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The Contribution of Short-Cycle Programs to Student Outcomes: Evidence from Colombia[1]

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Abstract

Short-cycle higher education programs (SCPs), lasting two or three years, capture about a quarter of higher education enrollment in the world and can play a key role enhancing workforce skills. In this paper, we estimate the program-level contribution of SCPs to student academic and labor market outcomes, and study how and why these contributions vary across programs. We exploit unique administrative data from Colombia on the universe of students, institutions, and programs to control for a rich set of student, peer, and local choice set characteristics. We find that program-level contributions account for about 60-70 percent of the variation in student-level graduation and labor market outcomes. Our estimates show that programs vary greatly in their contributions, across and especially within fields of study. Moreover, the estimated contributions are strongly correlated with program outcomes but not with other commonly used quality measures. Programs contribute more to formal employment and wages when they are longer, have been provided for a longer time, are taught by more specialized institutions, and are offered in larger cities.

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1. Introduction

By developing skilled human capital, higher education plays a critical role in a country's productivity and equity. Short-cycle programs (SCPs), which typically last two or three years, offer specialized and practical higher education training in areas and skills that are intentionally aligned with marketplace needs. As of 2017, enrollment in SCPs made up 24 percent of higher education enrollment worldwide (Ferreyra et al. 2021). In today's economy, where the demand for technical skills and analytical skills has grown rapidly—particularly since the COVID-19 pandemic—SCPs can play an important role in workforce upskilling and reskilling.

Despite the broad appeal of SCPs, little is known about the extent of their contributions to students' knowledge, employment opportunities, and earnings; or about the program characteristics that explain these contributions, particularly in developing countries.[6] Assessing how, and to what extent, SCPs contribute to student outcomes has crucial implications for regulatory bodies; for organizations that support individuals making decisions about higher education; and for those who create, replicate, or seek to expand good programs.

In this paper, we estimate the program-level value added contribution of SCPs[7] to student academic and labor market outcomes in Colombia.[8] We study how and why these contributions vary across programs and identify the program and institution characteristics and practices (or "quality determinants") as well as local market conditions associated with these contributions.

[6] Most recent evidence on SCPs' contributions to student and labor market outcomes is for developed countries. See, for instance, Belfield and Bailey (2011), Bahr (2016), Belfield and Bailey (2017), Bertrand et al. (2019), Bettinger and Soliz (2016), Carrell and Kurlaender (2019), Dadgar and Trimble (2015), Evans et al. (2020), Jepsen et al. (2014), Marcotte (2019), Minaya and Scott-Clayton (2022), Stange (2012), Stevens et al. (2015), and Xu and Trimble (2016).
[7] We define a program as a combination of degree and institution. For example, nursing at *UniMinuto* and nursing at *Tecnologico de Antioquia* are two different programs.
[8] The literature uses different terms to refer to value added, such as "productivity" (see Hoxby and Stange, 2020) and "contribution" (see Melguizo et al. 2016; Altonji and Mansfield, 2018; and Jackson, 2018). In this paper, we use the expressions "contribution" and "value added" interchangeably.

Since SCPs are more popular in Colombia than other Latin American countries, the ample supply of SCPs in Colombia provides an excellent context to study these programs' contributions.[9]

We collect countrywide administrative data on student background characteristics and outcomes, including learning outcomes at the end of the program (reading and quantitative reasoning test scores) as well as graduation and labor market outcomes (formal sector employment and wages). We combine the student-level data with detailed information on characteristics and practices from the universe of programs and SCP providers in the country and build novel, complementary measures of local SCP supply and the competitive environment facing institutions and programs. This rich data allows us to minimize self-selection when estimating program contributions (Hoxby, 2020).

Following Melguizo et al. (2016) and Smith and Stange (2016), we use program fixed-effect methods to estimate multiple value-added models. Like Minaya and Scott-Clayton (2022), we assess how estimates differ across models. We first control just for individual characteristics (I), then I and peer characteristics (Z), and subsequently include I and Z along with measures of local SCP supply (S, which includes measures of program supply, capacity, selectivity, and cost) at the student's high school city. We find that including additional controls beyond I yields substantially different estimates of the contribution to learning outcomes but not to graduation or labor market outcomes. This implies that, for the latter, self-selection is addressed appropriately by including only variables for individual characteristics, I. Since the specification that includes I, Z, S, and program-level fixed effects as regressors yields the lowest root mean squared residual by outcome, our analysis relies on this model.

[9] While less than 10 percent of higher education students in Latin America and the Caribbean were enrolled in SCPs in 2017, this share was about 30 percent in Colombia (Ferreyra et al. 2021), close to that in the United States.

To understand how much explained variation in student outcomes is due to *I, Z, S,* and program fixed effects, we conduct a Shapley-Owen decomposition of R-squared (Shapley 1953; Owen 1977; Huettner and Sunder 2012.) Which set of variable explains the most varies across outcomes. For learning outcomes, *I* and *Z* account for up to 70 percent of the explained variation, whereas for graduation and labor market outcomes, program fixed effects account for 60-70 percent of explained variation. Such large role for programs in graduation and labor market outcomes highlights the need to understand program-level contributions and leads us to focus on those outcomes (rather than learning outcomes) in the remainder of the paper.

We find tremendous variation in program contributions across programs (as in Melguizo et al. 2016) and explore it in four different ways. First, given the distributions of estimated value added, our estimates show that there is a 19-percentage point (pp) increase in formal employment probability—or about one-fourth of the average program's outcome (equal to 76 percent)—when going from a program whose formal employment contribution ranks in the 25th percentile to another that ranks in the 75th percentile. Further, value added varies not only across fields, but even more so within fields. For example, health programs make the greatest contribution to wages. However, among programs in the health field, moving from the 25th to the 75th percentile of value-added distributions entails a 27 percent increase in wages.

Second, we explore whether these value-added estimates reflect similar information to that contained in other, commonly used program quality measures, such as program average outcomes, tuition, or incoming students' average score in Colombia's mandatory high school exit exam. Our estimated contributions correlate strongly with program outcomes but not with the other measures. In other words, our value-added estimates have the desirable feature of capturing elements related to outcomes rather than inputs.

Third, we assess whether program-level contributions are systematically related to institution fixed effects (capturing, for instance, institutional resources or prestige) or field of study fixed effects (as some fields may offer, for example, better labor market opportunities than others). Our results indicate that, together, institution and field fixed effects account for about 40 and 60 percent of the variation in the contributions to graduation and labor market outcomes, respectively. More than 75 percent of the explained variation for all outcomes corresponds to the institution fixed effects, indicating that the role of institution-level resources, policies, and labor market connections is greater than that of fields of study.

Fourth, as in Dinarte et al. (2021), we look at program value added and its relationships to quality determinants—including program characteristics (duration, delivery modality, and age), institution characteristics (type of governance, type of institution, and size), and institution and program practices (selectivity, field of specialization, and program's accreditation status)—as well as local market conditions (institution's market power, local market concentration, and city size), while controlling for field fixed effects. We define a market as a combination of field of study and city (e.g., Nursing in Bogotá). To our knowledge, this is the first paper that analyzes the association between program contributions and local market conditions.

Our estimates suggest that programs contribute more to formal employment and wages when they last three years rather than two, have been offered for a longer time, are taught by more specialized institutions, and are offered in larger cities. Within a field, then, programs that exhibit these characteristics—which may proxy for reputation, instructional and training quality, and labor market opportunities—seemingly contribute more than others to student labor market outcomes. We also find that programs contribute less to graduation when they have been offered for a longer time and are taught by larger institutions or in more concentrated markets. Nonetheless, graduation and graduation value added must be considered carefully because institutions can manipulate graduation rates (for example, by changing graduation standards) in ways that do not necessarily reflect human capital accumulation.

Finally, we explore the implications of ranking programs based on their average outcomes or contributions. We construct multiple program rankings and find, as in Minaya and Scott-Clayton (2022), that they are highly sensitive to the underlying metric. Since different rankings convey widely different messages, rankings may not be a desirable vehicle to convey information.

A skeptical reader might question the external validity of our study because we focus on one country. Similar to Chile, Thailand, South Africa, and Kenya, Colombia is a middle-income country in the process of transitioning to high-income status. Therefore, the results of this study are relevant for other countries. Furthermore, our methodology can be applied to other countries as long as the corresponding administrative data are available. For example, Dinarte et al. (2021) recently used this approach to estimate SCP contributions in multiple Latin American countries.

The remainder of the paper is organized as follows: Section 2 reviews related literature and Section 3 describes the institutional context of SCPs in Colombia. Sections 4 and 5 describe the data and estimation approach, respectively. Section 6 discusses the results. Section 7 draws conclusions and presents some policy implications.

2. Related Literature

We contribute to several strands of literature. First, we contribute to work measuring program or institution value added to student outcomes in higher education.[10] For the United States (US), researchers have recently studied higher education contributions to educational attainment and

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[10] Shavelson et al. (2016) discuss at length the methodological challenges of estimating value added, while Hoxby and Stange (2020) similarly discuss the additional challenges of estimating higher education productivity.

labor market outcomes.[11] For Colombia, recent studies estimate program value added to learning outcomes for bachelor's programs, taking advantage of the availability of data on high school and college exit exams in addition to a rich set of student background characteristics.[12] Other studies estimate institution-level value added or the effects of attending selective institutions on learning and labor market outcomes.[13] Our paper differs from this literature because we estimate value added for SCPs (as opposed to bachelor degrees) while considering a broad range of outcomes.[14]

Second, we relate to the literature on community colleges (CCs) in the US. Despite the importance of these institutions and a relatively rich literature studying them, little research exists on quality differences among institutions,[15] although a greater number of studies have explored the labor market returns to certificates and associate's degrees from CCs. In recent years, researchers have gained access to panel datasets connecting degree attainment with earnings in multiple states in the US.[16] These studies generally find that CC students who obtained a certificate or associate degree benefited more in terms of labor market outcomes compared to those who did not enroll in a CC. While this literature quantifies the gains from CC attendance relative to not attending, our paper compares the relative gains from different SCPs and investigates why they across programs. Due to data limitations, and unlike the aforementioned studies, our paper compares programs among themselves (and not to a high school diploma). Since our results clearly

[11] See Cunha and Miller (2014), Hoxby (2015, 2019), Carrel and Kurlaender (2019), Mabel et al. (2019), Riehl et al. (2020), and Andrews et al. (2022).

[12] See Melguizo and Wainer (2015), Shavelson et al. (2016), Melguizo et al. (2016), and Cellini and Grueso (2021).

[13] See Saavedra (2009), Barrera-Osorio and Bayona-Rodriguez (2019), and Riehl et al. (2020).

[14] Data challenges have limited the number of studies on SCPs' value added. Garcia and Ospina (2019), however, are an exception because they use scores from the SABER T&T, a new college exit exam for students who complete technical and technological degrees, in order to estimate contributions to learning outcomes.

[15] An exception is Carrel and Kurlander (2020), who use data from the state of California to study institutions' effectiveness preparing students to transfer from two- to four-year institutions.

[16] See Bahr (2016), Liu et al. (2015), Dadgar and Trimble (2015), Dynarski et al. (2016), Bettinger and Soliz (2016), Jepsen et al. (2014), Minaya and Scott-Clayton (2022), Stevens et al. (2015), and Xu and Trimble (2016).

indicate how a regulator can target oversight efforts across SCPs, our findings are especially relevant to countries seeking to promote SCPs.

Finally, we contribute to the literature related to differences in value added and returns by institution and program characteristics. Overall, this literature finds great variation in net returns to higher education by field and study major.[17] Other studies also find that specific institution and program characteristics affect higher education returns, including selectivity,[18] funding availability,[19] public or private administration,[20] and for-profit institutions.[21] Our paper makes three additional contributions. First, it provides evidence of associations between program value added to outcomes and multiple program and institution characteristics and practices.[22] While some of these quality determinants have been analyzed in the literature, others, such as institutional specialization and high-quality accreditation, have not. Second, our analysis of the connections between program value added and local labor market conditions is novel. Lastly, evidence from the US is based on data from one state, whereas we rely on data from an entire country.

3. Institutional Context: Short-Cycle Programs in Colombia

The higher education system in Colombia offers bachelor degrees (typically lasting 5 years) and short-cycle programs (SCPs). SCPs award either technical (2 years) or technological (3 years) degrees. In 2019, SCPs in Colombia captured 32 percent of total higher education enrollment

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[17] See Altonji and Zimmerman (2017), Altonji et al. (2016), Altonji et al. (2012), Andrews et al. (2017), Bahr (2016), Falch et al. (2022), Hastings et al. (2013), Hastings et al. (2016), and Kirkeboen et al. (2016).
[18] See Barrera-Osorio and Bayona-Rodriguez (2019), Dale and Krueger (2014), and Hoekstra (2009).
[19] See Cohodes and Goodman (2014).
[20] See Teixeira et al. (2013), Hoxby and Bulman (2015), and Bound et al. (2010).
[21] See Cellini and Turner (2019) and Cellini and Chaudhary (2014).
[22] We follow an approach similar to the student-level estimations in Dinarte et al. (2021) for Brazil and Ecuador. In that paper, the authors also include program-level estimations with a rich set of program and institution practice and characteristics that they collected from a survey of five developing countries. In contrast, the current paper uses administrative data only.

through a total of 2,130 programs offered by 217 institutions (Ferreyra et al., 2021). The institutions that offer SCPs can be grouped into four categories: (i) universities, (ii) technological schools, (iii) technical and technological institutions (T&Ts), and (iv) SENA (*Servicio Nacional de Aprendizaje*). The first three categories are higher education institutions (HEIs), which fall under the purview of the Ministry of Education. SENA is a public institution that provides vocational and technical education throughout the country—not an HEI—and is overseen by the Ministry of Labor. While (i) and (ii) can offer bachelor degree programs as well as SCPs, (iii) can only offer SCPs. In 2019, SENA was the largest provider of SCPs in the country, with a SCP enrollment share of 65 percent (although, as explained below, SENA's market share was lower during our sample period). Private providers in Colombia currently represent 40 percent of all institutions but only 21 percent of SCP enrollment.

SCPs in Colombia are relatively affordable; the annual tuition of the average SCP is US$2,197 (Dinarte et al., 2021), which corresponds to about a third of the 2021 annual minimum wage. Yet, there is great variation in terms of tuition by type of institution. While SENA's programs are tuition-free, those offered by public or private HEIs charge tuition—equal, on average, to US$883 and US$2,930, respectively (Dinarte et al., 2021). SENA receives dedicated resources from labor tax revenues, and the Ministry of Education provides direct funding to public HEIs. Although students enrolled in public and private HEIs are eligible for loans from ICETEX (*Instituto Colombiano de Credito Educativo y Estudios en el Exterior*), a public financial institution, few students take up the loans.

Although SCPs in Colombia are typically open admission, SENA and public HEIs must often limit the number of students admitted due to capacity constraints. SENA uses interviews and non-test based procedures, whereas public HEIs are more likely to rely on student test scores on the mandatory high school exit exam, SABER 11 (Ferreyra et al., 2021). An HEI must be licensed to open or continue offering a SCP. In addition, HEIs and programs can voluntarily pursue high quality accreditation from the Ministry of Education by complying with the corresponding protocols and requirements (Ferreyra et al., 2021.)

Relative to bachelor's programs, SCPs attract more disadvantaged students—less prepared academically for higher education, with less educated mothers, and more likely to come from low-income households (Table A1). These disadvantages stress the need to determine whether and how SCPs contribute to students' academic and labor market outcomes.

4. Data Sources and Descriptive Statistics

4.1 Data Sources

Pre-higher education student information. We obtained the SABER 11 dataset from the Ministry of Education's Colombian Institute for Educational Assessment (*Instituto Colombiano para la Evaluación de la Educación, ICFES*). The dataset includes individual-level SABER 11 exam scores from all students who took the exam between 2000 and 2009 as well as student information reported at the time of the exam, including personal characteristics (gender, age, city where they completed high school) and socioeconomic information (family income and parental education).

Student-level higher education exit information. From ICFES, we also obtained individual-level test scores of students who took the higher education exit exam, SABER PRO. This exam includes general and subject-specific components.[23] We use data from the reading and quantitative reasoning portions of the general component of the test for the students who took it in the second

[23] The general component is based on the College Learning Assessment (CLA) and, since 2011, has included five mandatory modules: writing, English, reading/critical thinking, quantitative reasoning, and civic competencies. For a more detailed description of the SABER PRO exam, see Domingue et al. (2017) and Riehl et al. (2020).

semester of 2011 (2011-2), as this was the only semester for which the scores on the general component were comparable across programs.

