6,664	6,664	6,664	6,664	6,664
Panel B: Matched with baseline					
Treat	0.015	0.015	0.005*	0.011	0.009
	(0.019)	(0.010)	(0.002)	(0.009)	(0.006)
Observations	6,085	6,085	6,085	6,085	6,085
Panel C: Matched with baseline and follow-up					
Treat	0.008	0.013	0.006**	0.014	0.010
	(0.020)	(0.011)	(0.003)	(0.009)	(0.006)
Observations	5,225	5,225	5,225	5,225	5,225
Mean(y) control group	0.444	0.153	0.011	0.095	0.050

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table 10. Treatment Effects by Family Income and Gender (baseline matched to administrative data)

	Knows ICETEX (1)	Overall score (2)	Math (3)	Language (4)	College Enrollment (5)	Private College (6)	Top-10 College (7)	Academic Degree (8)	STEM Degree (9)
Panel A: Average effects									
Treat	0.038***	-0.005	0.043	-0.005	0.015	0.015	0.005*	0.011	0.009
	(0.014)	(0.030)	(0.034)	(0.029)	(0.019)	(0.010)	(0.002)	(0.009)	(0.006)
Observations	5,909	6,105	6,105	6,105	6,085	6,085	6,085	6,085	6,085
Panel B: Treatment effects by family income									
Low Income (≤2MW)	0.054***	-0.038	0.020	-0.053	0.003	0.021**	0.001	0.008	0.008
	(0.017)	(0.036)	(0.037)	(0.035)	(0.021)	(0.009)	(0.002)	(0.008)	(0.006)
Middle Income (>2MW)	0.009	0.050	0.082*	0.071*	0.037	0.009	0.012**	0.018	0.011
	(0.017)	(0.043)	(0.045)	(0.042)	(0.025)	(0.019)	(0.005)	(0.017)	(0.013)
P-value *(Low=Middle)*	0.017	0.088	0.178	0.013	0.176	0.530	0.050	0.612	0.814
Observations	5,909	6,105	6,105	6,105	6,085	6,085	6,085	6,085	6,085
Panel C: Treatment effects by Gender									
Female	0.022	-0.048	0.014	-0.051	-0.005	0.004	0.003	0.005	0.003
	(0.018)	(0.037)	(0.041)	(0.040)	(0.024)	(0.014)	(0.003)	(0.011)	(0.007)
Male	0.056***	0.039	0.072*	0.043	0.037*	0.026**	0.007*	0.018	0.016
	(0.018)	(0.040)	(0.042)	(0.035)	(0.021)	(0.013)	(0.004)	(0.012)	(0.010)
P-value *(Female=Male)*	0.120	0.071	0.235	0.056	0.114	0.226	0.401	0.404	0.272
Observations	5,909	6,105	6,105	6,105	6,085	6,085	6,085	6,085	6,085

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table 11. Treatment Effects by Non-Cognitive Factors (baseline matched to administrative data)

	Knows ICETEX (1)	Overall score (2)	Math (3)	Language (4)	College Enrollment (5)	Private College (6)	Top-10 College (7)	Academic Degree (8)	STEM Degree (9)
Panel A: Treatment effects by risk aversion									
Risk Loving	0.042	0.054	0.107	0.053	0.037	0.026	0.014	0.031*	0.038***
	(0.030)	(0.079)	(0.084)	(0.072)	(0.039)	(0.024)	(0.009)	(0.018)	(0.014)
Risk Averse	0.049***	-0.020	0.027	-0.018	0.009	0.013	0.003	0.008	0.005
	(0.016)	(0.032)	(0.035)	(0.032)	(0.019)	(0.012)	(0.002)	(0.009)	(0.007)
P-value (loving=averse)	0.833	0.389	0.340	0.380	0.443	0.656	0.223	0.212	0.022
Observations	5,133	5,893	5,893	5,893	5,874	5,874	5,874	5,874	5,874
Panel B: Treatment effects by self-concept									
Low	0.062***	0.006	0.058	-0.018	0.012	0.018	0.004	0.009	0.007
	(0.017)	(0.035)	(0.042)	(0.038)	(0.022)	(0.012)	(0.003)	(0.009)	(0.005)
High	0.028	0.020	0.055	0.045	0.027	0.015	0.008	0.018	0.015
	(0.019)	(0.042)	(0.045)	(0.039)	(0.025)	(0.017)	(0.005)	(0.015)	(0.011)
P-value (low=high)	0.114	0.765	0.959	0.217	0.597	0.848	0.530	0.528	0.451
Observations	5,289	6,063	6,063	6,063	6,043	6,043	6,043	6,043	6,043
Panel C: Treatment effects by self-efficacy									
Low	0.042**	-0.040	0.026	-0.056	0.008	0.012	0.003	0.003	0.003
	(0.017)	(0.036)	(0.042)	(0.035)	(0.020)	(0.011)	(0.003)	(0.011)	(0.007)
High	0.052***	0.072	0.089*	0.096**	0.024	0.021	0.007	0.025**	0.020**
	(0.019)	(0.045)	(0.047)	(0.047)	(0.025)	(0.016)	(0.005)	(0.012)	(0.010)
P-value (low=high)	0.641	0.038	0.284	0.007	0.522	0.586	0.441	0.177	0.126
Observations	5,285	6,052	6,052	6,052	6,032	6,032	6,032	6,032	6,032
Panel D: Treatment effects by perceived likelihood of enrollment									
Low	0.102***	-0.028	0.003	-0.028	0.007	-0.007	-0.002	0.005	-0.001
	(0.033)	(0.051)	(0.056)	(0.058)	(0.032)	(0.015)	(0.002)	(0.012)	(0.008)
High	0.038***	-0.001	0.050	-0.002	0.015	0.019	0.006**	0.015	0.012*
	(0.014)	(0.033)	(0.037)	(0.033)	(0.019)	(0.012)	(0.003)	(0.010)	(0.007)
P-value (low=high)	0.036	0.655	0.475	0.703	0.821	0.165	0.015	0.531	0.192
Observations	5,083	5,833	5,833	5,833	5,814	5,814	5,814	5,814	5,814

