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Decisions about Postsecondary Education, their Returns in Colombia

Monica Ospina-Londoño[1] & Fabiola Saavedra-Caballero[2]

Abstract

This study analyzes the economic returns to schooling decisions made by high school graduates in Colombia. We wanted to verify if the economic returns (wages) obtained by new postsecondary education graduates compensate for the economic and psychological investment they made to get that academic degree. To answer that question, we estimated these economic returns for each type of postsecondary degree available in Colombia (technical education, technological education, undergraduate studies, graduate studies) by origin of the institution (public or private). Our methodological strategy includes the generation of a micro-database that contains agents' socio-economic backgrounds and also their individual labor market outcomes. Because agents with very similar characteristics and the same schooling decisions might obtain different economic returnsfrom education, we considered as part of our empirical strategy the inclusion of an approximation of agents' cognitive abilities.

Keywords: postsecondary education, labor market outcomes

JEL CODE: I210, J24

1. Introduction

Essentially, postsecondary education demand is based on students' perceptions about their future economic returns. Nevertheless, these economic returns depend not only on the academic degree achieved but also on aspects such as the characteristics of the institution where the student obtained that degree, the features of the program he chose and the student's inherent cognitive abilities.

However, as Maxwell (1970) and Dolton and Vignoles (2000) show, investingin postsecondary education does notguarantee economic returns that pay off thefinancial and psychological investment the student made.

As result of this uncertainty about the future economic returns, the education system might suffer a loss of efficiency. First, an excess of demand for educational programs in specific knowledge areas can affect the costs of the programs, lower their quality and create a vicious circle affecting the expected economic returns. Second, any change of perception about the expected economic returns may increase desertion or extend the regular education cycle. Third, this uncertainty prevents policy makers from properly identifyingwhere to focus the funding and where to increase the education coverage. Finally, if there is no accuracy about the economic returns of postsecondary education, the investment made by the government is not optimal and is therefore not aligned with the productivity objectives of the country.

[1]Universidad EAFIT, Medellín – Colombia.

[2]Universidad EAFIT, Medellín – Colombia, Carrera 49 N° 7 Sur – 50, Bloque 26, segundo piso (Escuela de Economía y Finanzas). Email: fsaavedr@eafit.edu.co; fsaavedra.caballero@gmail.com

That is why the relevance of estimating the economic returns topostsecondaryeducation can be considered from different perspectives. From an individual perspective, it can determine if the investment a person makes to get that academic degree is compensated by a wage premium. From a labor market perspective, to estimate these economic returns will help validate if it is easier for an individual with a postsecondary educational level to get a better job (higher salary) than without that academic degree. Finally, from a public policy perspective, these estimations could help government to target the investmenton education more efficiently by focusing on academic degrees that bring higher economic returns to individuals, which means they are more productive.

Colombia is a perfect scenario to study the economic returns to postsecondary education due tothe availability of important information at the individual level such as socio-economic characteristics, Saber11 (standardized test) test scores and recently graduate workers' salaries. Saber 11 is an academic performance test taken by senior year students to evaluate their academic competences and abilities developed through secondary education. Regarding workers' salaries, the Employment Observatory for Education (OLE[3]) tracks recently postsecondary graduate students who work in the formal sector of the economy and gathers information about their salaries and places where they are working, classified by economic activity.

Our methodology is focused on the estimation of the individual economic returns to each postsecondary education degree in Colombia by type of academic degree and origin of institution. Then, we compared the returns obtain at university (bachelor degree) with each postsecondary education degree. Our objective is to answer: What would have happened to individuals who hold a bachelor degree as their higher educational level had they had a different post-secondary education degree? To accomplish our goal, we adapted Reyes et al. (2013) empirical strategy that proposes the inclusion of individuals' abilities in comparing the different scenarios of postsecondary education and complemented it with quasi-experimental techniques.

Therefore, the main contribution of this investigation is to include the heterogeneity of the economic returns into the analysis; thisis because agents with very similar characteristics and the same schooling decisions might get different economic returns. We attribute thesedifferences to cognitive abilities, whichalso reflect to an extent the individual'sinnate abilities such as student's intelligence, an education-supportiveenvironment, studying habits, motivation and discipline among others. Additionally, these characteristics influence studentsmaking their postsecondary schooling decisions, even though theymight not be totally aware ofthis.

Our results[4] show thatindividuals who attended universities have approximately 7% higher salaries than if they had held a technological degree. Nevertheless, their salaries are approximately 9% lower than if they had held a professional-technical degree (programs for a particular career or job), 61% lower than if they had held a specialization and 84% lower than if they had held a Master's degree. These results show an important impact over individual's economic returns (wages) once proficiency in a specific field is developed.