Student-level higher education and labor market outcomes. To determine student-level higher education and labor market outcomes, we relied on individual-level records from the Ministry of Education's System for the Prevention of College Dropout (*Sistema para la Prevención de la Deserción de la Educación Superior*, SPADIES) and the Labor Observatory for Education (*Observatorio Laboral para la Educacion,* OLE). SPADIES contains biannual information on all higher education students. It identifies the program and institution attended as well as the entry cohort, and tracks students until they drop out or graduate. We obtained biannual information spanning 2007 to 2015. OLE includes annual labor market information (formal employment and wages) for higher education graduates who made social security contributions between 2010 and 2013 and were therefore employed in the formal sector of the economy as paid employees or self-employed entrepreneurs. OLE records include salaries for paid employees but not earnings for self-employed individuals.

Program- and institution-level information. This dataset comes from the National System of Higher Education Information (*Sistema Nacional de Información de la Educación Superior, SNIES*) and includes information on higher education programs and institutions. For each SCP, it includes program length (two or three years); field of study (Agronomy and Veterinary Medicine, Arts, Economics and Business, Engineering and Architecture, Health, Social Sciences, and Math and Natural Sciences); mode of delivery (distance or traditional); location; enrollment; tuition; and institution. For each institution, the data includes the location and institution type (universities, technological schools, T&Ts, and SENA). If a single institution has multiple locations, then each one receives a different code and is treated separately. For example, SENA in Medellín and SENA in Bogotá are treated as two different institutions. This gives us a refined measure of the local supply of SCPs facing students in each location, as described below.

4.2 Estimation Samples

By merging the datasets described above, we create individual-level datasets for different samples depending on the outcome of interest. For learning outcomes ("learning sample") we focus on the cohort that took SABER PRO in 2011-2. For graduation ("graduation sample"), we use six cohorts that entered higher education between 2007-1 and 2009-2 and follow them for six years to establish whether they graduated within that window. For labor market outcomes, we use three cohorts of students who graduated from an SCP between 2010 and 2012, regardless of when they started; those students constitute the "employment sample." Of these students, 76 percent work in the formal sector of the economy as either paid employees (72 percent) or self-employed (4 percent). We use the term "formal employment" to encompass both types of formal work. We observe wages after graduation only for graduates who work formally as paid employees; these students constitute the "wage sample." While students in the employment sample represent all SCP graduates, students in the wage sample represent only those working as paid employees.

Figure A1 presents the number of SCPs and the students in each estimation sample. Note that the number of students differs between the employment and wage samples although the number of programs is the same. Thus, when we present *program*-level results on employment or wages, we refer to a single "labor market sample." Also note that SENA students appear only in the employment and wage samples but not in the learning or graduation samples. To ensure precise estimates of value-added contributions, we only include programs (and the corresponding students) with an average enrollment of ten students per year. We also remove 27 SENA programs that are abnormally large.

4.3 Outcomes and Other Relevant Variables

***Outcomes*.** Our *learning outcomes* are individual-level standardized SABER PRO exam scores in reading and quantitative reasoning. *Graduation* is an indicator of whether the student graduated within six years of starting the program. *Formal employment* is a binary variable that equals one if, having graduated between 2010 and 2012, the individual was employed or self-employed for at least one year between 2010 and 2013. *Wages* consist of the total annual labor income during the first post-graduation year of formal employment between 2010 and 2013. We use the 2019 purchasing power parity (PPP) conversion factor to carry out the adjustment of wages. Appendix 1 provides further details on the outcome measures.

Demand and supply side measures. A novel contribution of our paper is the inclusion of variables that allow us to address some empirical concerns in the estimation of SCP contributions to outcomes. We mitigate the self-selection concern by including a rich set student background characteristics (gender, age, household income, mother's education, and pre-SCP academic preparation proxied by SABER 11 exam score) and average characteristics of peers in the student's program (percentage of female peers, peers' average age, percentage of peers by category of mother's education, percentage of peers by bracket of household income, and peers' average SABER 11 score). Further, we also control for a rich and novel set of measures of the local SCP supply at the student's high school city, including the number of programs offered as well as their capacity, selectivity, and cost. These measures, which we computed overall as well as separately by field of study, provider type (public HEIs, private HEIs, and SENA), and program length (see Appendix 1 and Table A3), provide a detailed characterization of the SCP choices available to a student in her high school city and are, to our knowledge, unique in their detail.[24]

[24] The local SCP supply is particularly relevant because the vast majority (approximately 90 percent) of SCP students stay in their high school city to pursue the SCP.

When investigating the elements that explain the variation in program-level contributions, we recognize that programs operate in markets and compete among themselves, delivering contributions that may vary along with market conditions. For example, programs in more competitive markets may contribute more to than others to student outcomes. To account for market conditions, we define a *market* as a combination of field of study and city (e.g., Engineering in Bogota; Health in Cali). Markets are therefore local but vary across fields within a city and, as a result, an institution that offers multiple fields in a city participates in multiple markets.

We subsequently define three market-related conditions: the institution's market power, the market's concentration, and the size of the city where the program is offered (proxying for market size). The institution's market power consists of the number of programs offered by the institution in the market relative to all the programs offered in the market. The index ranges between 0 (low power) and 1 (high power). Market concentration is proxied by a Herfindahl-Hirschman index (HHI) using enrollment shares for all programs taught in each local market. This index ranges between 0 (perfectly competitive local market) and 1 (monopolistic or concentrated local market). Finally, city size is calculated as the number of inhabitants (in log) in the city, where cities are defined as in Duranton (2016).

Quality determinants. We follow Dinarte et al. (2021) to examine whether institution and program characteristics and practices are associated with student outcomes. We collected information on program features (duration, mode of delivery, and age) and institution characteristics (type of governance, type of institution, and size) and defined three program and institution practices (chosen by the institution or program) that are relevant in our context: institution selectivity, field specialization, and program accreditation status.

To determine selectivity, we compute the average SABER 11 of students in every HEI providing SCPs and rank the HEIs accordingly. HEIs in the top half of the ranking are considered selective. In terms of field specialization, for every institution we compute one index per field, equal to the share of programs offered by the institution in that particular field. The index ranges between 0 to 1; an index close to 1 indicates that the institution is highly specialized in that field. Program accreditation consists of an indicator of whether the program has successfully gone through the high-quality accreditation process. We collectively refer to all these program and institution characteristics and practices as "quality determinants."

4.4 Descriptive Statistics

Program and institution characteristics and practices. Table 1 presents descriptive statistics of the quality determinants for programs whose students constitute our estimation samples. In terms of program characteristics (Panel A), about 70 percent of SCPs in our estimation samples last three years (technological programs) rather than two (technical programs), and more than 86 percent of the SCPs are in-person. The average program is relatively new (about 4 years old) and affordable (average annual tuition is zero at SENA and $2,300 at other institutions.) In terms of institution characteristics (Panel B), the average institution is small (between 2,000 and 3,000 students total, excluding SENA), and most programs are offered by T&Ts HEI (40 percent) and private institutions (about 65 percent).

About half of SCPs are taught by selective institutions, yet only 11 percent of them have high-quality accreditation. Institutions are rather specialized but have little market power and operate in markets that are not concentrated (Panels C and D). Almost 60 percent of SCPs are taught in large cities (Bogotá, Medellín, Cali) with an average population of about 3.7 million. Economics and Business is the most popular field of study and accounts for about 40 percent of all programs (Panel E), followed by Engineering and Architecture, which includes computer-related fields.

Relative to non-SENA programs, SENA programs (column 4) on average are longer and newer. Further, SENA is less specialized than other providers in one field and is more likely to operate either in large or small cities. Particularly because of its greater presence in small cities—where there are relatively few providers—it has more market power.

Student characteristics. These differ, to some extent, across estimation samples (Table A2). Academic readiness is low in the graduation sample, which includes all students entering an SCP, but is higher in the other samples, which only include students who have graduated or found formal employment. When comparing students in the employment sample, we note that SENA students are less academically prepared and more disadvantaged than non-SENA students, and more likely to enroll in Engineering and Architecture programs.

Panel B shows the distribution of students by entry and graduation year. We use these variables to define student cohorts, which are used to construct the average peer characteristics and to define the cohort fixed effects in our estimations (more details available in section 5.1). The definition of cohort changes across estimation samples. For the learning sample, *cohort* corresponds to the 2011-2 semester, when students took the SABER PRO exam. For the graduation sample, cohort consists of the semester-year when the student entered the program. For the labor market samples, the cohort is the graduation year. All students in the learning sample and 71 percent of students in the graduation sample started higher education in 2008 or 2009. Moreover, about 80 percent of students in the labor market samples graduated in 2011 or 2012.

Outcomes. Individual-level outcomes vary greatly among students (Table A2, Panel D). On average, student academic performance is poor. Among those who approach graduation and take the SABER PRO exam, the average standardized reading and quantitative scores are -0.23 SD and -0.17 SD. In addition, only 30 percent of students who start a program graduate within six years. For those who graduate, however, labor market outcomes appear quite good, as 76 percent obtain formal employment (for comparison, only 36 percent of individuals aged 25-65 are formally employed in Colombia.) The average annual salary for formally employed SCP graduates is equal to US$11,507—about 60 percent above the annual minimum wage.

Similarly, program average outcomes vary widely among programs, as shown in Figure 1 (pink lines). Particularly for graduation and labor market outcomes, average outcome distributions are not only dispersed but also highly asymmetric. Further, outcomes differ greatly by field (Figure A2). Average SABER PRO scores in reading and quantitative reasoning are highest among those studying Arts and Engineering, respectively; graduation rates are highest among those studying Math and Natural Sciences; formal employment rates are highest for graduates in Math and Natural Sciences, Economics and Business, and Engineering and Architecture; and wages are highest for graduates in Health, Math and Natural Sciences, and Engineering and Architecture.

SCP supply measures. Students have vastly different levels of access to local SCPs in their high school cities (Table A3). These discrepancies occur overall but also by field, institution governance (public non-SENA, private, or SENA), and program duration. Students are most likely to have access to SCPs in Economics and Business or Engineering and Architecture, and these fields serve a larger number of students than others. Selectivity is relatively high in some programs (in Math and Natural Science, at public institutions, or lasting three years) but not others. On average, programs in the Arts or those offered at private institutions are the most expensive.

5. Empirical Strategy

5.1 An Approximation to the SCP Contribution

We estimate program-level contributions to five student outcomes: standardized scores of SABER PRO reading and SABER PRO quantitative reasoning, graduation, formal employment, and (log) wages. Following Melguizo et al. (2016) and Smith and Stange (2016), we consider student outcome Y_{ijc}^{k}, where *k* refers to each of the five outcomes of interest for student *i* who enrolled in program *j*, in cohort *c*. We model the outcome as follows:

$$Y_{ijc}^{k} = I_i{}'\alpha^k + Z_{ijc}{}'\beta^k + S_i{}'\gamma^k + u_j^k + \delta_c^k + \epsilon_{ijc}^k \qquad (1)$$

In this equation, vector I_i contains student *i*'s characteristics (gender, age, household income bracket, mother's education, and SABER 11 score). Following Carrell and Kurlaender (2019) and Kurlaender et al. (2016), we also include a vector of peer characteristics, Z_{ijc}, which contains the average of the same set of individual characteristics contained in *I* for student *i*'s cohort *c*.[25] S_i constitutes the four-category vector (program number, capacity, selectivity, and cost) characterizing student *I*'s access to the SCPs located in his high school city (Table A3). For outcome *k*, the program *j*'s fixed effect is u_j^k; δ_c^k is a cohort fixed effect[26] and ϵ_{ijc}^k represents the error term. Standard errors are clustered at the program level. The program-level fixed effect, u_j^k, represents the program *j*'s contribution to each outcome *k* of student *i*. Note that this regression does not include a constant term.

To assess how the various sets of control variables affect our estimates, we follow Minaya and Scott-Clayton (2022) and estimate three versions of (1) that incrementally include the vectors *I*, *Z*, and *S* (leading to Models I, I+Z, and I+Z+S). All three models include the program- and

[25] As in Sacerdote (2011), the average peer characteristics at the cohort level are estimated using all students in the cohort excluding the student herself.

[26] There are no cohort fixed effects in the estimations conducted with the learning sample since this sample is a cross-section of students who took SABER PRO in 2011-2. For the graduation sample, we include entry cohorts (semester-year) fixed effects. For estimations involving the labor market samples, we include graduation cohort fixed effects (year) and year fixed effects (corresponding to year in OLE).

cohort-fixed effects. To facilitate interpretation, for every model we demean the estimated program fixed effect, $\widehat{u_j^k}$, by removing their weighted average mean (weight is number of students). The demeaned fixed effect estimates are our estimates of program-level contributions; by construction, they average out to zero and measure *differences* relative to the average SCP contribution. A positive (negative) contribution indicates that the SCP's contribution is above (below) average.

To gauge the importance of program fixed effects relative to the other sets of variables that determine the learning, graduation, and labor market outcomes, we conduct a Shapley-Owen R-squared decomposition (Shapley 1953; Owen 1977; Huettner and Sunder 2012) of equation (1). This decomposition enables us to quantify the fraction of total explained variance for outcome k attributable to individual and peers' characteristics, local SCP supply, and program fixed effects.

5.2 Understanding Program Contributions

To assess which quality determinants and labor market conditions are associated with SCP contributions, we regress $\widehat{u_j^k}$ on a set of variables as follows:

$$\widehat{u_j^k} = \alpha^k + C_j{}'\mu^k + \phi_f^k + \epsilon_j \tag{2}$$

where $\widehat{u_j^k}$ represents the estimated program j's contribution to outcome k; C_j is the vector of quality determinants and local market conditions; ϕ_f represents field fixed effects; and ϵ_j is an error term. We estimate standard errors clustered by institution (recall that, in this context, an institution includes both the institution and city where it offers the SCP). To account for the estimation error of $\widehat{u_j^k}$, regressions are weighted by the inverse of $\widehat{u_j^k}$'s standard deviation.

5.3 Concerns and Limitations

An important concern related to Equation (1) is student self-selection into SCPs, which might bias the estimates. We mitigate self-selection by controlling for a large set of individual and peer characteristics (most notably SABER 11 score and family income) as well as measures of local

SCP supply in the student's high school city. To our knowledge, this is one of the most extensive sets of controls that has ever been used in this type of study. It is particularly effective for two reasons. First, sorting students across programs is driven to a large extent by the student's SABER 11 score and family income. SABER 11 is used by many institutions as an admission criterion and, in general, is informative to the students and others of her chances of success in higher education. For instance, a student with a high SABER 11 score is more likely than others to succeed in Engineering and Architecture. Family income, in turn, indicates which programs are affordable to the student. In combination with the supply-side measures that describe program supply, fields, selectivity, and costs, the individual-level variables address self-selection concerns to the greatest extent possible given the existing data. Second, peer characteristics further mitigate self-selection concerns because, when choosing a program, a student typically knows the profile of other students in the program and might base her choice on this information.

A limitation of our analysis is that our labor market outcomes are naturally censored: formal employment outcomes are available only for students who graduate, and wages are available only for graduates formally working as paid employees. Our estimated contributions must therefore be interpreted relative to these two types of SCP students rather than all SCP students. Another limitation is that only early career outcomes are available. Nonetheless, studies for the US have found that short- and medium-term contributions to labor market outcomes are highly (and positively) correlated (Minaya and Scott-Clayton, 2022), implying that our estimates might be informative about longer-term contributions as well.

6. Results

6.1 Value Added Estimates Across Models

We estimate the three versions of equation (1)—leading to Models I, I+Z, and I+Z+S—for each of the five outcomes of interest. Regression results for learning outcomes, graduation, and labor market outcomes are in Tables A4, A5, and A6, respectively. Figure 1 depicts the distribution of (observed) program average outcomes (in pink) and estimated program-level contributions (in blue). Table A7 compares measures of goodness of fit by model, variation of estimated value added, and correlation of value-added estimates across the different models.

