Unbundling Returns to Postsecondary Degrees and Skills: Evidence from Colombia

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Abstract

Using longitudinal data of college graduates in Colombia, we estimate labor market returns to postsecondary degrees and to various skills—including literacy, numeracy, foreign language, and field-specific skills. Graduates of academic programs and schools of higher reputation obtain higher earnings relative to vocational public programs. A one standard deviation increase in each skill predicts average earnings increases of one to three percent. Returns vary along the earnings distribution, with tenure, with the degree of job specialization, and by gender. Our results imply that degrees and skills capture different human capital components that are rewarded differently in the labor market.

Keywords: returns to skills, returns to education, numeracy, literacy, foreign language, field-specific, Colombia.

JEL classifications: I20, I24, J24, J31

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1 Introduction

Pursuing a college education is a significant decision, particularly for students in developing countries where the cost of schooling can be substantial. The choices of what to study and where to study play a crucial role in the decision to attend college and significantly impact students' future prospects in the labor market. This paper explores the economic implications of these choices on college students' future earnings by combining multiple measures of human capital. We show that both the type of degree (*where*) and skills acquired (*what*) have distinct economic returns. We estimate the labor market returns to various types of postsecondary degrees and several types of skills. We find that among individuals graduating from similar programs, a one standard deviation increase in skill level corresponds to an average wage premium of approximately 2 percent. Additionally, for students with comparable skills, the market value of postsecondary degrees is positive and varies significantly with the length and quality of the program.

We combine administrative records from a variety of sources to build a longitudinal dataset that follows students from high school to college and into the labor market. Students in Colombia are evaluated just before high school graduation by means of a mandatory standardized test (analogous to the SAT in the United States) on mathematics, language (Spanish), foreign language, and other subjects. We combine those data with census-like college records that allow us to observe enrollment and graduation from any postsecondary degree program in the country. For all college graduates, we observe a rich set of characteristics including their field of study, their type of academic degree, and a wide range of measures of skills. Students who are about to graduate from vocational and academic colleges are required to undergo evaluations on mathematics, literacy, and foreign language, as well as on specific tests related to their field of study (akin to the subject GRE). We link all these data with records from the Colombian Social Security Administration that contain information on wages and employment characteristics. Our sample corresponds to college graduates who are observed around ages 20 to 30, where the average is 27 years old, and work formally.[1]

We use an expanded Mincer earnings function to jointly estimate the labor market returns to different types of degrees and skills. We address ability bias concerns by controlling for a broad range of pre-college measures of skills, as well as measures of the quality of postsecondary programs. A similar approach has been taken by others in the literature to estimate the returns to cognitive and non-cognitive skills (e.g. Saiz and Zoido, 2005; Hanushek et al., 2015; Lindqvist and Vestman, 2011).

We first estimate returns to completing different types of higher education degrees, distinguishing among four types: i) vocational public programs; ii) vocational private

[1]Formality status corresponds to individuals who contribute to health or pensions.

programs; iii) academic public programs; and iv) academic private programs. We find that, conditional on skills, the annual returns to graduating from an academic private college are 20 percent higher than completing a vocational program at a public college. Following MacLeod et al. (2017), we compute a measure of college reputation, which corresponds to the average of the high school exit exam among students who graduate from the same college. We find that one standard deviation increase in this measure carries a wage premium of 2 percent.

We then estimate that, conditional on the degree, the program, its reputation, and initial abilities, an increase in one standard deviation in skills acquired during college yields a wage return of around 2 percent. Returns to skills are fairly homogeneous. The returns to purely academic skills, numeracy and literacy, are 2.5 and 2 percent, respectively. Returns to foreign language are 1.5 percent. Returns to field of study-specific skills (i.e., skills specific to the major of choice of the student, and called in what follows field-specific skills) are 2 percent. Controlling by types of degrees does not alter the magnitude of the returns to skills, implying that cognitive skills capture different human capital components that are rewarded differently in the labor market.

We explore different patterns of heterogeneity in the returns to degrees and skills. First, we explore heterogeneity across the wage distribution by estimating unconditional quantile regressions. Returns to degrees and skills are concave and larger among college graduates around the median of the earnings distribution. Second, consistent with Farber and Gibbons (1996), we find that returns to degrees are independent of labor market experience. Returns to skills are also persistent, except for field-specific skills that decrease with tenure. Skills that are observable by the employer are predicted to have higher returns in the first year on the job, but then dissipate as the employer updates its beliefs (Farber and Gibbons, 1996). We interpret our results as field-specific skills being more observable at the moment of recruiting, at least in the market of college graduates. Third, we find evidence for what we refer to as "returns to specialization". College graduates who work or study in more math-oriented fields and industries, for instance, have a higher return to numeracy, whereas individuals who graduate from social sciences have a larger return to literacy, and individuals who work in tourism have a higher return to foreign language skills. In addition, we find that the return to programs in private versus public colleges depend on the field of study; private programs have bigger returns in STEM and business, and lower in social sciences and humanities. Finally, we explore heterogeneity by gender and socioeconomic status. Returns to literacy, numeracy, and foreign language skills are larger for women. We do not observe heterogeneous returns to skills between graduates with low- and high-socioeconomic status nor by types of degrees.

This study contributes to a large literature estimating returns to skills. Most of the previous work provide estimates for developed countries but recent studies also include developing economies.[2] Our estimates for Colombia, a developing country with relatively low quality of education, fall within the range of estimates previously found in other studies. Returns to numeracy skills have been found to be on the order of 2 to 20 percent (Levine and Zimmerman, 1995; Murnane, Willett and Levy, 1995; Tyler, 2004; De Coulon, Marcenaro-Gutierrez and Vignoles, 2008; Song, Orazem and Wohlgemuth, 2008; Joensen and Nielsen, 2009; James, 2013; Hanushek et al., 2015). Returns to foreign language have been found to be around 2.5 to 60 percent (Bleakley and Chin, 2004; Saiz and Zoido, 2005; Christofides and Swidinsky, 2010; Azam, Chin and Prakash, 2013; Guo and Sun, 2014; Budría and Swedberg, 2015; Di Paolo and Tansel, 2015; Stöhr, 2015). Returns to literacy have been found to be as high as 20 percent (Ishikawa and Ryan, 2002; De Coulon, Marcenaro-Gutierrez and Vignoles, 2008; Fasih, Patrinos and Sakellariou, 2013; Hanushek et al., 2015; Sanders, 2016; Chua, 2017). Similar to this literature, we find that field-specific skills are as valued in the labor market as academic skills.[3]

To the best of our knowledge, we are the first to estimate labor market returns to a large set of measures of skills jointly. Aucejo and James (2021) study the impact of math and verbal skills on educational attainment, finding that both verbal skills play a bigger role in explaining university enrollment. We extend these results by estimating the labor market returns of different skills, finding also that numeracy and literacy skills are rewarded differently in the labor market.

This paper also contributes to the literature analyzing the heterogeneity in the returns to different types of postsecondary degrees. A big portion of the papers in this literature focuses on estimating the heterogeneous returns of graduating from different fields of study (Hastings, Neilson and Zimmerman, 2013; Kirkeboen, Leuven and Mogstad, 2016; Andrews et al., 2022; Eide, Hilmer and Showalter, 2016). Some others have estimated returns to obtaining a college degree (Nybom, 2017; Rodríguez, Urzúa and Reyes, 2015), and emphasizing if the degree comes from an elite program (Zimmerman, 2019; Black, Denning and Rothstein, 2023).[4] Most of these studies use workers with no college education as a counterfactual. An exception is Mountjoy (2022) who estimates a 9 percent diversion effect of not attending a four-year college program relative to a two-year community college degree in the United States. We contribute to this broad literature in two ways. First, we find that the types of degrees affect dramatically future income, even conditioning for a wide range of measures of skills and for the quality of the college (as measured by its reputation). Second, we estimate the

[2] Patrinos and Psacharopoulos (2020) and Ozawa et al. (2022) provide estimates for developing countries and contrast them with those for developed economies.

[3] Appendix Table 1 summarizes the results, methodologies, and samples used in previous studies.

[4] Several studies review the evidence of returns to education in Latin America. See for instance, Patrinos, Psacharopoulos and Tansel (2021), Psacharopoulos and Ng (1994), Behrman, Birdsall and Székely (2007), Bassi et al. (2012), and Lustig, Lopez-Calva and Ortiz-Juarez (2012).

returns to college reputation and find that this measure leads to sizable increases in wages.

The rest of the paper is organized as follows. Section 2 describes the Colombian education system and section 3 the data we use. Section 4 presents the results of estimating the returns to skills and postsecondary degrees. Section 5 presents some analysis of the heterogeneity of returns to types of postsecondary degrees and skills. Section 6 concludes.

2 Background

Education in Colombia is divided into primary school (first to fifth year), middle school (sixth to ninth year), high school (tenth and eleventh), and postsecondary education. Programs in postsecondary education are divided into vocational and academic programs, resembling those of the United States. We refer to all the institutions in postsecondary education as colleges.

During high school, students take classes in mathematics, language (Spanish), and foreign languages as part of the school curriculum. Most schools teach English as a foreign language; therefore, we refer to English and foreign language interchangeably.[5] During postsecondary education, the level and intensity of instruction in these areas depend on the student's major, but most institutions require a minimum of foreign language knowledge as a graduation requirement.

After graduation, students' abilities and qualifications are extremely valuable in finding a job. Moreover, a mismatch between occupations and skills is more likely among individuals with lower abilities. In a survey of employers of college graduates, the Ministry of Education found that 67 percent of firms have employed at least one graduate with less than two years of experience. Moreover, 73 percent of firms consider that knowledge or specific abilities constitute the main selection criteria for hiring a graduate (Ministerio de Educacion, 2016).

Measures of Skills. Since 1980, all *high school* seniors in Colombia have been evaluated before graduation through a mandatory, high-stakes exit exam (known as *Saber 11*). The exam is a requirement for graduation, and nearly four-fifths of colleges use students' performance in the exam as an admission criterion (OECD and The World Bank, 2012). The test resembles the SAT in the United States. It evaluates students in several subjects that we group into four broad areas: i) Numeracy (i.e., mathematics); ii) literacy (i.e., reading and language); iii) foreign language (i.e., English); and iv) subject skills (which includes biology, physics, chemistry, and social sciences).[6] The test is

[5] Over 95 percent of schools teach English as a foreign language.

[6] The mathematics test measures basic knowledge in algebra, calculus, geometry, probability, and statistics; students must interpret information, design solutions to problems, follow procedures, and justify

administered in two sessions, each of four hours and 30 minutes, including about 40 questions per subject.

Since 2003, *college* students who complete at least 75 percent of their coursework have been also required to take a college exit exam (known as *Saber Pro*). This exam is a graduation requirement and resembles the GRE, both the general and subject tests. The results are not typically visible to employers because they are difficult to interpret, and students do not usually include them in their curriculum. However, the Ministry of Education awards an academic distinction to the top 10 scores countrywide, which constitutes a strong signal in the job market (Busso, Montaño and Muñoz, 2023). In addition, colleges are routinely ranked by the Ministry of Education based on the average score of the students taking the exam each year. It is common for colleges to motivate the performance of their students through incentives like public recognition or discounts on mandatory fees.

The college exit exam has two main components: one is general and the other is specific to the field of study from which the student is graduating.[7] The general section includes tests in numeracy, writing, reading, English, and citizenship abilities. Students have four hours and 40 minutes to complete the test, which includes a total of 161 questions (35 in numeracy, 35 in reading, 35 in citizenship abilities, 55 in English, and one in writing). The numeracy section evaluates basic mathematics knowledge needed to analyze and solve problems using quantitative methods and procedures. The reading section examines the capacity to read analytically by understanding the text and identifying different perspectives and value judgments. The writing section evaluates the ability to communicate ideas of a particular given topic. The English section focuses on testing the ability to communicate effectively in English. The specific section evaluates basic knowledge in the student's field of study. There is a total of 40 specific exams, and students have 90 minutes to answer between 30 and 60 questions included in each of them. The questions, designed by experts in each of the different areas, follow specific standards that assure comparability of the exams. Economics majors, for instance, are advised to take an Economics Analysis test with micro, macro, and econometrics questions.[8]

Postsecondary Degrees. Similar to the experience in other Latin American countries, postsecondary education in Colombia has expanded dramatically in the last 10 years (Busso et al., 2017). Postsecondary education is delivered through vocational and aca-

steps in problem-solving. The reading test evaluates the student's ability to understand, interpret, and analyze critically written texts. The language exam tests the ability of the student to communicate in Spanish. The foreign language test evaluates reading, grammar, and vocabulary usually in English. The subject tests evaluate general knowledge in that given subject.