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.

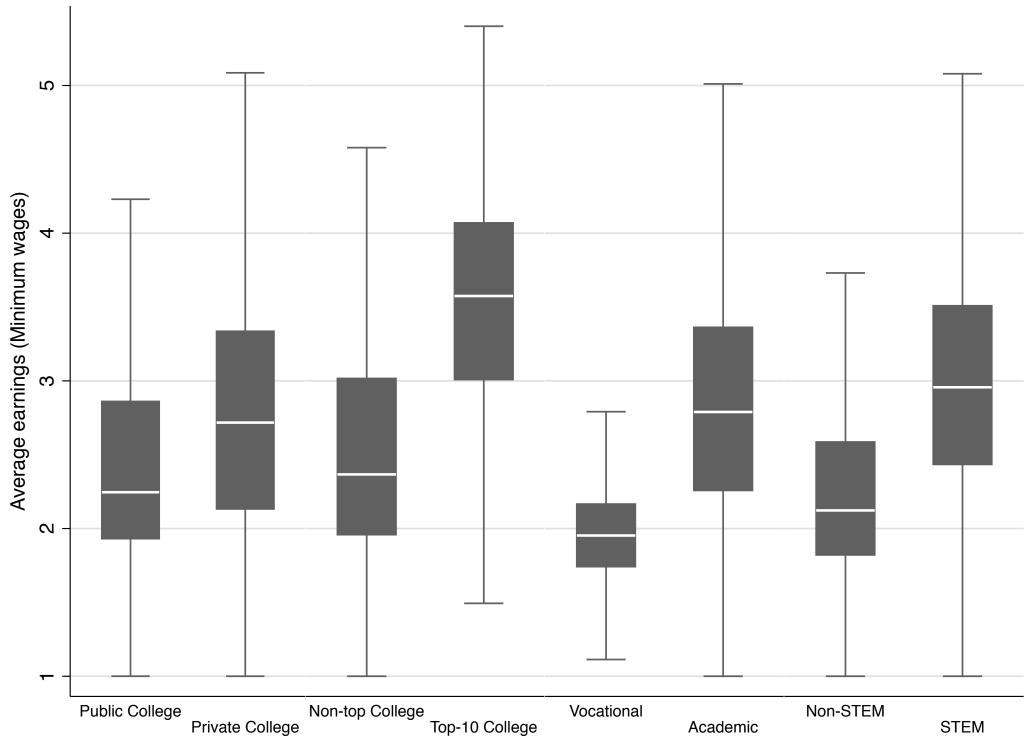
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table 12. Treatment Effects on College Aspirations

