Estimating the Contribution of Short-Cycle Programs to Student Outcomes in Colombia[1]

Maria Marta Ferreyra
The World Bank
Tatiana Melguizo*
University of Southern California
Angelica Maria Sanchez
Georgetown University
&
Gema Zamarro
University of Arkansas

*Corresponding author. University of Southern California Rossier School of Education, 3470 Trousdale Parkway, Waite Phillips Hall 702 G, Los Angeles, CA, 90089. Phone: (213) 740 3635 Fax: (213) 740 3889 Email: melguizo@usc.edu

---

[1] We would like to thank Andrea Franco Hernandez for exemplary research assistantship support.
[2] "SCPs identifies programs encompassed under the level 5 of UNESCO's ISCED, but expands the

In recent decades there has been a large increase in the offering of Short-Cycle Programs (SCPs)[2] by different types of higher education institutions (e.g., public, private non-for profit, technical, and technological institutions) in Latin America (Carfi, 2010; Ferreyra, Botero, Avitabile, Haimovich, & Urzua, 2017; Fordham & Pons, 2016; OECD, 2017; UNESCO, 2017). This growth has been mostly driven by the response from the different higher education systems to accommodate a growing demand from less-traditional students (e.g., adult and low-income populations) who need to work while attending college. In addition, there has been support from the central governments as well as international organizations such as the World Bank (Ferreyra et al., 2017; World Bank, 2003) and the Inter-American Development Bank (IADB) (Busso, Cristia, Hincapie, Messina, & Ripani, 2017) to promote Technical and Vocational Education and Training (TVET) in the region as a way to connect the knowledge and skills that students acquire in the higher education system with the labor demands of the local markets. The rationale for promoting the expansion of SCPs is that they are in theory more *aligned* with the knowledge and skills needed in the workplace, and given their *short duration* (e.g., two to three years) their opportunity costs are lower than those of students enrolling in traditional academic programs (e.g., four to five years). Despite substantial growth in the offering of SCPs in the last two decades, the reality is that with the exception of a couple of studies that evaluated the labor returns of these programs in Colombia (Attanasio, Kugler, & Meghir, 2011; Bernal, 2015), we don't know whether

[2] "SCPs identifies programs encompassed under the level 5 of UNESCO's ISCED, but expands the definition to include the traditionally longer duration of these programs in Latin America (1.3 to 3.5 years of full-time study at the higher education level). The level captures the lowest level of higher education, and is best represented by postsecondary, practical, occupationally specific programs designed to provide participants with professional knowledge, skills, and competencies that prepare them to enter the labor market. These programs may also provide a pathway to other higher education programs. For further details, please consult UNESCO-UIS, ISCED 2011, 12." (Ferreyra et al., 2017)

these programs are providing the students with the knowledge and skills necessary to enter and succeed in the job market. This study fills this gap in the literature.

The main objective of this study is to estimate the educational and early labor market benefits of attending SCPs in Colombia. Specifically, we provide estimates of the educational benefits in terms of both the value-added contributions to cognitive (e.g., reading and writing in Spanish, English, and quantitative reasoning) and graduation (e.g., attaining a certificate), as well as two early labor market indicators: finding employment in the formal sector, and early earnings. Three research questions guide this study: 1) How large is the variation in terms of the contribution in educational and early labor market outcomes for students attending SCPs?, 2) How much of the variation is explained by the Higher Education Institution (HEI), the field of study (e.g., health versus social sciences), and the program itself?, and 3) What characteristics of the program, institution, and market are associated with higher educational and early labor outcome contributions?

This study combines and leverages a number of national-level datasets with unique data on cognitive and labor outcomes for several cohorts of higher education students in Colombia. We use fixed-effects (FE)[3] methods to estimate value-added by college-program following Melguizo, Zamarro, Velasco, and Sanchez (2016). The models are conditional on individual characteristics (e.g., high school exit exam, parent's income and education, and other relevant factors associated with college persistence) and peer effects (e.g., average high-school exit score of the cohort and average mother's education) to minimize bias and address the inherent student self-

[3] We estimated the models using Aggregated Residuals (AR) as a robustness check for the findings. These results are available from the authors upon request.

selection problem associated with the study. In order to illustrate the benefits we estimated the value-added contribution by college-program combination at the 25th, 50th, and 75th percentiles. This means that we estimated the value-added in terms of the outcomes of interest for individuals who attended the college-program combination that were adding the least (e.g., 25th percentile), with those college-program combination that were adding the most (e.g., 75th percentile) and we compared the interquartile range of value-added (i.e., the difference between the 75th and 25th percentiles) in terms of educational and early labor market outcomes. We then used traditional variance decomposition technique (Lemieux, 2006) to better understand whether most of the variation in the outcomes was related to the characteristics of the Higher Education Institutions (*HEI*), the major *field* of study, or the *program* in which the student enrolled. We tried to further our understanding of the factors associated with additional value-added, by leveraging the richness of the data to explore which particular characteristics of the higher education institutions (e.g., type, control, size, mode of delivery and others) and the program's market share were positively associated with improvements in a selected number of outcomes.

The results of the study suggest that on average SCPs were not contributing much in terms of cognitive outcomes, that about one third of the students graduated, and that for those who found employment in the formal sector, their monthly salary corresponded to the minimum salary in the country. The findings illustrate a pattern of remarkable variation in value-added by outcome. Specifically, the college-programs in the 75th percentile illustrates substantial quantitative reasoning value-added compared to those in the 25th percentile. This pattern is consistent in terms of probability of graduation and formal employment. The college-programs at the top 75th implied increases of 25 and 22 percentage points respectively, which are substantial.

The results also suggest that there is not so much variation in value-added contribution *across* fields of study (e.g., health versus economics, business administration and accounting), but there is substantial variation *within* field of study in terms of cognitive outcomes, graduation, as well as gaining access to the formal sector and increases in early earnings. The results of the variance decomposition illustrated that most of the variation in outcomes is explained by program-specific characteristics, above and beyond the institution and field. Of the remaining variance, most of it is explained by the type of institution rather than the field of study. This result suggests that when individuals are choosing a program, what matters the most in terms of potential educational and labor market value-added is the program and institution attended, and not so much the field of study pursued.

As mentioned above we leveraged the richness of our dataset in order to test for associations between specific characteristics of the IHE (e.g., type, control, selectivity) and the educational and early labor market outcomes of interest. We found a number of associations between specific institutional characteristics and cognitive outcomes. For example, holding all else constant, students who attended a university as opposed to a technological institute had on average higher increases in the quantitative reasoning dimension. Similarly attending a public institution as opposed to a private not-for-profit university, contributed more on average to increases in quantitative reasoning. Looking at the benefits in terms of graduation and employment outcomes, the results suggest that enrolling in a technological program as opposed as a technical one resulted in larger improvements. There is also evidence that on average programs offered at either technological institutes or public higher education institutions are doing a better job in terms of adding value in terms of cognitive outcomes and gaining access to employment in the formal sector.

This study contributes to the literature by providing the first national-level estimates of the value-added contribution in terms of both educational and early labor market measures of attending SCPs. In addition, to the best of our knowledge the use of value-added models paired with variance decomposition techniques is unique in this literature. This is an important methodological tool that can enable policy makers to estimate which college-program combination contributes the most to educational and labor market outcomes. This tool can generate a ranking system that can then be used by policy makers and the general public to help them make informed decisions related to funding and enrollment. Policy makers can use these models to identify which are the SCPs where students are gaining more in terms of educational and early labor markets and incorporate these measures as part of a multiple measure index that can be used for accountability and/or resource allocation purposes. The general public, in particular potential students and employers, can use the information to help them make more informed decisions related to college enrollment and recruitment of talent.