Several interesting findings emerge from Table A7, where we compare results from models I, I+Z, and I+Z+S. The explanatory power proxied by R-squared and by root mean squared residual is very similar across models for each outcome (Table A7, Columns [2] and [3]). The progressive addition of controls (especially peer characteristics) substantially affects the value-added distribution for learning outcomes; however, it makes little difference for graduation and labor market outcomes, as shown by the distributions presented in Figure 1 and the standard deviation of value-added estimates in Table A7, Column [4]. Two more analyses corroborate this result. First, the statistical significance and magnitudes of most estimated coefficients on variables in the *I* vector for graduation and labor market outcomes remain quite similar after including the *Z* and *S* vectors (Tables A5 and A6), but this is not the case for learning outcomes (Table A4). As a result, program contribution estimates from the I model and the other two models have low correlations in the case of learning outcomes but almost perfect in the case of graduation and labor market outcomes (Table A7, Columns [6] and [7]). Second, Kolmogorov-Smirnov tests lead us to reject the null hypothesis of equal value-added distributions for learning outcomes from Model I and any of the other models (Table A7, Column [8]). In contrast, the test generally fails to reject the null hypothesis of equal value-added distributions for graduation and labor market outcomes, except in the case of Models I versus I+Z+S for employment (marginal rejection) or log wages (Table A7, Columns [8] and [9]). In sum, controlling for *I* vector seems sufficient to address self-selection problems for graduation and labor market outcomes. Lastly, given that Model I+Z+S yields the lowest root mean squared residual by outcome (Table A7, Column [3]), we focus exclusively on estimates from this model in what follows.

6.2 Decomposing the Variation in Student-Level Outcomes

The large variation in student-level outcomes is clearly worrisome from a policy perspective, and begs the question of what elements explain it. Therefore, we quantify the fraction of explained variation from Equation (1) attributable to student and peer characteristics, features of local SCP supply, and program-level contributions through a Shapley–Owen decomposition (Table 2). Our results show that program contributions account for 25-31 percent of the explained variation in learning outcomes, which is much less than individual characteristics (48-57 percent). In contrast, programs account for a staggering 58-72 percent of the explained variation in graduation and labor market outcomes. Interestingly, local program supply measures account for 16-19 percent of the explained variation in labor market outcomes—more than the fraction explained by individual characteristics (13 percent).

From a policy perspective, the large role of program-level contributions to graduation and labor market outcomes is promising, as it opens the possibility of closing the worrisome gap in student outcomes by raising program-level contributions. From a research perspective, the importance of those contributions indicates that programs make a greater difference on graduation and labor market outcomes than on learning outcomes, leading us to focus on them in what follows.

6.3 Variation of Program-Level Contributions

To document the variation in program-level contributions, we calculate the descriptive statistics of these contributions across all SCPs as well as separately by field of study (Table A8). In line with existing evidence that documents dispersion in value added (Melguizo et al., 2016), our results show that contributions vary widely across programs (see Table A8, row "All programs"). To illustrate the pattern of variation in contributions, we consider a student who transfers from a SCP that delivers a graduation contribution at the lowest 25th percentile to one that delivers the same contribution at the 75th percentile. This student gains no less than a 20-percentage point increase in graduation probability. Since the average program has a mere 30 percent graduation rate, this improvement is clearly substantive. Similarly, the rise from the 25th to the 75th percentile of contributions to formal employment implies a 19-percentage point increase in formal employment probability, or about one-fourth of the average SCP's 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 almost one standard deviation of actual wages, or a 12 percent wage increase. Comparing the top and bottom 10 percent of the distribution paints a similar, yet more dramatic, picture. For instance, a student gains 37 percentage points in formal employment probability and a wage increase of 26 percent as she moves from the 10th to the 90th percentile.

In the existing literature, several studies have documented gains for students enrolled in programs in specific fields, such as Health or STEM, both in terms of cognitive outcomes (Melguizo and Wainer 2015; Shavelson et al. 2016) and early labor market outcomes (Bahr 2016; Carnevale et al., 2012; Melguizo and Wolniak 2012). Hence, we explore the *between* and *within-field* variation in contributions to assess whether SCPs in specific fields make larger contributions than in other fields, or if their dispersion is greater in some fields than in others.

As shown in Table A8 and Figure A3, average program-level contributions vary across fields for each outcome. Programs in Math and Natural Sciences along with Health provide the largest contributions to graduation. Furthermore, Math and Natural Sciences programs deliver the greatest contributions to formal employment, and Health makes the greatest contribution to wages. Nonetheless, program contributions to outcomes vary even more within the field. Among Health programs, for instance, going from the 10^{th} to the 90^{th} percentile of value-added distributions entails a 45-percentage point increase in employment and a 51 percent increase in wages.

To summarize, program-level contributions vary across and within fields. While some fields are more likely to deliver an above-average contribution than others, all fields display great variation. The large within-field variation of SCP contributions implies that, for a student seeking a program with a high contribution, it is not enough to choose a field with a high average contribution, as low-contribution programs exist even within seemingly "good" fields. For the policymaker, it raises the need to carefully monitor program-level outcomes and contributions even within "good" fields to promote good programs and weed out bad ones.

6.4 Program-Level Contributions and Other Program "Quality" Measures

Program-level contributions are one possible measure of SCP quality. They might, however, not be publicly available or easily interpretable. The question is, then, how they correlate with other, publicly observable measures such as the outcomes themselves, or program tuition or selectivity. If they correlate highly, then these alternative measures might serve as proxies for program-level contributions.

We find that SCP contributions correlate closely with the corresponding average outcome (Table 3, Panel A). For example, the correlation between the SCP contribution to graduation and program graduation rate is 0.98. However, contributions correlate little with program tuition or selectivity. Given the substantial role that programs play in graduation and labor market outcomes (Table 2), our findings imply that the outcomes themselves are much more informative of SCP contributions than these other commonly held measures of quality. Reassuringly, the negative or low correlation between average SABER 11 scores and value-added contributions indicates that the latter relate minimally to inputs (or student characteristics) but strongly to outcomes. To the extent that they are publicly available, program-level outcomes are therefore more informative than tuition or selectivity of what students can expect to gain by attending these programs.

6.5 Decomposing the Variation in Program-level Contributions

We now explore the variation in program-level contributions to outcomes. Students look at fields as indicative of expected outcomes, preferring, for instance, fields such as Economics and Business or Health because of their perceived employability. They also look at institutions, choosing those with good reputations. We investigate the role of institution and field by regressing the program-level contributions on institution fixed effects and field fixed effects, and conduct Shapley-Owen decompositions of the resulting R-squared values.

As Table 4 reports, institution and field fixed effects together account for 62, 43, and 36 percent of the variation in contribution to graduation, formal employment, and wages, respectively. Of the explained variance of the program contribution to each outcome, more than three-quarters is attributable to institution fixed effects. Fields account for only 6 percent of the observed variance of graduation, but for 20 to 25 percent of labor market outcomes.

Since the importance of institution and field fixed effects varies by outcome, these findings have interesting implications. First, institutions seem more relevant for program-level contributions to graduation than to labor market outcomes. Although an institution might be able to enforce graduation standards and policies, it might have a less direct impact on labor market outcomes. Second, fields are less relevant than institutions in the three outcomes under analysis, which is consistent with our previous finding of greater within- than between-field variation of program-level contributions. Third, a substantial portion of variation (between 40 and 60 percent) in program contributions remains unexplained, indicating that elements not included in the regression—such as program characteristics and practices, or city-field market conditions—might be critical, particularly for labor market outcomes. This leads us to investigate the relationship between program contributions, quality determinants, and market conditions.

6.6 Associations between Program Contributions, Quality Determinants, and Local Market Conditions

Results from the estimation of Equation (2) are presented in Tables 5-7. We estimate six models per outcome: two using the full sample (with or without field fixed effects) and four models using key subsamples (large vs. small/medium cities and two-year vs. three-year programs).[27] Our preferred estimates are those from Column (2) (full sample with fixed effects); we focus on significant coefficients (at levels 1, 5, or 10 percent) and discuss Columns (3)-(6) to explore coefficient heterogeneity across subsamples. To facilitate coefficient interpretation, for each significant coefficient in Tables 5-7 (using Column [2]), Appendix Figure A4 shows the coefficient for binary variables (e.g., selective institution) or the coefficient estimate multiplied by the variable's standard deviation for non-binary variables (e.g., institution's market power). We emphasize that, while these regressions estimate the association between program-level contributions and right-hand side variables, they do not estimate the causal effect of the latter.

Graduation. For the full sample, three quality determinants are associated with a 2.8-4.4 percentage point (pp) reduction in graduation (Table 5, Column [2] and Figure A4, Panel A). Older

[27] "Large city" refers to cities with a population above 2.5 million inhabitants and "small/medium city" consists of cities with less than 2.5 million. We split the sample by city size to capture the fact that, for instance, wages might be higher and/or labor market opportunities better in large cities. Splitting the sample between two-year and three-year programs accounts for systematic differences between them, akin to the differences between certificate and associate's degrees in the US. We observe small differences in the average contributions across these four subsamples (see "Mean of dependent variable" row in Tables 5-7), especially for the contributions to formal employment.

programs, or those taught by larger institutions, contribute less to graduation. This might be due to the fact that older programs might have more outdated and rigid graduation standards—an association driven by programs in small cities or by three-year long programs (Columns [5] and [6], respectively). Larger institutions, in turn, may provide less personalized attention, which may be more salient for programs taught in large cities or three-year long programs (Columns [3] and [6], respectively). Institutions in more competitive markets (with lower HHI) contribute more to graduation. Facing greater competition, institutions may seek to differentiate themselves through a higher graduation rate, perhaps to place a higher share of students in the market. This result is driven by large cities and three-year long programs.

Formal employment. Several quality determinants and local market conditions are associated with 1.0-11.5 pp changes in formal employment (Table 6, Column [2] and Figure A4, Panel B). The largest increases are from SCPs taught by SENA (11.6 pp) and from three-year programs (6.6 pp). The higher formal employment attained by SENA programs relative to those taught by other institutions is driven by three-year SCPs and those taught in small/medium cities, suggesting that SENA's connections with employers may be particularly good in those markets. The greater contribution to formal employment of three-year programs compared to two-year programs is consistent with the emerging US literature at the state level (Jepsen et al. 2014; Liu et al. 2015; Xu and Trimble 2016; Bahr 2016).

Older programs make a marginally larger contribution than newer ones—a result driven by three-year programs, presumably because they have a longer-standing reputation with employers. In addition, larger institutions make higher contributions to formal employment, particularly in large cities. A 1-SD increase in the institution (log) enrollment is associated with an approximately

2.5 pp higher formal employment rate, indicating that larger institutions may have stronger connections with industry.

Two institutions' practices are also positively associated with program contributions to formal employment. SCPs taught by selective institutions have a 3.6 pp higher formal employment, a result driven by two-year programs. Such SCPs may have better faculty and higher standards than non-selective institutions. Moreover, a 1-SD increase in field specialization is associated with a 2.0 pp increase in formal employment—a result driven by large cities. Specialized institution may provide better training and be better known among employers.

In terms of local market conditions, SCPs taught in more concentrated markets have higher employment rates. A 1-SD increase in the HHI index is associated with an approximately 3.5-pp increase in formal employment rates. This result is driven by small cities, whose markets are more concentrated than those of larger cities and where the few institutions controlling the market may be well known to employers. Moreover, programs offered in larger cities have higher formal employment: a 1-SD increase in the number of inhabitants (log) in the local market is associated with 3-pp increase in formal employment rates, suggesting either that work opportunities are better in larger cities or that programs in those markets are systematically better at placing students. Lastly, programs taught by institutions with more market power contribute *less* to formal employment. An institution serving a larger share of the local market may focus less attention on satisfying employers' needs, thereby hurting students' employment.

Wages. Four quality determinants and one local market condition are associated with improvements in wages, ranging between 1.0-6.8 percent (Table 7, Column [2] and Figure A4, Panel C). The quality determinants with the strongest association to value added to wages are SCP duration (three-year programs, 6.8 percent) and type of institution (technological school, 2.7

percent). As is the case with formal employment, wages for three-year programs are approximately 7 percent higher than for two-year programs. This result is robust for all different specifications and subsamples. We find that older SCPs and those taught by technological schools have higher wages. A 1-SD increase in program age is associated with approximately a 1.0 percent increase in wages. Older SCPs may be better established in their field and enjoy a better reputation among employers. Moreover, graduates of SCPs taught at technological schools earn higher wages (by approximately 3.0 percent) than graduates from programs offered elsewhere. This association is driven by SCPs that are longer in duration and those taught in large cities.

Lastly, one institutional practice (field specialization) and one labor market condition (city size) are associated with greater contributions to wages. Specialized institutions may deliver higher-quality instruction than others in their field, particularly for two-year SCPs. Additionally, graduates of SCPs taught in larger cities earn higher wages, likely indicating, as in the case of formal employment, that work opportunities are better in larger cities.

Taking stock. Appendix Figure A5 summarizes the results discussed above. Programs that are longer, older, taught by more specialized institutions, or offered in larger cities contribute more to employment and wages than other programs. Moreover, graduates of programs offered by SENA or by selective institutions have higher employment rates than others, and graduates of programs taught by technological schools earn higher wages than others. Interestingly, some quality determinants and local market conditions are related negatively to graduation but positively to labor market outcomes. For example, older programs have lower graduation rates (as they might be more demanding or outdated) but higher employment and wages (since they might have better private sector connections). These results suggest that institutions should weigh the trade-offs created by some of their characteristics and practices. At the same time, a practice commonly regarded as indicative of quality—obtaining high-quality accreditation—does not seem to contribute to graduation or labor market outcomes.

Do our quality determinants and local market conditions explain much of the variation in program-level contributions? The regressions with only institution and field fixed effects discussed in section 6.5 have higher explained variation (between 36 and 62 percent) than the determinant regressions estimated in this section (less than 27 percent). Although our observed quality determinants and local market conditions may not explain much variation, they nonetheless succeed in identifying features that enhance program contributions and can therefore close the worrisome gap between "good" and "bad" programs.

6.7 The Challenges of Using Outcomes or Contributions to Rank Programs

An appealing yet controversial feature of program-level outcomes and contributions is that they could, in principle, be used to rank programs. Would these rankings be sensitive to the specific metrics used to construct them? To investigate this matter, we construct six different rankings: one for each of the three outcomes of interest and one for each of the corresponding contributions. We then compute the correlation among these rankings. Since this correlation might be low because the rankings are based on ordinal positions, we group programs into deciles for each ranking and compute the percent of programs that move three or more deciles across the rankings (a lower percent indicates more correlated rankings.)

Table 8, Panel A shows that the ranking of programs based on graduation (whether by outcome or value added) has almost zero correlation with rankings based on formal employment or wages (columns 1 and 2). In contrast, rankings based on wages and formal employment (whether by outcome or value added) have a correlation of about 0.5 (columns 3 and 4). While higher than zero, this correlation is well below one, indicating that not even the two labor market outcomes deliver highly correlated rankings. This low correlation of rankings among themselves is similar to the results from Minaya and Scott-Clayton (2022). Table 8, Panel B reinforces these findings. About half of the SCPs move three or more deciles when going from a graduation-based ranking to an employment- or wage-based ranking (columns 1 and 2) and about a third of programs move three or more deciles when going from a wage- to an employment-based ranking (columns 3 and 4). Overall, these results indicate substantial ranking instability.

Figure 2 offers a different take on the same issue. For each field of study, it shows the average rank percentile of the programs by field in three rankings, which differ on their underlying metric (contributions to graduation, employment, and wages). Which field ranks highest, on average, depends on which ranking we use. Despite the different answers provided by each ranking, we can identify certain patterns. The average program in Economics and Business as well as in Health ranks above the median in the three rankings, whereas the opposite is true for Agronomy and Veterinary and Social Sciences. If we focus exclusively on formal employment and wages, the average programs in Health, Economics and Business, and Engineering and Architecture rank above the median in the two rankings.

To summarize, rankings are highly sensitive to the underlying metric. Although their intent might be good—conveying information in a simple, clear way—they also be extremely misleading and should therefore be used with great caution.

7. Conclusions and Policy Implications

Using a novel dataset that combines a rich set of individual and peer characteristics, quality determinants, SCP local supply measures, and local market conditions for SCPs in Colombia, we estimate program-level contributions to learning, graduation, and labor market outcomes. We document a great deal of variation in student outcomes. In the case of graduation and labor market outcomes, SCPs explain about three quarters of the explained variation. Program-level contributions vary across fields but even more so within fields. After controlling for field fixed effects, we find that SCP value added to labor market outcomes is higher for older and longer programs taught at more specialized institutions or in larger cities.

These results have important policy implications. The great variation in program-level contributions is a source of concern from the point of view of policy, as some students might enroll in programs that would contribute little to their outcomes. While strong oversight and regulation are called for, our findings provide a rationale for focusing on programs with poor outcomes or poor value added—or programs that, based on their determinants and local market conditions, would more likely have low value-added contributions.