	Enroll College (1)	Private College (2)	Top-10 College (3)	Academic Degree (4)	STEM Degree (5)
Panel A: After, All students in follow-up					
Treat	-0.001	0.014	0.022	0.021*	0.032**
	(0.003)	(0.015)	(0.018)	(0.012)	(0.013)
Observations	5,976	5,914	5,914	5,914	5,914
Panel B: After, Students in baseline					
Treat	-0.000	0.017	0.022	0.021	0.034**
	(0.003)	(0.015)	(0.019)	(0.013)	(0.014)
Observations	5,389	5,333	5,333	5,333	5,333
Panel C: Difference-in-differences					
Treat × Post	-0.001	0.004	-0.007	0.002	0.007
	(0.004)	(0.016)	(0.023)	(0.013)	(0.015)
Post	0.004	0.009	-0.000	-0.028***	-0.006
	(0.003)	(0.012)	(0.018)	(0.009)	(0.010)
Observations	11,006	10,862	10,862	10,862	10,862
Mean(y) at baseline	0.983	0.232	0.457	0.892	0.417

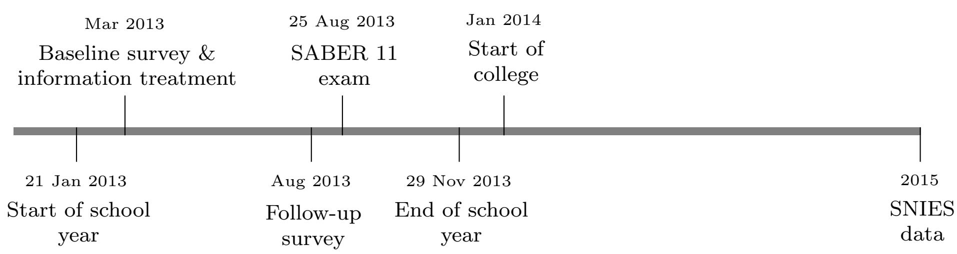
Source: Authors' calculations from BHELPS survey.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel correspond to a separate OLS regression. Panels A and B control for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Panel C presents coefficients for difference-in-difference regression that control for individual fixed-effects. Standard errors are clustered at school-level.

Figure 1. Average Earnings of Recent Graduates



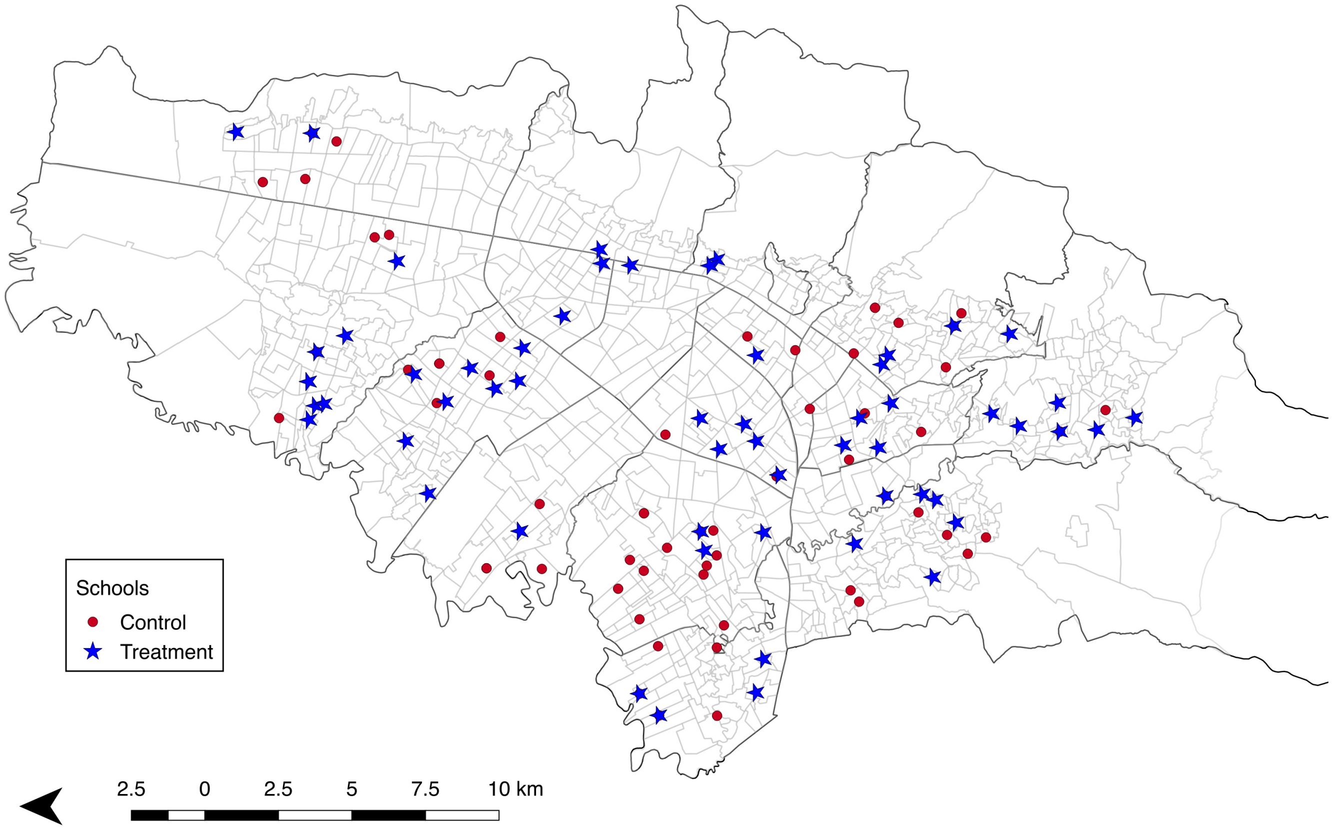
Source: Authors' elaboration from Labor Observatory data.
Notes: The figure shows the distribution of initial earnings for different categories of college and degree. Monthly earnings are expressed in minimum wages, and correspond to the average pay of recent graduates by college, level, and field as defined in Section 2. The grey box represents the 25th and 75th percentiles, the white line denotes the median, and the whiskers denote the upper/lower adjacent values.