[7] Although the general part of the exam started in 2003, field-specific exams were introduced by a staggered roll out. By the second semester of 2011, all students were taking the general tests, while the specific exams have been applied since then to a large share of students.

[8] More information and details about the different measures of skills are given in Appendix B.

demic degrees. Vocational degrees are primarily focused on technical skills for specific trades or crafts and typically last about two years. Academic degrees, on the other hand, are oriented towards broader professional and theoretical knowledge, usually requiring at least four years of study, and are equivalent to a bachelor's degree in the United States. Colombian postsecondary education is delivered through public and private institutions; 30 percent of the postsecondary institutions in the country are public, while the other 70 percent are private. We classify postsecondary programs into four categories: i) vocational public, ii) vocational private, iii) academic public, and iv) academic private. In addition, our data also allow us to identify individuals who have pursued graduate studies.

The degrees that students receive vary, not only in terms of the length of study required, but also in terms of quality, reputation, and tuition cost, among other dimensions.[9] In Colombia, as in the case of most countries in Latin America, each program (major) in each college makes its own admissions decisions. This decision is decentralized and puts a heavy weight on the high school exit exam. Following MacLeod et al. (2017), we compute a measure of reputation by program-college as the average of the high school exit exam among students admitted in each program-college combination. The measure relies on the assumption that better regarded programs-colleges (i.e., with better reputations) can be more selective and will admit a set of applicants with higher high school exit exams. Therefore, this measure captures information about college reputation and peer quality.

3 Data and Estimation Samples

The data used in this paper corresponds to a unique dataset that we assembled in collaboration with the Colombian Ministry of Education. We merged four different administrative records:

1. We use test score measures from the college exit exam from 2011 to 2015. After 2011, the general components are compulsory for all students, while the field-specific component is required only if the student's college agrees to participate. So, for instance, students graduating from economics are evaluated in Microeconomics, Macroeconomics, Econometrics, and Economic History if their respective college indicates so. Most colleges opt for their students to be evaluated in their respective field exams. However, some programs (or majors) do not have a field-specific exam available.[10] For this reason, we only observe field-specific test scores for a subgroup of students.

[9] We lack information on the cost of tuition for each program in each university that would allow us to net out the cost of attending each program in calculating returns.

[10] Majors for which there are no available tests include: music, design, public health, library sciences,

2. We merge data on the high school exit exam from 1996 to 2013. These data include information on multiple subjects and, in addition, include information on the student's municipality, school, and some individual characteristics, such as gender and age.

3. We merge records of all students enrolled in college between 1998 and 2016. These records include yearly information on graduation and enrollment of all students in postsecondary education for all universities and programs, and have detailed information on the program of study, as well as socioeconomic information about the student and her family.

4. We merge longitudinal yearly earnings records for workers who graduated from college. These data include individual earnings from 2011 to 2016 of all the workers who finished any college program after 2001, and who contributed to the Social Security System. Four-digit industry codes, the municipality where the contribution was paid, and establishment identifiers are also included.[11]

The final sample includes 363,330 college graduates who took the college exit exam between 2011 and 2015, graduated after 2011, and worked formally between 2012 and 2016. The high school and college exit exams are not fully comparable across their different editions. Hence, all test scores are standardized to have mean zero and standard deviation one within each test's edition. We use two different samples: i) test-takers from 2011 to 2015 who are working formally ($N = 363,330$), and ii) test-takers with field-specific scores available who are working formally ($N = 155,939$).[12]

Descriptive Statistics. Individuals included in the main sample are on average 27 years old. Sixty percent are female, 73 percent live in urban areas, and 45 percent belong to low-income households.[13] The majority (82 percent) are graduates of academic programs, and the main fields of study are science, technology, engineering, and mathematics (hereafter STEM) (26 percent), business and economics (31 percent), social sciences and humanities (16 percent), and health and education (22 percent).

philosophy, anthropology, geography, history, political science, sociology, biomedical engineering, and military sciences.

[11] Workers who do not contribute to health or pensions are not included in the data.

[12] Appendix C describes in detail the steps followed to build the data and each sample. It also describes selection issues in the estimation sample caused by no-mergers with the social security records. This selection can happen because, upon graduation, college graduates do not contribute to the social security system or because they leave the country. Our sample is representative of those college graduates who take a formal job. This population represents 75 percent of the total sample of college graduates.

[13] We identify low-income households using the Colombian housing stratification system. For purposes of targeting social assistance, all houses in the country are assigned to an economic stratum from one to six, depending on the neighborhood and house. We defined low-income households as those living in the first two strata.

More than half are employed in the services sector.[14]

We compute the correlation matrix of all the different test score measures across samples.[15] Several highlights are in order. First, all correlations are positive and large which, as suggested by Rindermann (2007), indicates that these measures are capturing in part a broader trait such as cognitive ability. Second, the largest correlations are found within exams (shown in bold type). This is suggestive of skill complementarities. Third, the correlations within subjects and across time (shown in non-bold type) are large and positive which suggests the existence of self-productivity (Cunha and Heckman, 2007; Cunha, Heckman and Lochner, 2006). Fourth, the magnitudes of the correlations are very stable across both panels.

4 Returns to Degrees and Skills

The following equation describes our expanded Mincer earnings equation which we use to estimate jointly returns to degrees and skills:

$$\log(W_{ifct}) = \beta_1 P_{ifct} + \beta_2 T_{ifc\tau} + \beta_0 \theta_i + \alpha_1 CR_{ct} + X_i \gamma + \mu_f + \mu_t + \mu_\tau + \mu_s + \varepsilon_{ipct}. \quad (1)$$

W_{ifct} is the wage of individual i who graduated from field of study f at college c in year t. Given that we observe wages for multiple periods, we use the first observed earnings after graduation as dependent variable.[16] Using this measure as an outcome allows us to estimate returns at the moment of graduation and not returns that change with tenure in the job. P_{ifct} is a vector that includes three indicator variables that take the value of one if the individual has a postsecondary degree corresponding to: i) a vocational private program, ii) an academic public program, or iii) an academic private program. The estimation sample corresponds to college graduates, therefore the omitted category are those college graduates who obtained a vocational public degree. $T_{ipc\tau}$ is a vector of college exit test scores that includes measures of numeracy, literacy, and foreign language. Individual i's test scores correspond to results observed in edition τ of the college exit exam. Depending on the sample, the vector $T_{ipc\tau}$ also includes measures of field-specific skills. We include the measure for college reputation (CR_{ct}), and a vector of individual characteristics, X_i, that include gender, age, age-squared, mother's education, an indicator variable for graduate studies, and socioeconomic status. The variables μ_f, μ_t, and μ_τ correspond to the field of study,

[14]In Appendix Table 2 we describe the different estimation samples. In addition, Appendix Table 3 presents descriptive statistics by type of degree.

[15]See Appendix Table 4.

[16]We provide results with alternative measures such as the average wage observed for each individual, the last observed wage after graduation, and the average earnings between 25 and 30 years of age as robustness checks.

cohort, and test edition fixed effects, respectively.[17]

To reduce ability bias concerns, we include as control variables a vector of measures of initial ability, θ_i, built using the test scores from the high school exit exam. We include the four measures of pre-college skills (i.e., numeracy, literacy, foreign language, and subject components) as controls. As previously shown, these four measures correlate between each other but the correlation is far from perfect, indicating that they capture complementary skills. To further control for initial skills and sorting into colleges, we additionally include high school fixed effects, μ_s.[18]

Equation 1 is an ordinary least squares (OLS) estimation with a rich set of controls, including pre-college measures of ability. It resembles an estimation of a *value-added* measure in which the effect on students' knowledge is conditioned on initial knowledge.[19] Value-added models typically use test scores as the dependent variable and condition on previous test scores to estimate the added value in terms of learning. In our case, however, we estimate the economic return to skills enhanced during college and to types of degrees, conditioning on the abilities that each student had at the time of starting college. An advantage of this specification is that it eliminates observed and unobserved confounding elements about the history of parental and school inputs, and, therefore, reduces remarkably the likelihood of suffering of omitted variable bias (Rivkin, Hanushek and Kain, 2005). The inclusion of θ_i in equation (1) together with the full set of skills measures and fixed effects attempts to address possible concerns regarding ability bias of $\hat{\beta}$.

We interpret $\hat{\beta}_1$ as the return to skills acquired or enhanced during college –conditional on skills prior to college. $\hat{\beta}_2$ should be interpreted as the economic return to type of degrees, conditioning on the skills a student has before and after graduation. Note that estimating these jointly isolates the returns of attending a specific program independently of college and peer quality (which is controlled by the measures of skills and the measure of college reputation).

If our set of control variables is not rich enough to ensure our estimators are unbiased, our resulting estimates may still be informative about the relative returns if the bias is the same for all coefficients in the vectors $\hat{\beta}_1$ and $\hat{\beta}_2$. In other words, similar to methodology underpinning some of the previous related literature (Hanushek et al., 2015; Lindqvist and Vestman, 2011), the difference between coefficients will eliminate the bias, and we will still be able to correctly rank the returns to skills and types of

[17]Fields of study correspond to: accounting, agricultural sciences, architecture, arts, business and related fields, economics, education, engineering, health, humanities, journalism, medicine, natural and exact sciences, nursing, law, psychology, social sciences, and sports.

[18]High schools in Colombia are strong predictors of family income, college progression, and levels of cognitive skills.

[19]A considerable amount of papers have used value-added measures to estimate the return to better teachers. A discussion of this model is presented in Hanushek and Rivkin (2010).

degrees.[20]

Table 1 presents OLS estimates of equation (1).[21] Columns (1) and (2) present the estimation in the full sample. Columns (3) to (6) restrict the sample to those individuals with field-specific skills. Columns (2) and (6) include the measure of college reputation; these are our preferred estimates.

Returns to different types of degrees are fairly heterogeneous. Using the point estimates in column (2) we find that, relative to vocational public degrees, finishing a vocational private degree increases earnings by 7 percent. The returns to academic programs are sizable relative to vocational public programs. Academic public programs increase earnings by 15 percent, whereas academic private programs increase them by 21 percent. Adjusting by the years it takes to graduate from each program (i.e., two years for vocational and four years for academic), we find that an additional year of education increases wages by 3.5 percent for vocational private, 3.7 percent for academic public, and 5.3 percent for academic private degrees. The reputation of the program also carries a wage premium of three percent. These point estimates are somewhat comparable to the 9 percent return found in the United States of attending a four-year versus a two-year college program (Mountjoy, 2022).

Returns to skills conditional on education are meaningful and comparable to the annual returns to types of degrees. Among the returns to skills, numeracy seems to have the largest return (up to 2.6 percent). Literacy, foreign language, non-cognitive, and field-specific skills have a similar return of approximately 1.5 percent. These results are fairly stable across columns, which vary both the specification and the sample used in the estimation.

Sensitivity of the Mincer Earnings Equation. We analyze the sensitivity of the point estimates of the expanded Mincer equation by estimating alternative specifications and present the results in Table 2. Column (1) presents estimates of the returns to degrees unconditionally of the returns to skills and field of study, whereas column (2) includes field of study fixed effects aiming to control for potential pre-graduation sorting into fields. Columns (3) to (6) present the returns to skills across different samples, but unconditionally of the types of degrees and field of study. In columns (7) and (8) we include field of study fixed effects, again aiming to control for potential pre-graduation sorting. Comparing these estimates with those in Table 1 give informative evidence on the degree to which the returns to degrees complement the returns to skills.