This first part of thearticlegives an overview about our research. In section two, we depict the Colombian postsecondary education system structure and its characteristics,and, in section three, we present a review about the economic returns to postsecondary education. Section four encloses our model and empirical strategy; it also contains a description of our data and information sources.

Section five describes the results of our estimations. Finally, in section six, we discuss the results and provide some conclusions.

[3]"Observatorio Laboral para la Educación" in Spanish.

[4]The estimation controls for individual's abilities, socioeconomic background, institution'scharacteristics and tuition costs among others (these covariates are detailed on Section 4)

2. Postsecondary Education in Colombia

As the Colombian Political Constitution of 1991 states, education is a right for Colombian people and also a public service that the government has to provide and supervise. That is why the government has the responsibility to guarantee adequate coverage and also the minimal conditions for people to access and to stay in the education system.

According to the Colombian Ministry of Education (MEN[5]), the Colombian Education System has five different stages: Initial Education, Preschool, Basic Education, Medium Education and Higher Education (this last one is known as *Educación Superior*). Basic Education includes five years of elementary education and four years of high school. The fourth stage, called "Medium Education", includes junior and senior years and finalizes with the high school diploma. After receiving the high school diploma and taking a compulsory standardized test provided by the government (SABER-11)[6], the student can access "Higher Education" that,from now on, we will call "Postsecondary Education" to harmonize this term with international standards.

There are two different levels of Postsecondary Education: undergraduate and graduate;each of them awards different degrees to their graduates. The undergraduate level includes the Technical Level, Technological Level and Professional Level.The Graduate level includes Specialization,MasterDegree and Doctoral Degree.

It is important to mention that the Colombian Education System proposes propaedeutic cycles (each previous education level serves as basis for the next one), which means that students should begin postsecondary education at the technical level, then advance until the technological level, get a professional degree and then move to a graduate level (specialization then master's and finally doctorate), to gather knowledge and skills at different levels in the same knowledge area.

Postsecondary education is provided by Institutions of Higher Education (IES[7]), and they can be classified by two different criteria. The first one, the academic criteria, reflects the scope each IES has and the programs that can be taught at them. The second one is the origin of the institution, which means that the IES can be public or private. Table 1 summarizes which type of programs can be given according to the academic criteria of the IES.

There is also anothertype of institution that offerssome postsecondary educationbut that we are not including in our study because of their educative objectives. The first one is the National Training Service SENA (*Servicio Nacional de Aprendizaje)*, which offers free training programs focused on vulnerable people and the unemployed. The second one is the Regional Centers for Higher Education CERES *(Centros Regionales de Educación Superior)*,which are decentralized educative centers that offer some postsecondary education programs in distant areas; they are supervised academically by one or various IES that are in charge of the design and strategy of these programs.

As mentioned before, to access Postsecondary Education, students must present SABER-11 test results. This test is provided by ICFES*(Instituto Colombiano para la Evaluación de la Educación)*, the Colombian Institute for Educational Evaluation that supports the MEN by providing information related to the quality of education of the country. The SABER-11 test measures the achievement of students who are at the senior year (last year of secondary education) in sixdifferent areas: Language, Math, Social Sciences, Biology, Chemistry and Physics. Each area is graded over 100 points, and even though there is no pass mark, if the student gets a score from 0 to 30, it is considered low; if the score is between 30.01 and 70, it is average; andif the score is above 70.01, it is considered high.

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[5]In Spanish "Ministerio de Educación Nacional"

[6] It is worth to mention that even though SABER 11 test is compulsory and should be used as reference to admit students in postsecondary education, some institutions of postsecondary education prefer to complement it with their own tests to admit students.

[7]In Spanish: Instituciones de Educación Superior - IES

Because of the SABER-11 test design, it grades not only the student's knowledge about a specific subject, but also measureshis competences. These competences can be understood as the mental processes and tools that he uses to solve the questions, which reflect somehowthe cognitive abilities of the student.

3. Economic Returns to Postsecondary Education

Every day, young high school graduatesdecide to invest in postsecondary education programs because they believe that "education pays off". People invest not only between three and five years of their lives, but alsoconsiderable amounts of money that are usually financed by credit (Eckel et al., 2007; Neill, 2008; Carmichael and Finnie, 2008). Their motivation lies in increasing the likelihood of getting a job in the future that will generate revenues enough to recover their high investments.

This logic is supported by several academic studies that have demonstrated the existence of a positive correlation between the education level and the income of an individual throughout his life (Willis and Rosen, 1979; Kane and Rouse, 1995, Card, 1999). Similarly, Cheeseman Day and Newburger (2002) note that American workers who hold a bachelor degree earn through their lifetimes approximately 77% higher incomes than individuals who only graduate from high school. Among recent studies, Carnevale et al. (2012) suggest that postsecondary education is the key to access future economic opportunities because individuals with that level of education have substantially higher incomes over their lifetimes (approximately 84%[8]) compared to those who did not attend postsecondary education.