Our results also indicate that, if estimating or using value-added contributions were not possible, the outcomes themselves may provide better quality measures than commonly used metrics such as tuition and program selectivity. Collecting and disseminating program average outcomes is therefore crucial for students and policymakers alike. At the same time, our findings indicate the pitfalls of using program-level contributions or outcomes to build rankings.

Finally, we highlight the need to further understand which elements make programs "good." Although we document the role of the quality determinants and local market conditions that are available in administrative datasets, we conjecture that other SCP quality determinants and local market conditions such as links with local labor market (which are not measured in these data sets) are more likely to add value. Dinarte et al. (2021) surveyed SCP directors in five countries to analyze SCP quality determinants. Their results provide rich and useful information for policy makers who are interested in understanding what makes an SCP "good" and in expanding the supply of such programs.

7. References

Altonji, J. G., and R. K. Mansfield. 2018. Estimating Group Effects Using Averages of Observables to Control for Sorting on Unobservables: School and Neighborhood Effects. *American Economic Review*, 108(10):2902–2946.

Altonji, J. G., and S. D. Zimmerman. 2017. "The Costs of and Net Returns to College Major." (No. w23029). National Bureau of Economic Research.

Altonji, J. G., P. Arcidiacono, and A. Maurel. 2016. "The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects." In *Handbook of the Economics of Education* 5:305–96. Elsevier.

Altonji, J. G., E. Blom, and C. Meghir. 2012. "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers." *Annual Review of Economics* 4(1):185–223.

Andrews, R. J., S. A. Imberman, and M. F. Lovenheim. 2017. "Risky Business? The Effect of Majoring in Business on Earnings and Educational Attainment." (No. w23575). National Bureau of Economic Research.

Andrews, R. J., S.A. Imberman, M. F. Lovenheim, and K. M. Stange. 2022. "The Returns to College Major Choice: Average and Distributional Effects, Career Trajectories, and Earnings Variability" (No. w30331). National Bureau of Economic Research.

Bahr, P. R. 2016. "The Earnings of Community College Graduates in California." (CAPSEE Working Paper). New York, NY: Center for Analysis of Postsecondary Education and Formal Employment.

Bailey, T., Bashford, J., Boatman, A., Squires, J., Weiss, M., Doyle, W., Valentine, J. C., LaSota, R., Polanin, J. R., Spinney, E., Wilson, W., Yeide, M., & Young, S. H. 2016. *Strategies for postsecondary students in developmental education – A practice guide for college and university administrators, advisors, and faculty*. Washington, DC: Institute of Education Sciences, What Works Clearinghouse

Barrera-Osorio, F., and H. Bayona-Rodriguez. 2019. "Signaling or Better Human Capital: The Causal Effect of Prestigious University Attendance on Educational Trajectory and Labor Market: Evidence from Colombia." *Economics of Education Review* 70:20–34.

Belfield, C. R., and T. Bailey. 2017. "Model Specifications for Estimating Labor Market Returns to Associate's Degrees: How Robust Are Fixed Effects Estimates?" (CAPSEE Working Paper). New York, NY: Center for Analysis of Postsecondary Education and Formal Employment.

Belfield, C. R., and T. Bailey. 2011. "The Benefits of Attending Community College: A Review of the Evidence." *Community College Review* 39(1):46–68.

Bettinger, E., and A. Soliz. 2016. "Returns to Vocational Credentials: Evidence from Ohio's

Community and Technical Colleges. (CAPSEE Working Paper). New York, NY: Center for Analysis of Postsecondary Education and Formal Employment.

Bound, J., M. F. Lovenheim, and S. Turner. 2010. "Why have College Completion Rates Declined? An Analysis of Changing Student Preparation and Collegiate Resources." *American Economic Journal: Applied Economics* 2(3):129–57.

Carnevale, A. P., S. J. Rose, and A. R. Hanson. 2012. "Certificates: Gateway to Gainful Formal Employment and College Degrees." Washington, DC: Center on Education and the Workforce, Georgetown University.

Carrell, S. E., and M. Kurlaender. 2019. "Estimating the Productivity of Community Colleges in Paving the Road to Four-Year Success." (No. w22904). National Bureau of Economic Research.

Cellini, S. R., and H. Grueso. 2021. Student Learning in Online College Programs. *AERA Open* 7(1):1–18.

Cellini, S. R., and N. Turner. 2019. "Gainfully Employed? Assessing the Employment and Earnings of For-Profit College Students Using Administrative Data." *Journal of Human Resources* 54(2):342–70.

Cellini, S. R., and L. Chaudhary. 2014. "The Labor Market Returns to a For-Profit College Education." *Economics of Education Review* 43:125–40.

Cohodes, S. R., and J. S. Goodman. 2014. "Merit Aid, College Quality, and College Completion: Massachusetts' Adams Scholarship as an In-Kind Subsidy." *American Economic Journal: Applied Economics* 6(4):251–85.

Cunha, J. M., and T. Miller. 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., and M. J. Trimble. 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.

Dale, S. B., and Krueger, A. B. (2014). "Estimating the Effects of College Characteristics over Career Using Administrative Earnings Data." *Journal of Human Resources* 49(2):323–58.

Dinarte Diaz, L., M. M. Ferreyra, S. Urzua, and M. Bassi. 2021. "What Makes for a Good? Evidence from Short-Cycle Higher Education Programs in Five Developing Countries." Policy Research Working Paper Series No. WPS 9722. The World Bank Group.

Domingue B., D. Lang, M. L. Cuevas, M. Castellanos, C. Lopera, J. P. Marino, A. Molina, and R. Shavelson. 2017. "Measuring Student Learning in Technical Programs: A Case Study from Colombia." *AERA Open*. doi: 10.1177/2332858417692997

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

Falch, T., J.M.V. Iversen, O.H. Nyhus, and B. Strøm, 2022. Quality Measures in Higher Education: Norwegian Evidence. *Economics of Education Review*, *87,* p.102235.

Ferreyra, M. M., L. Dinarte Diaz, S. Urzua, and M. Bassi. 2021. "The Fast Track to New Skills: Short-Cycle Higher Education Programs in LAC." *Directions in Development.* Washington, DC: World Bank. Forthcoming.

Garcia, L., and M. Ospina. 2019. *Valor Agregado y Educación Técnica y Tecnológica en Colombia.* Unpublished manuscript.

Hastings, J. S., C. A. Neilson, and S. D. Zimmerman. 2013. "Are Some Degrees Worth More Than Others? Evidence from College Admission Cutoffs in Chile." (No. w19241). National Bureau of Economic Research.

Hastings, J. S., C. A. Neilson, A. Ramirez, and S. D. Zimmerman. 2016. "(Un)informed College and Major Choice: Evidence from Linked Survey and Administrative Data." *Economics of Education Review* 51:136–51.

Hoekstra, M. 2009. "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach." *The Review of Economics and Statistics* 91(4):717–24.

Hoxby, C. 2015. "Computing the Value-Added of American Post-Secondary Institutions." Washington, DC: Internal Revenue Service.

Hoxby, C. M. and G. B. Bulman. 2015. The effects of the tax deduction for postsecondary tuition: Implications for structuring tax-based aid. *Economics of Education Review* 51:23-60.

Hoxby, C. 2020. The Productivity of US Postsecondary Institutions. In Hoxby, C. and K. Stange (Eds.) *Productivity in Higher Education* (pp. 31-66). University of Chicago Press.

Hoxby, C. and K. Stange. 2020. "Introduction to Productivity in Higher Education." In Hoxby, C. and K. Stange (Eds.) *Productivity in Higher Education* (pp. 31-66). University of Chicago Press.

Huettner. F. and M. Sunder. 2012. "Axiomatic arguments for decomposing goodness of fit according to Shapley and Owen values." *Electronic Journal of Statistics,* 6:1239 – 1250.

Kurlaender, M., Carrell, S. and Jackson J. 2020. "The Promises and Pitfalls of Measuring Community College Quality". *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2(1):174-190.

Jackson, C. K. 2018. "The full measure of a teacher: using value-added to assess effects on student behavior." *Education Next*, 19(1):62-68.

Jepsen, C., K. Troske, and P. Coomes. 2014. “The Labor-Market Returns to Community College Degrees, Diplomas, and Certificates.” *Journal of Labor Economics* 32(1):95–121.

Kirkeboen, L. J., E. Leuven, and M. Mogstad. 2016. “Field of Study, Earnings, and Self-Selection.” *The Quarterly Journal of Economics* 131(3):1057–111.

Liu, V., C. Belfield, and M. Trimble. 2015. “The Medium-Term Labor Market Returns to Community College Awards: Evidence from North Carolina.” *Economics of Education Review* 44(C):42–55.

Mabel, Z., C. J. Libassi, and M. Hurwitz. 2020. “The value of using early-career earnings data in the College Scorecard to guide college choices.” *Economics of Education Review*, *75*, p.101958.

Marcotte, D. 2019. “The Returns to Education at Community Colleges: New Evidence from the Education Longitudinal Survey.” *Education Finance and Policy* 14(4):523–47.

Melguizo, T., and H. Coates. 2017. “The Value of Assessing Higher Education Student Learning Outcomes (editorial).” *AERA Open Higher Education Special Topic* 3(3):1–2.

Melguizo, T., and J. Wainer. 2015. “Toward a Set of Measures of Student Learning Outcomes in Higher Education: Evidence from Brazil.” *Higher Education* 72(3):381–401.

Melguizo, T., and G. Wolniak. 2012. “The Earnings Benefits of Majoring in STEM Fields among High Achieving Minority Students. *Research in Higher Education* 53(4):383–405.

Melguizo, T., G. Zamarro, T. Velasco, and F. J. Sanchez. 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):424–48.

Minaya, V., and Scott-Clayton, J. (2022). Labor market trajectories for community college graduates: How returns to certificates and associate's degrees evolve over time. *Education Finance and Policy*, *17*(1), 53-80.

Owen, G. 1977. Values of Games with a Priori Unions. In Henn, R., Moeschlin, O. (Eds.) *Mathematical Economics and Game Theory. Lecture Notes in Economics and Mathematical Systems vol 141*. Springer, Berlin, Heidelberg.

Riehl, E., J. E. Saavedra, and M. Urquiola. 2020. “Learning and Earning: An Approximation to College Value Added in Two Dimensions.” (No. w22725). National Bureau of Economic Research.

Saavedra, J. E. 2009. “The Returns to College Quality: A Regression Discontinuity Analysis.” Cambridge, MA: Harvard University.

Sacerdote, B. 2011. “Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far?” In *Handbook of the Economics of Education* 3:249–77. Elsevier.

SEDLAC. 2016. A Guide to SEDLAC- Socio-Economic Database for Latin America and the Caribbean. Washington, DC: World Bank.

Shapley, L. S. "The Value of an N-Person Game." In Kuhn H. W. and A. W. Tucker. (Eds.) *Contributions to the Theory of Games*. Princeton University Press.

Shavelson, R. J., B. Domingue, J. Marino, A. M. Mantilla, J. A. Morales, and E. Wiley. 2016. “On the Practices and Challenges of Measuring Higher Education Value Added: The Case of Colombia.” *Assessment and Evaluation in Higher Education* 41(5):695–720.

Smith, J., and K. Stange. 2016. “A New Measure of College Quality to Study the Effects of College Sector and Peers on Degree Attainment.” *Education Finance and Policy* 11(4):369–403.

Stevens, A., M. Kurlaender, and M. Grosz. 2015. “Career-Technical Education and Labor Market Outcomes: Evidence from California Community Colleges.” (CAPSEE Working Paper). New York, NY: Center for Analysis of Postsecondary Education and Formal Employment.

Teixeira, P., V. Rocha, R. Biscaia, and M. F. Cardoso. 2013. “Competition and Diversification in Public and Private Higher Education.” *Applied Economics* 45(35):4949–58.

Xu, D., and M. Trimble. 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):272–92.

Tables

Table 1. Program Characteristics by Estimation Sample

	Learning Sample	Graduation Sample	Labor Market Sample	Labor Market Sample: SENA	Labor Market Sample: Non-SENA
	(1)	(2)	(3)	(4)	(5)
Panel A. Program Characteristics					
Three-year program	0.73	0.69	0.74	0.85	0.71
Distance program	0.14	0.13	0.09	0.00	0.11
Program age (years)	3.88	4.15	3.76	0.89	4.43
Annual tuition (US$)	2,386.00	2,329.82	1,858.78	0.00	2,283.57
Panel B. Institution Characteristics					
T&T	0.41	0.39	0.34	-	0.41
Technological school	0.35	0.35	0.28	-	0.34
University	0.24	0.26	0.20	-	0.24
Institution size (in thousands of students)	3.15	2.43	34.00	168.60	3.07
Private HEI	0.66	0.65	0.52	-	0.64
Public HEI	0.34	0.35	0.30	-	0.36
SENA	0.00	0.00	0.19	1.00	0.00
Panel C. Program and Institution Practices					
Selective institution	0.54	0.52	0.45	0.00	0.55
Institution field specialization (index)	0.48	0.47	0.45	0.35	0.47
High-quality accreditation	0.11	0.08	0.08	0.00	0.10
Panel D. Local Market Conditions					
Institution market power (index)	0.21	0.22	0.24	0.39	0.21
Market concentration (HHI index)	0.17	0.18	0.17	0.20	0.16
Population (in thousands)	3,723.18	3,466.35	3,543.69	2,663.23	3,745.99
City size (%)					
Large city	0.58	0.57	0.62	0.75	0.59
Medium city	0.25	0.24	0.21	0.04	0.25
Small city	0.17	0.18	0.17	0.20	0.16
Panel E. Field of Specialization					
Agronomy and Veterinary	0.03	0.03	0.04	0.06	0.03
Arts	0.09	0.10	0.09	0.09	0.09
Health	0.06	0.06	0.06	0.06	0.05
Social Sciences	0.05	0.06	0.05	0.03	0.05
Economics and Business	0.42	0.40	0.38	0.28	0.41
Engineering and Architecture	0.33	0.33	0.37	0.43	0.35
Math and Natural Sciences	0.01	0.01	0.02	0.05	0.01
Observations	481	621	851	159	692

Source: Authors' calculations using administrative data. See Appendix 1 for the definition of the variables.
Notes: This table shows program-level statistics for each estimation sample (Columns [1] to [3]) and for the labor market subsamples of SENA programs (Column [4]) and non-SENA programs (Column [5]). All variables are dummies except when the unit of measure is indicated in parentheses. Indices range between 0 and 1. Differences in number of programs are due to the definition of estimation samples and data availability. For example, in the learning sample we exclude programs without students taking the SABER PRO exam in 2011-2. Moreover, the labor market sample is

larger than the other two samples because it includes SENA programs, which are not observed in the datasets used for the learning and graduation samples. An institution consists of an institution in a city where it operates. For example, SENA in Medellin and SENA in Bogota are two different institutions in our data. HHI=Herfindahl-Hirschman Index. T&T= technical and technological institutions.

Table 2. R-squared Shapley–Owen Decomposition for Student Outcomes
Estimations Using Student-Level Data

	(1) Reading	(2) Quantitative Reasoning	(3) Graduation	(4) Formal Employment	(5) Wages (log)
Percent of explained variation attributable to:					
Individual characteristics	57.11	48.34	18.13	13.16	13.81
Peer characteristics	13.21	15.15	4.62	6.87	9.54
Program-level fixed effects	24.62	31.39	72.17	63.68	57.55
Local SCP supply measures	5.06	5.12	5.08	16.29	19.10
R-squared	0.36	0.32	0.14	0.15	0.16
Observations	13,461	13,461	120,712	64,108	46,068

Source: Authors' calculations using administrative data. For the list of variables included in individual and peer characteristics, see Section 4.3. See Table A3 for the list of variables included in local SCP supply measures.
Notes: This table presents results from the R-squared Shapley-Owen decomposition for the regressions (models I+Z+S) reported in Tables A4 (Columns [1] and [2] for learning outcomes), A5 (Column [3] for graduation) and A6 (Columns [5] and [6] for formal employment and wages) estimated using student-level data. For each regression, the table shows the R-squared and the percent of the explained variation attributable to each set of individual or peer characteristics, program-level fixed effects, and local SCP supply measures. "Observations" indicates number of students (equal to the number of observations in the underlying regression).