Figure 2. Timing of Intervention and Data Recollection



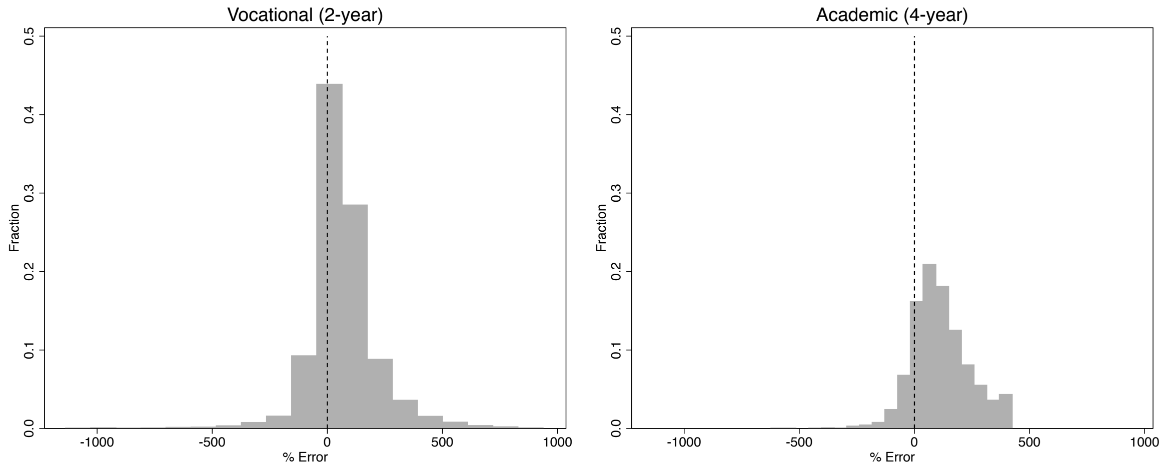
Source: Authors' elaboration.

Figure 3. Geographic distribution of treatment and control schools



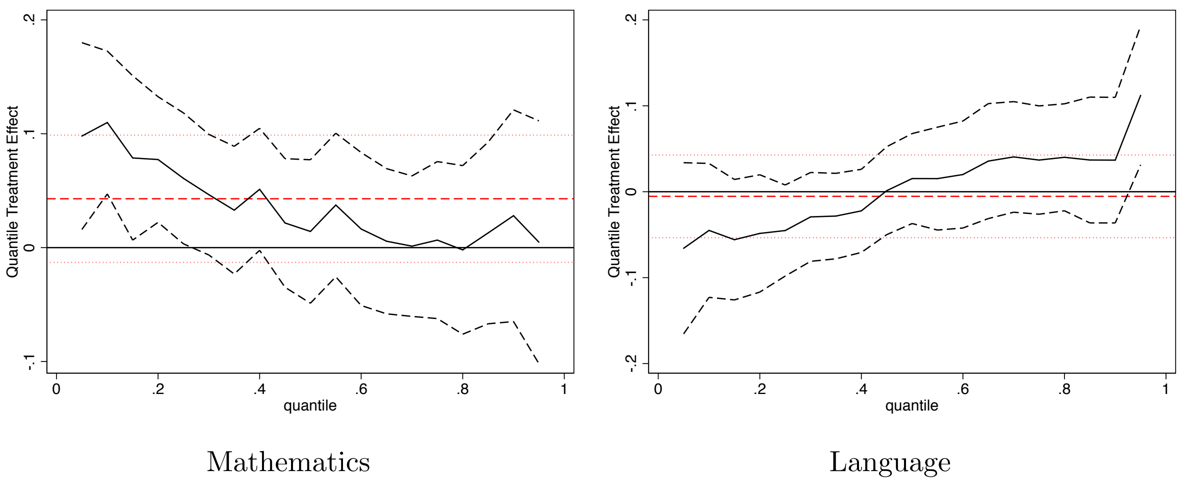
Source: Authors' elaboration from Secretary of Education's School Census and BHELPS.