[20] Assume a true model of the form: $W = \alpha + \beta_1 T_1 + \beta_2 T_2 + \theta + u$. If the estimated model is $W = \alpha + \beta_1 T_1 + \beta_2 T_2 + \varepsilon$, where $\varepsilon = \theta + u$, then the probability limits of the difference between the OLS estimators will be: $\text{Plim}(\hat{\beta}_1 - \hat{\beta}_2) = (\beta_1 - \beta_2) + (\hat{\beta}_{\theta T_1} - \hat{\beta}_{\theta T_2})$, where $\hat{\beta}_{\theta T_1}$ is the coefficient of a regression of θ and T_1. Our assumption states that $\hat{\beta}_{\theta T_1} \sim \hat{\beta}_{\theta T_2}$.

[21] In Appendix Table 5 we present estimates using the alternative measures of earnings as dependent variables. The results are essentially the same.

The results in Column (1) are quite different from the returns to types of degrees in column (2) of Table 1. This difference can be attributed to the exclusion of the field of study fixed effects or the measures of skills. Including back the fixed effects in column (4), we recover point estimates very close to those in Table 1. This implies that including the measures of skills does not affect the coefficients on the types of degrees.

Similar results are obtained in columns (3) to (8) where we present estimates of returns to skills unconditionally from the returns to degrees and fields of study. We do see that excluding these controls slightly affects the magnitudes, especially in the return to numeracy skills. However, controlling for potential pre-graduate sorting into fields recovers point estimates similar to those obtained in Table 1.

These results as a whole imply that measures of skills and measures of types of degrees capture different information when estimating economic returns. In fact, it poses strong evidence suggesting that the returns to human capital cannot be exclusively attributed either to returns to education or returns to skills, but rather that a combination of both is important.

We further explore the sensitivity of the returns to skills in Table 3 by including every measure of skills separately, and conditioning on types of degrees.[22] In column (1) we present the same results as in Table 1, for comparison. Columns (2) to (4) show the point estimates of regressions that use equation (1), but including each measure of skills separately. Columns (5) to (10) follow the same format but for the sample of college graduates with measures of field-specific skills. All the returns to skills decrease when estimating them jointly (columns 2-4 versus column 1 for the full sample, and columns 7-10 versus columns 5 and 6 for the specific sample), indicating that cognitive skills complement each other when being rewarded in the labor market.

Taken together, these estimates indicate that a one standard deviation increase in numeracy skills have a return that ranges between 2 and 3 percent, literacy a return between 1.6 percent and 2.2 percent, foreign language skills between 1 and 2 percent, and specific skills from 1.6 percent to 2.5 percent. These ranges include upper (regressions with each test score alone) and lower bounds (regressions with all the measures simultaneously). Our results also imply that skills capture different human capital components than types of degrees, which are rewarded differently in the labor market.

5 Beyond Average Returns

The average returns estimated previously can be explained by multiple mechanisms that are related to the potential heterogeneity that the average effects are not

[22] Appendix Table 6 presents the same results in Table 3, but unconditional of the type of degrees.

able to estimate. In this section we focus on the heterogeneity of returns to degrees and skills. First, we explore heterogeneity across the wage distribution. Second, we present returns by tenure. Third, we provide evidence of the existence to the returns to specialization. Finally, we provide estimates of heterogeneous returns by gender and socioeconomic status.

5.1 Returns Across the Wage Distribution

We estimate conditional regression quantiles following Firpo, Fortin and Lemieux (2009) for each type of postsecondary degree and present the results in Figure 1. OLS point estimates are plotted to allow comparisons. We use the specification in column (2) of Table 1. Figure 1a shows the results for vocational private, figure 1b for academic public, and 1c for academic private.

The results suggest an important degree of heterogeneity in the returns to postsecondary degrees when compared to public vocational degrees. The three graphs show strictly increasing returns with earnings until, roughly, the 60th percentile and then decreasing among further quantiles. Postsecondary degrees tend to matter more among people concentrated around the median. Note that the lowest point estimate among academic private degrees is around 0.5, which is slightly above the point estimates on returns to skills. It means that taking individuals from a vocational public program and placing them in an academic private program, keeping abilities constant, will increase the wage by at least 5 percent even if they get a job that pays in the first decile of the wage distribution. A similar increase in wage would be achieved if those same persons stayed in a vocational public program but increased their numeracy skills by more than one standard deviation.

In Figure 2 we present the results of unconditional regression quantiles for each measure of skills. We use again the main specification as in column (2) of Table 1 and contrast the quantile point estimates with the OLS.[23]

The returns to all the measures of skills are mostly positive along all deciles. They are lowest among people in the lowest quantiles and, again, increase monotonically until roughly the median. The returns to foreign language skills, however, are zero in the lowest quantiles and strictly increasing in the rest of the distribution, ranging from zero to 2 percent. The returns to numeracy remain stagnant beyond the median, although these are the highest returns we observe. The returns to literacy and field-specific skills decrease slightly beyond the 60th percentile.

[23]For the case of specific skills we use specifications (6) of Table 1, estimating the models in the corresponding restricted samples.

5.2 Returns to Skills and Degrees Over Job-Tenure

Our main estimates capture the returns to types of degrees and skills at the moment of graduation. These returns, however, might vary during further years of tenure depending on how employers update their beliefs about workers' skills, which may vary in how observable they are at the moment of recruiting (Farber and Gibbons, 1996). We restrict the sample of college graduates to those who do not change jobs in the first four years after graduation (71 percent of the full sample are job-stayers) and estimate equation 1 when they are observed with one, two, three, and four years of tenure. Figures 3 and 4 present the returns to types of degrees and measures of skills across years of tenure, respectively.[24]

Figure 3 shows that returns to types of degrees are non-decreasing with tenure, suggesting that the role of schooling on the level of earnings is independent of labor market experience (Farber and Gibbons, 1996). This implies that earnings gaps relative to graduates of vocational public degrees, conditional on skills, are persistent at least during the first four years of tenure.

Returns by years of tenure for each measure of skills are presented in Figure 4. We additionally include the results among students with field-specific scores for comparability. The returns using the complete sample of students are plotted with circles, and the corresponding confidence intervals are represented with a dark area. The returns for field-specific skills are plotted in a separate figure. The results show that numeracy and literacy tend to increase with tenure. The returns to foreign language, on the contrary, increase in the first three years of tenure and then decrease in the fourth one. These patterns are very similar among college graduates in the full and the specific samples.

The returns to field-specific skills slightly decrease across years of tenure, contrasting with the observed patterns in the other measures of skills. Specific skills could be more observable for employers than other skills, at least in the labor market for college graduates. During hiring processes employers may apply tests that allow them to know their applicants' level of specific abilities. Applicants could also reveal their specific skills during interviews in order to increase their probability of being hired. Skills that are more observable to employers tend to have higher returns in the first years of tenure and then decrease as employers update their beliefs (Farber and Gibbons, 1996).

Altogether, these results suggest that returns to types of degrees and skills increase with tenure. Returns to field-specific skills seem to be decreasing with tenure, plausibly because they are somehow more observable to employers at the moment of re-

[24]The point estimates among job-stayers during their first year of tenure are very similar to those of the full sample displayed in column (2) of Table 1.

cruiting.

5.3 Returns to Specialization: Field of Study and Economic Sector

Returns to degrees and skills can in part reflect specialization. For instance, individuals with better mathematics skills can choose careers that place greater emphasis on those abilities. Then, they can find jobs that value their skills, receiving higher payments for greater levels. We explore whether the magnitude of the returns varies with the person's specialization (either in field of study or in economic sector). In Appendix Table 7 we present the returns to degrees and skills across groups of similar postsecondary programs or study areas.[25] We estimate the returns for graduates of STEM, business and economics, social sciences and humanities, health and education, and agronomy and arts. We present results using the full and specific samples. When presenting the results using the specific sample, we display point estimates unconditional and conditional of field-specific skills for comparison.

We find two main results. First, the positive gradient between vocational and academic degrees (by which academic degrees pay more than vocational degrees) is observed in all fields of study, but private programs do not always have higher returns that public ones. Graduates from private colleges earn more than those of public colleges in STEM, business and economics, and arts degrees, but this is not the norm. Among vocational programs in social sciences and humanities, public programs have higher returns than private ones, and among academic degrees in health and education public and private programs have similar returns.

Second, there is some evidence of positive returns to specialization. Two arguments support this claim. On the one hand, numeracy skills have the highest return in STEM, and business and economics, but not in social sciences and humanities; for these individuals, the largest return is to literacy skills. In addition, graduates from health and education degrees have similar returns across numeracy and foreign language skills. On the other hand, field-specific skills are positive and tend to be homogeneous across fields, except for agronomy and arts. These results indicate a certain return that is tied to specialization in the field of study.

If returns to skills reflect returns to specialization, then is also expected that the returns are larger among economic sectors where the skills are more demanded. We present the returns among workers in different economic sectors in Appendix Table 8. We find clear returns to specialization, in particular for workers in the trade and tourism industries, in which the highest return is to foreign language skills (above 3 percent). Field-specific skills have a sizable and precise return in manufacturing, trade,

[25]Estimations of returns across different areas of study use specifications (2) and (5) in Table 1 without including field of study fixed effects.Table 2 presents overall estimates without field of study fixed effects, for comparison.

and services. Numeracy skills show the biggest return for manufacturing and services. We also observe some heterogeneity in the gradient of returns to degrees, although in the tourism sector the differences between vocational and academic degrees is much more attenuated.

5.4 Heterogeneity by Gender and Socioeconomic Status

Returns to degrees and skills may vary by gender and socioeconomic status. We explore these two margins of heterogeneity in Appendix Figure 1. The returns to postsecondary degrees do not vary gender. However, female graduates obtain larger returns to literacy, numeracy, and foreign language skills as opposed to men. The difference is particularly large in foreign language, where the return is fully driven by females and the point estimate is twice larger than for men. These results could be explained by female workers being more likely to be employed in industries such as tourism and trade where the returns to literacy and foreign languages are bigger (see Appendix Table 8).

Returns to types of degrees and skills do not differ strongly between graduates from low- and high- socioeconomic status. Even though the return to foreign language skills has a bigger point estimate for low-socioeconomic status students, we cannot reject that these two are statistically different. The magnitudes of all the other point estimates remain very close, indicating that both groups obtain similar returns to types of degrees and skills.

6 Conclusion

Understanding the reasons that make some workers earn higher wages than others is a key question in labor economics. In this paper, we investigate how skills and postsecondary degrees relate to labor market outcomes later in life. Our paper differs from the previous literature in that we are able to jointly measure the importance of a broad set of skills (literacy, numeracy, foreign language, and field-specific) and different types of postsecondary degrees (by length, quality, and field of study).

Exams required for graduation from high school and college in Colombia evaluate students in multiple areas including mathematics, language (Spanish), foreign language (English), and subject skills. We combine a vast vector of test scores from these exams with college enrollment and graduation data and with Social Security records to create a data set that follows individuals from high school to college and into the first years in the labor market. This uniquely rich dataset allows us to unbundle the returns to postsecondary education: we jointly estimate returns to different skills and to different types of degrees, accounting for the length, quality, and field in which those degrees were granted.

We view the results outlined in this paper as a building block towards a better understanding of the labor market value of different types of skills and degrees. Our evidence confirms that returns to basic skills (like mathematics, literacy, foreign language, and non-cognitive) are sizable even for people who graduated from essentially the same program. On average, a one standard deviation increase in numeracy skills has a return of around 2.5 percent, in literacy skills of 2 percent, and in foreign language of 1.5 percent. Specific skills are also important by accounting for an average increase of 2 percent. These are equivalent to half the yearly return in an academic education, relative to vocational programs. We also find that the type of postsecondary degrees individuals obtain are associated with very different wage returns, and the returns to college reputation are as high as the returns to skills.

The results in this paper can be useful for a number of related literatures. There is a large literature in economics evaluating the effect of education interventions aimed at improving learning (most frequently of numeracy and literacy skills), including i) school choice (e.g., competition, vouchers), ii) human resources policies (e.g., teacher pay, incentives, and training), iii) school and classroom management policies (e.g., class sizes and student tracking), and iv) school resources (e.g., spending, computers, remedial teaching, student incentives). Many of these studies lack cost-benefit analysis, in part because it is difficult to monetize the benefits. Our paper provides wage returns that could be used for that purpose.