In Latin America, there is also a positive correlation (Psacharopolous and Chu Ng, 1992, Behrman et al., 2007; Mancorda et al., 2010); nevertheless, the magnitude of the estimated returns is much lower than the estimates for developed countries. For example, Contreras et al. (2005) estimated 9% of higher returns for individuals with postsecondary education in Chile; Morales-Ramos (2011) estimated returns between 8.2% and 8.4% higher per additional year of education in Mexico, while Lustig et al. (2012) notes that tertiary education returns are 2 percentage points above the returns to secondary education in Argentina and 4 percentage points in Brazil.

There are also some studies that analyze the economic returns to Postsecondary Educationspecifically in Colombia. Sanchez & Nuñez (2012),for example, based on urban household surveys from 1976 to 1998,estimated returns to education through a Mincer equation using a cohort technique.

They foundthat individuals who completed college have the highest returns to education and that these returns are approximately 80% above of those obtained by individuals who only completed high school.

Mora (2003) applied the Hungerford and Solon Test (1987) to anincome quantile regression using the National Household Survey for year 2000. The results of the estimation showed that a university degree generates returns between 17.2% and 27.8% compared to returns of high school diploma that range between 7.6% and 17.1%.

Garcia et al. (2009), in order to overcome Mincer equation methodological criticisms,estimated the internal rate of return to higher education according to the methodology of Heckman et al. (2005). Based on National Household Surveys from 2001 to 2005, they estimated an internal rate of return of education as if it were a financial project and compared its potential reward to two different interest rates for Colombia (fixed term interest rate and the natural interest rate). The results show that university is a high return investment and that it is at least 1% above any of the two interest rates. Prada (2006) also found that even though the returns to education from university are the highest compared to secondary and primary education, they are unstable and very sensitive to changes in the economic cycle. Additionally, for individuals who hold a university degree, Forero & Ramirez (2008) identified the most important determinants for labor income to be age, gender, parents' education level, the area of knowledge of the job,

[8] During his lifetime, an individual who holds a bachelor degree can earn incomes 84% above the income of individuals with a high school diploma.

whether the individual lives in the capital city (Bogotá) and whether the IES where the agent obtained the degree is certified.

Even though the preceding studies show that in Colombia there are better economic returns for graduates who hold a postsecondary degree, there is no study that compares the returns of each postsecondary degree to another; these studies also do not include the effect of the cognitive abilities of the individuals as part of the explanation of those returns. These abilities are an important factor in making the decision about whether to invest in postsecondary education because they reflect the skills an individual has to successfully complete the degree he has chosen.

As Hunter (1986) found, general cognitive ability is positively related to performance in all jobs. This implies that people with higher cognitive abilities are prone to stand out at work and also at educational processes. These cognitive abilities are intellectual skills such as understanding, remembering and reasoning that individuals use to solve problems. However, we consider that cognitive skills also reflect to an extent unobservable characteristics (noncognitive abilities) such as motivation, habits, preferences, discipline, persistence, self-esteem, etc. that cannot be directly observed but also affect the individual's decisions.

That is the reason why we aim to estimate the rates of return to postsecondary education in Colombia controlling for individuals' cognitive abilities. They will help us capture the unobserved heterogeneity that may be causedbypeople with the same endowments and the same postsecondary education degree getting different economic returns.

4. Model and Empirical Strategy

We split our empirical strategyinto two different phases. In the first one, we estimated an approximation of the individual's cognitive abilities represented by SABER-11 test results. We consider that, even though cognitive skills captured in SABER-11 test results do not totally represent noncognitive abilities, they reflect them to a degree. In addition, Heckman et al. (2006a) found that even though cognitive skills affect the variance of wages the most, cognitive and noncognitive abilities effects over the variance of wages are very similar.

In the second phase, we estimated the labor market outcomes[9] for each type of postsecondary degree including the previous estimation of abilities as a covariate. We compare basic scenario (Bachelor degree) economic returns with the economic returns of Professional-Technical degree, Technological degree, Specialization degree and Master degree[10]. These estimations were made through matching techniques.

4.1. Assessing Individuals' Abilities

Following Carneiro et al. (2003), Hansen et al. (2004) and Reyes et al. (2013), we used standardized test scores (SABER-11 test) to approximate individuals' abilities. We also kept in mind the assumption proposed initially by Heckman et al. (2006a) that states that at the moment the individual makes a decision about his postsecondary education, his abilities(cognitive and non-cognitive) are fixed and are known by him but not by the researcher.

We used scores of SABER-11 test for the following knowledge areas: language, math, biology, chemistry and physics. Because the SABER-11 test is taken at the senior year, these abilities are observed before the individual decides which level of postsecondary education to attend. Thus, as mentioned before, they can be considered by the individual as a sign of how well prepared he is for postsecondary education.