The paper is structured as follows. We proceed to present a review of the relevant literature, followed by a description of the empirical strategy and description of the results. We conclude with main conclusions and policy implications.

Literature Review

This paper builds on two different but complementary strands of the higher education and economics of education literatures. The emerging literature of estimating value-added in higher education in particular in terms of cognitive development (See, Arum & Roksa, 2011; Barrera-Osorio & Bayona-Rodriguez, 2014; Cunha & Miller, 2014; Domingue, Lang, Cuevas, Castellanos, Lopera, Marino, Molina, & Shavelson, 2017; Hoxby, 2015; Matsudaira, 2016; Melguizo & Coates, 2017; Melguizo et al., 2016; Melguizo & Wainer, 2015; Rossefky-Saavedra & Saavedra, 2011; Saavedra, 2009; Shavelson, Marino, Mantilla, Morales, & Wiley, 2016; Steedle, 2012), and a relatively recent empirical labor market literature in the U.S. that has capitalized on recently available state-level panel data to estimate the labor market impacts of attaining a certificate or associate degree (A.A.) in the community college sector (Bahr, 2016; Belfield, Liu, & Trimble, 2014; Dadgar & Trimble, 2015; Dynarski, Jacob, & Kreisman, 2016; Bettinger & Soliz, 2016; Jepsen, Troske, & Coomes, 2014; Minaya & Scott-Clayton, 2017; Stevens, Kurlaender, & Grosz, 2015; Xu & Trimble, 2016). In the following section we summarize key findings from recent studies in these two strands of the literature.

Accurately Measuring Value-Added in terms of Cognitive Outcomes in Higher Education

It is worth noting that the emerging literature related to measuring value-added in higher education, in particular on cognitive outcomes has mostly used country level datasets in Colombia, and Brazil, which have compulsory high-school and college-exit exams that are key to estimating potential value-added in terms of cognitive development. It is also important to mention that the empirical studies that have attempted to measure value-added in higher education, are all well aware of the issue of student self-selection into programs and institutions, and they have all tried to offer a methodological tool-set to ameliorate the potential estimation bias (Hoxby, 2015; Shavelson et al., 2016). The main challenge with estimating value-added is the fact that students sort themselves into specific types of institutions that in turn are selecting students who are more likely to attain a degree. As a result, estimates of higher education value-added might be biased if researchers can't control for observable (e.g., academic preparation) and unobservable (e.g., motivation) characteristics of students associated with degree attainment. Shavelson et al. (2016) provide a very careful and systematic evaluation of all the methodological challenges associated with estimating value-added measures in higher education. Melguizo et al. (2016) furthered this work by applying and comparing multiple value-added methods and concluded that the college-program fixed effect (FE) model was the method that had more promise in terms of ameliorating the selection bias. Most recently Hoxby (2015) proposed a comprehensive and rigorous method that leverages national-level data from the College Board and the National Student Cleaning house (NSC), to identify plausible "experiments" in which students who are the same end up in different colleges. She used statistical techniques to combine the results of multiple "experiments" efficiently, and offered an important tool-set that can be used to identify colleges that are adding more value in multiple dimensions.

A number of empirical studies have used data from Colombia and applied rigorous methods to estimate the value-added in cognitive outcomes. Saavedra (2009) used a regression discontinuity design (RDD) to compare students at the cutoff of the high-school exit exam used by colleges to grant admission. He concluded that students who attended the most-selective institution gained about 0.2 percent of a standard deviation in cognitive outcomes, had higher probability of being employed, and reported higher earnings compared to those who attended a less-selective institution. Barrera-Osorio and Bayona-Rodriguez (2014) also used a RDD to explore a similar question and they found benefits in terms of enrollment, graduation, and earnings but not in terms of cognitive outcomes. They concluded that their findings give some credence to the signaling theory (Spence, 1973) as opposed to the human capital theory (Becker, 1962) given that students at selective private institution were more likely to benefit in terms of obtaining formal employment even though there were no improvements in terms of knowledge and skills development. Melguizo et al. (2016) used multiple estimating methods (e.g., FE, random effects (RE), and aggregated residuals (AR)) also concluded that students were not gaining much in terms of developing cognitive outcomes such as generic knowledge (e.g., reading, writing, and quantitative reasoning) but that they were gaining in terms of degree attainment and earnings. Finally, Shavelson et al. (2016) in the context of Colombia and Melguizo et al. (2015) in the context of Brazil both found gains in terms of cognitive outcomes but for the subject-specific knowledge (e.g., knowledge related to a particular field such as engineering). Shavelson et al. (2016) found that value-added estimates of subject-specific knowledge as opposed to the generic knowledge explained a much larger proportion of the variability in the college-program combination. It is worth noting that all of the studies reviewed above have attempted to estimate value-added models for cognitive outcomes for students attending traditional colleges and universities. Domingue et al. (2017) used Colombian data to identify the measurement or psychometric challenges related to estimating value-added of cognitive outcomes at technical programs given that the cognitive measures were originally designed for students at traditional higher education institutions. Specifically, they tested whether assessments of student learning can be jointly administered to both university and technical school students. They applied item response theory models to allow for differences in response behavior as a function of school context. They concluded that items show small yet consistent differential functioning in favor of university students. These differences are shown to affect inferences regarding effect size differences between the university and technical students (effect sizes can fall by 44% in quantitative reasoning and 24% in critical reading). Differential test functioning influences the rank orderings of institutions by up to roughly 5 percentile points on average. This is an important finding that suggest that the current college-exit exam used to estimate value-added in the context of SCPs might not be the most appropriate to reflect the knowledge and skills gained by students in technical and technological programs as opposed to traditional programs leading to baccalaureate degrees.

Finally, Hoxby (2015) provides one of the most methodologically innovative and comprehensive studies related to the measuring value-added on multiple outcomes in the context of higher education. She leveraged data from the College Board and the National Clearinghouse and produced value-added estimates for over 6,800 institutions in the U.S. She found higher value-added for the most selective institutions but she cautions that these institutions spend more on instructional and related activities per students so the estimates might be biased in the sense that these institutions trigger students to spend more on graduate and professional education. The most interesting finding was related to the substantial variation in value-added among low selectivity institutions. This was not the case at either the selective of middling selectivity institutions. This finding has important policy implications and a ranking could be helpful for students to easily identify the institutions that are indeed contributing to educational and labor market outcomes.

Labor Market Returns of Attaining Certificates and Associate Degrees in Community Colleges

There has been a recent surge in the literature related to measuring the labor market returns of certificates or associate degrees (A.A.) in community colleges in the U.S. (Bahr, 2016; Belfield et al., 2014; Dadgar & Trimble, 2015; Dynarski et al., 2016; Bettinger & Soliz, 2016; Jepsen et al., 2014; Minaya & Scott-Clayton, 2017; Stevens et al., 2015; Xu & Trimble, 2016). In recent years, researchers had been able to gain access to panel data connecting degree attainment and earnings on multiple states including: Ohio, Virginia, North Carolina, and Tennessee. The majority of the studies have used individual-level FE models (Belfield & Bailey, 2016)[4] and have mostly concluded that indeed community college students who attained a certificate or A.A. degree benefited in terms of either increasing the probability of being employed or increasing their earnings. They have also found evidence in favor the A.A. and long-term certificates compared to short-term ones, and that the highest returns are for certificates in biological sciences, engineering and industrial technologies, health, law, and public and protective services (Bahr, 2016).