Table 3. Correlations between Program Contributions, Average Outcomes, and Other "Quality" Measures

	Program contribution to:		
	Graduation	Formal Employment	Wages (log)
	(1)	(2)	(3)
Panel A. Average Outcomes			
Graduation	0.98***	-0.01	-0.02
Obs.	621	418	418
Formal Employment	-0.11**	0.94***	0.32***
Obs.	418	851	851
Wages (log)	-0.06	0.30***	0.93***
Obs.	418	851	851
Panel B. Quality Measures			
Tuition	0.02	-0.16***	0.04
Obs.	621	851	851
SABER 11	-0.12***	0.10***	0.19***
Obs.	611	832	832

Source: Authors' calculations using administrative data. See Appendix 1 for the definitions of the variables.
Notes: This table shows the correlation between estimated program contributions and average outcomes (Panel A) and other commonly used quality measures (Panel B). We include tuition and SABER 11 as quality measures since they are available in administrative sources. Average outcomes in Panel A are estimated across all students that are part of the sample used for the underlying regression of program contributions. Average SABER 11 was calculated across all students in each program. Correlations are weighted by the program number of students. "Obs." corresponds to number of programs. Differences in the number of observations is due to data availability. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. R-squared Shapley–Owen Decomposition for Program-Level Contributions

	Graduation	Formal Employment	Wages (log)
	(1)	(2)	(3)
Percent of explained variation attributable to:			
Institution	93.82	79.32	75.74
Field of study	6.18	20.68	24.26
R-squared	0.62	0.43	0.36
Observations	621	851	851

Source: Authors' calculations using administrative data.
Notes: This table presents the results from the R-squared Shapley-Owen decomposition for the regressions of program-level contributions to institution fixed effects and field fixed effects (one regression per outcome). For each regression, the table shows the R-squared and the percent of the explained variation attributable to each set of fixed effects. "Observations" indicates number of programs (equal to the number of observations in the underlying regression).

Table 5. Associations between Program-Level Contribution to Graduation, Quality Determinants, and Local Market Conditions

	Full Sample		Large Cities	Small/Med Cities	Two-year Programs	Three-year Programs
	(1)	(2)	(3)	(4)	(5)	(6)
Program Characteristics						
Three-year program	3.33	3.48	4.34*	-0.08		
	(2.54)	(2.47)	(2.47)	(4.17)		
Distance program	-2.78	-3.53	-10.43**	0.50	-3.96	-3.67
	(3.73)	(3.65)	(4.23)	(3.81)	(6.17)	(4.28)
Program age (years)	-0.88***	-0.77***	-0.48*	-1.18***	-0.45	-0.72**
	(0.27)	(0.28)	(0.28)	(0.43)	(0.62)	(0.31)
Institution Characteristics						
Public HEI	0.72	0.72	0.80	-3.27	-7.96	3.71
	(3.14)	(3.11)	(4.24)	(4.36)	(4.89)	(3.48)
Technological school	3.13	2.37	4.95	-0.95	0.10	1.71
	(2.92)	(2.83)	(3.08)	(4.95)	(5.07)	(3.25)
University	-3.05	-3.43	-2.63	0.42	4.61	-5.68*
	(3.19)	(3.04)	(3.56)	(4.58)	(7.19)	(3.25)
Institution size (log enrollment)	-2.69**	-2.08**	-3.06**	0.52	0.38	-3.15***
	(1.03)	(1.00)	(1.31)	(1.40)	(1.96)	(1.17)
Program and Institution Practices						
Selective institution	0.08	0.93	1.20	1.72	6.78	-1.42
	(2.95)	(2.92)	(3.72)	(4.56)	(5.44)	(3.13)
Institution field specialization (index)	-6.43	-3.52	4.16	-12.87**	5.20	-5.04
	(3.96)	(4.22)	(4.73)	(6.17)	(6.81)	(5.19)
High-quality accreditation	1.63	1.58	-0.47	-3.13	3.18	2.30
	(2.79)	(2.63)	(2.27)	(9.06)	(7.30)	(2.52)
Local Market Conditions						
Institution market power (index)	13.25*	9.74	4.44	9.60	1.62	11.53
	(7.34)	(8.33)	(12.36)	(8.81)	(12.54)	(10.80)
Market concentration (HHI index)	-8.07	-12.49*	48.73**	-9.02	-5.99	-14.37*
	(7.10)	(7.03)	(18.76)	(7.92)	(11.79)	(8.30)
City size (log population)	0.42	-1.00	-4.61	-1.13	-3.67	-0.04
	(1.31)	(1.32)	(3.71)	(2.33)	(3.94)	(1.36)
Constant	17.40	32.91*	87.32	24.61	48.79	31.70
	(19.67)	(19.38)	(52.95)	(33.34)	(58.90)	(19.15)
Field FE		X	X	X	X	X
Mean of Dependent Variable	0.00	0.00	0.28	-0.51	-2.17	0.98
Adjusted R-squared	0.08	0.12	0.25	0.10	0.12	0.13
Observations	621	621	356	265	192	429

Source: Authors' calculations using administrative data. See Appendix 1 for the definition of the variables.
Notes: This table reports the associations between program-level contribution to graduation (between 0 and 100), quality determinants, and local market conditions. See Figure A4, Panel A for an illustration of coefficients' relative size. A program is the unit of observation. All variables are dummies except when the unit of measure is indicated in parentheses. Indices take a value between 0 and 1. Regressions are weighted by $1/v$, where v is the standard deviation of the estimated program-level contribution. Specifications control for field fixed effects (FE), except in Column (1). Standard errors clustered at the institution level are in parentheses. Significance levels: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. HHI=Herfindahl-Hirschman Index.

Table 6. Associations between Program-Level Value Added to Formal Employment, Quality Determinants, and Local Market Conditions

	Full Sample		Large Cities	Small/Med Cities	Two-year Programs	Three-year Programs
	(1)	(2)	(3)	(4)	(5)	(6)
Program Characteristics						
Three-year program	6.68***	6.57***	6.45**	10.61***		
	(1.83)	(2.08)	(2.65)	(2.37)		
Distance program	1.95	2.16	-4.65*	7.94***	-5.37	4.14**
	(2.11)	(2.09)	(2.79)	(2.46)	(7.08)	(2.06)
Program age (years)	0.26	0.31*	0.35	0.13	0.04	0.44*
	(0.19)	(0.17)	(0.22)	(0.27)	(0.23)	(0.24)
Institution Characteristics						
Public HEI	-1.48	-1.90	-0.82	-0.44	-1.25	-2.24
	(1.87)	(1.93)	(2.27)	(2.91)	(3.79)	(1.96)
Technological school	1.83	1.86	1.21	1.54	0.01	4.22**
	(1.95)	(1.90)	(2.30)	(3.13)	(3.06)	(2.09)
University	1.17	0.48	-1.85	3.05	-6.38*	2.64
	(2.41)	(2.33)	(2.57)	(3.32)	(3.72)	(2.60)
SENA	9.43***	11.61***	2.17	14.98***	-3.03	14.21***
	(2.90)	(2.80)	(3.55)	(3.49)	(4.54)	(3.13)
Institution size (log enrollment)	1.81***	1.28**	1.79**	0.76	2.00**	1.50**
	(0.54)	(0.53)	(0.68)	(0.78)	(0.96)	(0.61)
Program and Institution Practices						
Selective institution	2.02	3.61*	1.90	-0.27	7.21**	2.28
	(1.85)	(1.90)	(1.86)	(2.92)	(2.98)	(1.88)
Institution field specialization (index)	14.38***	7.58**	6.36*	4.23	11.64**	5.28*
	(2.84)	(3.24)	(3.41)	(4.27)	(5.58)	(3.07)
High-quality accreditation	-2.66	-1.27	-2.16	2.13	-0.13	-0.77
	(1.66)	(1.57)	(1.93)	(2.77)	(3.34)	(1.71)
Local Market Conditions						
Institution market power (index)	-11.16**	-8.14*	2.77	-6.55	-11.37	-7.15
	(4.89)	(4.84)	(8.99)	(4.61)	(9.06)	(5.14)
Market concentration (HHI index)	9.89*	12.83**	-47.45*	9.11*	19.37**	11.92**
	(5.60)	(4.96)	(27.63)	(5.09)	(9.18)	(5.56)
City size (log population)	0.81	1.80**	2.13	0.78	2.96	0.99
	(0.68)	(0.74)	(1.76)	(1.14)	(2.25)	(0.79)
Constant	-42.33***	-51.54***	-55.28*	-36.78**	-74.10**	-35.91***
	(9.83)	(10.41)	(28.59)	(16.94)	(30.45)	(10.36)
Field FE		X	X	X	X	X
Mean of Dependent Var.	0.00	0.00	2.02	-4.98	-5.77	1.52
Adjusted R-squared	0.17	0.25	0.27	0.23	0.24	0.23
Observations	851	851	529	322	223	628

Source: Authors' calculations using administrative data. See Appendix 1 for the definitions of the variables.
Notes: This table reports the associations between program-level contribution to formal employment (between 0 and 100), quality determinants and local market conditions. See Figure A4, Panel B for an illustration of the coefficients' relative size. A program is the unit of observation. All variables are dummies except when the unit of measure is indicated in parentheses. Indices can take a value between 0 and 1. Regressions are weighted by $1/v$, where v is the standard deviation of the estimated program-level contribution. Specifications control for field fixed effects (FE), except in Column (1). Standard errors clustered at the institution level are in parentheses. Significance levels: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. HHI=Herfindahl-Hirschman Index.

Table 7. Associations between Program-Level Value Added to Wages (log), Quality Determinants, and Local Market Conditions

	Full Sample		Large Cities	Small/Med Cities	Two-year Programs	Three-year Programs
	(1)	(2)	(3)	(4)	(5)	(6)
Program Characteristics						
Three-year program	0.07***	0.07***	0.06***	0.09***		
	(0.01)	(0.01)	(0.02)	(0.02)		
Distance program	-0.03	-0.02	-0.04	0.01	0.00	-0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)
Program age (years)	0.003**	0.003**	0.005**	-0.000	0.002	0.003**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Institution Characteristics						
Public HEI	0.01	-0.00	-0.03	0.03	0.01	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Technological school	0.04**	0.03**	0.04**	0.04	0.001	0.03**
	(0.01)	(0.01)	(0.02)	(0.03)	(0.021)	(0.02)
University	0.03*	0.01	0.01	0.02	0.03	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
SENA	0.03	0.03	0.07**	0.01	0.03	0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)
Institution size (log enrollment)	-0.01	-0.01	-0.01	0.001	-0.003	-0.01
	(0.01)	(0.01)	(0.01)	(0.009)	(0.007)	(0.01)
Program and Institution Practices						
Selective institution	0.001	0.02	0.03**	-0.01	0.03	0.01
	(0.012)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Institution field specialization (index)	0.07**	0.04*	0.06	0.04	0.10**	0.02
	(0.03)	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)
High-quality accreditation	0.02	0.02	0.01	0.04	0.03	0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Local Market Conditions						
Institution market power (index)	-0.02	-0.01	-0.06	0.02	-0.04	0.01
	(0.04)	(0.03)	(0.08)	(0.03)	(0.05)	(0.03)
Market concentration (HHI index)	-0.02	-0.04	-0.12	-0.02	-0.01	-0.04
	(0.05)	(0.05)	(0.17)	(0.04)	(0.06)	(0.05)
City size (log population)	0.01*	0.01*	0.00	0.02**	0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Constant	-0.24***	-0.19***	-0.06	-0.43***	-0.28**	-0.08
	(0.07)	(0.08)	(0.22)	(0.11)	(0.13)	(0.09)
Field FE		X	X	X	X	X
Mean of Dependent Variable	0.00	0.00	0.00	-0.01	-0.03	0.01
Adjusted R-squared	0.12	0.19	0.22	0.18	0.15	0.14
Observations	851	851	529	322	223	628

Source: Authors' calculations using administrative data. See Appendix 1 for the definitions of the variables.
Notes: This table reports the associations between program-level contribution to wages (in log) and quality determinants and local market conditions. See Figure A4, Panel B for an illustration of the coefficients' relative size. A program is the unit of observation. All variables are dummies except when the unit of measure is indicated in parentheses. Indices can take a value between 0 and 1. Regressions are weighted by $1/v$, where v is the standard deviation of the estimated program-level contribution. Specifications control for field fixed effects (FE), except in Column (1). Standard errors clustered at the institution level are in parentheses. Significance levels: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. HHI=Herfindahl-Hirschman Index.

Table 8. Stability of Rankings Based on Various Program-Level Outcomes and Value-Added Contributions

Panel A. Correlation of Rankings

	Graduation		Formal Employment	
	Outcome	Value Added	Outcome	Value Added
	(1)	(2)	(3)	(4)
Formal employment	-0.00	0.08		
Wages (log)	-0.05	0.05	0.54***	0.50***

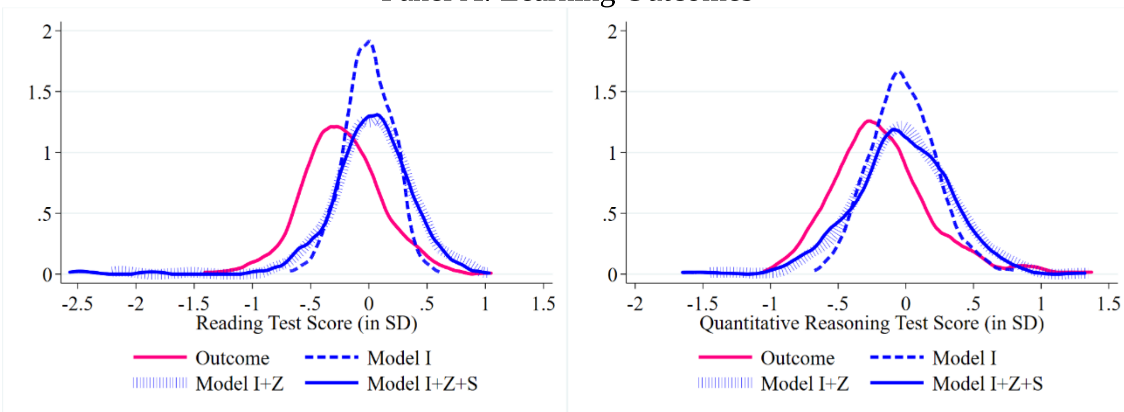
Panel B. Percent of Programs that Move 3 or More Deciles Across Rankings

	Graduation		Formal Employment	
	Outcome	Value Added	Outcome	Value Added
	(1)	(2)	(3)	(4)
Formal employment	57	55		
Wages (log)	51	51	34	34

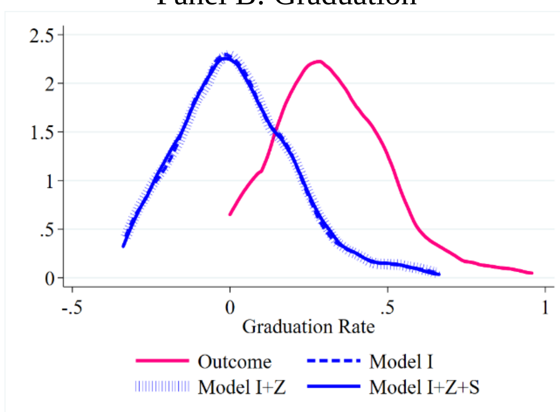
Source: Authors' calculations using administrative data.
Notes: This table shows the stability of program rankings based on program-level average outcomes or value added (6 rankings in total). Panel A shows the correlation among rankings based on a given outcome or value added. For instance, the correlation of the rankings based on (log) wages and formal employment is 0.54, whereas the rankings based on (log) wage value added and formal employment value added have a correlation of 0.50. Panel B shows the percent of programs whose decile position differs by at least 3 deciles across rankings. Since the number of programs for which we estimate value added differs across outcomes, we compute only these correlations for the programs that are common across all samples. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1. Distribution of Average Program Outcomes and Program-level Contributions