Figure 4. Distribution of Earning Premium Beliefs at Baseline



Source: Authors' elaboration from BHELPS baseline 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 $(\pi^{perceived} - \pi^{actual})/\pi^{actual}$.

Figure 5. Quantile treatment effects for SABER 11 test scores



Source: Authors' elaboration from ICFES and BHELPS survey.
Notes: Estimates based on baseline matched to administrative data (N=6,105). 90% Confidence intervals in black dashed/red dotted lines. OLS estimate in red dashed line. Standard errors clustered at the school-level.

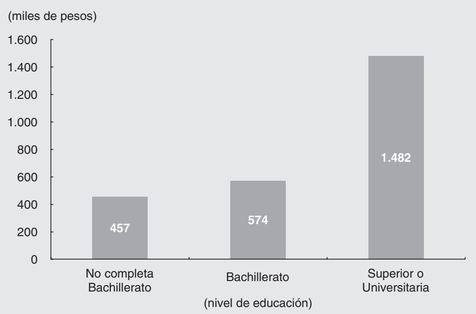
Appendix

A.1 Student Handout

¡La educación superior paga!

La relación entre estudios e ingresos

La educación superior es un factor determinante de la situación económica y por tanto la calidad de vida de las familias. En el siguiente gráfico se presentan los salarios promedio por nivel educativo en Bogotá.



Fuente: Encuesta de Hogares 2011, DANE

Como se puede observar, mayor educación se traduce en salarios más altos. Sólo con terminar el Bachillerato se pasa de ganar 457.000 a 574.000 por mes. El salto es más evidente para aquellos con un título de nivel superior, ya que el salario promedio mensual crece a 1.482.000. Estas estadísticas presentan un mensaje claro: vale la pena estudiar.

¿Cómo puedo averiguar cuanto ganaría en la carrera que a mí me interesa?

Es probable que usted ya tenga una idea sobre las carreras que le interesarían y la institución donde quisiera realizar estos estudios. Si es así, ¿hay alguna manera de saber cuánto puede esperar ganar en su situación específica?

Existen dos lugares donde pueden consultar el salario promedio de los graduados por institución y carreras. Estas son:

1. Calculadora de salarios promedios para graduados: www.finanzaspersonales.com.co

Esta página cuenta con una herramienta que le permite consultar el salario promedio por región, institución educativa, programa de estudio y género de las personas que obtuvieron su título entre 2001-2011.

¿Cómo funciona?

- Acceda al enlace y busque la *Calculadora de Salario por profesión para Graduados*
- Escoja la región donde quiere realizar la búsqueda (por ejemplo, Bogotá)
- Seleccione la institución donde quiere realizar sus estudios y el programa que planea cursar

2. Observatorio laboral del Ministerio de Educación: www.graduadoscolombia.edu.co

Está página también provee información sobre los salarios promedios de personas con título de educación superior para toda Colombia. Además, le permite conocer las perspectivas laborales del programa de estudio de su interés.

¿Cómo funciona?

- Acceda al enlace y busque el botón rojo que dice *Sistema de información del Observatorio Laboral.*
- Si quiere conocer el número de graduados por carrera, acceda a la pestaña que dice "Perfil nacional". Después, escoja el departamento donde planea estudiar y obtendrá los datos de graduados por área de estudio.

Si desea saber cuántos individuos en su área de interés tienen un empleo formal (cotizando a la seguridad social) y cuanto ganan en promedio vaya a ¨Vinculación laboral recién graduados¨. Aquí tiene la opción de buscar por institución o por carrera.

Recuerde que estas páginas le permiten conocer el salario promedio de los profesionales graduados en su área de interés.

¿Qué necesito para entrar a la Universidad y la carrera que me interesa?

1. Buenos resultados académicos: Uno de los criterios más importantes a la hora de buscar admisión a una institución de educación superior es el rendimiento académico. Muchas instituciones utilizan el puntaje del ICFES (SABER 11), y otras instituciones como la Universidad Nacional que tienen su propio examen de admisión. En cualquier caso, estudiar aumenta las posibilidades de ser admitido y también las posibilidades de acceder a becas o financiación.