[4] Dynarski et al. (2016) wrote a methodological note related to the advantages and limitations of using an individual FE estimation strategy.

Methodology

Value-added (VA) models have their origin in K-12 education and are often used to evaluate teacher or school quality (Briggs, 2012; Buddin & Zamarro, 2009; Chetty, Friedman, & Rockoff, 2011; Gorard, 2008; Kane & Staiger, 2008; Sass, Hannaway, Xu, Figlio, & Feng, 2012). The two main challenges related to estimating VA models in higher education in the U.S. are: 1) having access to a reliable and valid instrument that measures the knowledge and skills gained by students in college, and 2) addressing selection bias from students deliberately choosing to attend certain colleges. Without good predictors of college choice, it is difficult to separate the college's contribution to learning from students' unobserved attributes such as motivation and previous academic preparation.

As mentioned above, Colombia has invested substantial resources in the development of a set of valid and reliable instruments to measure the knowledge and skills gained by students in high school (i.e., the SABER 11 national high school exit exam) and college (i.e., the SABER PRO college exit exam). Specifically, the national level datasets available in this country are ideal for conducting empirical estimations of VA models. First, Colombia has results for each student from instruments designed to measure learning at the end of high school (SABER 11) and college (SABER PRO). Second, Colombian students who want to access postsecondary education apply not only to specific colleges but also to a specific program (e.g., economics). Each college then selects students into a specific program mainly by looking at the student's SABER 11 scores. Given that we have access to information on the SABER 11 exam, which is the key driving factor of college-program enrollment decisions in Colombia, we are better able to correct for selection of students into universities and programs and to assess the importance of such sorting bias.[5] Only after correcting for this selection bias will we be able to assess whether VA models based on college-exit exams are promising methods to obtain meaningful estimates of the cognitive outcomes gained by students in different programs in different postsecondary institutions.

Data

SABER 11 and SABER PRO

SABER 11 is a compulsory high school-exit exam in Colombia. This test takes place twice every year (fall and spring) corresponding to two different high school graduation cohorts. As part of the test, socio-economical information of the students is gathered and knowledge in areas such as mathematics, physics, chemistry, biology, language, philosophy, social science and English is evaluated. A substantial number of private and public universities in the country use the score in the SABER 11 exam to admit students into selective postsecondary institutions and all of them require the applicant students to have successfully presented the test in order to be considered for admission (Barrera-Osorio & Bayona-Rodríguez, 2014).

SABER PRO[6] is the college-exit exam; since 2009, it has been compulsory for graduation for all students who completed 75% of the college program. It is composed of a generic and a subject-specific component. The generic part is based on the College Learning Assessment (CLA) and, since 2011, includes four modules: writing, English, reading/critical thinking, and problem solving/quantitative reasoning. The Colombian Institute for the Evaluation of Education (ICFES, acronym in Spanish) has been

[5] For a more detailed description of the potential of the Colombian data to ameliorate the self-selection issue see: Melguizo et al., (2016).
[6] For a more detailed description of SABER PRO see Domingue et al. (2014).

designing the subject-specific exams since 2007. Thus, it has implemented different versions of this part of the test since that year. Nevertheless, all modules of the generic component have been compulsory for students since the second semester of 2011. Also, since 2011 every program in the country has a subject-specific component, in addition to the generic component described above. In this paper we use the combined score of the generic component for all the students who have taken the test since the second semester of 2011, when the generic exam was fully developed and the SABER PRO was a compulsory requirement for graduation.

Datasets used to track students in college and after graduation

In order to identify the semester of entrance, graduation and labor market entrance for each student, we use two different datasets: the System for the Prevention of College Dropout (SPADIES, acronym in Spanish) and the information of the Labor Observatory for Education (OLE by its acronym in Spanish). Both sources are administered by the Colombian Ministry of Education (MEN by its acronym in Spanish). The first one gathers biannual information on all students who enter higher education, tracking them until they either drop out or graduate. In particular, this dataset provides us with information about the program a student attended, the college s/he attended, whether the student has graduated or drop out and her/his entrance cohort. The second dataset collects annual information for all graduates of higher education in Colombia on employment status, economic sector, and current salary.

Data and Sample

We use a comprehensive dataset that links information collected by the ICFES that collected the SPADIES and the OLE data. The Colombian Education Ministry linked the information for each student in these datasets and created a unique identification that allows us to track each student from the time they take SABER 11 until they appear in the OLE data. Our dataset includes information for multiple cohorts of students, which we use to conduct the estimates for the outcomes of interest. In the case of SABER PRO, we focus on students who took the test on 2011-2 (2011-2 refers to students who took the test in the second semester of 2011). In the case of graduation, we focus on cohorts of students who enrolled between 2007-1 and 2009-1 and we follow them to six years to graduate. For the analyses related to early labor market outcomes, the focus is on cohorts of students who graduated between 2010 and 2012. This data is censored for the late cohorts, since an individual who graduated in 2010 will be in the dataset for a longer period of time than the individual who graduated in 2012. However, given that most students get a job within two years after graduation, we think that this relatively shorter period is appropriate to observe the early labor outcomes of interest in this study.

Our sample for each outcome in the described cohorts is composed as follows: for SABER PRO we observe 15,327 students. They represent 786 programs with students in one of the following program categories: agriculture and veterinary, arts, education, health, social sciences and humanities, economics and business, engineering and architecture, and math and natural sciences. For the case of graduation, we observe 123,558 students. Finally, for early labor market outcomes, we observe 51,362 graduated students from 839 different colleges.[7]

[7] Tables A.1., and Table A.2., provide a description of the sample characteristics of the students. We decided to include it in the Appendix in order to focus the attention of the reader in the value-added results.

Empirical Models

We estimate value-added contributions by college-program to students' outcomes using versions of the following equation:

Consider outcome Y_{ijt}^{k}, where k=1, 2, 3, 4 refers to the four outcomes of interest, i to the student, j to the program, and t to the year. The contribution of program j to student i's outcome k can be expressed as follows:

$$Y_{ijt}^{k} = X_i\alpha^k + Z_{jt}\beta^k + u_j^k + \delta_t^k + \epsilon_{ijt}^k$$

Where Y_{ijt}^{k} denotes either standardized results in SABER PRO by graduating cohort and year, or measures of graduation or formal employment of student *i* of cohort *t* that graduates from college *c* and program p. X_i contains the following relevant student demographic information that determines both the outcome of interest and selection in specific colleges and programs: student gender, parental socio-economic status and mother's education. *Z* represents peer characteristics (average SABER 11 and average mother's education) in the student's available cohort; u_j is a program fixed effect, and δ_t^k is a year fixed effect. These variables, in particular the student's test results in SABER 11, allow us to control for selection bias due to students' choices of college and program. In that way we control for differential peer cohort qualities and obtain value-added college contributions purged of cohort effects. Finally, SABER PRO cohort dummies in regressions for SABER PRO, entrance to college cohort effects for regressions on graduation, and graduating cohort effects for analysis of labor market participation are in the specification to control for any remaining cohort effects. Finally, u_j^k our main parameters of interest, identifies college by program effects. By construction, these average out to zero. For a given college-program, this term measures the program's contribution to the student's outcome. Since, by constructions, these terms average out to zero, they estimate the difference between a program's contribution and the average contribution (which is equal to zero). Hence, a positive (negative) college-program effect indicates that the program's contribution is above (below) average. Since we only have data on students who have enrolled in SC programs, the college-program effects can only be interpreted in relation with each other, and not relative to the outcome the student would have obtained if she had not enrolled. Note that by estimating models that do not include a constant term, we are able to estimate these effects for all possible college-program combinations in our data, avoiding the problem of having to choose a college-program as reference.