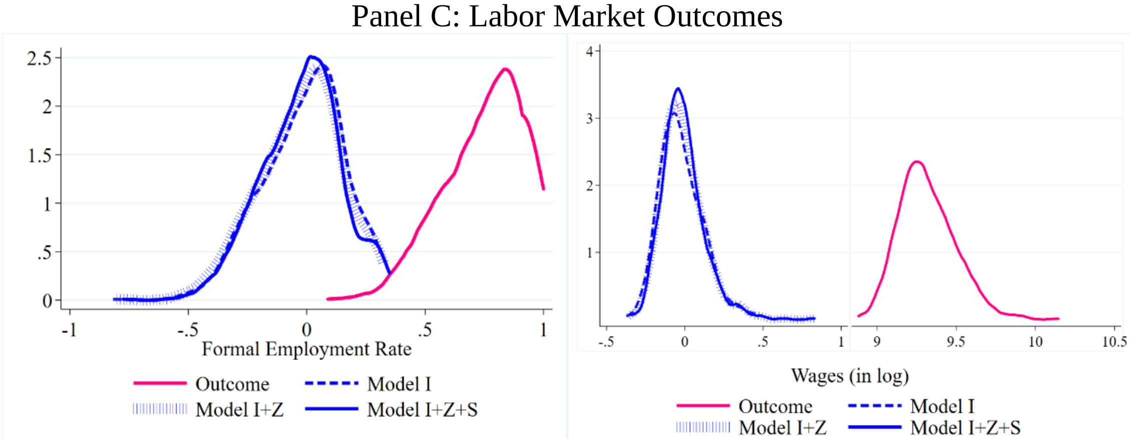
Panel A: Learning Outcomes



Panel B: Graduation

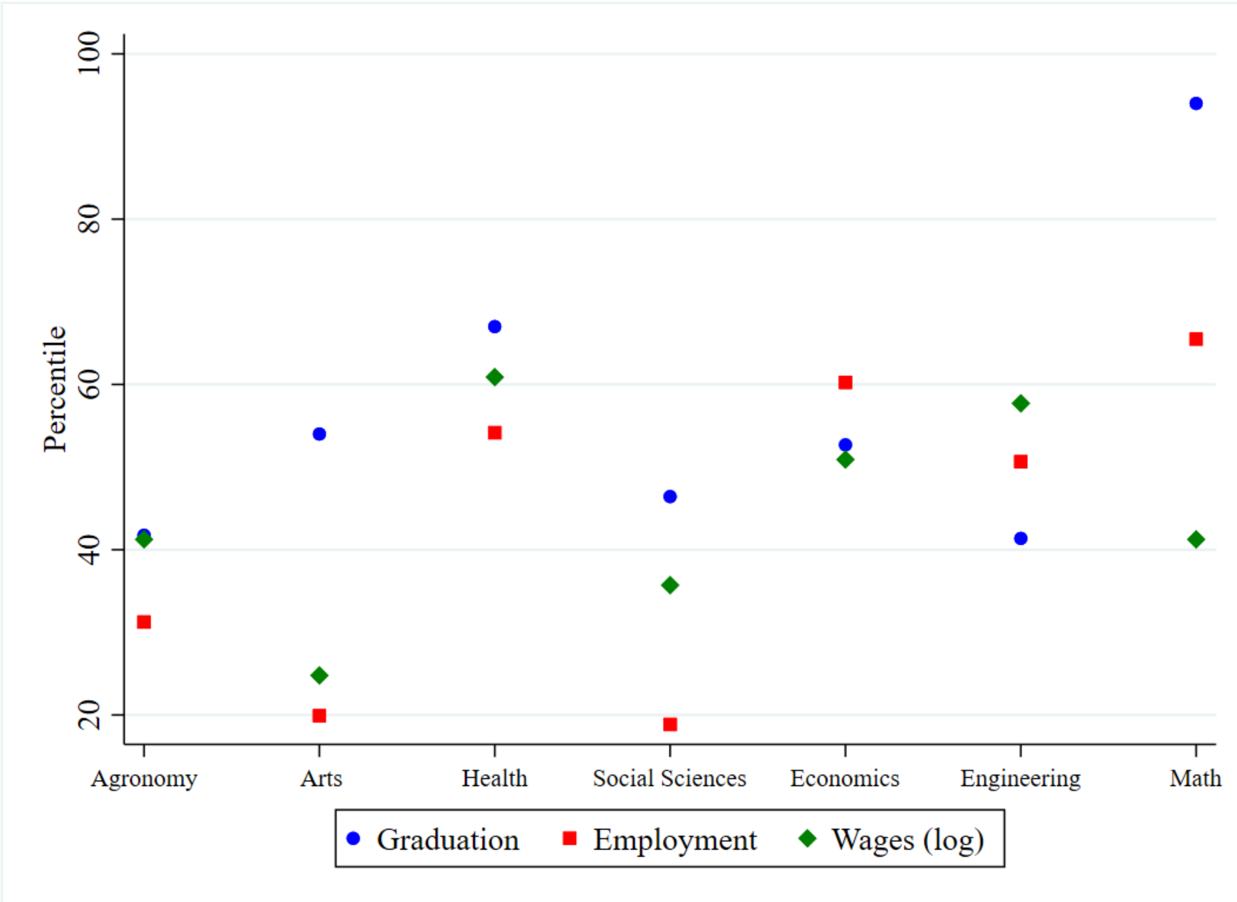


Panel C: Labor Market Outcomes



Source: Authors' calculations using administrative data.
Notes: These figures show the smoothed kernel distribution (using the Epanechnikov kernel function) of program-level average outcomes (in solid pink) and program-level contributions (in blue). Outcomes are defined in Appendix 1. Program-level outcomes are weighted by the number of students in the program. Program-level contributions are estimated as program fixed effects using specification (1). By construction, program-level contributions average out to zero for each outcome. Model I controls only for individual characteristics; Model I+Z controls for individual and peer characteristics; Model I+Z+S controls for individual and peer characteristics and for program local supply measures. Results from these regressions are reported in Tables A4-A6. Graduation and formal employment are between 0 and 1. SD=standard deviations.

Figure 2. Average Rank Percentile by Field



Source: Authors' calculation using administrative data.
Notes: To build this figure, we rank programs based on their value-added contribution to graduation, employment, and (log) wages (three separate rankings). For each ranking, we show the average percentile (or ranking position) of programs from a given field. Percentiles are computed only for programs that are common across all estimation samples.

Data Appendix

Appendix 1. Description of Outcomes and Other Variables

Outcomes from individual-level administrative data

Learning outcomes. We use individual-level standardized test scores on the reading and quantitative components of the SABER PRO exam taken by the cohort of students who that took the test in 2011-2 as our learning outcomes. As in Domingue et al. (2017), we focus on reading and quantitative reasoning scores because these general skills may be more directly related to SCP value added.

Educational attainment. Using data from SPADIES, we create an indicator for graduation as our measure of educational attainment. Every semester, we track cohorts of students who entered higher education between 2007-1 and 2009-2 and define graduation as an indicator that takes the value of 1 if the student graduated within six years after entering the program, and 0 if the student dropped out or has not graduated within six years.

Labor market outcomes:

- <u>Formal employment:</u> Since we only observe the status of individuals who make social security contributions (paid employees or self-employed entrepreneurs), we define formal employment as a binary variable that equals one if, having graduated between 2010 and 2012, the individual was employed or self-employed during any period between 2010 and 2013. Note that individuals who do not make social security contributions could either be unemployed or employed in the informal sector.
- <u>Annual wage:</u> To construct this outcome, we use only the labor income reported during the first year of the individual's employment between 2010 and 2013 to avoid salary changes associated with experience. Moreover, we use only the sample of paid employees because the salaries of self-employed entrepreneurs are recorded as zero in OLE. In sum, the wage measure is the total annual labor income during the first year of formal employment after graduation. Annual wages are expressed in dollars; we conducted a purchasing power parity (PPP) adjustment of wages using the 2019 PPP conversion factor.

Individual characteristics

Academic readiness for higher education. To proxy for a student's ability before enrolling in an SCP, we use the individual's standardized SABER 11 score. This is a mandatory that test evaluates students' knowledge of various subjects (critical reading/language, mathematics, social sciences, natural sciences, philosophy, and English). The measure of individual-level academic readiness pre-SCP is the average of all the student's SABER 11 subject scores, standardized by semester-year.

Age is a variable whose meaning differs across estimation samples. Age is the student's age when entering the program for the graduation sample; the age when she took the SABER PRO exam in the learning sample; and the age when she was employed in the labor market samples.

Relocated to pursue a SCP is a variable that equals to 1 if the student moved away from the student's high school city to participate in the SCP. We construct this variable based on the municipality codes of the student's high school city and the city where she enrolls in her SCP.

Entry year indicates the year the student started the program in the graduation sample. This year is estimated for the other samples as follows: entry year = student graduation year – average time to degree at the student's specific program.

Graduation year consists of the year when the student graduated in the graduation, employment, and wage samples; and the year when she took the SABER PRO test in the learning sample.

Measures of institution and program practices and other supply and local market conditions

Institution and program practices. Using data from SPADIES, we define three practices that are relevant to our context:

- *Selective institution.* To proxy for institution selectivity, we estimate the average 2008 SABER 11 exam score across all programs taught by each institution providing SCPs, and rank institutions based on it. Institutions in the upper half of the ranking are classified as "selective."
- *Institution field specialization.* For a particular field, this is the share of programs that an institution offers in that field relative to all the programs it offers. The index ranges between 0 to 1; an index close 1 indicates that the institution is highly specialized in that field. For example, if 60% of the programs offered by the institution are in Health and the remaining 40% are in Business, then the institution has specialization indices equal to 0.6 and 0.40 for Health and Business, respectively, and equal to 0 for the other fields. If the institution has branches in multiple cities, we construct these indices for each city.

- *High-quality accreditation.* A program has a high-quality accreditation if it has satisfactorily passed through a special accreditation process (beyond the usual licensing and authorization requirements) established by the Ministry of Education, and commonly regarded as a signal of quality.

Local market conditions. We define three conditions within each local market (recall that a market is a city-field combination).

- *Institution market power* consists of the number of programs taught by the institution in each local market divided by the total number of programs in the local market. The index ranges between 0 and 1; a higher index indicates that the institution wields more power in the local market.
- *Market concentration.* We estimate a Herfindahl-Hirschman index (HHI) at the local market-level. It is calculated as the sum of squared enrollment shares for all programs taught in each local market. This index ranges between 0, indicating a perfectly competitive local market, and 1, signifying a monopolistic or concentrated local market.
- *City size.* We use data on population from Duranton (2016) to create a measure of city size, which we calculate as the number of inhabitants (in log) in each city. This measure varies across cities but, within a city, it is the same across fields.

Local SCP supply measures. To characterize students' program choice and mitigate horizontal selection concerns (Hoxby, 2020), we construct a rich set of supply-side variables to characterize the local supply facing the student in her high school city. We focus on local SCP supply because more than 90 percent of SCP students in our data enroll in a program offered in the same city as their high school. Specifically, we create four measures of SCP supply in the student's high school city (see below); we calculate them for the city overall and separately by field, institution governance (public non-SENA, private, or SENA), and program length:

- *Program supply* is the number of available SCPs in the student's high school city.
- *Capacity* is quantified as the total enrollment across programs in the student's high school city.
- *Selectivity* is proxied by the average SABER 11 standardized test score across the programs in the student's high school city. The higher the score, the more selective the program.

- *Cost* consists of the average annual tuition in dollars across programs in the high school city. Purchasing power parity (PPP) adjustment of tuition was carried out using the 2019 PPP conversion factor.

Other variables

City size. We used the following definitions for city sizes: A “large city” has a population above 2.5 million; a “medium city” has a population between 400,000 and 2.5 million; and “small city” has a population below 400,000.

Appendix Tables

Table A1. Characteristics of Students in Bachelor's Degree Programs and SCPs

	Bachelor's Degree Programs	Short-Cycle Programs
SABER 11 score (SD)	0.65	0.08
Family income (%)		
5 or more MMW	0.12	0.03
3-5 MMW	0.17	0.10
2-3 MMW	0.21	0.20
1-2 MMW	0.35	0.49
<1 MMW	0.15	0.19
Age at entry (years)	16.69	16.92
Female (%)	0.54	0.48
Mother's education (%)		
Primary	0.23	0.35
Secondary	0.33	0.43
Short-cycle degree	0.17	0.13
At least a bachelor's degree	0.27	0.08
Field of study (%)		
Agronomy and Veterinary	0.02	0.02
Arts	0.03	0.10
Education	0.11	0.00
Health	0.10	0.04
Social Sciences	0.20	0.05
Economics and Business	0.25	0.39
Engineering and Architecture	0.27	0.40
Math and Natural Sciences	0.02	0.01
Number of students	99,382	31,805

Source: Own estimations using administrative data obtained from SABER 11 (pre-higher education student information) and the System for the Prevention of College Dropout (*Sistema para la Prevencion de la Desercion de la Educacion Superior,* SPADIES). See Section 4.1 for a description of these two datasets.

Notes: This table shows average characteristics for bachelor's degree and SCP students belonging to the cohort that entered higher education the first semester of 2008. The data comes from SPADIES. MMW=monthly minimum wage; SD=standard deviations.

Table A2. Student Characteristics by Estimation Sample

	Learning Sample	Graduation Sample	Employment Sample			Wage Sample		
			All	SENA	Non-SENA	All	SENA	Non-SENA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Individual and Family Characteristics								
SABER 11 score (SD)	0.16	0.10	0.22	0.12	0.24	0.25	0.16	0.27
Female (%)	0.57	0.49	0.56	0.49	0.58	0.54	0.46	0.56
Age (years)	23.09	19.43	23.40	22.96	23.53	23.52	22.97	23.69
Family income (%)								
5 or more MMW	0.04	0.04	0.03	0.02	0.03	0.03	0.01	0.03
3-5 MMW	0.09	0.10	0.09	0.05	0.10	0.09	0.05	0.10
2-3 MMW	0.19	0.21	0.20	0.16	0.21	0.20	0.17	0.21
1-2 MMW	0.47	0.48	0.48	0.49	0.48	0.49	0.51	0.49
<1 MMW	0.22	0.18	0.20	0.28	0.18	0.19	0.25	0.17
Mother's education (%)								
Primary	0.38	0.34	0.37	0.43	0.35	0.37	0.42	0.36
Secondary	0.41	0.44	0.42	0.43	0.42	0.43	0.44	0.42
Short-cycle degree	0.12	0.13	0.13	0.09	0.14	0.13	0.10	0.14
At least a bachelor's degree	0.09	0.09	0.08	0.04	0.09	0.07	0.04	0.08
Panel B. Entry and Graduation Cohort								
Entry year (%)								
2006	-	-	0.14	0.00	0.18	0.15	0.00	0.20
2007	-	0.28	0.38	0.55	0.33	0.40	0.59	0.34
2008	0.76	0.34	0.41	0.44	0.40	0.38	0.40	0.38
2009	0.24	0.37	0.07	0.01	0.09	0.07	0.01	0.08
Graduation year (%)								
Before 2009	-	0.07	-	-	-	-	-	-
2010	-	0.18	0.19	0.00	0.25	0.21	0.00	0.27
2011	1.00	0.26	0.41	0.61	0.35	0.42	0.65	0.36
2012	-	0.28	0.40	0.39	0.40	0.37	0.35	0.38
2013	-	0.15	-	-	-	-	-	-
After 2014	-	0.06	-	-	-	-	-	-

Panel C. Field of Study								
Field of study (%)								
Agronomy and Veterinary	0.03	0.02	0.03	0.07	0.02	0.02	0.06	0.01
Arts	0.08	0.11	0.08	0.05	0.09	0.07	0.04	0.08
Health	0.06	0.05	0.05	0.04	0.06	0.05	0.05	0.05
Social Sciences	0.03	0.05	0.03	0.02	0.03	0.02	0.02	0.02
Economics and Business	0.48	0.38	0.41	0.30	0.44	0.43	0.31	0.46
Engineering and Architecture	0.31	0.38	0.38	0.47	0.35	0.39	0.48	0.36
Math and Natural Sciences	0.01	0.01	0.02	0.04	0.01	0.02	0.05	0.01
Panel D. Outcomes								
SABER PRO-Reading score (SD)	-0.23	-	-	-	-	-	-	-
SABER PRO-Quant score (SD)	-0.17	-	-	-	-	-	-	-
Graduation (%)	-	0.30	-	-	-	-	-	-
Formal Employment (%)	-	-	0.76	0.75	0.77	1.00	1.00	1.00
Wage (annual, in 2019 PPP dollars)	-	-	11,507.40	11,135.45	11,616.32	11,507.40	11,135.45	11,616.32
Observations	13,461	120,712	64,108	14,786	49,322	46,068	10,434	35,634

Sources: Own estimations using administrative data. See Appendix 1 for more details on data sources and definitions of outcomes and entry and graduation year variables.

Notes: This table shows average student characteristics in each estimation sample (Columns [1], [2], [3] and [6]). To document differences between SENA and non-SENA graduates, we present descriptive statistics for these two groups separately using data from the employment (Columns [4] and [5]) and wage samples (Columns [7] and [8]). Annual wage=12 times monthly wage. MMW=monthly minimum wage, and SD =standard deviations.

