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What Makes a Program Good? Evidence from Short-Cycle Higher Education Programs in Five Developing Countries

Lelys Dinarte-Diaz
The World Bank

Maria Marta Ferreyra
The World Bank

Sergio Urzua
University of Maryland

Marina Bassi
The World Bank

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What Makes a Program Good? Evidence from Short-Cycle Higher Education Programs in Five Developing Countries

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Abstract

Short-cycle higher education programs (SCPs) can play a central role in skill development and higher education expansion, yet their quality varies greatly within and among countries. In this paper we explore the relationship between programs' practices and inputs (quality determinants) and student academic and labor market outcomes. We design and conduct a novel survey to collect program-level information on quality determinants and average outcomes for Brazil, Colombia, Dominican Republic, Ecuador, and Peru. Categories of quality determinants include training and curriculum, infrastructure, faculty, link with productive sector, costs and funding, and practices on student admission and institutional governance. We also collect administrative, student-level data on higher education and formal employment for SCP students in Brazil and Ecuador and match it to survey data. Using machine learning methods, we select the quality determinants that predict outcomes at the program and student levels. Estimates indicate that some quality determinants may favor academic and labor market outcomes while others may hinder them. Two practices predict improvements in all labor market outcomes in Brazil and Ecuador—teaching numerical competencies and providing job market information—and one practice—teaching numerical competencies—additionally predicts improvements in labor market outcomes for all survey countries. Since quality determinants account for 20-40 percent of the explained variation in student-level outcomes, quality determinants might have a role shrinking program quality gaps. Findings have implications for the design and replication of high-quality SCPs, their regulation, and the development of information systems.

Keywords: Higher education, Short-cycle degrees, quality.
JEL codes: I22, I23, I26, J24.

1 Introduction

Higher education can be a powerful source of social mobility and economic growth. Although bachelor's programs attract about three quarters of higher education enrollment worldwide, their returns vary widely and are not necessarily the best option for all students.[1] Further, the recent COVID-19 pandemic has shown the urgent need for workforce upskilling and reskilling. Shorter and more practical than bachelor's programs, short-cycle higher education programs (SCPs) are uniquely suited to these roles. SCPs are two- or three-years long and correspond to associate degrees in the US, where they are typically taught at community colleges.[2] They prepare students for the labor market, often with a strong occupational content. They can play a central role addressing to rapidly changing market needs, expanding higher education to nontraditional students, and providing lifelong learning opportunities.

Despite their promise, SCPs have some shortcomings. Crucially, student academic and labor market outcomes vary greatly among SCPs. This holds for multiple countries and after controlling for student and peer characteristics.[3] Taking program costs into account, net economic returns vary greatly as well and are negative for many SCPs. Whether program quality is measured by outcomes or returns (raw or adjusted by student characteristics), high- and low-quality programs clearly

[1] For bachelor's enrollment rates worldwide, see UNESCO (http://data.uis.unesco.org/). On the variation of returns to bachelor's programs, see, for instance, Hoxby and Stange (2019) and Lovenheim and Smith (2022) for the US, and Ferreyra et al. (2017) for the developing world.

[2] These programs have different names depending on the country. In this paper, we follow UNESCO's nomenclature of short-cycle programs, corresponding to level-5 programs in the International Standard Classification of Education (ISCED).

[3] See, for instance, Jepsen et al., 2014; Dadgar and Trimble, 2015; Stevens et al., 2019; Liu et al., 2015; Grosz, 2020, and Mountjoy, 2021 for the US; Aucejo et al. (2020) for the UK; and Ferreyra et al., 2021; Ferreyra et al, 2020 for Latin America and the Caribbean.

coexist in the market. Nonetheless, little is known about what makes a program "good"—what is distinctive of high-quality programs—and, as result, SCP quality remains a "black box".