Our preferred specification treats these effects as fixed effects and will then control for any correlation among the college-program effects and our explanatory variables. We believe this to be the most appropriate specification as one would expect that college-program contributions would potentially correlate with the explanatory variables, especially those related to the selection of students into colleges and programs. That is, one would expect that those institutions that contribute more to students' general knowledge, graduation, or labor outcomes might be also those with students that arrive with above average academic preparation and motivation into their college or programs.

Not controlling for this potential correlation could lead to biased estimated coefficients, including biased measures of college-program effects.[8]

We then applied a variance decomposition technique to our estimates of value-added, in order to understand the drivers of the variance of value-added among college-programs. Finally, to further our understanding of the institutional and market-level characteristics associated with variation in value-added, we used regression analysis as a way to identify the specific characteristics of the HEI (e.g., type, control, selectivity, mode of delivery and others) as well as the market (degree of concentration and competition, number of institutions in the field) that are associated with higher value-added for selected outcomes of interest.

Limitations

Two observations are in order. First, self-selection of students into programs might bias the estimated program-level contributions. As argued in Melguizo et al. (2016), our rich set of student characteristics largely mitigates this concern. Second, outcome data are not available for students who do not enroll in SCPs, or who enroll but do not finish. Hence, our estimated contributions might have omitted variable bias and it is important to remember that are relative to other SCPs; with the exception of graduation, they are conditional on students finishing the program.

[8] In order to test for the robustness of the results, we also test for other specifications often used in the context of K-12 education (e.g., aggregated residual methods). Aggregated Residual Methods (e.g., Kane and Staiger, 2008) where college-program effects are eliminated from the estimation equation and college-program contributions are obtained as averages of the estimated residuals after controlling for the rest of the covariates in equation (1). By comparing results with these two methods, we are able to assess how sensitive our college-program contribution estimates are to alternative specifications.

Results

We proceed to describe the results from the analyses. First, we present the results of value-added estimations and report the findings by college-program combination for the 25th, 50th, and 75th percentiles. Second, we describe the results of Figures 1-3, which illustrate the variation in value-added both *across* and *within fields of study*. Third, we present the results of the variance decomposition estimation followed by the regression analysis conducted to identify the association between selected HEI characteristics for three main outcomes: value-added in cognitive outcomes, graduation, and employment in the formal sector.

Value-Added Contribution in terms of Educational and Early Labor Market Outcomes

Table 1 presents results for cognitive (e.g., English, writing, reading, and quantitative reasoning), graduation, and labor market outcomes (e.g., formal employment and wages). Columns 1 and 2 show the mean and standard deviation of the actual outcomes, whereas columns 3 through 6 show statistics from the distribution of estimated value-added (standard deviation, and 25th, 50th, and 75th percentile). Column 7 shows the interquartile range of value-added (i.e., the difference between the 75th and 25th percentiles).

As column 1 shows, in the average program students score below average in the exit exam in English, writing, reading, and quantitative reasoning.[9] In the average program, 32.4 percent of students graduate, with a standard deviation. Of those who graduate, 76.3 percent of students find formal employment, and their average monthly

[9] Recall that test scores have mean zero and standard deviation one for the whole population of test takers, which includes students in bachelor's programs.

salary is equal to COP$884,000 (about US$300). This number corresponds to the official minimum salary in Colombia.

Columns 3 through 7 show remarkable variation in value-added by outcome. For instance, the standard deviation of value-added for each outcome (column 3) amounts to at least 67 percent of the standard deviation of the actual outcome (column 2). The difference between the 75th and the 25th percentile (column 7) accounts for 67 percent of the standard deviation of the actual outcome.

To further illustrate this variation, consider a student that goes from a college-program that delivers quantitative reasoning value-added in the 25th percentile to another that delivers value-added in the 75th percentile. For this student, the value-added is equal to 34 percent of a standard deviation (column 7), or 83 percent of the standard deviation of the actual outcome. Large variation in value-added prevails also in the other learning outcomes.

In terms of graduation, going from the 25th to the 75th percentile of the distribution of value-added implies an increase of 25 percentage points in the probability of graduation. Since the average program only has a 32 percent graduation rate, this improvement is clearly substantive.

There is also large value-added variation in terms of labor market outcomes. Going from the 25th to the 75th percentile of the distribution implies an increase of 22 percentage points in the probability of formal employment, or about one third of the average program outcome (equal to 76 percent). In terms of wages, going from the 25th to the 75th percentile of the value-added distribution entails an increase of COP$195,000, larger than the standard deviation of actual wages and equal to 22 percent of the mean program's wage.

Taken together, these results show that college-programs differ widely in their value-added contributions to student outcomes. This information is critical for policy makers who are trying to identify college-programs combinations that are doing a good job and therefore could serve as exemplars to other institutions. It is also critical for the government to identify these programs given that they are the ones that are bringing competition to SENA, the government provider of vocational and technical education in Colombia. Future studies should conduct similar analyses but focusing exclusively on the programs offered by SENA. Comparisons of value-added measures between SENA and other SCPs providers is critical as it would help the government identify the top ranked college-program combination in the nation and focus on strengthening them instead of expanding the supply through providers that are not contributing much in terms of critical outcomes.

<<Table 1>>

Value-Added Contribution in terms of Cognitive and Early Labor Market Outcomes by Field of Study

A number of studies have documented benefits both in terms of cognitive outcomes (Melguizo & Wainer, 2015; Shavelson et al., 2016) as well as early labor outcomes for students enrolled in particular fields such as health or Science, Technology, Engineering and Math (STEM) fields (Bahr, 2016; Carnevale, Rose, & Hanson, 2012; Melguizo & Wolniak, 2012). We wanted to explore the variation in value-added *across* field of study as a way to identify whether college-program combinations in particular fields such as engineering and architecture were adding more value than other fields such as social sciences. In addition, we wanted to explore the *within* field variation as a way to identify whether fields such as math had lower inter-quartile dispersion, and as a result more students enrolled in college-programs within this field experienced larger benefits in terms of educational and early labor market outcomes.

We present the estimates of value-added by field of study for the educational and early labor market outcomes (Figures 1 through Figure 4). Figure 1 presents the distribution of value-added in the four cognitive dimensions: writing, reading, English, and quantitative reasoning. Looking at the averages for the different fields for each of these dimensions, it is clear that there is not substantial variation across fields, as field-level averages are all very similar and close to the overall average of zero. This means that none of the college-program combination in these fields is substantially contributing to helping students with their writing skills. The results are similar for the figures illustrating the average value-added in terms of reading, English, and quantitative reasoning. In other words, we find evidence of little variation in value-added *across fields of study*.

Looking at the four different dimensions illustrated in Figure 1, there is evidence of substantial variation in value-added *within fields of study*. For example, students enrolled in economics, administration and accounting had impacts that ranged from a negative standard deviation to a positive standard deviation in terms of contribution in their writing skills. This result was prevalent for all the fields of study. The larger within-field variation was evident in economics, administration, and accounting, and engineering and architecture, whereas the fields with the narrower within field dispersion were health, math and natural sciences, and agronomy and veterinary. In summary, the picture that emerges from this analysis is that there is wide variation in terms of value-added in cognitive outcomes within fields of study. The fields where more variation was present were economics, administration and accounting, and engineering and architecture.