Finally, our results also provide some insights into a number of policy debates. First, wage gains associated with admission to some schools and fields can be sizable and, in fact, explain a substantial part of the variation of the wage variance. This suggests that interventions aimed at helping low-income and qualified students gain admission to certain fields and programs can improve welfare (Hoxby and Turner, 2013). Second, returns to skills are positive and large, both on average and for most wage quantiles. This suggests that, in the presence of resources constraints, policies that aim at improving the quality of education of low-income individuals can be expected to reduce wage inequality.

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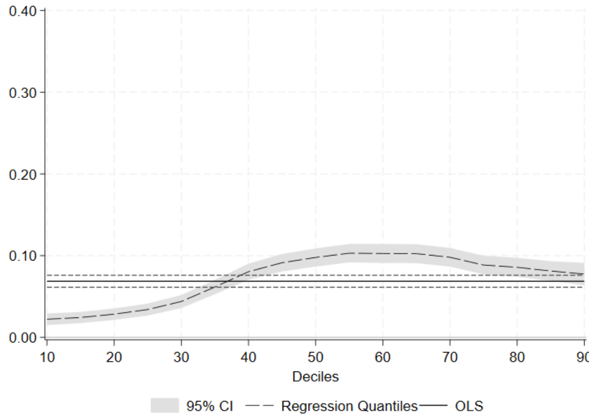
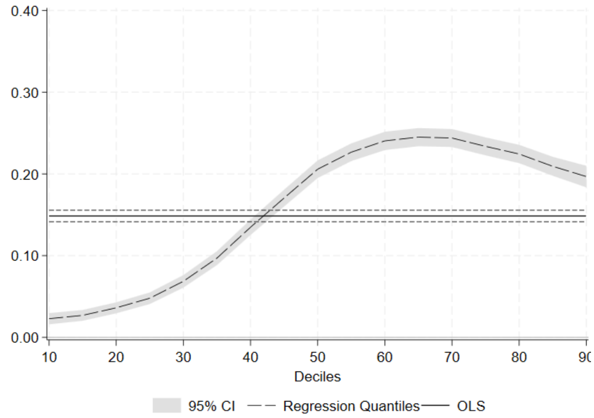
Figures and Tables

Figure 1: Returns to Types of Degrees at Unconditional Quantiles of the Wage Distribution

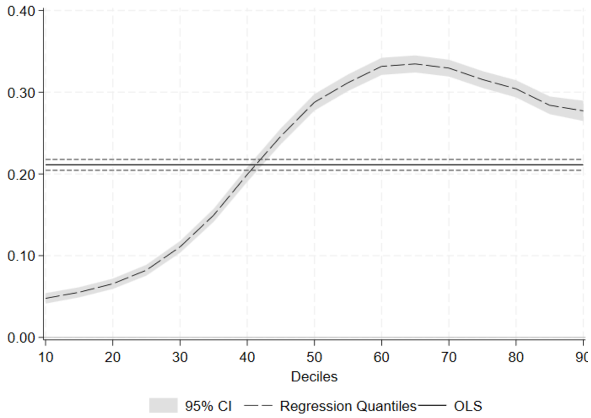
(a) Vocational Degree (Private)



(b) Academic Degree (Public)

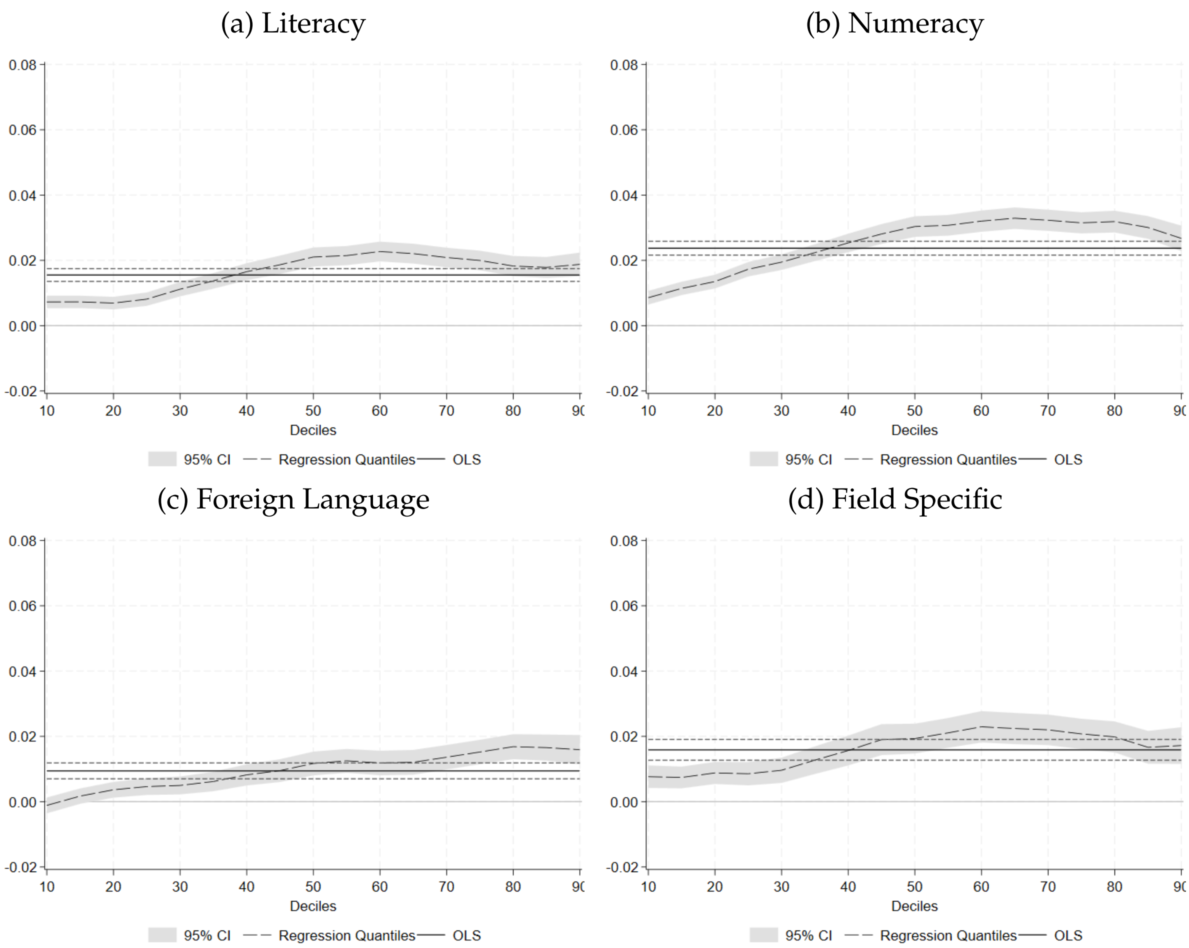


(c) Academic Degree (Private)



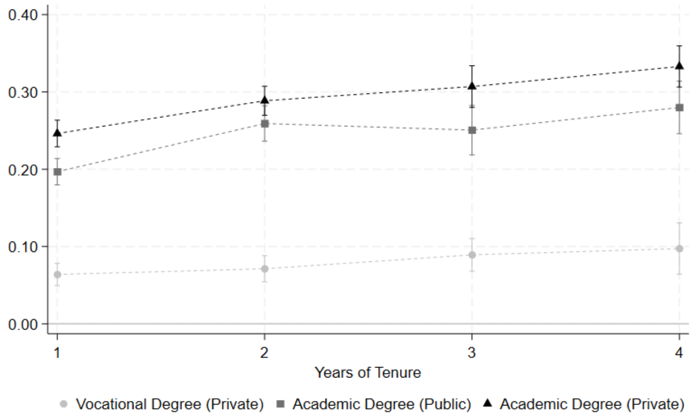
Notes. Figures 1a, 1b, and 1c used the full sample of students who graduated from 2011 to 2016. The dashed lines represent the regression quantiles using Firpo, Fortin and Lemieux (2009) estimator. The solid lines correspond to an OLS specification. Quantile and OLS estimations for private vocational degree, and academic degree programs used the following specification (The estimates have to be compared to earnings of college graduates from vocational public degrees): The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Measures of literacy, numeracy and foreign language skills were included. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects were included. Pre-college skills are proxied using test scores from the high school exit exam. OLS standard errors are clustered at the municipality level. Regression quantiles standard errors computed using 20 bootstrap replications. Confidence intervals of 95% are presented for all estimates.

Figure 2: Returns to Skills at Unconditional Quantiles of the Wage Distribution



Notes. Figures 2a, 2b, and 2c used the full sample of students who graduated from 2011 to 2016. Figure 2d used, the sample of students with field-specific test scores available. The dashed lines represent the regression quantiles using Firpo, Fortin and Lemieux (2009) estimator. The solid lines correspond to an OLS specification. Quantile and OLS estimations for literacy, numeracy, foreign language and field-specific skills used the following specification: The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Dummies for private vocational degree, and academic degree programs were included. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects were included. Pre-college skills are proxied using test scores from the high school exit exam. OLS standard errors are clustered at the municipality level. Regression quantiles standard errors computed using 20 bootstrap replications. Confidence intervals of 95% are presented for all estimates.

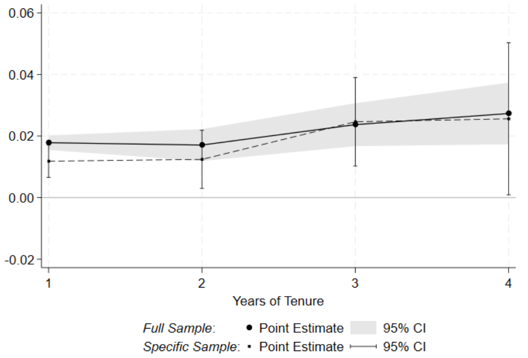
Figure 3: Returns to Degrees by Years of Tenure



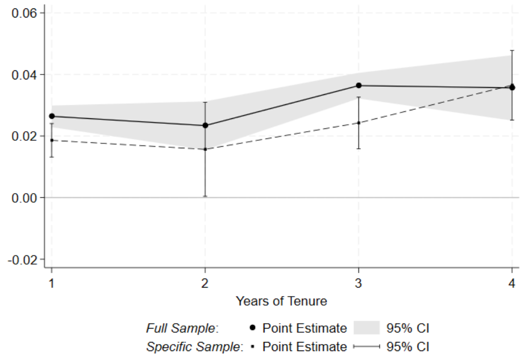
Notes. This Figure used the sample of individuals who graduated from 2011 to 2016 who were not observed to change their job (N = 258,226). The plotted circles, squares and triangles represent the point estimates of private vocational degrees, public academic degrees and private academic degrees, respectively.The estimates have to be compared to earnings of college graduates from vocational public degrees. Separate regressions were run among workers with different years of tenure to the estimate simultaneously the returns to different types of degrees. OLS estimations for types of degrees used the following specification: The dependent variable is the log of wage for each year of tenure. Measures of literacy, numeracy and foreign language skills were included. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects were included. Pre-college skills are proxied using test scores from the high school exit exam. OLS standard errors are clustered at the municipality level. Confidence intervals of 95% are presented for all estimates.