Because SABER-11 test results are not comparable across years, we calculated percentiles specific for each year to have an indicator of the individual's academic performance by knowledge area. These results were used as covariates while applying matching algorithms allowing us to control for individuals' abilities.

[9] We use the terms "labor market outcomes" and "economic returns" interchangeably.

[10] We didnot include "Doctoral Degree" because of the size of our sample (a very small number of doctoral graduates were part of OLE's database)

4.2. Labor Market Outcomes

Weanalyzed the economic returns of postsecondary education through comparison by setting a basic scenario (Bachelor degree) and comparing it one by one with the three postsecondary degrees.

The empirical strategy applied consisted of estimating the average treatment effect on the treated (ATT) through matching algorithms. By applying this technique, we are able to calculate the economic returns the individual who holds a bachelor degree would have had, had he chosen a different postsecondary degree.

To have a proper counterfactual to compare the economic returns with, we represented the individual's decision through a logistic regression of the binary category university/other postsecondary degree. Then, we match these individuals with other individuals with similar propensities.
To estimate this propensity, we controlled for covariates includingindividual's characteristics, institution characteristics, tuition costs and the individual's abilities (previously estimated) that are summarized in a propensity score.

Regarding the identification strategy, matching techniques balance covariate distributions between treated[11] (other postsecondary degree) and non-treated individuals (bachelor degree). The treatment (T) is assigned independent of potential outcomes Y(i), where i=1 for other postsecondary degree labor market outcomes and i=0 for bachelor degree labor market outcomes. Therefore, we expect similar average outcomes if both groups receive the same treatment or if none of them do, which can be represented by the following equations:

$$E[Y(1)|T=1]=E[Y(1)|T=0]=E[Y(1)] \quad (1)$$
$$E[Y(0)|T=1]=E[Y(0)|T=0]=E[Y(0)] \quad (2)$$

These equations show that the average potential outcome for the treatment group under treatment is equal to the average potential outcome of the control group had it been treated (equation 1), and that the average potential outcome for the treated group, had it not been treated, is equal to the average potential outcome of the control group with no treatment (equation 2).

Based on this, the ATT is estimated using the following equation, where $E[Y(0)|T=1]$ represents the counterfactual:

$$E[Y(1)-Y(0)|T=1]=E[Y(1)|T=1]-E[Y(0)|T=1] \qquad (3)$$

However, the estimation of the ATT would only be correct if treatment were assigned randomly, thus making the outcomes independent. Unfortunately, this was not the case because we set which individuals were controls and which were to be treated. As a consequence, we will use the conditional independence assumption (CIA), which ensures that the distributions of key covariates are balanced across the treatment and control groups.

At this point, we have specified our identification strategy (propensity matching score); however, there are many matching metrics available to achieve our goals. The best matching metric, the one that provides the best balance across our covariates of interest, is the estimations of "nearest neighbor"[12], which considers each treated (control) unit and searches for a control (treated) unit with the closest propensity score. We used the variation in this metric that includes replacement, which means that an untreated individual can be used more than once as a match for treated units.

4.3. Data Description

One of the advantages of our data is that the information at individual level that we have merged hasnot been use altogether before, such as the SABER 11 test scores, the socio-economic characteristics of the recent graduates, their salaries and the tuition costs of the programs.

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[11] We will use traditional "matching" jargon and use the term "treatment group" when referring to the other postsecondary degree we are comparing the economic returns with, and "control group" when referring to the basic scenario (bachelor degree).

[12] We compared estimations using nearest neighbor (NN) with different metrics, and NN is the one that provided the best balance.

Our database includes information from year 2007 until year 2011 restricted to individuals aged 18 until 35 years old. We used administrative records at the individual level from OLE to get the monthly approximation to individuals' wages (we used as a proxy for salaries the nominal income used to estimate the individual's contributions for health and pensions). We also used information from the OLE related to the characteristics of the institutions where the individuals obtained their academic degree.

We integrated this information with individual data from the MEN related to the socioeconomic characteristics of the individuals and their households at the time they took the SABER-11 test and of course the SABER-11 test scores. Finally, also from the MEN, we gathered information about program's annual tuition costs (provided by program and year).

Unfortunately there are data limitations too, such as that OLE information is only available for postsecondary education graduates.

This constraint prevents us from comparing the economic returns with individuals who drop out of postsecondary education and also with those who decided not to attend postsecondary education at all.

Our sample has 190,111 observations, and after estimating the returns for the whole sample (general estimation) we split it into two different subsamples by origin of the institution (public and private). The private subsample has 106,350 observations and the public subsample has 83,761 observations.