<<Figure 1 >>

Figure 2 presents value-added in terms of graduation. There is some evidence that students who pursued a major field of study in either health or mathematics and natural sciences benefitted more, on average, in terms of graduation compared to peers pursuing a degree in all the others fields of study: social sciences, economics, business, and accounting, engineering, agronomy and veterinary, and arts. There is also evidence of substantial within field of study variation in terms of graduation value-added, in particular for students enrolled in the fields of fine arts, as well as economics, business administration and accounting, and engineering and architecture. This finding is consistent with the results of value-added in terms of student cognitive outcomes.

<<Figure 2>>

The early labor outcomes value-added in terms of obtaining employment in the formal sector as well as an increase in early wages are illustrated in Figures 3 and 4. Figure 3 paints a slightly different picture in terms of formal employment compared to cognitive outcomes and graduation rates. The greatest value-added in terms of obtaining employment in the formal sector and wages are concentrated in three fields: economics, business administration and accounting, engineering and architecture, and math and natural sciences. It is worth noting that unlike the field of math and natural sciences, where there is relatively low within field variation, there is a wide spread in the contribution to degree attainment for students enrolling in economics, business administration and accounting as well as in engineering and architecture. This finding is probably related to the fact that there much less college-program combinations in the fields of math and natural sciences (See Table A.2).

<<Figure 4>>

Figure 4 presents the results in terms of gains in monthly wages. Consistent with the previous findings, there is not much variation across fields. Once again, the results suggest substantial within field variation. It is important to highlight the wide variation in high-demand fields such as economics, business administration and accounting, engineering and architecture. The results suggest that the value-added to early earnings for college-program combinations in engineering and architecture range from about minus COP$400,000 (e.g., US$130) to about COP$700,000. (e.g., about US$225).

<<Figure 5>>

Decomposition of the Variance of the Value-Added

The previous results paint a clear picture of substantial within field variation in terms of college-program combination for all the cognitive outcomes and early labor market outcomes of interest. We were interested in gaining a better understanding of whether the variation is explained more by the institution attended, the field of study or the program. We use a variance decomposition technique (Lemieux, 2006) to further explore this issue and report the results in Table 2.

Table 2 presents the results of the variance decomposition for each of the educational and labor outcomes of interest. We decompose the variance into three components: institution, field, and program-specific. Panel 1 shows the variances themselves, and panel 2 shows the fraction of the total variance of value-added attributable to each component.

Looking at the results in Panel 2, it is clear that between 44 and 67 percent of the total variance of value-added is attributable to the program itself, above and beyond institutions and fields (for instance, whether the program has an entrepreneurial director, or whether it has an internship requirement). Of the remaining variance, institutions account for a much larger fraction of the variation than fields, as they account for 78-97 percent of the remaining variance.

Taken together these findings suggest that while most of the variation in value-added is accounted for by program-specific characteristics, above and beyond those of the institution and field, much of the remaining variation is due to the institutions rather than the field.

<<Table 2>>

Selected Characteristics of Higher Education Institutions Associated with Value-Added in Quantitative Reasoning, Graduation, and Employment in the Formal Sector

The final set of analyses report the association between program value-added and some institutional and market characteristics. For the purposes of this analysis, a market is defined as a combination of knowledge area and city (for instance, health in Bogota). We focus on value-added for three outcomes of interest: quantitative reasoning, graduation, and employment in the formal sector[10] (See Tables 3-5). We leveraged the richness of our data to explore which were some of the institutional characteristics such

[10] We estimated the models for value-added in the other dimensions of the cognitive outcomes, as well as wages. These results are available in the Appendix.

as: duration and type of the program (technical program, lasting 2 years, vs. technological programs, lasting 3 years), type of institution (universities, technological schools, technical and technological institutes), SENA's presence in the market (e.g., a dummy variable that identifies whether SENA offers a SC-program), control and selectivity of the institution (selective-public, selective-private, non-selective public, and non-selective private), control (e.g., public or private), size (number of SCPs offered by the institution in the city), Herfindahl index of competition (this ranges from 0 to 1, where 1 means that one program captures all the enrollment in the market), market share (the program's share of enrollment in the market), mode of delivery (brick and mortar versus online or hybrid program), share of students who pay a high tuition (based on student's self-reported tuition at the time of taking the college-exit exam), and accreditation (equal to one if the program received high-quality accreditation from the MEN).

Table 3 presents the results of the regression analysis between the value-added in terms of quantitative reasoning and selected institutional and market characteristics. We estimated Models 1 through 7, which include selected groups of institutional characteristics (e.g., Model 1 includes relevant HEI characteristics including the selectivity-control variable, Model 2 includes relevant HEI excluding selectivity-control, and includes only control (e.g., public versus private), and so on and so forth). We only report findings of associations that were statistically significant for the different model specifications.

The results suggest that larger gains in quantitative reasoning were more prevalent at technological schools than universities or technical and technological institutions. Similarly, public institutions contributed more than private, particularly selective public institutions. Finally, we found that programs with a higher share of the market, and therefore compete in a more concentrated market, had lower value-added in quantitative reasoning.

<<Table 3>>

Looking at the association between specific HEI characteristics and market share and value-added in terms of graduation it is clear that the technological (3-year) programs were doing a much better job than the technical (2-year) programs. Contributions are lower in universities than technological schools or technical adn technological institutes. Institutions that teach more programs in the market have lower value-added. Selective public institutions have higher value-added. In markets where SENA is present, value-added is lower. Not surprisingly, attending a brick and mortar program as opposed to an online program was associated with more gains in terms of graduation. Attending a program with quality accreditation, in contrast, delivers lower gains.

<<Table 4>>

The last set of results refers to the value-added in terms of gaining employment in the formal sector. In this case again attending a technological (3-year) as opposed to a technical (2-year) program was associated with a 3 percent higher likelihood of gaining employment in the formal sector (with the exception of models 3 and 5). The results based on selectivity and control of the institution are also intuitive in the sense that the larger gains in formal employment were in the more selective programs at private institutions. In other words there is suggestive evidence that the high-end private institutions were outperforming their low-end private, low-end public and high-end public institutions in terms of obtaining employment in the formal sector. We also found evidence that programs that have a larger share of the market and therefore face less competition were not as effective in adding value in terms of employment in the formal sector. These results suggest that the high-end private institutions might have an advantage in terms of leveraging their established connections with the formal sector to place their students.

<<Table 5>>

Conclusions and Policy Implications

The results suggest great variation in the contribution made by programs to student cognitive, graduation, and labor market outcomes. This means that even though SC-programs are providing the part-time flexibility and short duration that non-traditional students need in order to pursue a postsecondary degree, the wide dispersion in terms of college-program "quality" is worrisome, and possibly calls for stronger monitoring on the part of the policymaker.