Figure 4: Returns to Skills by Years of Tenure

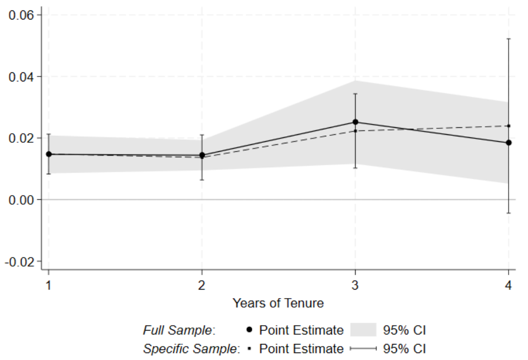
(a) Literacy



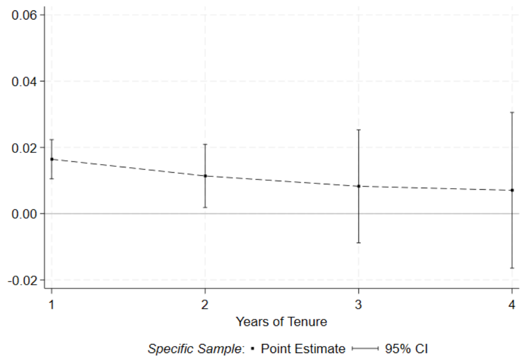
(b) Numeracy



(c) Foreign Language



(d) Field Specific



Notes. This Figure used the sample of individuals of students who graduated from 2011 to 2016 who were not observed to change their job from both the full sample and the specific sample (N = 258,226 and N = 119,302 respectively). The plotted circles and squares represent the point estimates for each measure of skills using, respectively. Separate regressions were run among workers with different years of tenure to the estimate simultaneously the returns to numeracy, literacy, foreign language and field-specific skills. OLS estimations for skills used the following specification: The dependent variable is the log of wage for each year of tenure. Dummies for private vocational degree, and academic degree programs were included. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects were included. Pre-college skills are proxied using test scores from the high school exit exam. OLS standard errors are clustered at the municipality level. Confidence intervals of 95% are presented for all estimates.

Table 1: Returns to Skills and Types of Degrees of Graduates of Post-secondary Education

	Dependent Variable: log(First Wage After Graduation)					
	Full Sample		Specific Sample			
	(1)	(2)	(3)	(4)	(5)	(6)
Post-secondary degree type :						
Vocational Degree (Private)	0.074	0.069	0.065	0.064	0.061	0.061
	[0.012]	[0.009]	[0.012]	[0.012]	[0.010]	[0.010]
Academic Degree (Public)	0.178	0.149	0.190	0.190	0.154	0.156
	[0.014]	[0.010]	[0.019]	[0.019]	[0.013]	[0.013]
Academic Degree (Private)	0.227	0.211	0.239	0.241	0.219	0.221
	[0.021]	[0.017]	[0.024]	[0.024]	[0.019]	[0.019]
College Exit Exam :						
Literacy	0.017	0.016	0.015	0.011	0.013	0.009
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]
Numeracy	0.026	0.024	0.024	0.019	0.022	0.018
	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.002]
Foreign language	0.013	0.009	0.017	0.014	0.013	0.011
	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]	[0.003]
Field-Specific				0.018		0.016
				[0.002]		[0.003]
College Reputation		0.026			0.031	0.029
		[0.005]			[0.005]	[0.005]
Observations	363,330	363,330	155,939	155,939	155,939	155,939
R-squared	0.194	0.196	0.235	0.236	0.237	0.237
Controls:						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the estimates of equation 1 using the log of the first observed wage from 2011 to 2016 after graduation as outcome. The point estimates corresponding to types of degrees have to be compared to earnings of college graduates from vocational public degrees. The college reputation variable is computed following MacLeod et al. (2017) and then standardized to have mean zero and standard deviation one within each sample. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. Standard errors are clustered by municipality and in brackets.

Table 2: Unconditional Returns to Types of Postsecondary Degrees and Skills

	Dependent Variable: log(First Wage After Graduation)							
	Full Sample				Specific Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-secondary degree type :								
Vocational Degree (Private)	0.043	0.068						
	[0.009]	[0.009]						
Academic Degree (Public)	0.110	0.149						
	[0.014]	[0.010]						
Academic Degree (Private)	0.206	0.209						
	[0.010]	[0.016]						
College Reputation	0.031	0.032						
	[0.005]	[0.005]						
College Exit Exam :								
Literacy			0.012	0.016	0.009	0.011	0.015	0.011
			[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]
Numeracy			0.040	0.023	0.045	0.047	0.025	0.021
			[0.004]	[0.001]	[0.003]	[0.003]	[0.001]	[0.002]
Foreign language			0.010	0.021	0.010	0.010	0.021	0.019
			[0.001]	[0.004]	[0.002]	[0.002]	[0.003]	[0.004]
Field-Specific						–0.010		0.015
						[0.002]		[0.003]
Observations	363,330	363,330	363,330	363,330	155,939	155,939	155,939	155,939
R-squared	0.110	0.193	0.098	0.182	0.126	0.127	0.226	0.226
Controls:								
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study		Yes		Yes			Yes	Yes

Notes. The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. The point estimates corresponding to types of degrees have to be compared to earnings of college graduates from vocational public degrees. Columns (1) and (2) include measures of postsecondary degrees unconditionally of skills. Columns (3) to (8) include measures of skills –literacy, numeracy and foreign language– excluding measures of postsecondary degrees. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. Standard errors clustered at the municipality level and in brackets.

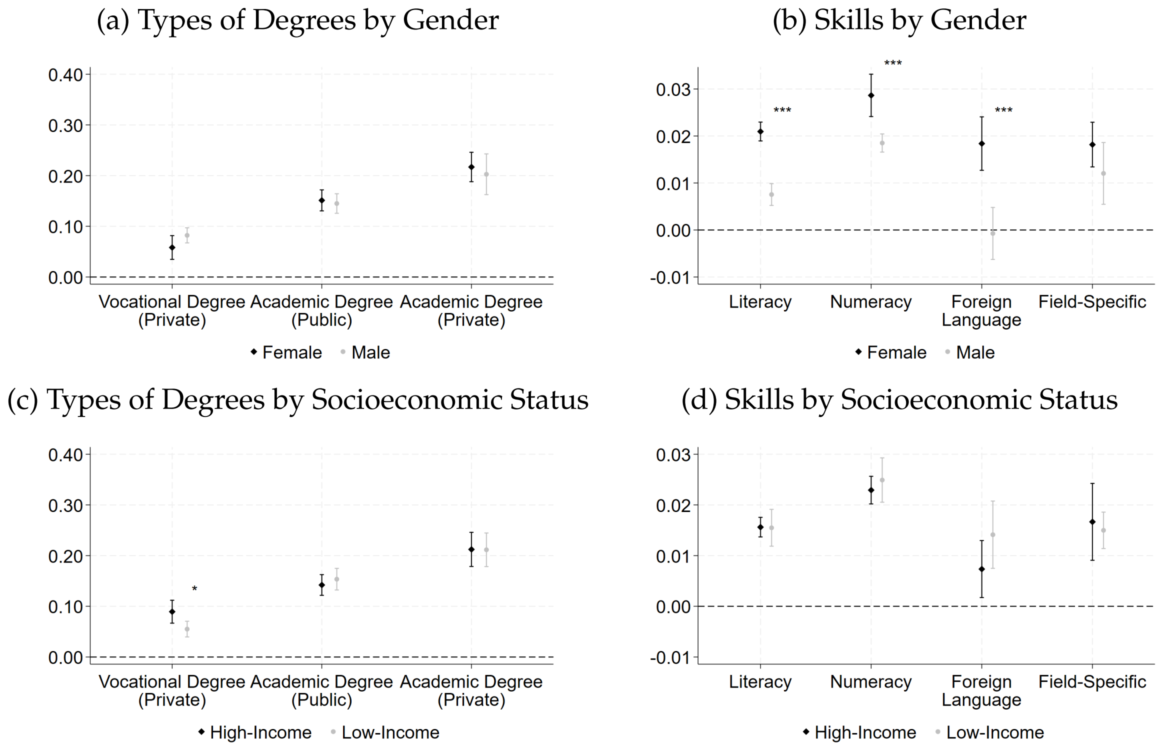
Table 3: Ranges for the Returns to SKills

	Dependent Variable: log(First Wage After Graduation)									
	Full Sample				Specific Sample					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Literacy	0.016	0.022			0.013	0.009	0.019			
	[0.001]	[0.001]			[0.001]	[0.002]	[0.002]			
Numeracy	0.024		0.029		0.022	0.018		0.027		
	[0.001]		[0.002]		[0.001]	[0.002]		[0.002]		
Foreign language	0.009			0.017	0.013	0.011			0.019	
	[0.003]			[0.003]	[0.003]	[0.003]			[0.003]	
Field-Specific						0.016				0.025
						[0.003]				[0.002]
Observations	363,330	363,330	363,330	363,330	155,939	155,939	155,939	155,939	155,939	155,939
R-squared	0.196	0.194	0.195	0.194	0.237	0.237	0.235	0.236	0.235	0.236
Controls:										
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Types of Degrees	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes.*The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Columns (1), (5) and (6) show simultaneous estimations while the remaining columns display returns to skills estimated separately. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. Types of degrees include dummies for academic and private vocational degrees. Standard errors clustered by municipality and in brackets.

A Appendix: Additional Results

Appendix Figure 1: Returns to Types of Degrees and Skills by Gender and Socioeconomic Status



Notes. This figure shows heterogeneous returns to types of degrees and skills across gender, and income. The estimation of all coefficients used the full sample of students who graduated from 2011 to 2016, except for the specific skills coefficient which used the sample of students with field-specific test scores available. Results for females are compared to males, and results for high-income households (third stratum or higher) are compared low-income households (second stratum or lower). OLS estimations literacy, numeracy , foreign language and specific skills as well as for private vocational degree, and academic degree programs used the following specification (The estimates have to be compared to earnings of college graduates from vocational public degrees): The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects were included. Pre-college skills are proxied using test scores from the high school exit exam. OLS standard errors are clustered at the municipality level. Confidence intervals of 95% are presented for all estimates. Results marked with asterisks are different from each other with a statistical significance of 10% (*), 5% (**) and 1% (***).

Appendix Table 1: Estimates of the Effect of Cognitive Skills from Previous Literature

Skills	Reference	Country/ City	Population in Estimating Sample	Identification Strategy	Estimation	Dependent Variable (log)	Range[a] Lowest Estimate	Highest Estimate
Panel A: Numeracy								
	Levine and Zimmerman (1995)	USA	1980 HS graduates	Selection on Observables	OLS	1990 & 1986 weekly wage	0.028	0.030[b]
	Murnane, Willett and Levy (1995)	USA	1972 and 1980 HS graduates	Selection on Observables	OLS	1978 & 1986 hourly wage	0.026	0.069[c]
	Tyler (2004)	Florida (USA)	HS dropouts	Selection on Observables	OLS	1995-1999 quarterly earnings	0.063	0.074
	Song, Orazem and Wohlgemuth (2008)	USA	College graduates	Selection on Observables	IV	1993 earnings	0.181	0.210[d]
	Joensen and Nielsen (2009)	Denmark	1986 and 1987 HS graduates	Quasi-experiment	IV	1999-2002 annual earnings	0.12	0.32[e]
	Hanushek et al. (2015)	Several	Adults aged 20 to 50 from 23 OECD countries	Selection on Observables	OLS	2011-2012 hourly earnings	0.079	0.178[f]
Panel B: Literacy								
	Ishikawa and Ryan (2002)	USA	Adults above 16	Selection on Observables	OLS	weekly wages	0.001	0.008[g]
	Fasih, Patrinos and Sakellariou (2013)	Several	Males aged 22 to 65 from 20 countries, mostly OECD	Selection on Observables	OLS	hourly wage	0.021	0.210[h]
	Hanushek et al. (2015)	Several	Adults aged 20 to 50 from 23 OECD countries	Selection on Observables	OLS	1993 earnings	0.068	0.171
	Sanders (2016)	USA	Populations represented in 5 longitudinal surveys	Selection on Observables	OLS	real wages	-0.056	-0.024

[a] Estimates points correspond to standardized test scores, unless another interpretation is suggested. [b] Estimations correspond to the number of mathematics classes taken during high school. [c] Point estimates are given originally for levels of a mathematics score. Since a one standard deviation is 6.25, then coefficients are translated into this scale. Lower and upper bounds correspond, respectively, to 1972 and 1980 high school graduates. [d] The mathematics score is estimated in levels. [e] Numeracy is a dummy valued 1 if individuals took a high-level mathematics course during high school. Reported bounds correspond to the pilot school sample. [f] Numeracy is also estimated using literacy as instrument and the coefficient found is 0.201. [g] Lower and Upper bounds correspond to the point estimates for Black men's and Hispanic men's samples, which respectively are the lowest and highest point estimates. Literacy was estimated in levels. [h] Lower and Upper bounds correspond to the point estimates for Denmark and Bermuda, which are respectively the lowest and largest estimates found. See the paper for more details.