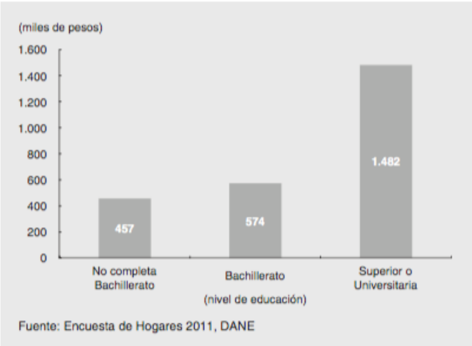
2. Financiación: Existen varias maneras de financiar la educación superior en Colombia. En general, tendrán preferencia los alumnos de escasos recursos y buen desempeño académico. Las siguientes son algunas opciones a tener en cuenta:

- Becas proveídas por cada institución por mérito académico y/o escasos recursos. Consulte las políticas de beca ya que estas son diferentes para cada institución.
- ICETEX: http://www.icetex.gov.co
- Secretaría de Educación de Bogotá (Banco de cupos, Fondo de Financiamiento de Educación Superior de Bogotá): http://www.sedbogota.edu.co/index.php/educacion-superior.html

Post-secondary education pays!

The relation between studies and income

Higher education is a determining factor of wages and the quality of life of families. The following figure presents average wages by level of completed education in Bogotá:



Clearly, more education is related with higher wages. By only finishing high school, wages move from 457,000 to 574,000 pesos each month. The difference is even more marked for those with a college degree, since their average monthly wage increases to 1,492,000. These statistics present a clear pattern: studying is worth it.

How can I learn about how much people earn who finished the degree I'm interested in?

It is very likely that you already have a good idea about the degrees and institutions where you would like to pursue your studies. If this is true, is there a way to know how much I could expect to earn?

There are two places where you can obtain information on average wages for graduates by institution and degree. These are:

1. Average wage calculator for graduates: www.finanzaspersonales.com.co

This website counts with a tool that allows to calculate average wages by region, institution, degree and gender of people who graduated between 2001 and 2011.

How does it work?

- Visit the website and search for *Wage calculator by degree for Graduates.*
- Select the region where you are interested in searching (e.g. Bogotá)
- Select the institution and the degree you are interested in evaluating

2. Labor Observatory of the Ministry of Education: www.graduadoscolombia.edu.co

This website also provides information about average wages for the whole country. Additionally, you can learn about the labor prospects for your degree of interest

How does it work?

- Visit the website and click on the red button reading *Information System of the Labor Observatory*
- If you would like to know the number of graduates by degree, click on the "National Profile" tab. Next, select the department where you plan to study and you will find data on graduates by degree.

If you are interested in the number of individuals who pursued your degree of interest who have a formal job (paying social security) and how much they earn on average, select "*labor link of recent graduates"*. Here you have the option to search by institution and degree.

Remember that these websites allow to learn about the average wages of recent graduates for your degree of interest.

What will I need to enroll in a University and in my degree of interest?

1. **Good academic results**: One of the main criteria for admissions in University if academic performance. Many institutions use the ICFES (SABER 11) score, and other institutions like the National University also have their own admissions test. Nevertheless, studying will increase the probability of being admitted and also of obtaining financial aid or financing.
2. **Financing:** There are many ways to finance higher education in Colombia. In general, financing institutions have preferences for students of low income and good academic performance. The following are some organizations to keep in mind:

- Scholarships provided by each institution according to academic merit of financial need. Consult the scholarship policies for each institution given that they may differ.
- ICETEX: http://www.icetex.gov.co
- Secretary of Education in Bogotá (FDFESBO): http://www.sedbogota.edu.co/index.php/ed- ucacion-superior.html

A.2 Additional Tables

Table A.1. Attrition diagnostics

	BHELPS: Baseline to Follow-Up	BHELPS to ICFES	BHELPS to SNIES
	(1)	(2)	(3)
Panel A: Attrition Rates			
Baseline N	6,636	6,636	6,636
Final N	6,141	6,323	6,303
Attrition Rate	0.075	0.047	0.050
Panel B: Random attrition tests (OLS)			
Treatment	-0.009	-0.021	-0.021
	(0.039)	(0.016)	(0.016)
R^2	0.000	0.002	0.002

Source: Author's calculations from BHELPS survey.
Notes: * Significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors are clustered at school-level.