The tool-set developed in this paper can be used to create an interactive tool where potential students can clearly see the rank of the different college-program combinations. This tool might help students identify and apply to the SC-programs that are contributing more in terms of cognitive outcomes and early labor market outcomes. A potential unintended consequence of relying on this ranking system is that by design it will create more demand for the highly ranked programs, which will in turn make them more selective, which could potentially serve as a tracking mechanism for savvy middle-income students and families to gain access to the limited number of places at the top ranked institutions. In order to avoid this potential negative outcome, the policy maker might want to create incentives for these programs to expand and use the ranking as one of the multiple measures used for accountability and resource allocation purposes. This finding is in line with early recommendations from the World Bank (2003) for the need to create a system with the dynamic capacity for monitoring and evaluation, and disseminate to all stakeholders information about tertiary education its opportunities and costs, and include information about labor market perspectives and that also must cater for students from all groups of society by promoting greater equity in access to university and technical tertiary education, and diversify and provide flexible academic credit transfer mechanisms between tiers of higher education institutions.

Finally, even though this study is one of the first to provide value-added estimates in the context of SC-programs, the reality in Colombia is that SENA is the largest provider of VTET offering training throughout the Colombian territory. Therefore it is imperative that the tool-set developed in this paper is replicated using data from SENA. Only then the government will be able to gain a complete picture of the realities of SC-programs in the country and use the ranking system for accountability and resource allocation purposes.

References

Arum, R., & Roksa, J. (2011). Academically adrift: Limited learning on college campuses. University of Chicago Press.

Attanasio, O., Kugler, A., & Meghir, C. (2011). Subsidizing vocational training for disadvantaged youth in Colombia: Evidence from a randomized trial. *American Economic Journal: Applied Economics,* 3(3), 188-220.

Bahr, P. R. (2016). The Earnings of Community College Graduates in California. A CAPSEE Working Paper. Center for Analysis of Postsecondary Education and Employment.

Barrera-Osorio, F., & Bayona-Rodríguez, H. (2014). The causal effect of university quality on labor market outcomes: Empirical evidence from Colombia. V Seminario Internaciónal ICFES sobre Investigacion en la Calidad de la Educación, Bogotá, Colombia.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, 70(5, Part 2), 9-49.

Bailey, T., Jenkins, D., Belfield, C. R., & Kopko, E. (2016). Matching talents to careers: From self-directed to guided pathways. Matching students to opportunity, 79-98.

Belfield, C., Liu, Y. T., & Trimble, M. J. (2014). Labor Market Returns to Community College: Evidence from North Carolina. Research Brief. Center for Analysis of Postsecondary Education and Employment.

Bernal, R. (2015). The impact of a vocational education program for childcare providers on children's well-being. *Economics of Education Review*, 48, 165-183.

Bettinger, E., & Soliz, A. (2016). Returns to Vocational Credentials: Evidence from Ohio's Community and Technical Colleges. A CAPSEE Working Paper. Center for Analysis of Postsecondary Education and Employment.

Briggs, D. C. (2012). Making value-added inferences from large-scale assessments. Improving large-scale assessment in education: Theory, issues and practice, 186-206.

Buddin, R., & Zamarro, G. (2009). Teacher qualifications and student achievement in urban elementary schools. *Journal of Urban Economics*, 66(2), 103-115.

Busso, M., Cristia, J., Hincapié, D., Messina, J., & Ripani, L. (Eds.). (2017). Learning Better: Public Policy for Skills Development. Inter-American Development Bank.

Carfi, C. J. (Ed.). (2010). Recent trends in technical education in Latin America. Paris, France: UNESCO, International Institute for Educational Planning. Retrieved August 19, 2018, from http://www.iiep.unesco.org/en

Carnevale, A. P., Rose, S. J., & Hanson, A. R. (2012). Certificates: Gateway to gainful employment and college degrees. Washington, DC: Center on Education and the Workforce, Georgetown University.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2011). The long-term impacts of teachers: Teacher value-added and student outcomes in adulthood (No. w17699). National Bureau of Economic Research.

Cunha, J. M., & Miller, T. (2014). Measuring value-added in higher education: Possibilities and limitations in the use of administrative data. *Economics of Education Review*, 42, 64-77.

Dadgar, M., & Trimble, M. J. (2015). Labor market returns to sub-baccalaureate credentials: How much does a community college degree or certificate pay?. *Educational Evaluation and Policy Analysis*, 37(4), 399-418.

Domingue B, Lang D†, Cuevas ML, Castellanos M, Lopera C, Marino JP, Molina A, Shavelson R. (2017). Measuring student learning in technical programs: A case study from Colombia. *AERA Open*. doi: 10.1177/2332858417692997

Dynarski, S., Jacob, B., & Kreisman, D. (2016). The Fixed-Effects Model in Returns to Schooling and Its Application to Community Colleges: A Methodological Note. Center for Analysis of Postsecondary Education and Employment.

Ferreyra, M. M., Avitabile, C., Botero Álvarez, J., Haimovich Paz, F., & Urzúa, S. (2017). At a crossroads: higher education in Latin America and the Caribbean. The World Bank.

Fordham, E., & Pons, A. (2016). Education in Colombia. Paris, France: OECD Publishing. doi:10.1787/9789264250604-en

Gorard, S. (2008). The value - added of primary schools: what is it really measuring?. *Educational Review*, 60(2), 179-185.

Hoxby, C. (2015). Computing the value-added of American postsecondary institutions. Internal Revenue Service, US Department of the Treasury, Washington, DC.

Jepsen, C., Troske, K., & Coomes, P. (2014). The labor-market returns to community college degrees, diplomas, and certificates. *Journal of Labor Economics*, 32(1), 95-121.

Kane, T. J., & Staiger, D. O. (2008). Estimating teacher impacts on student achievement: An experimental evaluation (No. w14607). National Bureau of Economic Research.

Lemieux, T. (2006). Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?. *American Economic Review*, 96(3), 461-498.

Matsudaira, J. (2016). Defining and measuring institutional quality in higher education. In Quality in the undergraduate experience: What is it? How is it measured? Who decides? (pp. 57-80). National Academies Press, Washington DC.

Melguizo, T. & Coates, H. (2017). The value of assessing higher education student learning outcomes (editorial). *AERA Open Higher Education Special Topic*, 3(3), 1-2.

Melguizo, T., & Wainer, J. (2015). Toward a set of measures of student learning outcomes in higher education: evidence from Brazil. *Higher Education*, 72(3), 381-401.

Melguizo, T., & Wolniak, G. (2012). The earnings benefits of majoring in STEM fields among high achieving minority students. *Research in Higher Education,* 53(4), 383-405.

Melguizo, T., Zamarro, G., Velasco, T., & Sanchez, F. J. (2016). The methodological challenges of measuring student learning, degree attainment, and early labor market outcomes in higher education. *Journal of Research on Educational Effectiveness*, 10(2), 424-448.

Minaya, V., & Scott-Clayton, J. (2017). Labor Market Trajectories for Community College Graduates: New Evidence Spanning the Great Recession. A CAPSEE Working Paper. Center for Analysis of Postsecondary Education and Employment.

OECD. (2017). Education at a Glance 2017: OECD Indicators. Paris, France: OECD. Publishing. doi:10.1787/eag-2017-76-en

Saavedra, A. R., & Saavedra, J. E. (2011). Do colleges cultivate critical thinking, problem solving, writing and interpersonal skills?. *Economics of Education Review*, 30(6), 1516-1526.

Saavedra, J. E. (2008). The returns to college quality: A regression discontinuity analysis. Harvard University, Cambridge, MA.

Sass, T. R., Hannaway, J., Xu, Z., Figlio, D. N., & Feng, L. (2012). Value added of teachers in high-poverty schools and lower poverty schools. *Journal of urban Economics,* 72(2-3), 104-122.