Table A3. Descriptive Statistics of Local SCP Supply Measures

	Mean	SD	Min.	Max.
Panel A. Program Supply (Number of SCPs)				
Total	*239.74*	*209.28*	*1.00*	*581.00*
Field of study				
Agronomy and Veterinary	1.54	1.59	0.00	7.00
Arts	32.08	34.22	0.00	87.00
Health	9.82	8.37	0.00	26.00
Social Sciences	13.92	13.90	0.00	38.00
Economics and Business	91.16	81.32	0.00	226.00
Engineering and Architecture	89.02	71.89	0.00	220.00
Math and Natural Science	2.21	2.24	0.00	8.00
SENA	54.15	46.36	0.00	167.00
Public institution	24.64	23.60	0.00	86.00
Private institution	160.95	174.79	0.00	486.00
2-year program	110.16	112.77	0.00	314.00
3-year program	129.58	103.39	0.00	303.00
Panel B. Capacity (Total Enrollment, Number of Students)				
Total	*41,164.91*	*41483.3*	*1.00*	*136,409.00*
Field of study				
Agronomy and Veterinary	136.90	247.72	0.00	1,042.00
Arts	4,391.51	5,039.42	0.00	14,673.00
Health	1,379.62	1,496.45	0.00	5,350.00
Social Sciences	1,312.85	1,321.28	0.00	4,255.00
Economics and Business	17,138.27	19,325.07	0.00	63,006.00
Engineering and Architecture	16,258.39	14,696.80	0.00	48,399.00
Math and Natural Science	547.38	697.99	0.00	2,271.00
SENA	13,443.15	17,640.91	0.00	59,750.00
Public institution	8,140.38	8,412.11	0.00	33,907.00
Private institution	19,581.37	22,742.30	0.00	66,871.00
2-year program	19,598.65	25,698.75	0.00	75,247.00
3-year program	21,566.25	18,304.06	0.00	79,022.00
Panel C. Selectivity (Average SABER 11, in SD)				
Total	*0.15*	*0.23*	*-1.01*	*2.70*
Field of study				
Agronomy and Veterinary	0.13	0.32	-1.74	2.70
Arts	0.26	0.13	-0.41	0.64
Health	0.02	0.16	-0.81	0.42
Social Sciences	0.06	0.20	-1.06	0.70
Economics and Business	0.09	0.20	-0.75	1.22
Engineering and Architecture	0.27	0.26	-0.90	2.68
Math and Natural Sciences	0.32	0.24	-0.04	0.73
SENA	0.04	0.22	-1.83	0.62
Public institution	0.46	0.49	-1.01	2.68
Private institution	0.13	0.19	-0.50	2.70
2-year program	0.11	0.19	-1.06	0.88
3-year program	0.22	0.27	-0.84	2.70

Panel D. Cost (Average Tuition, in 2019 PPP Dollars)				
Total	*1,590.41*	*836.22*	*0.00*	*4,071.10*
Field of study				
Agronomy and Veterinary	2,443.19	1,602.90	0.00	5,037.41
Arts	2,708.17	979.04	0.00	4,116.40
Health	1,773.01	951.30	0.00	3,707.27
Social Science	2,042.38	1,011.04	0.00	3,484.74
Economics and Business	1,631.74	847.87	0.00	3,749.00
Engineering and Architecture	1,336.49	728.52	0.00	3,749.00
Math and Natural Science	346.81	456.92	0.00	1,537.96
SENA	0.00	0.00	0.00	0.00
Public institution	1,068.92	256.23	618.29	2,033.39
Private institution	2,945.90	336.80	1,171.47	5,037.41
2-year program	1,337.03	979.28	0.00	3,421.01
3-year program	1,839.12	785.76	0.00	5,037.41
Observations (students)	41,582			

Sources: Own estimations using administrative data. See Appendix 1 for more details on data sources and definitions of local SCP supply variables.
Notes: This table shows statistics of the local SCP supply (in the student's high school city) available to students. We use the cohort of students who started an SCP in 2008-1; statistics are robust to the use of other entry cohorts. SD=standard deviations.

Table A4. Estimation of Program-Level Contribution to Learning Outcomes

	Reading			Quantitative Reasoning		
	Model I (1)	Model I+Z (2)	Model I+Z+S (3)	Model I (4)	Model I+Z (5)	Model I+Z+S (6)
Age (years)	0.132***	0.138***	0.035	0.049	0.049	0.022
	(0.046)	(0.046)	(0.054)	(0.045)	(0.045)	(0.055)
Age squared	-0.003***	-0.003***	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.034**	0.024	0.026	-0.164***	-0.193***	-0.198***
	(0.015)	(0.026)	(0.026)	(0.013)	(0.022)	(0.022)
Family income (%)						
5+ MMW	0.092**	0.116	0.121	0.129***	0.140*	0.146**
	(0.047)	(0.084)	(0.084)	(0.042)	(0.074)	(0.071)
3–5 MMW	0.089***	0.043	0.026	0.104***	0.047	0.041
	(0.030)	(0.051)	(0.052)	(0.028)	(0.049)	(0.049)
2–3 MMW	0.069***	0.048	0.034	0.040*	0.020	0.016
	(0.022)	(0.038)	(0.039)	(0.021)	(0.035)	(0.036)
1–2 MMW	0.049***	0.022	0.011	0.059***	0.058*	0.052*
	(0.019)	(0.034)	(0.034)	(0.018)	(0.032)	(0.031)
Mother's education (%)						
Secondary	0.014	0.034	0.036	0.023*	0.010	0.005
	(0.014)	(0.024)	(0.024)	(0.014)	(0.023)	(0.023)
Short-cycle degree	0.064***	0.063*	0.072**	0.046**	0.014	0.011
	(0.022)	(0.036)	(0.037)	(0.022)	(0.037)	(0.037)
At least a bachelor's degree	0.057**	0.112**	0.128***	0.037	0.053	0.055
	(0.028)	(0.047)	(0.047)	(0.027)	(0.048)	(0.048)
SABER 11 score (SD)	0.562***	0.572***	0.571***	0.435***	0.453***	0.450***
	(0.008)	(0.014)	(0.014)	(0.009)	(0.015)	(0.016)
Individual characteristics (I)	X	X	X	X	X	X
Peer characteristics (Z)		X	X		X	X
Supply measures (S)			X			X
Adjusted R-squared	0.355	0.355	0.360	0.320	0.320	0.324
Observations (students)	13,461	13,461	13,461	13,461	13,461	13,461

Sources: Own estimations using administrative data for the learning sample. See Appendix 1 for more details on data sources and definitions of variables.

Notes: This table shows estimation results from specification (1), excluding the constant and including program fixed effects (not shown). Clustered standard errors by program are reported in parentheses. Model I (Column [1]) includes only individual characteristics, Model I+Z (Column [2]) contains individual and peer characteristics, and model I+Z+S (Column [3]) controls for individual and peer characteristics and local supply measures. All models exclude the constant and include program and entry cohort (year-semester) fixed effects (not shown). The sample includes students who were 16–25 years old at entry and who started the program between 2008-1 and 2009-2. The omitted categories are: Mother's education: primary, and Family income <1 MMW. The cohort used to estimate the peer characteristics (Z) consists of high school students enrolled in the corresponding program in the 2011-2 semester and who took the SABER PRO exam. The supply measures vector includes all categories presented in Table A3, except for the Total row. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Estimation of Program-Level Contribution to Graduation

	(1) Model I	(2) Model I+Z	(3) Model I+Z+S
Age (years)	-10.974***	-10.967***	-10.824***
	(1.058)	(1.054)	(1.092)
Age squared	0.253***	0.253***	0.235***
	(0.025)	(0.025)	(0.026)
Female	8.460***	8.462***	8.370***
	(0.420)	(0.421)	(0.418)
Family income (%)			
5+ MMW	-4.052***	-4.085***	-3.859***
	(1.023)	(1.027)	(1.029)
3–5 MMW	-2.341***	-2.390***	-2.145***
	(0.592)	(0.594)	(0.573)
2–3 MMW	-1.733***	-1.739***	-1.557***
	(0.502)	(0.503)	(0.473)
1–2 MMW	-0.793*	-0.803*	-0.744*
	(0.408)	(0.409)	(0.397)
Mother's education			
Secondary	-0.227	-0.234	-0.278
	(0.335)	(0.335)	(0.334)
Short-cycle degree	1.008**	1.023**	0.937**
	(0.473)	(0.474)	(0.474)
At least a bachelor's degree	3.450***	3.485***	3.543***
	(0.592)	(0.592)	(0.589)
Standardized SABER 11 score	6.907***	6.901***	6.745***
	(0.246)	(0.246)	(0.246)
Individual characteristics (I)	X	X	X
Peer characteristics (Z)		X	X
Supply measures (S)			X
Adjusted R-squared	0.139	0.139	0.140
Observations (students)	120,712	120,712	120,712

Sources: Own estimations using administrative data for the graduation sample. For more details on data sources and definitions of variables, see Appendix 1.
Notes: This table shows estimations of program contributions to graduation using specification (1). To facilitate the interpretation, we multiplied the estimated coefficients by 100. Model I (Column [1]) includes only individual characteristics, Model I+Z (Column [2]) contains individual and peer characteristics, and model I+Z+S (Column [3]) controls for individual and peer characteristics and local supply measures. All models exclude the constant and include program and entry cohort (year-semester) fixed effects (not shown). The student is the unit of observation. The program entry cohort is also used to estimate the peer characteristics (Z). We focus on students who were 16-25 years old at entry. The omitted categories are: Entry cohort 2007-1, Mother's education: primary, and Family income <1 MMW. The supply measures vector includes all categories presented in Table A3, except for the Total row. Standard errors clustered at the program level are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Estimation of Program-Level Contribution to Labor Market Outcomes

	Formal Employment			Wages (Log)		
	Model I	Model I+Z	Model I+Z+S	Model I	Model I+Z	Model I+Z+S
	(1)	(2)	(3)	(4)	(5)	(6)
Age (years)	12.584***	12.589***	9.901***	0.082***	0.081***	0.079***
	(1.575)	(1.573)	(1.632)	(0.014)	(0.014)	(0.014)
Age squared	-0.227***	-0.228***	-0.186***	-0.001***	-0.001***	-0.001***
	(0.032)	(0.032)	(0.033)	(0.000)	(0.000)	(0.000)
Female	-3.367***	-3.382***	-3.323***	-0.046***	-0.046***	-0.047***
	(0.440)	(0.445)	(0.442)	(0.004)	(0.004)	(0.004)
Family income (%)						
5+ MMW	-1.238	-1.090	-2.804**	0.019	0.022*	0.018
	(1.166)	(1.173)	(1.179)	(0.012)	(0.013)	(0.012)
3–5 MMW	0.841	1.009	-0.837	0.004	0.005	0.000
	(0.774)	(0.786)	(0.796)	(0.008)	(0.008)	(0.008)
2–3 MMW	1.852***	1.997***	0.445	0.007	0.007	0.002
	(0.608)	(0.615)	(0.620)	(0.006)	(0.006)	(0.006)
1–2 MMW	2.384***	2.478***	1.321**	0.015***	0.015***	0.011**
	(0.508)	(0.517)	(0.514)	(0.005)	(0.005)	(0.005)
Mother's education (%)						
Secondary	-0.148	-0.237	-0.058	0.005	0.005	0.006*
	(0.359)	(0.365)	(0.359)	(0.004)	(0.004)	(0.004)
Short-cycle degree	0.190	0.131	0.345	0.021***	0.022***	0.024***
	(0.582)	(0.591)	(0.589)	(0.006)	(0.006)	(0.006)
At least a bachelor's degree	-3.269***	-3.458***	-2.726***	-0.008	-0.008	-0.002
	(0.833)	(0.836)	(0.831)	(0.008)	(0.008)	(0.008)
Standardized SABER 11 score	2.025***	1.999***	1.856***	0.031***	0.031***	0.029***
	(0.235)	(0.239)	(0.235)	(0.002)	(0.003)	(0.002)
Individual characteristics (I)	X	X	X	X	X	X
Peer characteristics (Z)		X	X		X	X
Supply measures (S)			X			X
Adjusted R-squared	0.149	0.150	0.155	0.155	0.156	0.162
Observations (students)	64,108	64,108	64,108	46,068	46,068	46,068

Sources: Own estimations using administrative data for the employment and wage samples. See Appendix 1 for more details on data sources and definitions of variables.

Notes: This table shows estimations of program contributions to formal employment and wages using specification (1). To facilitate the interpretation, we multiplied estimated coefficients of formal employment by 100. Model I (Columns [1] and [4]) controls for individual characteristics, Model I+Z (Columns [2] and [5]) includes individual and peer characteristics, and Model I+Z+S (Columns [3] and [6]) controls for individual and peer characteristics and local supply measures. All models exclude the constant and include program, graduation cohort, and time (year in OLE when student was formally employed) fixed effects (not shown). The student is the unit of observation. The graduation cohort is also used to estimate the peer characteristics (Z). The sample includes students who are recorded in the OLE dataset as being 20–29 years old. The omitted categories are: Graduation cohort: 2010, OLE year: 2010, Mother's education: primary, and Family income <1 MMW. The supply measures vector includes all categories presented in Table A3, except for the Total row in that table. Standard errors clustered at the program level are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** p

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Table A7. Goodness of Fit, Variation, and Correlation of Value-Added Models

		Mean Outcome	Adj. R-squared	RMSE	SD of Value-Added Estimation	Corr. with Model I	Corr. with Model I+Z	*P*-value KS test Model I vs.:	*P*-value KS test Model I+Z vs.:
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reading	Model I	-0.23	0.36	0.69	0.18	1.00			
	Model I+Z	-0.23	0.36	0.69	0.33	0.51	1.00	0.00	
	Model I+Z+S	-0.23	0.36	0.69	0.34	0.44	0.97	0.00	0.89
Quantitative Reasoning	Model I	-0.17	0.32	0.69	0.22	1.00			
	Model I+Z	-0.17	0.32	0.69	0.31	0.38	1.00	0.02	
	Model I+Z+S	-0.17	0.32	0.69	0.32	0.34	0.97	0.01	0.70
Graduation	Model I	30.26	0.14	42.64	15.66	1.00			
	Model I+Z	30.26	0.14	42.63	15.90	1.00	1.00	1.00	
	Model I+Z+S	30.26	0.14	42.59	15.78	0.99	1.00	1.00	1.00
Employment	Model I	76.35	0.15	39.19	15.44	1.00			
	Model I+Z	76.35	0.15	39.17	15.64	0.99	1.00	0.40	
	Model I+Z+S	76.35	0.16	39.05	15.02	0.96	0.99	0.07	0.82
Wage (log)	Model I	9.27	0.16	0.35	0.12	1.00			
	Model I+Z	9.27	0.16	0.35	0.12	0.99	1.00	0.36	
	Model I+Z+S	9.27	0.16	0.34	0.11	0.97	0.98	0.02	0.54

Source: Authors' estimations using administrative data.

Notes: This table shows the average outcome and goodness-of-fit statistics for each value-added (VA) estimation model (models I, I+Z, I+Z+S) as well as the standard deviation SD) of VA by estimation model; the correlation (Corr.) among the three sets of estimates; and the *p*-values of the Kolmogorov-Smirnov ("KS") test of equality of distributions for the VA estimates (the distributions are represented by the blue lines in Figure 1). We calculate the average fixed effect (weighted by number of students) and use it to demean the program fixed effects. The demeaned fixed effects are our estimates of the program-level contributions. The mean outcome in Column (1) was estimated at the student level. The standard deviation of VA and correlations are weighted by number of students enrolled in the SCP. The units of measure for the outcomes in Columns (1) and (4) are the following: Reading and Quantitative Reasoning test scores are in standard deviations; graduation and employment are in percentage points, and wages are in log. RMSE=Root mean squared residual.