Table A.2. Treatment Effects on Beliefs: Robustness

	Robust Premium Error Degree and Field			Robust Premium Error Degree, College, and Field		
	All (1)	Under (2)	Over (3)	All (1)	Under (2)	Over (3)
Panel A: After, Matched with baseline						
Treat	-0.054	0.187	-0.089	0.021	-0.020	0.034
	(0.091)	(0.202)	(0.090)	(0.217)	(0.516)	(0.228)
	3,947	784	3,163	2,772	590	2,182
Panel B: Difference-in-differences						
Treat × Post	0.146	0.106	0.122	-0.003	-0.005	-0.022
	(0.099)	(0.265)	(0.098)	(0.100)	(0.316)	(0.099)
Post	-0.091	1.243***	-0.337***	-0.116	0.977***	-0.347***
	(0.064)	(0.160)	(0.068)	(0.072)	(0.170)	(0.071)
Observations	8,020	1,468	6,552	5,618	1,114	4,504
Mean(y) at baseline	1.613	-0.581	2.059	1.369	1.180	1.873

Source: Authors' calculations from BHELPS survey.
Notes: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel correspond to a separate OLS regression. Panels A controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Panel B presents coefficients for difference-in-difference regressions that control for individual fixed-effects. Standard errors are clustered at school-level.

Table A.3. Treatment Effects by Family Income and Gender (balanced sample)

	Knows ICETEX (1)	Overall score (2)	Math (3)	Language (4)	College Enrollment (5)	Private College (6)	Top-10 College (7)	Academic Degree (8)	STEM Degree (9)
Panel A: Average effects									
Treat	0.047***	0.007	0.054	0.003	0.008	0.013	0.006**	0.014	0.010
	(0.015)	(0.032)	(0.037)	(0.031)	(0.020)	(0.011)	(0.003)	(0.009)	(0.006)
Observations	5,333	5,238	5,238	5,238	5,225	5,225	5,225	5,225	5,225
Panel B: Treatment effects by family income									
Low Income (≤2MW)	0.060***	-0.022	0.026	-0.044	-0.007	0.021**	0.000	0.010	0.008
	(0.017)	(0.038)	(0.040)	(0.037)	(0.023)	(0.011)	(0.002)	(0.009)	(0.006)
Middle Income (>2MW)	0.024	0.053	0.098**	0.077	0.038	0.003	0.017***	0.024	0.015
	(0.017)	(0.047)	(0.048)	(0.047)	(0.026)	(0.020)	(0.005)	(0.017)	(0.013)
P-value (low=middle)	0.064	0.173	0.128	0.028	0.097	0.371	0.004	0.437	0.640
Observations	5,333	5,238	5,238	5,238	5,225	5,225	5,225	5,225	5,225
Panel C: Treatment effects by Gender									
Female	0.029	-0.025	0.031	-0.034	-0.019	0.003	0.005	0.007	0.002
	(0.018)	(0.038)	(0.043)	(0.043)	(0.027)	(0.016)	(0.003)	(0.011)	(0.007)
Male	0.066***	0.042	0.076	0.042	0.038*	0.024*	0.008*	0.021	0.019*
	(0.019)	(0.044)	(0.047)	(0.038)	(0.022)	(0.014)	(0.005)	(0.013)	(0.010)
P-value (female=male)	0.102	0.172	0.378	0.145	0.041	0.279	0.485	0.413	0.201
Observations	5,333	5,238	5,238	5,238	5,225	5,225	5,225	5,225	5,225

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER 11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table A.4. Treatment Effects by Direction of Belief Error (baseline matched to administrative data)

	Knows ICETEX (1)	Overall score (2)	Math (3)	Language (4)	College Enrollment (5)	Private College (6)	Top-10 College (7)	Academic Degree (8)	STEM Degree (9)
Panel A: Average effects									
Treat	0.038***	-0.005	0.043	-0.005	0.015	0.015	0.005*	0.011	0.009
	(0.014)	(0.030)	(0.034)	(0.029)	(0.019)	(0.010)	(0.002)	(0.009)	(0.006)
Observations	5,909	6,105	6,105	6,105	6,085	6,085	6,085	6,085	6,085
Panel B: Treatment effects by direction of belief error									
Underestimates	0.054	-0.001	0.127	-0.014	0.045	0.000	0.000	0.024	0.023
	(0.034)	(0.079)	(0.079)	(0.079)	(0.033)	(0.025)	(0.005)	(0.021)	(0.014)
Overestimates	0.049***	-0.012	0.028	-0.007	0.007	0.018	0.005*	0.008	0.008
	(0.016)	(0.031)	(0.034)	(0.031)	(0.019)	(0.011)	(0.003)	(0.009)	(0.007)
P-value (over=under)	0.885	0.901	0.211	0.933	0.264	0.490	0.432	0.473	0.349
Observations	5,909	6,105	6,105	6,105	6,085	6,085	6,085	6,085	6,085