The covariates used in the estimations are the individual's characteristics (age, sex, mother's education, father's education, and the number of income contributors in the household), individual's abilities (math, language, biology, chemistry and physics SABER-11 test scores[13]), IES characteristics (if the IES has a high quality accreditation, methodology[14]andtuition costs) andfinally, the number of related undergrad programs taken. These covariates were used to estimate the returns using the public and private subsamples; nevertheless, along with using the whole sample, we included an extra covariate that controls for the origin of the IES.

5. Estimation and Results

As earlier mentioned, our empirical strategy specified in Section 4 wasfirst applied to the full sample (general). Table 2, shows significantestimates (t-stat) from comparing the returns obtained as a result of holding a bachelor degree (basic scenario) with four different postsecondary degree labor market outcomes. It is worth mentioning that all the estimates registered over 99% of common support (except by Master degree which registered 92% of common support) and the key covariates were balanced across the treatment and control groups (Annex 1).

As can been seen, the economic returns of an individual who holds a bachelor degree,had he chosen a professional-technical program, would have been 9,24% higher compared with the average bachelor degree monthly wage. The reason for this might be that professional-technical programs are focused on specific job and career needs, which means that the individual developed a certain degree of proficiency on specific tasks that are compensated through a higher salary.

On the other hand, had the individual chosen a technological program, his returns would have been approximately 7, 17% lower than the average bachelor degree monthly wage. Usually, technical programs have a 1 or 2 year duration (compared with the 4 or 5 year duration of bachelor degree) and the tuition costs are lower than those of bachelor degrees.

Finally, improving a bachelor degree with a specialization or with a master course increases the economic returns by 61,6% and 83,9%, respectively. It can be noted that gaining expertise in specific knowledge areas brings higher economic returns to individuals.

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13 Recalculated using the method me mentioned earlier (section 4.1)

14 On-line courses (*a distancia*) or if the student has to attend classes physically (*presencial)*

Analyzing the data by the institution origin, it can be seen that the results are slightly different. Table 3 shows the results for those degrees obtained at private institutions[15]. Under this setup, it can be seen that even though the magnitudes of the variations in the economic returns change, the direction of the effectsis concordant with the results obtained with the full sample (general).

Analyzing the economic returns that an individual who holds a bachelor degree from a private institution would have had had he chosen a professional-technical degree also from a private institution, an increase of 72, 86% on his returns (much higher than on a general scenario) is observed. Had the individual chosen a technological degree, his wage would have been 3,41% lower.

Finally, had the individual chosen a specialization, his economic returns would have been 35,46% higher, and had he held a Master degree, his returns would have been 49,98% higher.Comparing these results with those obtained with the full sample, it can be inferred that private institutions report higher economic returns as more specific abilities are developed (professional-technical).

Table 4 exhibits the results for the public institutions subsample estimations[16]; they show that had an individual who held a bachelor degree from a public institution chosen a professional-technical degree, he would have gotten a 29, 37% lower wage. Similarly, had he chosen a technological program, his returns would have been 14, 28% lower.

On the other hand, had an individual who holds a bachelor degree chosen to attend a specialization, his economic returns would have been 70, 66% higher than the average bachelor degree monthly wage. Similarly, had the individual chosen to attend a master's program, his wage would have been more than twice the wage he receives as a bachelor graduate.This shows that only specialization and master programs at public institutions would have reported higher economic returns than alternative scenarios.

6. Conclusions

By integrating information at the individual level that includes socioeconomic background, labor market outcomes, IES characteristics, tuition costs and especially individuals' cognitive abilities, we were able to obtain novel empirical evidence about the economic returns of postsecondary education in Colombia. These estimations are much more precise because they consider the presence of heterogeneity by including individuals' abilities[17]; this makes the estimation of parallel scenarios (comparing postsecondary education degrees' labor market outcomes) much more useful for public policy than previous research.

Our estimations are based on comparing the economic returns across postsecondary education academic degrees using as the returns perceived while holding a bachelor degree as the basic scenario. The estimations show in a broad sense that getting a master's degree or a specialization degree will always be better than a bachelor's degree. For private institutions, a master's degree would increase individual's wage in 41% and for public ones the increase would be approximately 114%. For specializations, in private institutions, this degree increases wages approximately 35, 56%, and in public institutions, 70, 66%.

This also gives a hint about higher wages if the academic degree (graduate degree) was obtained from public institutions.

When comparing the results with professional-technical degrees, it is interesting to note that the results vary different depending on the origin of the institution. If the professional-technical degree was obtained from a private institution, wages are 72, 86% higher, but if this degree was obtained from a public institution, the wages would be 29, 37% lower.

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15 All the estimates for the private subsample registered over 95% of common support (except by Master Degree, which registered 94% of common support) and the key covariates were balanced across the treatment and control groups.

16 All the estimates for the private subsample registered over 98% of common support (except by Master Degree, which registered 87% of common support) and the key covariates were balanced across the treatment and control groups.