This knowledge gap is largely due to a data gap, as researchers often lack information on student outcomes and, more importantly, on program practices (e.g., how programs relate to local employers) and inputs (e.g., facilities for practical training)—henceforth, quality determinants. Thus, in this paper we open the SCP quality "black box" to identify the quality determinants associated with good academic and labor market outcomes for students.[4] We adopt two complementary approaches. The first one is a regional (aggregated) analysis of program-level average academic and labor market outcomes for five countries in Latin America and the Caribbean (LAC). The second is a country-level analysis for two of those countries using individual-level data on graduation and labor market outcomes.[5]

Underpinning both approaches is a new and unique survey, the World Bank Short-Cycle Program Survey (WBSCPS), which we designed and implemented in five countries in LAC, namely Brazil (in the states of São Paulo and Ceará), Colombia, the Dominican Republic, Ecuador, and Peru (for licensed programs). Together, these countries account for more than half of the SCP enrollment in LAC. The survey contains data from nationally representative samples of SCP providers for a total of 2,103 programs. It collects rich program-level information about quality determinants that are not reported in administrative datasets but might be associated with student outcomes (Bailey et al, 2015). We group them in six categories: training and curriculum (T&C),

[4] Throughout this paper, "determinants" refers to practices and inputs that programs can choose. Other program or institutions characteristics (for example, institution's age or public/private status) are not quality determinants because they are not equally flexible.

[5] We initially set out to collect individual-level data for each of these five countries. However, most countries in the region either do not collect this type of data, merge datasets as needed (for example, those from higher education and social security), or make datasets available to researchers. Building good information systems and facilitating data access remains a key task in developed and developing countries alike.

infrastructure, faculty, link with productive sector (LPS), costs and funding, and other practices related to student admission and institutional governance. By complementing WBSCPS data with administrative program-level information from official sources and program websites, we obtain a novel, multi-country dataset with program-level information on student academic and labor market outcomes as well as quality determinants and characteristics of the program, institution, and student body.

In the regional approach, we exploit this dataset to find the association between program-level outcomes (dropout rate, time to degree, formal employment, and wages) and quality determinants for the five survey countries. For the country-level approach, we complement program-level information with individual-level administrative datasets from Brazil and Ecuador, which combine information from higher education censuses, national high school learning assessments, and social security records for each country. We exploit these sources to estimate the contribution of program quality determinants to student-level outcomes (formal employment and wages for both countries, plus graduation rate for Brazil) while accounting for student and peer background characteristics and former labor market experience as well as program and higher education institution (HEI) characteristics. To our knowledge, this is the first paper to measure the associations between a large set of quality determinants and academic and labor market outcomes by exploiting program- and individual-level data for multiple countries.

This wealth of information allows us to characterize the SCP sector well beyond what was previously possible and to examine the association between student outcomes and program quality determinants. The sheer amount of information, however, poses the challenges of selecting the right set of explanatory variables (to avoid both omitted variable bias and model overfit) and overcoming the confirmation bias from selecting only the variables that confirm researchers' priors. To address these challenges, we use a machine learning method implemented in a two-stage estimation approach. First, we select the set of explanatory variables for student outcomes by using the adaptive Least Absolute Shrinkage and Selection Operator (LASSO) technique.[6] Second, we estimate OLS regressions of academic and labor market outcomes on the set of explanatory variables selected by LASSO to estimate the associations between outcomes and quality determinants while accounting for student, program, and HEI characteristics.

Our findings highlight four main conclusions. First, our program-level survey data shows great variation—within and across countries—in program outcomes and quality determinants. While some practices—such as providing labor market information to students or updating the curriculum to meet firms' needs—are commonly reported, others are reported by less than a fifth of the programs (for example, requiring a second language for graduation).

Second, outcomes are generally associated with quality determinants from multiple categories. The most frequently selected determinants—and those associated with the greatest outcome improvements—correspond to the T&C, LPS, faculty, and other practices categories. The specific predictors of outcome improvements are different in the regional and country-level analyses. In the regional analysis, improving academic and labor market outcomes is associated with practices such as teaching a fixed curriculum, training students to work under pressure, teaching numerical competencies, running an employment center, and providing labor market information. In Brazil, three practices are associated with an improvement in graduation and all labor market outcomes—frequent analysis of student performance, use of tests as a graduation requirement, and students' access to bank loans—and one practice—teaching numerical competencies—is positively

[6] See Zou, 2006; Bühlmann and Van de Geer, 2011; Chetverikov et al., 2019. A recent application of machine learning methods (including LASSO) is Filmer et al. (2021), which seeks to identify predictors of teacher effectiveness.

associated with all labor market outcomes. In Ecuador, improvements in all labor market outcomes are associated with four practices: teaching numerical competencies, gauging student satisfaction frequently, providing labor market information, and training students for job interviews. These differences in selected quality determinants are not surprising given the large variation in program outcomes and quality determinants across countries (e.g., 74 percent of program directors in Brazil report that almost all their graduates work in the formal sector relative to 39 percent in Ecuador).