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.
Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table A.5. Treatment Effects by Non-Cognitive Factors (balanced sample)

	Knows ICETEX (1)	Overall score (2)	Math (3)	Language (4)	College Enrollment (5)	Private College (6)	Top-10 College (7)	Academic Degree (8)	STEM Degree (9)
Panel A: Treatment effects by risk aversion									
Risk Loving	0.042	0.069	0.112	0.064	0.048	0.022	0.019**	0.030	0.033**
	(0.030)	(0.087)	(0.089)	(0.083)	(0.042)	(0.027)	(0.009)	(0.020)	(0.016)
Risk Averse	0.049***	-0.006	0.040	-0.009	0.000	0.012	0.004	0.014	0.008
	(0.016)	(0.036)	(0.039)	(0.034)	(0.021)	(0.013)	(0.003)	(0.009)	(0.007)
P-value (loving=averse)	0.833	0.424	0.419	0.421	0.228	0.761	0.119	0.438	0.125
Observations	5,133	5,051	5,051	5,051	5,039	5,039	5,039	5,039	5,039
Panel B: Treatment effects by self-concept									
Low	0.062***	0.011	0.059	-0.011	0.011	0.022*	0.005*	0.013	0.010*
	(0.017)	(0.038)	(0.046)	(0.038)	(0.024)	(0.012)	(0.003)	(0.009)	(0.006)
High	0.028	0.046	0.087*	0.055	0.016	0.006	0.010*	0.022	0.014
	(0.019)	(0.046)	(0.051)	(0.044)	(0.028)	(0.019)	(0.006)	(0.015)	(0.011)
P-value (low=high)	0.114	0.499	0.618	0.222	0.855	0.447	0.378	0.598	0.696
Observations	5,289	5,201	5,201	5,201	5,188	5,188	5,188	5,188	5,188
Panel C: Treatment effects by self-efficacy									
Low	0.042**	-0.027	0.042	-0.042	0.011	0.009	0.004	0.011	0.007
	(0.017)	(0.040)	(0.045)	(0.039)	(0.023)	(0.012)	(0.003)	(0.011)	(0.007)
High	0.052***	0.082	0.091*	0.094*	0.002	0.021	0.010*	0.022	0.017
	(0.019)	(0.051)	(0.051)	(0.053)	(0.027)	(0.018)	(0.005)	(0.014)	(0.010)
P-value (low=high)	0.641	0.076	0.411	0.044	0.750	0.568	0.416	0.517	0.417
Observations	5,285	5,195	5,195	5,195	5,182	5,182	5,182	5,182	5,182
Panel D: Treatment effects by perceived likelihood of enrollment									
Low	0.102***	0.013	0.020	0.001	0.001	-0.007	-0.003	0.005	0.002
	(0.033)	(0.052)	(0.058)	(0.059)	(0.034)	(0.015)	(0.003)	(0.011)	(0.007)
High	0.038***	0.007	0.060	0.002	0.009	0.016	0.008***	0.019*	0.014*
	(0.014)	(0.036)	(0.040)	(0.036)	(0.021)	(0.013)	(0.003)	(0.010)	(0.007)
P-value (low=high)	0.036	0.918	0.550	0.985	0.811	0.257	0.004	0.381	0.202
Observations	5,083	5,002	5,002	5,002	4,990	4,990	4,990	4,990	4,990

Source: Authors' calculations from ICFES, SNIES, and BHELPS survey.

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%. Each column and panel corresponds to a separate OLS regression that controls for student and household attributes (male, age, age squared, family income, and parental education) and school characteristics (average SABER11 score in previous years, has computer lab, shift indicators, and school size). Standard errors are clustered at school-level.

Table A.6. Baseline Balance in Student Aspirations

	Control		Treatment		Difference
	Mean	(SD)	Mean	(SD)	P-value
Enroll	0.988	(0.108)	0.988	(0.108)	1.000
Public College	0.628	(0.484)	0.629	(0.483)	0.944
Private College	0.220	(0.415)	0.234	(0.423)	0.403
Top-10 College	0.451	(0.498)	0.470	(0.499)	0.442
Academic degree (4-year)	0.886	(0.317)	0.897	(0.304)	0.359
STEM degree	0.403	(0.491)	0.430	(0.495)	0.089

Source: Authors' calculations from baseline BHELPS survey.
Notes: The last column presents the p-value of the difference in the attribute between treatment and control groups calculated by regression with clustered standard errors at the school-level.