Skills	Reference	Country/ City	Population in Estimating Sample	Identification Strategy	Estimation	Dependent Variable (log)	Range: Lowest Estimate	Range: Highest Estimate
Panel C: Foreign Language								
	Bleakley and Chin (2004)	USA	1960-1974 Young immigrants	Quasi-experiment	IV	1990 annual wage	0.222	0.334[i]
	Saiz and Zoido (2005)	USA	College graduates	Selection on Observables	OLS	1997 hourly wage	0.025	0.028[j]
	Christofides and Swidinsky (2010)	Quebec (CA)	Fulltime native workers aged 15 to 64	Selection on Observables	OLS	2000 earnings	0.109	0.139[k]
	Azam, Chin and Prakash (2013)	India	Male workers aged 18 to 65	Selection on Observables	OLS	2005 earnings	0.345	0.603[l]
	Guo and Sun (2014)	China	College graduates	Selection on Observables	OLS	2010 monthly wage	0.033	0.131[m]
	Budría and Swedberg (2015)	Spain	Male immigrants aged 18 to 65	Quasi-experiment	IV	2006-2007 hourly wages	0.049	0.204[n]
	Di Paolo and Tansel (2015)	Turkey	Male workers	Selection on Observables	OLS	2007 wage	0.107	0.072[o]
	Stöhr (2015)	Germany	Fulltime workers	Selection on Observables	OLS	2005-2006 gross monthly wage	0.033	0.093[p]

[i] The independent variable takes 1 as value if individual speaks English very well. [j] IV, Panel and PSM estimations are also considered. For instance, PSM point estimates ranged from 0.020 to 0.021. [k] Point estimates correspond to a subsample of only men. The independent variable takes 1 as value if individual uses English in his/her workplace. Estimations are also carried for women and ranged from 0.068 to 0.076. [l] Point estimates for a dummy variable that takes 1 as value if the individual is fluent in English. Estimations for knowing little English can be seen in the paper. [m] The English score of CET-4 test is used to measure foreign language proficiency, check the paper for more details. [n] Lower bound corresponds to OLS estimation and Upper bound corresponds to IV estimation using simultaneously the following instruments: 1(arrived before 12), 1(has a child proficient in spanish) and 1(willingness to stay in Spain). [o] The independent variable takes 1 as value if the individual knows english. Other languages are estimated (French, German, Arabic and Russian), but those who know english account for 76%. [p]The independent variable takes 1 as value if the individual's occupation requires expertise in a foreign language.

Appendix Table 2: Descriptive Statistics

	Estimation Sample				Mean Difference
	Full (N = 363,330)		Specific (N = 155,939)		
	Mean	Std. dev.	Mean	Std. dev.	p-value
	(1)		(2)		(1) - (2)
Panel A: Socioeconomic Statistics					
Age	26.93	3.44	26.86	3.5	0.00
Share female	0.61	0.49	0.63	0.48	0.00
Share living in big urban areas	0.73	0.45	0.71	0.45	0.00
Share living in low income households	0.45	0.50	0.43	0.50	0.00
Share graduate students	0.02	0.14	0.03	0.17	0.00
Panel B: Education Statistics					
Share graduated from:					
STEM	0.26	0.44	0.26	0.44	0.29
Business and Economics	0.31	0.46	0.27	0.45	0.00
Social Sc. and Humanities	0.16	0.36	0.15	0.36	0.00
Health and Education	0.22	0.41	0.28	0.45	0.00
Share postsecondary degrees:					
Vocational Degree (Private)	0.09	0.29	0.04	0.20	0.00
Vocational Degree (Public)	0.10	0.30	0.05	0.21	0.00
Academic Degree (Private)	0.50	0.50	0.56	0.50	0.00
Academic Degree (Public)	0.32	0.47	0.36	0.48	0.00
Panel C: Occupation Statistics					
Share working in:					
Manufacturing	0.07	0.26	0.07	0.26	0.00
Trade	0.03	0.18	0.03	0.17	0.00
Services	0.54	0.50	0.55	0.50	0.00
Tourism	0.01	0.10	0.01	0.09	0.00
Retail	0.04	0.20	0.04	0.19	0.00
Panel D: Labor Statistics					
Current Wage	16.86	11.24	17.48	11.59	0.00
First Wage	13.42	8.48	14.07	8.88	0.00
Average Wage	15.17	8.86	15.8	9.21	0.00
Current Tenure	1.77	1.02	1.78	1.11	0.00

Notes. Descriptive statistics of students who took the college exit exam from 2011 to 2015 for whom data were matched to earnings and college records. Big urban area refers to the largest 13 cities in Colombia. Low-income households refer to individuals in the first two income strata designated by place of residence. Wages are presented in nominal 2016 USD currency (1 USD = 3,050.98 COP).

Appendix Table 3: Average Characteristics by Types of Degrees

	Type of Degree and Estimation Sample							
	Vocational (Public)		Vocational (Private)		Academic (Public)		Academic (Private)	
	Full	Specific	Full	Specific	Full	Specific	Full	Specific
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Socioeconomic Statistics								
Age	26.65	26.86	26.88	27.22	27.27	27.13	26.77	26.65
Share female	0.55	0.54	0.56	0.54	0.60	0.62	0.63	0.65
Share living in big urban areas	0.73	0.74	0.83	0.84	0.60	0.60	0.79	0.78
Share living in low income households	0.68	0.67	0.59	0.59	0.55	0.54	0.32	0.33
Share graduate students	0.00	0.00	0.00	0.00	0.02	0.03	0.03	0.03
Panel B: Education Statistics								
Share graduated from:								
STEM	0.37	0.40	0.26	0.35	0.28	0.28	0.23	0.23
Business and Economics	0.44	0.36	0.48	0.39	0.22	0.21	0.31	0.30
Social Sc. and Humanities	0.01	0.00	0.01	0.00	0.12	0.09	0.23	0.21
Health and Education	0.13	0.20	0.10	0.16	0.33	0.39	0.18	0.23
Panel C: Occupation Statistics								
Share working in:								
Manufacturing	0.11	0.11	0.09	0.09	0.07	0.07	0.07	0.07
Trade	0.06	0.06	0.05	0.05	0.02	0.02	0.03	0.03
Services	0.46	0.47	0.49	0.52	0.54	0.54	0.56	0.57
Tourism	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01
Retail	0.06	0.07	0.07	0.06	0.03	0.03	0.04	0.04
Panel D: Labor Statistics								
Current Wage	12.52	13.26	13.54	14.73	16.36	16.57	18.62	18.62
First Wage	10.26	10.06	11.05	10.94	13.17	13.53	14.63	14.98
Average Wage	11.40	11.67	12.32	12.86	14.81	15.10	16.65	16.82
Current Tenure	1.79	2.09	1.82	2.10	1.70	1.71	1.79	1.76

Notes. Average characteristics of students who took the college exit exam from 2011 to 2015 for whom data were matched to earnings and college records. Big urban area refers to the largest 13 cities in Colombia. Low-income households refer to individuals in the first two income strata designated by place of residence. Wages are presented in nominal 2016 USD currency (1 USD = 3,050.98 COP).

Appendix Table 4: Correlation Matrix across Test Scores

	High School Exit Exams				College Exit Exams		
	Subject	Literacy	Numeracy	Foreign	Literacy	Numeracy	Foreign
Panel A: Full Sample (N = 363,330)							
High School Exit Exams:							
Literacy	**0.595***						
Numeracy	**0.546***	**0.394***					
Foreign Language	**0.571***	**0.460***	**0.428***				
College Exit Exams:							
Literacy	0.497*	0.438*	0.314*	0.390*			
Numeracy	0.553*	0.394*	0.487*	0.401*	**0.449***		
Foreign Language	0.515*	0.414*	0.393*	0.678*	**0.458***	**0.464***	
Panel B: Specific Sample (N = 155,939)							
High School Exit Exams:							
Literacy	**0.593***						
Numeracy	**0.553***	**0.396***					
Foreign Language	**0.573***	**0.459***	**0.431***				
College Exit Exams:							
Literacy	0.513*	0.446*	0.331*	0.401*			
Numeracy	0.579*	0.409*	0.509*	0.424*	**0.470***		
Foreign Language	0.526*	0.419*	0.405*	0.687*	**0.472***	**0.490***	
Field-Specific	0.496*	0.394*	0.344*	0.345*	**0.519***	**0.511***	**0.413***

Notes. Pairwise correlations are estimated using the Pearson's formula. For both the college exit exam (*Saber Pro*) and the high school exit exam (*Saber 11*), individuals' scores are standardized with respect to the corresponding average in each test edition. The specific scores from the college exit exam are standardized with respect to the average of the test edition and the corresponding group of related programs. The subject score from the high school exit exam is computed as the standardized average of biology, philosophy, physics, chemistry, and social science tests. The non-cognitive scores were computed as the predictions from a factor model considering categorical answers to nine questions. † $p<0.1$, * $p<0.05$.

Appendix Table 5: Other Outcomes

	Dependent Variable:					
	log(Avg. Wage Since Graduation)		log(Current Wage)		log(Avg. Earnings ages 25 to 30)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-secondary degree type :						
Vocational Degree (Private)	0.078	0.077	0.080	0.084	0.079	0.073
	[0.011]	[0.009]	[0.014]	[0.012]	[0.000]	[0.014]
Academic Degree (Public)	0.174	0.171	0.174	0.156	0.172	0.178
	[0.010]	[0.012]	[0.011]	[0.013]	[0.000]	[0.014]
Academic Degree (Private)	0.244	0.244	0.249	0.236	0.244	0.253
	[0.018]	[0.018]	[0.020]	[0.021]	[0.000]	[0.026]
College Exit Exam :						
Literacy	0.022	0.016	0.026	0.020	0.022	0.016
	[0.001]	[0.002]	[0.001]	[0.002]	[0.000]	[0.002]
Numeracy	0.030	0.022	0.034	0.025	0.032	0.024
	[0.001]	[0.002]	[0.002]	[0.003]	[0.000]	[0.002]
Foreign language	0.014	0.015	0.015	0.015	0.011	0.014
	[0.004]	[0.005]	[0.006]	[0.006]	[0.000]	[0.004]
Field-Specific		0.019		0.021		0.021
		[0.004]		[0.004]		[0.004]
College Reputation	0.031	0.032	0.032	0.031	0.034	0.032
	[0.004]	[0.005]	[0.004]	[0.005]	[0.000]	[0.005]
Sample:	Full	Specific	Full	Specific	Full	Specific
Observations	363,330	155,939	363,330	155,939	230,296	94,339
R-squared	0.233	0.264	0.194	0.219	0.242	0.285
Controls:						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes	Yes	Yes

Notes. In columns (1) and (2) the dependent variable is the log of the average wage since graduation from 2011 to 2016. In Columns (3) and (4) the dependent variable is the log of the last observed wage for each individual from 2011 to 2016. In columns (5) and (6) the dependent variable is the log of the last observed earnings after graduation from 2011 to 2016. The point estimates corresponding to types of degrees have to be compared to earnings of college graduates from vocational public degrees. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. Standard errors clustered at the municipality level and in brackets.

Appendix Table 6: Estimates' Ranges Unconditional on Types of Degrees

	Dependent Variable: log(First Wage After Graduation)									
	Full Sample				Specific Sample					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Literacy	0.016	0.021			0.013	0.010	0.019			
	[0.001]	[0.001]			[0.001]	[0.002]	[0.002]			
Numeracy	0.023		0.028		0.021	0.017		0.026		
	[0.002]		[0.002]		[0.002]	[0.002]		[0.002]		
Foreign language	0.006			0.013	0.009	0.007			0.015	
	[0.003]			[0.003]	[0.003]	[0.003]			[0.003]	
Field-Specific						0.016				0.024
						[0.003]				[0.002]
Observations	363,330	363,330	363,330	363,330	155,939	155,939	155,939	155,939	155,939	155,939
R-squared	0.207	0.205	0.206	0.205	0.249	0.249	0.248	0.248	0.248	0.249
Controls:										
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
College	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Columns (1), (5) and (6) show simultaneous estimations while the remaining columns display returns to skills estimated separately, all unconditional on types of degree. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. College controls include codes for both the postsecondary education institution and program. Standard errors clustered at the municipality level and in brackets.