17 As mentioned before, we consider that standardized test scores such as SABER-11 reflect not only individuals' cognitive abilities, but also non-cognitive ones to an extent.

Regarding technological degrees, our results show lower wages than the bachelor degree in all scenarios. If the institution was private, the economic returns were 3,41% lower, and if the institution was public, the wages were 14,28% lower.

These results lead to the question of how much the labor market valuates the origin of the institution and if the quality of the degrees is associated with it;this is because our estimations always show lower wages for all postsecondary degrees that were obtained in a public institution.

In addition, these results permit us to identify which academic degrees of postsecondary education bring higher economic returns to individuals. For private institutions, professional-technical degrees bring higher economic returns, and for public institutions, master degrees. The implications of these results can be used when prioritizing public expenditure on postsecondary education.

Through these results, we can also determine which postsecondary education degrees require further analysisto identify the reasons for their low economic returns, such as the technological degrees (from both public and private institutions) and the professional-technical degree from public institutions.

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Table 1: IES Academic Classification

Academic Classification of IES	Undergraduate Programs	Graduate Programs
Professional-Technical Institutions(programs for a particular career or job)	- Professional Technical Programs	- Professional Technical Specializations
Technological Institutions (1)	- Professional Technical Programs -Technological Programs	- Professional Technical Specializations -Technological Specializations
University Institutions (all undergraduate programs and graduate programs up to specializations)	- Professional Technical Programs -Technological Programs -Professional Programs	- Professional Technical Specializations -Technological Specializations -Professional Specializations
Universities (all undergraduate and all graduate programs)	- Professional Technical Programs -Technological Programs -Professional Programs	- Professional Technical Specializations -Technological Specializations -Professional Specializations -Master Degree Programs -Doctoral Degree Programs

Source: Authors withinformation from the MEN

Note: Each type of IES by academic classification is also divided by origin (public or private)
1. Technological institutions are focused on different knowledge areas than professional-technical institutions. The latter are focused on upgrading specific career or job knowledge.

Table 2: General Control Group: Bachelor Degree

Academic Degree (treatment)	Treated	Controls	Difference	S.E.	t-stat	Variation respect to the mean
Professional-Technical	854.494,36	772.243,67	82.250,68	35.707,99	2,30	9,24%
Technological	695.850,18	759.643,58	-63.793,40	13.274,04	-4,81	-7,17%
Specialization	1.517.165,61	968.857,14	548.308,47	40.131,27	13,66	61,60%
Master	1.814.679,02	1.067.787,56	746.891,47	155.487,64	4,80	83,90%

Table 3: Private Control Group: Bachelor Degree

Academic Degree (treatment)	Treated	Controls	Difference	S.E.	t-stat	Variation respect to the mean
Professional-Technical	1.340.089,34	643.879,90	696.209,44	102.151,92	6,82	72,86%
Technological	676.397,54	709.002,43	-32.604,89	16.723,48	-1,96	-3,41%
Specialization	1170973,87	832.128	338.846	64.475	5,26	35,46%
Master	1408647,08	1017058,54	391.589	185.256	2,11	40,98%

Table 4: Public Control Group: Bachelor Degree

Academic Degree (treatment)	Treated	Controls	Difference	S.E.	t-stat	Variation respect to the mean
Professional-Technical	640.891,82	874.420,06	-233.528,24	28.643,51	-8,15	-29,37%
Technological	726.809,07	840.365,25	-113.556,18	22.019,38	-5,16	-14,28%
Specialization	1.607.368,22	1.045.586,09	561.782,13	50.126,07	11,21	70,66%
Master	2.026.075,65	1.120.506,97	905.568,68	204.213,23	4,43	113,90%

Annex 1: Balance across Covariates

In order to verify if the covariates were balanced across treatment and control groups, we used the following criteria for balance:

Unbalance level 3 (U3)	Unbalance level 2 (U2)	Unbalance level 1 (U1)	Balanced (*)
>2,6	1,96=< t < 2,6	1,64=< t < 1,96	t < 1,64
Serious	Moderate	Small	

Even though most of our covariates are balanced (covariates' means do not significantly different across treatment and control groups) we identified some covariates with a U3 level of unbalance. In that case, we applied the rule of a thumb that states that a percentage of bias of less than 10% is acceptable.