Table A8. Descriptive Statistics of Program-level Contributions

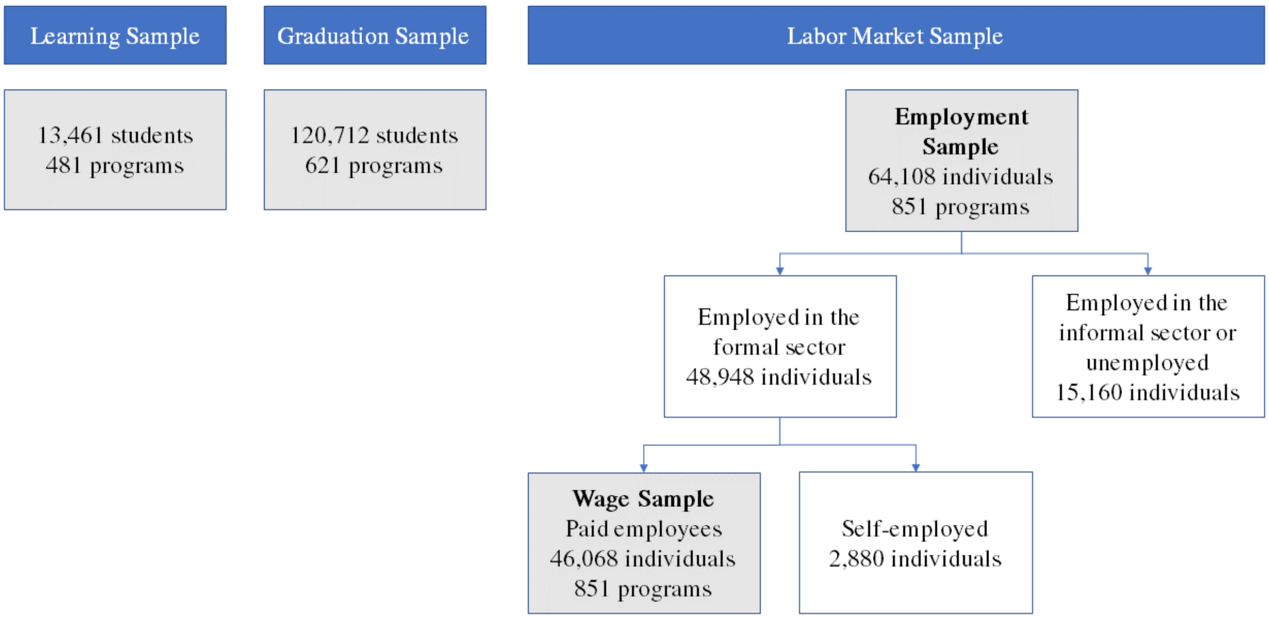
Overall and by Field of Study

Outcome	Contribution				ΔContribution	
	Mean	P25	P50	P75	P75-P25	P90-P10
	(1)	(2)	(3)	(4)	(5)	(6)
Graduation						
All programs	0.00	-10.67	-0.09	9.20	19.87	40.87
Agronomy and Veterinary	-5.09	-19.25	-6.87	5.02	24.27	40.27
Arts	1.65	-7.68	7.36	9.75	17.44	34.98
Health	11.90	1.68	12.08	24.28	22.60	28.81
Social Sciences	-1.76	-14.55	-3.39	5.36	19.91	38.89
Economics and Business	2.72	-6.51	2.34	13.15	19.66	45.37
Engineering and Architecture	-4.67	-13.74	-7.04	3.04	16.77	36.01
Math and Natural Sciences	18.37	-6.22	31.75	34.36	40.58	47.61
Formal Employment						
All programs	0.00	-9.41	1.72	9.84	19.25	36.66
Agronomy and Veterinary	-10.22	-25.77	-16.07	-4.40	21.36	59.25
Arts	-13.61	-21.12	-12.20	-4.76	16.36	30.93
Health	-1.07	-14.20	-0.27	11.73	25.92	44.67
Social Sciences	-15.10	-22.08	-16.20	-8.93	13.14	31.51
Economics and Business	3.48	-3.99	5.52	12.36	16.35	30.50
Engineering and Architecture	0.98	-5.64	2.06	8.58	14.23	35.36
Math and Natural Sciences	8.53	5.03	11.71	12.14	7.11	30.77
Wages (Log)						
All programs	0.00	-0.07	-0.01	0.05	0.12	0.26
Agronomy and Veterinary	-0.10	-0.14	-0.11	-0.10	0.04	0.15
Arts	-0.08	-0.16	-0.09	-0.01	0.15	0.23
Health	0.08	-0.05	0.03	0.21	0.27	0.51
Social Sciences	-0.08	-0.15	-0.07	-0.01	0.14	0.22
Economics and Business	-0.01	-0.07	-0.02	0.04	0.10	0.19
Engineering and Architecture	0.03	-0.05	0.01	0.08	0.13	0.27
Math and Natural Sciences	0.03	-0.01	0.01	0.06	0.07	0.31

Source: Authors' estimations using administrative data.
Notes: In this table, a program is the unit of observation. Statistics are weighted by number of students enrolled in the program. Program-level contributions are estimated with fixed-effect models (results from Model I+Z+S are in Tables A4-A6) and average zero for each outcome. Graduation and formal employment probabilities are in percent. P=percentile, and Δ Contribution=difference in contributions between programs located in two percentiles of the distribution of contributions (75th and 25th, or 90th and 10th).

Appendix Figures

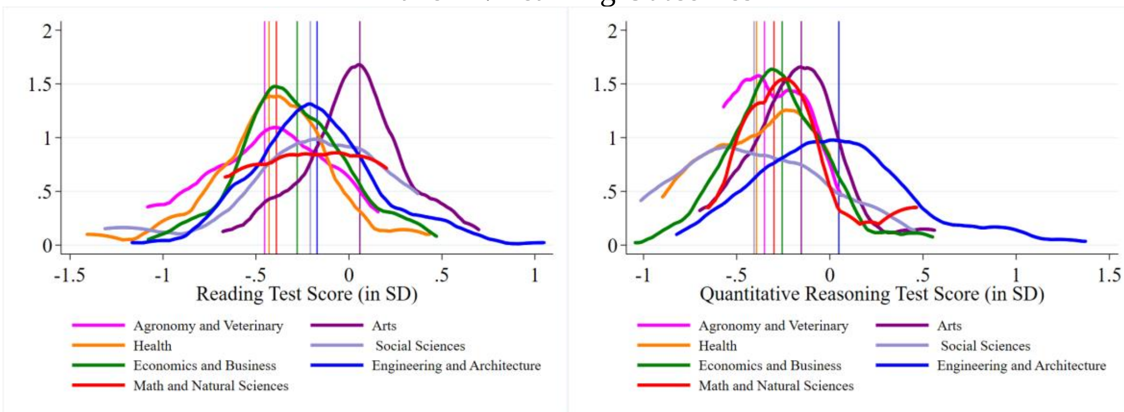
Figure A1. Estimation Samples



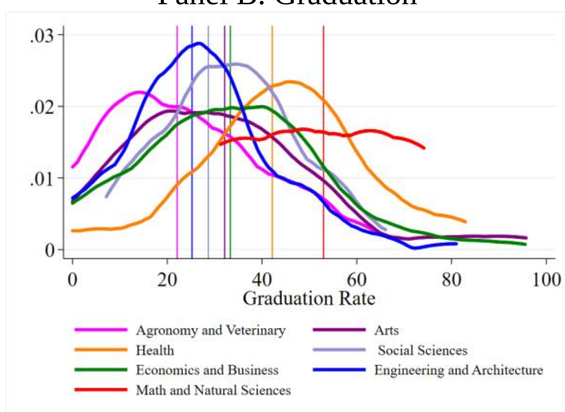
Source: Own calculations using sample sizes from the estimation samples. See Section 4.2 for more details.
Notes: This diagram shows the number of students and programs for each estimation sample. It also presents how the employment and wage samples are defined. The four estimation samples are highlighted in grey boxes. The number of SCPs in the graduation sample is larger than the number of programs in the learning sample because from the latter we exclude SCPs with no students taking the SABER PRO test, SCPs whose students took the exam after 2011-2, or where fewer than 10 students took the test. The employment samples—but not the learning and graduation samples—include SENA.

Figure A2. Outcomes Distribution by Field of Study

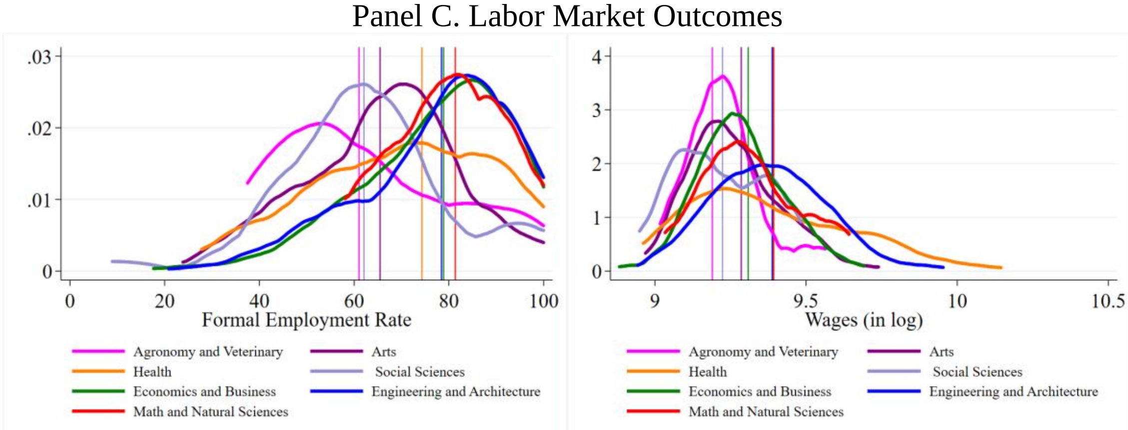
Panel A: Learning Outcomes



Panel B. Graduation



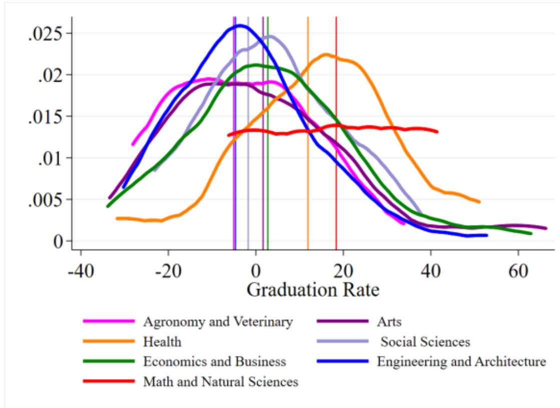
Panel C. Labor Market Outcomes



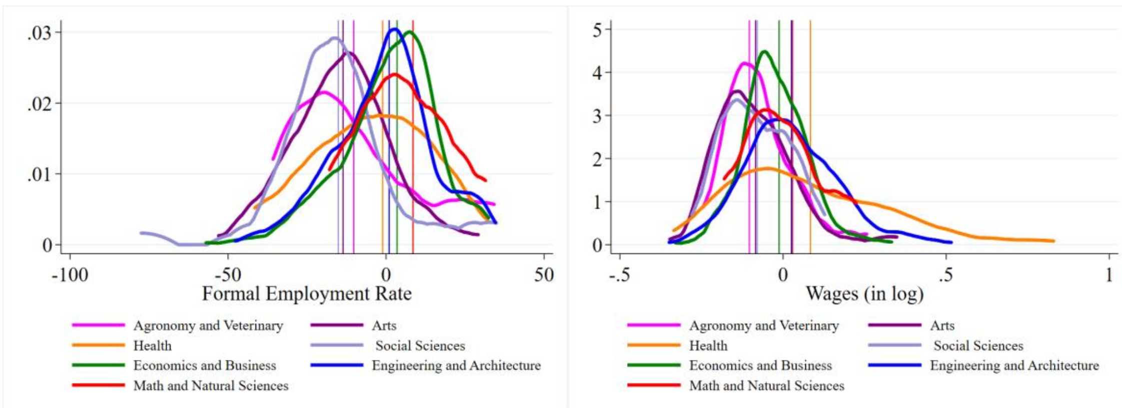
Source: Authors' calculations using administrative data.
Notes: These figures show the smoothed kernel distribution calculated using the Epanechnikov kernel function of program-level average outcomes across fields (in solid black) and for each field (in grey). Outcomes are defined in Appendix 1. Program-level averages are weighted by the number of students in the program. Reading and quantitative test scores have been standardized relative to the full population of students taking the SABER PRO test. Graduation and Formal Employment rate are in percent. SD=standard deviations.

Figure A3. Distribution of Program Contributions to Outcomes by Field

Panel A: Graduation



Panel B: Labor Market Outcomes

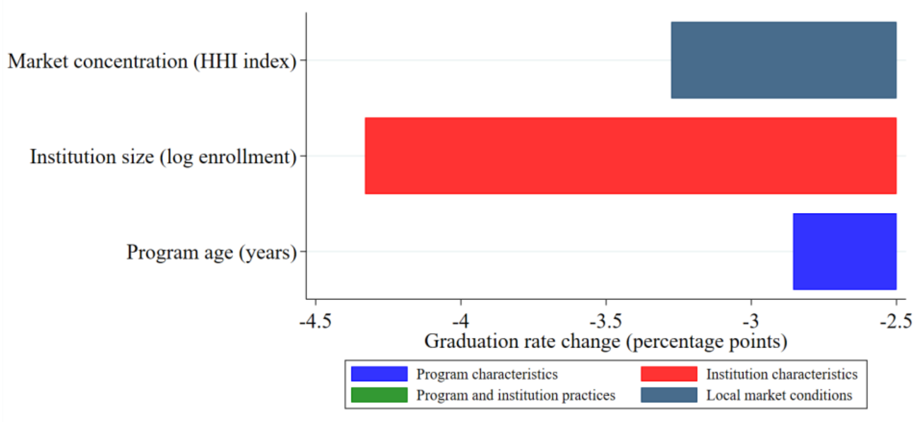


Source: Authors' calculations using administrative data.

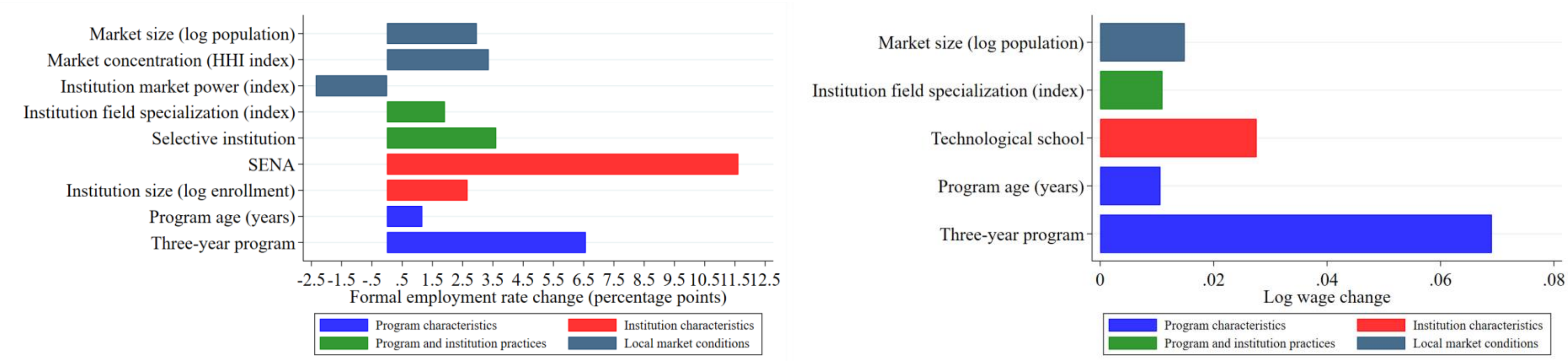
Notes: These figures show the smoothed kernel distribution calculated using the Epanechnikov kernel function of program-level contributions to student outcomes for each field (in grey). Outcomes are defined in Appendix 1. Program-level averages are weighted by the program's number of students. . Graduation and Formal Employment rate are in percent. SD=standard deviations.

Figure A4. Association Between Program-Level Contributions, Quality Determinants, and Local Market Conditions

Panel A: Graduation



Panel B: Labor Market Outcomes



Source: Own estimations using administrative data.

Notes: The figure shows the change in program contributions to graduation (Panel A) and formal employment and wages (Panel B) that are associated with quality determinants and local market conditions. It presents only estimated coefficients that are statistically significant at 10% or less, based on results presented in Column (2) in Tables 5 to 7. All variables are dummy indicators, except when the unit is indicated in parentheses. For non-dummy variables, we report the corresponding coefficient multiplied by the determinant's standard deviation (= *coefficient*one SD of the variable*). A positive change denotes an improvement in the outcome; a negative change indicates a deterioration.

Figure A5. Summary of Associations Between Program Contributions, Quality Determinants, and Local Market Conditions

Categories	Characteristics	Graduation	Formal Employment	Wage
Program characteristics	Three-year program		+	+
	Program age (years)	—	+	+
Institution characteristics	Technological school			+
	SENA		+	
	Institution size (log enrollment)	—	+	
Institution practices	Selective institution		+	
	Institution field specialization (index)		+	+
Local market conditions	Institution market power (index)		—	
	Market concentration (HHI index)	—	+	
	City size (log population)		+	+

Notes: The figure shows program and institutions' characteristics and practices as well as labor market conditions and codes their association with the respective program contribution to graduation, formal employment or wage. The symbol "+" corresponds to a positive and significant (at least 10%) association, and "-" indicates a negative and statistically significant (at least 10%) association.