Appendix Table 7: Heterogeneous Estimates by Study Area

	Dependent Variable: log(First Wage After Graduation)														
	Study Area:														
	STEM			Business and Economics			Social Sciences and Humanities			Health and Education			Agronomy and Arts		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Post-secondary degree type :															
Vocational Degree (Private)	0.042	0.037	0.037	0.029	0.020	0.019	–0.101	–0.137	–0.143	0.118	0.143	0.143	0.080	0.025	0.028
	[0.013]	[0.021]	[0.021]	[0.013]	[0.027]	[0.027]	[0.025]	[0.102]	[0.101]	[0.031]	[0.038]	[0.038]	[0.012]	[0.065]	[0.066]
Academic Degree (Public)	0.166	0.174	0.179	0.070	0.063	0.061	0.217	0.209	0.203	0.270	0.238	0.240	0.094	0.081	0.086
	[0.017]	[0.027]	[0.025]	[0.024]	[0.035]	[0.035]	[0.018]	[0.072]	[0.069]	[0.023]	[0.023]	[0.023]	[0.015]	[0.065]	[0.065]
Academic Degree (Private)	0.231	0.255	0.261	0.174	0.167	0.166	0.260	0.243	0.236	0.262	0.237	0.239	0.124	0.108	0.113
	[0.032]	[0.041]	[0.039]	[0.010]	[0.025]	[0.026]	[0.016]	[0.072]	[0.070]	[0.021]	[0.016]	[0.016]	[0.020]	[0.060]	[0.059]
College Exit Exam :															
Literacy	0.011	0.011	0.008	0.021	0.018	0.013	0.017	0.024	0.018	0.014	0.009	0.004	0.012	0.018	0.019
	[0.002]	[0.003]	[0.004]	[0.001]	[0.002]	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]	[0.004]	[0.011]	[0.011]
Numeracy	0.025	0.019	0.015	0.026	0.028	0.022	0.008	0.003	–0.001	0.022	0.025	0.021	0.015	0.027	0.031
	[0.002]	[0.002]	[0.004]	[0.004]	[0.005]	[0.005]	[0.003]	[0.005]	[0.005]	[0.002]	[0.003]	[0.004]	[0.003]	[0.012]	[0.012]
Foreign language	0.008	0.009	0.007	0.004	0.004	0.001	0.008	0.012	0.010	0.024	0.027	0.025	0.007	–0.008	–0.008
	[0.003]	[0.004]	[0.004]	[0.006]	[0.010]	[0.010]	[0.003]	[0.005]	[0.005]	[0.003]	[0.006]	[0.006]	[0.007]	[0.009]	[0.009]
Field-Specific			0.017			0.022			0.019			0.017			–0.012
			[0.007]			[0.003]			[0.004]			[0.003]			[0.010]
College Reputation	0.020	0.026	0.024	0.046	0.049	0.046	0.031	0.037	0.035	0.012	0.016	0.014	0.013	0.015	0.016
	[0.002]	[0.003]	[0.003]	[0.014]	[0.015]	[0.014]	[0.005]	[0.008]	[0.008]	[0.004]	[0.005]	[0.005]	[0.005]	[0.011]	[0.011]
Sample:	Full	Specific	Specific	Full	Specific	Specific	Full	Specific	Specific	Full	Specific	Specific	Full	Specific	Specific
Observations	95,270	40,668	40,668	112,184	42,572	42,572	56,568	23,697	23,697	78,526	43,690	43,690	20,782	5,312	5,312
R-squared	0.172	0.221	0.221	0.239	0.309	0.310	0.192	0.280	0.280	0.374	0.428	0.429	0.244	0.460	0.460
Controls:															
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Estimations are within the set of individuals belonging to the population of interest –defined by the categories on top of the table. In the study area vector, the STEM samples in columns (1) to (3) includes individuals graduated from engineering, mathematics and natural sciences. Columns (4) to (6) include individuals graduated from business and economics, columns (7) and (9) from social sciences and humanities, columns (10) and (12) from health and education sciences, and columns (13) and (15) from agronomy and arts. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. College controls include codes for both the postsecondary education institution and program. Standard errors clustered at the municipality level and in brackets.

Appendix Table 8: Heterogeneous Estimates by Economic Activity

	Dependent Variable: log(First Wage After Graduation)														
	Manufacturing			Trade			Services			Tourism			Retail		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Post-secondary degree type :															
Vocational Degree (Private)	0.041	0.020	0.021	0.028	0.056	0.052	0.080	0.092	0.092	0.046	0.259	0.257	0.078	0.073	0.073
	[0.015]	[0.027]	[0.027]	[0.024]	[0.033]	[0.034]	[0.012]	[0.015]	[0.015]	[0.052]	[0.142]	[0.134]	[0.020]	[0.042]	[0.042]
Academic Degree (Public)	0.167	0.166	0.172	0.119	0.099	0.100	0.170	0.184	0.186	0.069	0.125	0.122	0.167	0.183	0.185
	[0.017]	[0.024]	[0.024]	[0.027]	[0.042]	[0.042]	[0.014]	[0.017]	[0.017]	[0.040]	[0.179]	[0.174]	[0.033]	[0.044]	[0.043]
Academic Degree (Private)	0.219	0.200	0.206	0.189	0.182	0.185	0.232	0.247	0.249	0.133	0.184	0.182	0.249	0.277	0.278
	[0.017]	[0.027]	[0.027]	[0.024]	[0.050]	[0.051]	[0.019]	[0.023]	[0.023]	[0.047]	[0.184]	[0.178]	[0.020]	[0.032]	[0.032]
College Exit Exam :															
Literacy	0.021	0.023	0.019	0.017	0.017	0.009	0.014	0.011	0.008	0.017	0.007	0.003	0.015	0.014	0.012
	[0.005]	[0.008]	[0.008]	[0.006]	[0.014]	[0.014]	[0.001]	[0.002]	[0.002]	[0.017]	[0.050]	[0.042]	[0.005]	[0.012]	[0.012]
Numeracy	0.039	0.041	0.036	0.029	0.020	0.010	0.020	0.017	0.013	0.001	–0.004	–0.008	0.016	0.025	0.023
	[0.003]	[0.008]	[0.008]	[0.007]	[0.016]	[0.015]	[0.002]	[0.002]	[0.002]	[0.016]	[0.047]	[0.053]	[0.006]	[0.010]	[0.009]
Foreign language	0.016	0.026	0.025	0.032	0.034	0.029	0.007	0.007	0.006	0.031	0.085	0.084	0.012	0.024	0.024
	[0.005]	[0.008]	[0.008]	[0.015]	[0.012]	[0.013]	[0.002]	[0.003]	[0.003]	[0.028]	[0.042]	[0.041]	[0.005]	[0.013]	[0.013]
Field-Specific			0.018			0.039			0.014			0.018			0.009
			[0.007]			[0.017]			[0.003]			[0.050]			[0.013]
College Reputation	0.025	0.029	0.026	0.031	0.026	0.025	0.027	0.031	0.028	0.035	0.024	0.023	0.025	0.039	0.037
	[0.008]	[0.014]	[0.013]	[0.010]	[0.013]	[0.012]	[0.004]	[0.004]	[0.004]	[0.014]	[0.043]	[0.041]	[0.013]	[0.013]	[0.013]
Sample:	Full	Specific	Specific	Full	Specific	Specific	Full	Specific	Specific	Full	Specific	Specific	Full	Specific	Specific
Observations	23,492	9,610	9,610	12,335	4,907	4,907	194,934	86,051	86,051	3,916	1,410	1,410	13,549	5,300	5,300
R-squared	0.374	0.496	0.496	0.469	0.620	0.622	0.235	0.298	0.299	0.636	0.803	0.803	0.465	0.620	0.620
Controls:															
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Estimations are within the set of individuals belonging to the population of interest –defined by the categories on top of the table. Economic activity categories were defined by grouping four-digit industry codes. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, a proxy of pre-college skills, high school fixed effects, cohort fixed effects, and test edition fixed effects. Pre-college skills are proxied using test scores from the high school exit exam. College controls include codes for both the postsecondary education institution and program. Standard errors clustered at the municipality level and in brackets.

B Appendix: Skills Measures

In this appendix, we describe the cognitive abilities evaluated in the college exit exam and the high school exit exam. We also describe the different measures of skills used in the paper.

The abilities tested in the college exit exam (Saber Pro) are divided into two sections. The first section has five mandatory general tests and consists of 160 multiple choice questions and one open question, lasting a maximum of four hours and 40 minutes. The main objective of this section is to evaluate common abilities that students from the wide range of fields should be able to apply in non-specialized tasks. On the other hand, some students also take a second section with specific tests. This section is only available if the student's college previously decided which specific tests will be applied to their undergraduate programs. There are 40 specific tests and combinations of theses suggested for each field of study or group of related programs.[26] Following those combinations, colleges can require up to three specific tests. The maximum time allowed for students taking one specific test is one hour and 30 minutes, while students taking two or three specific tests have a maximum of four hours and 30 minutes. Appendix Table 9 presents more details on the abilities evaluated and a sample question for each general test. It also shows one question for the Economic Analysis test, to present an example for one of the specific tests evaluated in the second part of the college exit exam.

We standardize these measures with respects the test's edition mean and standard deviation. Let ${\eta_t}_i$ be student i's scores for η_t, which is test η applied in time t. Let μ_{η_t} be the mean of η_t, this is:

$$\mu_{\eta_t} = \frac{1}{|I_t|} \sum_{i \in I_t} {\eta_t}_i$$

where I_t is the set of students who took η_t. Thus, the standardized score of ${\eta_t}_i$ with respect to μ_{η_t} is $\tau_{ti} = \frac{(\eta_{ti} - \mu_{\eta_t})}{\sigma_{\eta_t}}$, where the standard deviation of η_t is defined as:

$$\sigma_{\eta_t} = \sqrt{\frac{1}{|I_t| - 1} \sum_{i \in I_t} ({\eta_t}_i - \mu_{\eta_t})^2}.$$

Now let $\mu^s_{\eta_t}$ be the mean of η_t, but computed within a sample $s \subseteq |I_t|$. If $i \in s$, then $\tau^s_{t\,i}$ is the standardized score of ${\eta_t}_i$ within sample s.

Taking the previous framework into account, we use the test scores from the Saber Pro exam to compute literacy, numeracy and foreign language measures as the standardized scores within the samples mentioned in Appendix C. For each individual in

[26]Throughout the years there have been changes in some of these specific evaluations and, thus, our data contains a total of 87 specific tests. For instance, some specific tests were divided into others, and some have disappeared.

a sample, the numeracy ability level is the standardized score of the quantitative reasoning test with respect to the mean in the time period in which the test was taken, considering only individuals within the sample. The foreign language ability level is computed as the standardized score of the English proficiency test within each sample. To define the literacy measure we first compute the average score of written communication and critical reading tests, and then standardized the resulting vector in the same way as we did for numeracy and foreign language. To compute the specific skills measure, we average all field-specific test scores available for each student and then proceed to standardize the resulting vector, considering both the sample and group of related majors.