General Sample

	Technical - Profesional					*Technological*				
	Treated	**Control**	**%bias**	**t-test**		**Treated**	**Control**	**%bias**	**t-test**	
age	24,76	24,83	-4,7	1,61	*	24,68	24,70	-1,6	1,33	*
sex	0,55	0,54	2,1	-0,12	*	0,49	0,49	-0,2	-1,55	*
edu_mom	3,20	3,19	0,7	1,00	*	3,17	3,14	2,0	1,09	*
edu_dad	3,20	3,21	-0,2	1,13	*	3,14	3,12	1,3	1,03	*
matricula	5.300.000	5.300.000	-1,0	1,34	*	5.000.000	5.000.000	-3,3	0,73	*
meto	1,04	1,03	3,8	1,52	*	1,12	1,11	4,3	-1,76	U1
acred	0,00	0,00	0,0	0,05	*	0,12	0,10	4,5	1,90	U1
pre_afines	0,02	0,01	2,3	1,67		0,040	0,038	0,6	-1,16	*
aportantes	1,58	1,60	-2,8	-1,04	*	1,54	1,55	-1,3	1,70	U1
math	37,47	36,77	2,5	1,73	U1	38,58	38,42	0,6	1,10	*
language	31,98	31,96	0,1	1,28	*	34,94	34,66	1,0	1,43	*
biology	32,59	32,73	-0,5	1,36	*	35,46	35,19	1,0	1,56	*
chemistry	32,27	32,25	0,1	1,65	U1	35,80	35,55	0,9	1,93	U1
physics	36,63	36,53	0,4	1,06	*	39,67	39,83	-0,6	1,35	*
ies_orig	1,698	1,705	-1,3	-1,47	*	1,39	1,41	-4,7	1,88	U1

	Specialization					*Master*				
	Treated	**Control**	**%bias**	**t-test**		**Treated**	**Control**	**%bias**	**t-test**	
age	25,18	25,14	3,2	-1,64	U1	25,20	25,27	-5,1	-1,08	*
sex	0,37	0,37	-0,1	0,82	*	0,53	0,48	10,7	1,9	U1
edu_mom	4,55	4,38	10	-1,1	*	4,89	4,57	1,8	-1,58	*
edu_dad	4,56	4,37	11	-1,31	*	4,97	4,72	14	-1,36	*
matricula	6.600.000	6.300.000	9,5	-1,67	U1	6.400.000	6.200.000	8,6	-1,05	*
meto	1,02	1,03	-4,8	2,31	U2	1,01	1,01	0	0,94	*
acred	0,53	0,41	5,4	-1,63	*	0,86	0,70	3,8	-1,47	*
pre_afines	0,45	0,54	-2,6	-2,70	**U3**	0,40	0,60	-6,7	-2,11	U2
aportantes	1,58	1,58	0,5	1,02	*	1,61	1,61	0	0,6	*
math	51,49	49,64	6,3	-1,94	U1	66,20	64,01	7,3	-1,72	U1
language	53,74	50,35	8,7	-1,49	*	65,32	62,61	6,2	-0,81	*
biology	52,63	49,95	9,2	-1,71	U1	65,41	64,53	8,3	-1,41	*
chemistry	54,21	51,51	9,3	-1,56	*	70,15	66,68	7,5	-1,28	*
physics	50,52	48,57	6,7	-0,47	*	65,54	64,80	2,5	-1,29	*
ies_orig	1,79	1,78	1,7	-1,65	U1	1,63	1,64	-3,9	-4,42	**U3**

Private Institutions Subsample

	Technical - Profesional					*Technological*				
	Treated	**Control**	**%bias**	**t-test**		**Treated**	**Control**	**%bias**	**t-test**	
age	24,93	24,95	-1,4	-1,25	*	24,63	24,67	-2,7	1,65	U1
sex	0,68	0,67	1,1	-1,01	*	0,51	0,49	3,1	-2,19	U2
edu_mom	2,81	2,78	1,6	1,64	U1	3,03	3,00	1,9	1,76	U1
edu_dad	2,85	2,88	-2,1	1,57	*	3,00	2,98	1,6	1,02	*
matricula	5.800.000	5.800.000	2,9	1,51	*	4.800.000	4.800.000	-1,9	0,94	*
meto	1,00	1,00	0,5	0,34	*	1,16	1,15	3,5	-0,93	*
acred	0,01	0,01	1,7	0,59	*	0,19	0,17	3,7	1,26	*
pre_afines	0,00	0,00	0,9	-0,5	*	0,02	0,02	2,2	-0,6	*
aportantes	1,53	1,50	3,5	1,85	U1	1,50	1,50	0,9	1,74	U1
math	35,59	35,57	0,1	1,49	*	39,44	39,08	1,3	2,67	**U3**
language	24,72	25,23	-2,0	1,7	U1	35,85	35,88	-0,1	1,81	U1
biology	27,70	27,66	0,2	0,73	*	36,19	35,85	1,2	1,39	*
chemistry	29,11	29,81	-2,6	1,98	U2	36,38	35,74	2,3	1,22	*
physics	35,49	37,12	-6,0	2,23	U2	39,98	39,27	2,5	1,96	U2