Shavelson RJ, Domingue B, Marino J, Mantilla AM, Morales JA, Wiley, E. (2016). On the Practices and Challenges of Measuring Higher Education Value Added: The Case of Colombia. *Assessment and Evaluation in Higher Education*. doi:10.1080/02602938.2016.1168772

Spence, M. (1973): Job market signaling, *Journal of Labor Economics*, 87, 355-374.

Steedle, J. T. (2012). Selecting value-added models for postsecondary institutional assessment. *Assessment & Evaluation in Higher Education*, 37(6), 637-652.

Stevens, A. H., Kurlaender, M., & Grosz, M. (2015). Career technical education and labor market outcomes: Evidence from California community colleges (No. w21137). National Bureau of Economic Research.

UNESCO Santiago. (2017). Technical and Vocational Education and Training (TVET) in Latin America and the Caribbean. A regional approach towards 2030(pp. 1-32, Working paper). Santiago, Chile: UNESCO Santiago.

World Bank Group. (2003). Tertiary Education in Colombia: Paving the Way for Reform. Washington, D.C.: World Bank Group. Retrieved August 24, 2018, from http://documents.worldbank.org/

Xu, D., & Trimble, M. (2016). What about certificates? Evidence on the labor market returns to nondegree community college awards in two states. *Educational Evaluation and Policy Analysis*, 38(2), 272-292.

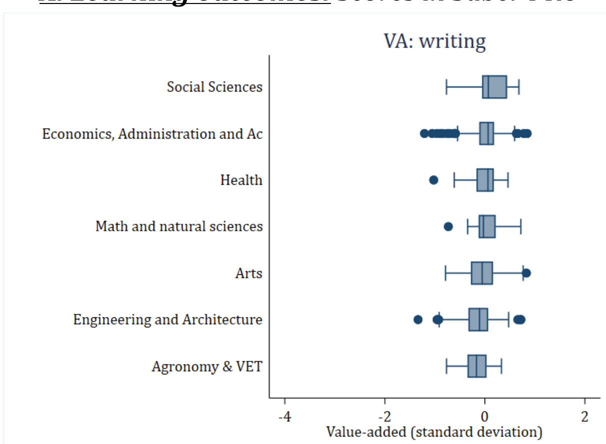
Table 1. Estimates of the Relative Value-Added Distribution by Student Learning and Early Labor Market Outcomes

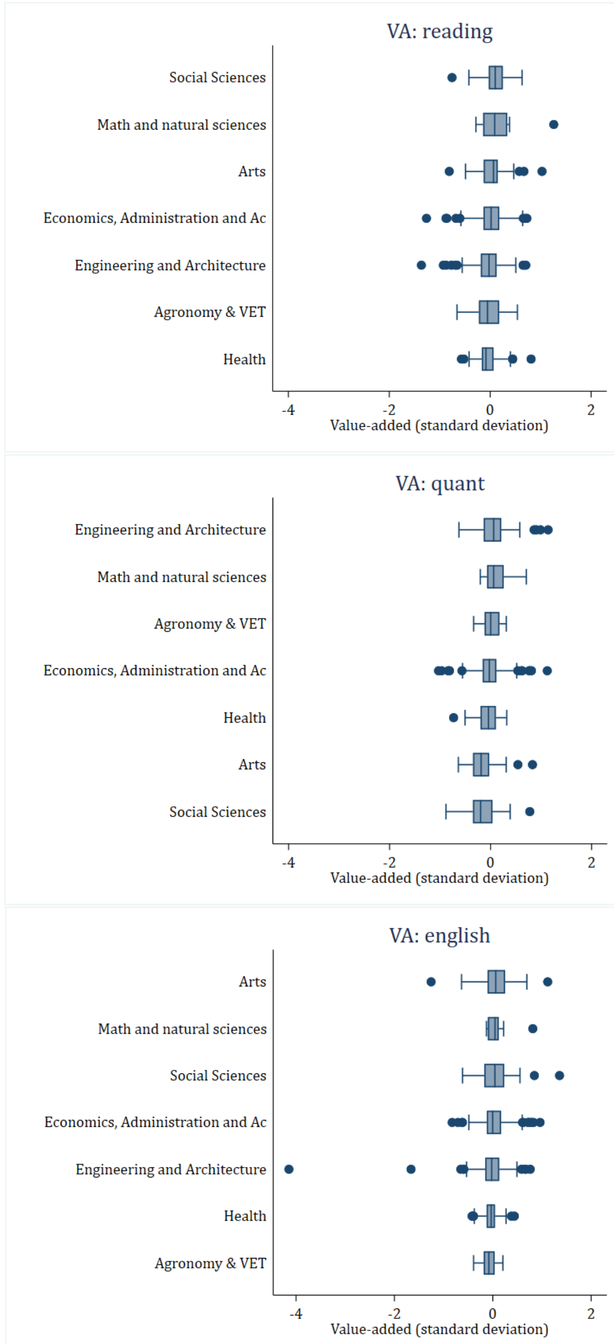
	Outcomes		Value Added				ΔOutcome
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome	mean	Sd.	Sd. VA	p25_VA	p50_VA	p75_VA	p75-p25
Learning outcomes							
English	-0.217	0.423	0.300	-0.129	-0.005	0.154	0.283
Writing	-0.310	0.363	0.314	-0.219	-0.020	0.161	0.380
Reading	-0.243	0.384	0.269	-0.156	0.000	0.160	0.316
Quant	-0.189	0.407	0.272	-0.191	-0.014	0.147	0.338
Graduation							
Graduation	0.324	0.195	0.196	-0.109	0.012	0.144	0.253
Labor market outcomes							
Employment	0.763	0.160	0.156	-0.112	0.016	0.105	0.216
Wage	884.370	172.722	158.189	-127.066	-41.016	67.806	194.872

Note: Stats are measures by program. Value added is outcome to model with fixed effect and including age.

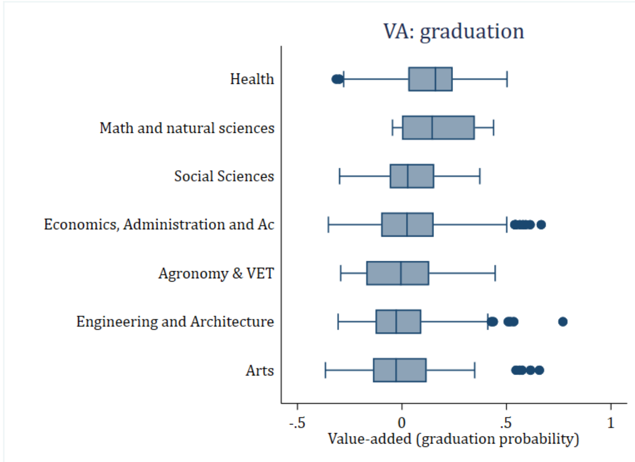
Figures 1-3. Variation of the College-Program level Average Outcomes and Estimated Value-Added by Field of Study