Appendix Table 9: Description of Tests and Abilities Evaluated in the Saber Pro Exam

Test	Evaluated Abilities	Sample Question
Section 1:		
Critical Reading (35 Questions)	Abilities that allow individuals to understand, interpret and analyze texts found in both, common life and non-specialized academic scenarios.	The text's author states that "seeking justice is the eternal seeking of human happiness". This statement: A) implies that "every human pursues hapiness", B) does not imply that "seeking justice is seeking happiness"
Quantitative Reasoning (35 Questions)	Mathematic abilities that every citizen should have, independently of their profession or occupacion, such as: algebra, calculus, geometry, statistics, interpretation of numeric information, use of mathematics to formulate and execute plans, and use of mathematics to solve problems.	Four utility companies estimated their daily efficiency to solve customer complaints: Electricity: 2 out of 3 solved complaints per day. Aqueduct: 5 out of 6. Telephone: 9 out of 10. The average efficiency for one of these companies is : A) 72%, B) 79%
Citizenship Abilities (35 Questions)	Knowledge and abilities to understand the social environment and its issues, as well as abilities to analyze positions taken by different parties involved in a conflicting situation.	To reduce traffic jams within a city, a major decided to restrict the free circulation of vehicles using the last digit of license plates. The offer of public transporation in the city is limited and has low quality. What undesired effects may cause to the mentioned policy for citizens using the public transportation?
Written Communication (1 Open Question)	Abilities to communicate ideas in writing, regarding a given topic. Students are asked to produce a text in response to a non-specialized problem.	Some consider that national and international sport competitions are used for political and commercial means. Do you agree or disagree with this opinion? Discuss.
English Proficiency (55 Questions)	Communication abilities in English throughout reading, grammar and vocabulary tasks.	The Ozone Layer is a "blanket" (1) ______ earth. It protects (2) ______ from the sun's UV rays. Fill the blanks: (1) A) around, B) through; (2) A) our, B) us.
Section 2:		
Specific Tests (30 - 60 Questions)	Abilities that different postsecondary programs must provide to its students. These abilities have been defined between the Ministry of Education, the academic and professional community, and the industry.	(Economic Analysis Test:) Consider a linear model $y = X\beta + \varepsilon$, where ε is an error term. Assuming that $E(X'\varepsilon) = 0$, then: A) OLS are consistent, and 2SLS are consistent and efficient. B) OLS are inconsistent and 2SLS are consistent and efficient. (OLS: Ordinary Least Squares; 2SLS: Two-Stage Least Squares)

Notes. Information adapted by the authors from Icfes (2017).

College Reputation. Following MacLeod et al. (2017), we used the administrative records of undergraduate students to build a measure of college reputation or quality. This measure is defined as the mean admission score of graduates, then for college c, in time t, the reputation measure is:

$$R_{ct} = \frac{1}{|G_{ct}|} \sum_{i \in G_{ct}} \tilde{\eta}_i$$

where G_{ct} is the set of students graduating from college c in time t, and $\tilde{\eta}_i$ is the percentile score of individual $i \in G_{ct}$ in the high school exit exam. We then standardized R_{ct} to have mean zero and standard deviation one.

C Appendix: Data Construction and Sample Selection

In this appendix, we explain how we constructed the data used in the paper. The population of interest is the students who took the Saber Pro exam between 2011 and 2015.[27] We begin by appending individual-level exam records that are originally split into different files, with one file per year. The exam authority, the Colombian Institute for the Evaluation of Education (ICFES), administers the exam twice a year. Each test edition is specifically designed for one of two (mutually exclusive) groups of fields of study. Consequently, students in a given field can only take the exam once a year. The exam is a graduation requirement for all college students, who are allowed to take it after completing three-fourths of their degree credits. Given that some students take the exam more than once—for example, if a student is enrolled in different fields—we only use the information from the first time they were evaluated.

The Saber Pro exam data allow us to observe student performance in different tests, including critical reading, English proficiency, quantitative reasoning, and written communication. Our data cover nearly 785,000 exam takers, for whom we also observe college enrollment data and pre-college test scores.[28] This is our universe of analysis. A field-specific exam is also administered to students when their college agrees to participate. The exam authority suggests a list of potential specific tests for each college program or major, and colleges choose from this pool the specific exams

[27] We focus on exam takers from 2011 onward since all college students in Colombia are required to take the Saber Pro exam starting from this time period. Information before 2011 may suffer from selection concerns, as the exam, as a graduation requirement, was not fully enforced across colleges and college programs. Additionally, from 2004 to 2010, college students in certain fields were exempted from taking the exam.

[28] The college enrollment information comes from SPADIES (or Sistema para la Prevención de la Deserción de la Educación Superior, in Spanish), a dataset that covers the entire universe of individuals who have enrolled in any higher education program between 2006 and 2016. These data provide detailed information on the student's enrollment history, their intended majors, and their access to college financial aid. Pre-college test scores are observed from the Saber 11 exam, which is administered to most high school seniors in Colombia and represents an enrollment requirement for any college student. We observe test scores for different subjects, including math, physics, chemistry, biology, language, philosophy, geography, history, social sciences, and English. The records from Saber 11 also allow us to observe socioeconomic variables such as gender, household stratum, and a code identifying the high school from which the student graduated.

their students are taking. Students can take up to three field-specific tests.[29] Our data include scores from this field-specific component of the Saber Pro exam for almost 370,000 students. We observe a smaller sample size because not all college programs have a field-specific exam available.

The second step in our data construction is to merge exam takers' individual-level data with labor market records. The Ministry of Education collects this information from the Social Security Administration Office.[30] These data include formal sector earnings, the city or municipality where individuals work, four-digit industry codes, and the tax identification numbers of all employers. The earnings observed for each worker correspond to their most recent employment between April and September of a given year. Five years are covered in our data, from 2012 to 2016.

Appendix Table 10: Description of the Estimation Sample

	Full Sample	%	Specific Sample	%
Universe Under Analysis	784,541	100	369,089	100
Panel A: Merge with Labor Market Data				
College Graduates' Records (OLE)	515,769	65.74	220,031	59.61
Panel B: Data Restrictions				
Consistent Covariate Information	438,483	55.89	188,915	51.18
Labor Market Earnings	363,330	46.31	155,939	42.25

Notes. This table describes the process we use to obtain our estimation sample. The universe of analysis corresponds to college students who took the Saber Pro exam between 2011 and 2015 for whom we observe college enrollment records and performance in their high school exit exam ($N = 784,541$). Panel A presents the number of individuals that were merged with the administrative data of college graduates (OLE) collected by the Ministry of Education, which records formal sector labor market outcomes. We merge 515,769 exam takers with OLE. Panel B presents the number of individuals that remain in our sample after we make additional restrictions. 438,483 students remain in our sample when we drop observations with inconsistent or missing information across covariates. Covariates include gender, age, socioeconomic stratum, college graduation date, field of study codes, and college identifying codes. The last row shows the sample used in the paper to estimate the results across tables and figures.

We link these datasets using students' national identification numbers, but we also rely on fuzzy merge or record linkage procedures based on students' names and dates of birth to improve the merge rates.[31] An important caveat is that the Ministry only collects labor market outcomes only for higher education graduates. Consequently, we are unable to link exam takers who received their diplomas after 2016 or who may

[29] For additional details on skill measures and test scores, see Appendix B.

[30] We were given access to these data by the Observatory of the Labor Market for Higher Education (OLE, in Spanish), which is part of the Ministry of Education.

[31] In Colombia, the national identification number changes when individuals turn 18. Since a large fraction of the population graduates high school before this age, using the identification number recorded in the Saber Pro exam records is insufficient to achieve a high merge rate with the high school, college, and labor market datasets. To increase the merge rate, we use a crosswalk of national identification numbers between youth IDs (before they turn 18) and adult IDs (after they turn 18) provided by the Colombian registry's office (Registraduría General de la Nación, in Spanish). This crosswalk minimizes the number of fuzzy matches. For the remaining sample, we rely on students' names and birthdates to link the data.

have dropped out of college after taking the Saber Pro exam. We successfully merged 515,769 individuals, as shown in Panel A of Appendix Table 10.

After emerging these datasets, we apply additional restrictions to have a more homogeneous sample. We exclude individuals with inconsistent or missing information in any of the covariates used across regression specifications. The remaining sample includes 438,483 students. Finally, we condition on observing labor market earnings, which results in a final or *full sample* of 363,330 exam-takers. The *specific sample* consists of college students for whom we also observe field-specific test scores, and includes 155,939 individuals.

Sample Selection. Appendix Table 10 suggests that a considerable portion of the sample of college graduates is lost in the data cleaning procedures. Of course this implies that our final sample could be heavily selected. Two potential sources of selection exists in our data. First, college graduates could not appear in our sample because they migrated upon graduation. Colombian students could find better paid jobs elsewhere, inducing them to migrate. Second, graduates could decide to not join the labor force, or join it in the informal sector (i.e., not contributing to health or pensions). In both cases we would not be able to observe them in our sample.

Appendix Table 11: Sample Selection Among College Graduates

Year	Total Students	Migrants (%)	Working (%)	Working Formally (%)
2012	1,929,587	3.15	79.68	74.06
2013	2,092,891	3.43	80.36	74.70
2014	2,220,652	3.63	80.69	76.99
2015	2,293,550	3.70	81.10	75.37
2016	2,394,434	3.38	79.54	74.75
2017	2,446,314	3.35	79.55	72.84
2018	2,440,367	3.44	77.77	74.96

Notes. This table shows the total number of students who graduated in a given year in column (1) calculated using the college records. Column (2) presents the share of students who left the country in a given year. These values are computed using the records by the Colombian migration authorities (migración Colombia) and dividing them by the values in column (1). Column (3) presents the share of college graduates between the ages of 25 and 30 who are employed in a given year. Column (3) present the share of college graduates between the ages of 25 and 30 who work formally (i.e., contribute to health or pensions). Columns (2) and (3) are calculated using the Colombian household survey.

To give a sense of the degree of selection, and to describe sample represented in our data, we use the Colombian household survey, and migration records, to characterize our sample of study in Appendix Table 11. We present the total of college graduates, the number of them who migrated in a given year, the share that are employed, and the share that are employed formally (this is the population observed in the social security records).

Migration seems not to be a big issue since only three percent of the sample moves out of the country upon graduation. The largest selection comes by the decision to enter the labor market. We observe that around 80 percent of college graduates joins the labor market, and around 5 percent do it in the informal sector. This means that combining the college record data with the social security records gives us a sample that represents around 75 percent of the population of Colombian college graduates.

Selection on Observables. Given that our paper deals with potential selection on unobservables, we provide estimates of the bounding procedure suggested by Oster (2019) in Appendix Table 12. We provide estimates of the fully controlled and fully uncontrolled model. Reassuringly, we observe that the all the bounds, except for foreign language skills, exclude the zero and are very tight around the point estimates presented in the main text.

Appendix Table 12: Selection of Unobservables: Oster Bounds

	Dependent Variable: log(First Wage After Graduation)							
	Controlled Model	Uncontrolled Model					δ for $\beta = 0$	Oster Bounds for β
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-secondary degree type:								
Vocational Degree (Private)	0.073	0.056					–0.891	(0.073 ,0.178)
	[0.012]	[0.019]						
Academic Degree (Public)	0.182	0.188					–2.709	(0.182 ,0.423)
	[0.014]	[0.010]						
Academic Degree (Private)	0.228	0.280					1.712	(0.228 ,0.508)
	[0.021]	[0.026]						
College Exit Exam:								
Literacy	0.020		0.059				1.314	(0.006 ,0.020)
	[0.001]		[0.001]					
Numeracy	0.030			0.079			1.255	(0.007 ,0.030)
	[0.001]			[0.002]				
Foreign language	0.017				0.072		0.622	(–0.013 ,0.017)
	[0.003]				[0.003]			
Field-Specific	0.020					0.054	1.219	(0.004 ,0.020)
	[0.002]					[0.004]		
Observations	363,330	363,330	363,330	363,330	363,330	155,939		
R-squared	0.194	0.035	0.014	0.024	0.020	0.011		
Controls:								
Individual	Yes							
Field of study	Yes							

Notes. Selection of unobservables is conducted using the "psacalc" command from Oster (2019). δ is the coefficient of selection proportionality between unobservables and observables. Bounds for β are calculated using $\delta = 0$ & $\delta = 1$. $R^2_{max} = 1.2R^2_{Controlled}$ is used as it is standard. The Field specific coefficient on the controlled model was estimated separately with the specific sample size and an R-Squared of 0.219. The dependent variable is the log of the first observed wage for each individual from 2011 to 2016 after graduation. Column (1) shows the controlled model, columns (2) to (6) show the uncontrolled models which are the simple linear regression of each coefficient and the independent variable, column (7) shows the value of delta that would explain out the controlled model coefficient, finally column (8) shows the Oster bounds for types of degrees and skills. Individual control variables include gender, age, age squared, socioeconomic stratum, mother's education level, a dummy for graduate studies, high school fixed effects, cohort fixed effects, and test edition fixed effects. Standard errors clustered by municipality and in brackets.

These estimates are based on strong assumptions, especially that selection on observables are informative about selection on unobservables. However, our results are reassuring about the sensitivity of our estimates.