	Specialization					*Master*				
	Treated	**Control**	**%bias**	**t-test**		**Treated**	**Control**	**%bias**	**t-test**	
age	25,04	25,10	-3,8	-0,97	*	25,01	25,28	-9,5	-2,31	U2
sex	0,43	0,48	-9,7	-2,2	U2	0,49	0,50	-2,6	-1,23	*
edu_mom	3,96	3,99	-1,6	-1,29	*	3,72	3,80	-4,4	-2,48	U2
edu_dad	3,94	3,95	-0,7	-1,26	*	3,70	3,87	-9,8	-4,31	U3
matricula	6.500.000	6.500.000	2,4	-1,52	*	6.200.000	6.000.000	14,7	-1,17	*
meto	1,03	1,04	-5,7	1,22	*	1,00	1,00	---	---	---
acred	0,46	0,37	16,7	0,14	*	0,78	0,75	5,8	-1,92	U1
pre_afines	0,37	0,37	-0,9	-1,57	*	0,34	0,36	-3,7	-1,09	*
aportantes	1,55	1,56	-1,3	-0,43	*	1,57	1,61	-5,9	-1,05	*
math	51,81	48,35	7,6	0,41	*	58,40	63,50	-6,9	-1,69	U1
language	52,80	50,90	6,6	-2,19	U2	50,86	56,93	-7,0	-1,65	U1
biology	52,74	51,25	5,1	-3,3	**U3**	52,71	53,71	-3,2	-0,7	*
chemistry	53,51	50,82	9,1	0,18	*	57,05	57,70	-2,1	-1,72	U1
physics	50,11	44,41	11,6	4,73	**U3**	53,79	52,76	3,2	-2,29	U2

Public Institutions Subsample

	Technical - Profesional					*Technological*				
	Treated	**Control**	**%bias**	**t-test**		**Treated**	**Control**	**%bias**	**t-test**	
age	24,68	24,73	-2,70	1,55	*	24,76	24,74	1,50	1,51	*
sex	0,49	0,49	-0,50	-1,02	*	0,46	0,45	2,70	-1,58	*
edu_mom	3,37	3,37	0,10	0,07	*	3,38	3,35	2,00	1,31	*
edu_dad	3,36	3,36	0,20	0,09	*	3,37	3,33	2,10	1,53	*
matricula	5.100.000	5.100.000	-2,30	1,74	U1	5.300.000	5.400.000	-2,80	1,02	*
meto	1,05	1,04	5,30	-1,65	U1	1,04	1,04	3,00	1,93	U1
acred	0,00	0,00	---	---	---	0,01	0,01	-0,10	2,06	U2
pre_afines	0,02	0,02	-0,20	1,48	*	0,07	0,06	3,90	1,13	*
aportantes	1,60	1,57	3,40	0,45	*	1,59	1,59	0,50	0,36	*
math	38,27	37,87	1,50	1,53	*	37,21	37,21	0,00	1,38	*
language	35,12	35,81	-2,60	1,68	U1	33,49	33,48	0,00	1,86	U1
biology	34,71	34,62	0,30	1,39	*	34,29	33,82	1,80	1,72	U1
chemistry	33,65	33,10	2,10	1,22	*	34,87	35,02	-0,60	1,89	U1
physics	37,14	36,68	1,70	1,93	U1	39,17	38,29	3,20	1,47	*

	Specialization					*Master*				
	Treated	**Control**	**%bias**	**t-test**		**Treated**	**Control**	**%bias**	**t-test**	
age	25,19	25,21	-1,00	-1,76	U1	25,32	25,38	-4,60	-1,35	*
sex	0,36	0,35	1,50	1,08	*	0,55	0,50	9,80	-1,55	*
edu_mom	4,69	4,49	1,70	-1,96	U2	5,54	5,05	3,30	-0,90	*
edu_dad	4,71	4,48	3,70	-1,46	*	5,69	5,16	9,30	-1,29	*
matricula	6.600.000	6.300.000	6,90	-2,17	U2	6.400.000	6.600.000	-10,90	-2,10	**U2**
meto	1,02	1,03	-2,20	-3,31	U3	1,02	1,00	3,80	1,30	*
acred	0,54	0,42	5,30	-1,42	*	0,90	0,77	9,20	-11,49	**U3**
pre_afines	0,46	0,56	-7,10	-1,65	U1	0,40	0,62	-8,70	-2,39	U2
aportantes	1,59	1,56	5,20	1,55	*	1,64	1,57	10,40	0,68	*
math	51,29	50,40	3,00	-1,8	U1	70,16	61,10	10,70	-1,76	U1
language	53,67	51,14	8,70	-4,1	**U3**	73,06	68,09	8,10	-1,31	*
biology	52,54	50,71	6,30	-1,57	*	71,85	67,69	5,40	-1,36	*
chemistry	54,09	51,45	9,20	-2,16	U2	76,49	74,33	7,50	-1,92	U1
physics	50,51	48,46	7,10	-1,14	*	71,57	67,45	8,70	-1,59	*