A. Learning outcomes: *Scores in Saber PRO*

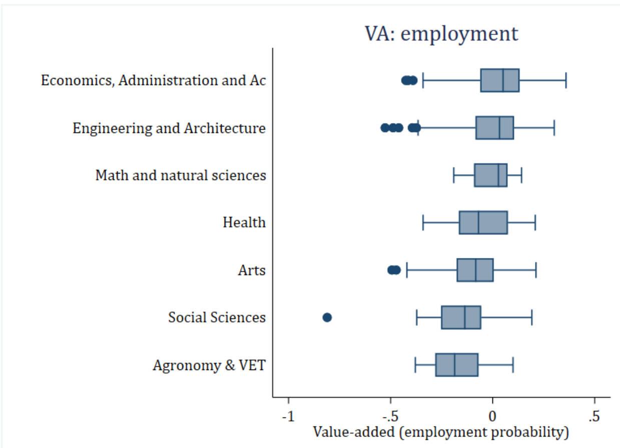




B. Graduation:



C. Labor market outcomes: *Employment and wages*



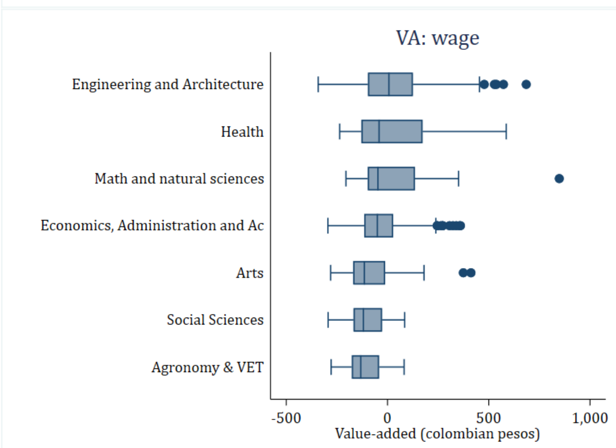


Table 2. Value-added variance decomposition

	Writing	English	Reading	Quant	Graduation	Employment	Wage
1. Overall variance	0.0987	0.0903	0.0723	0.0741	0.0384	0.0243	25023.78
2. Variance explained by differences across programs	0.0663	0.0609	0.0475	0.0489	0.0169	0.0112	14831.89
3. Variance explained by differences across institutions	0.0263	0.0290	0.0240	0.0194	0.0205	0.0104	8410.68
4. Variance explained by differences across fields	0.0075	0.0009	0.0016	0.0063	0.0008	0.0030	1430.98
5. Covariance between institutions and fields	-0.0006	-0.0003	-0.0004	-0.0002	0.0002	-0.0002	175.12
In relative terms							
% variance explained by differences across programs (2/1)	67.12	67.46	65.69	65.90	43.89	46.23	59.27
% variance explained by differences across institutions & fields (3+4+5)/1	33.53	32.87	34.86	34.39	55.69	54.47	40.03
% variance explained by differences across institutions (3/1)	26.60	32.18	33.20	26.21	53.24	42.69	33.61
% variance explained by differences across fields (4/1)	7.59	1.02	2.21	8.47	2.04	12.47	5.72
% non-program variance explained by differences across institutions (3/ (3+4))	77.80	96.93	93.76	75.57	96.30	77.40	85.46

Table 3. Association between Contribution to Quantitative Reasoning and Selected Institutional and Market Characteristics

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5	(6) est6	(7) est7
3-year program	0.010 (0.023)	0.007 (0.022)	0.006 (0.022)	0.006 (0.022)	0.006 (0.022)	0.006 (0.022)	0.013 (0.021)
Technological School	0.050** (0.024)	0.056** (0.023)	0.049** (0.023)	0.050** (0.024)	0.050** (0.023)	0.050** (0.024)	
University	0.019 (0.028)	0.029 (0.027)	0.027 (0.027)	0.027 (0.027)	0.027 (0.027)	0.027 (0.027)	
HEI size	0.002* (0.001)	0.002* (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	
Low-end Private	-0.050** (0.024)						
Low-end Public	0.013 (0.030)						
High-end Public	0.075** (0.032)						
Public institution		0.063*** (0.022)	0.074*** (0.022)	0.074*** (0.022)	0.075*** (0.022)	0.075*** (0.022)	0.059*** (0.022)
HH index in the market			-0.088** (0.040)	-0.090* (0.048)			
SENA (2y) is in the market				-0.002 (0.027)		-0.001 (0.027)	
Market share					-0.087** (0.038)	-0.088** (0.045)	
Face-to-face program							0.016 (0.030)
% tuition >COP$3000k							-0.003 (0.061)
Quality accreditation							0.048 (0.037)
Constant	-0.065** (0.029)	-0.088*** (0.024)	-0.062** (0.027)	-0.061* (0.033)	-0.068*** (0.025)	-0.067** (0.031)	-0.061* (0.033)
r2_a							
N	746.000	786.000	786.000	786.000	786.000	786.000	786.000

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Association between Contribution to Graduation and Selected Institutional and Market Characteristics

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5	(6) est6	(7) est7
3-year program	0.027***	0.026***	0.027***	0.025***	0.026***	0.024**	0.029***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Technological school	-0.011	-0.006	-0.004	0.003	-0.006	0.004	
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	
University	-0.077***	-0.073***	-0.074***	-0.069***	-0.073***	-0.067***	
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	
HEI size	-0.004***	-0.004***	-0.003***	-0.003***	-0.004***	-0.003***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Low-end private	0.015						
	(0.010)						
Low-end public	0.015						
	(0.012)						
High-end public	0.033**						
	(0.013)						
Public institution		0.017*	0.011	0.010	0.016*	0.014	-0.013
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
HH index in the market			0.040**	0.005			
			(0.018)	(0.020)			
Sena (2y) is in the market				-0.038***		-0.048***	
				(0.011)		(0.011)	
Market share					0.006	-0.034*	
					(0.017)	(0.019)	
Face-to-face program							0.027*
							(0.015)
% tuition >$3000k							0.022
							(0.030)
Quality accreditation							-0.062***
							(0.018)
Constant	0.066***	0.073***	0.061***	0.088***	0.071***	0.102***	0.016
	(0.012)	(0.011)	(0.012)	(0.014)	(0.011)	(0.013)	(0.017)
r2_a							
N	701.000	704.000	704.000	704.000	704.000	704.000	481.000

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Association between Contribution to Gaining Employment in the Formal Sector and Selected Institutional and Market Characteristics

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5	(6) est6	(7) est7
3-year program	0.036* (0.019)	0.033* (0.019)	0.029 (0.019)	0.032* (0.019)	0.028 (0.019)	0.032* (0.019)	0.036* (0.021)
Technological School	0.046** (0.020)	0.042** (0.019)	0.028 (0.019)	0.020 (0.019)	0.029 (0.019)	0.019 (0.019)	
University	0.008 (0.023)	0.014 (0.023)	0.013 (0.023)	0.008 (0.023)	0.013 (0.023)	0.007 (0.023)	
HEI size	0.002** (0.001)	0.002** (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	
Low-end Private	-0.056*** (0.020)						
Low-end Public	-0.084*** (0.024)						
High-end Public	-0.044* (0.025)						
Public institution		-0.039** (0.018)	-0.020 (0.018)	-0.020 (0.018)	-0.021 (0.018)	-0.020 (0.018)	-0.034 (0.021)
HH index in the market			-0.191*** (0.036)	-0.144*** (0.042)			
SENA (2y) is in the market				0.048** (0.023)		0.055** (0.022)	
Market share					-0.167*** (0.034)	-0.118*** (0.039)	
Face to face Program							0.020 (0.030)
% tuition >$3000k							0.022 (0.069)
Quality accreditation							-0.003 (0.032)
Constant	-0.040* (0.024)	-0.065*** (0.020)	-0.012 (0.023)	-0.048* (0.028)	-0.027 (0.022)	-0.064** (0.027)	-0.051 (0.033)
r2_a							
N	793.000	839.000	839.000	839.000	839.000	839.000	612.000

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$