Third, we find important commonalities despite these differences. Two practices contribute to *all* labor market outcomes in Brazil and Ecuador—teaching numerical competencies and providing labor market information—and one practice—teaching numerical competencies—contributes to *all* labor market outcomes in *all* analyses, including the regional one. Besides their intrinsic importance, numerical competencies may proxy for related skills such as logical reasoning, problem solving, and critical thinking. Further, these competencies may enhance students' human capital given their serious cognitive deficiencies at entry. Providing labor market information, in turn, is quite rare in Latin America, where HEIs typically regard job placement as the students' sole responsibility. By providing this information, HEIs take the first step towards the job placement of their graduates and show their engagement with this process.

Lastly, we find that program quality determinants account for a substantial share of the explained variation of academic and labor market outcomes. Across countries, quality determinants account for 50-60 percent of the explained variation in dropout rates, time to degree and formal employment but only 15 percent of the explained variation in wages, which are mostly explained by country fixed effects. Within countries, quality determinants account for a substantive 19-40 percent of the explained outcome variation in Brazil and 32-38 percent in Ecuador. Although most of the variation in program outcomes remains unexplained within and across countries, these findings are consistent with the notion that shrinking the gap in quality determinants might also shrink the gap in outcomes.

This paper contributes to several literatures. First, we link to work on the role of program quality determinants in higher education on graduates' outcomes. This literature typically focuses on bachelor's degree programs, uses data from a single country, and examines a single determinant such as availability or use of funding options;[7] curriculum structure, training, and academic remediation;[8] availability of infrastructure for practical training;[9] practices related to faculty assessment, training, and hiring;[10] practices to promote student employability and industry engagement;[11] and other program and institution characteristics such as governance.[12] Bailey et al (2015) focus on community colleges in the US and describe the practices of successful institutions and programs yet do not provide systematic, quantitative evidence. Our paper is novel in collecting evidence and analyzing multiple determinants for several countries and specifically SCPs.[13]

[7] See studies on scholarships, grants, and awards (Andrews et al., 2020; Barrow et al., 2014; Castleman et al., 2016; Cohodes and Goodman, 2014; Field, 2009), loan availability and take-up (Armona et al., 2018; Wiederspan, 2016), and tuition (Denning, 2017; Dynarski and Scott-Clayton, 2013; Martorell et al., 2014; Scott-Clayton, 2011).

[8] Examples are studies on credits for longer degrees or transfers (Andrews and Lovenheim, 2014), teaching a second language (Chin et al., 2013), teaching math or reading skills (Xu and Jaggars, 2011), and providing academic remediation (Bettinger and Long 2009).

[9] This literature refers mostly to online training (Bettinger et al., 2017; Cellini and Grueso, 2021; Deming et al., 2016; Figlio et al., 2013; Johnson and Mejia, 2014; Jaggars and Xu, 2016). Evidence is lacking on the effects of other types of infrastructure for practical training.

[10] Evidence on faculty characteristics mostly refers to gender (Bettinger and Long, 2005; Carrell et al., 2010; Kofoed et al., 2019; Lim and Meer, 2019; Porter and Serra, 2020). On faculty-related practices, the literature focuses on faculty assessment (Hoffmann and Oreopoulos, 2009; Kane and Staiger, 2012; Daniel et al., 2007), without robust evidence on faculty training or hiring practices.

[11] Most of these papers analyze internship agreements between firms and HEIs (Di Meglio et al. 2022; Jaeger et al. 2020; Wesley et al. 2019; Yi 2018); few papers study industry engagement in curriculum design (Plewa et al., 2015).

[12] See Teixeira et al. (2013), Hoxby and Bulman (2015), and Bound, Lovenheim, and Turner (2010).

[13] Our paper is also in the spirit of Dobbie and Fryer (2013) for K-12 education. The authors collect data on charter school practices and use it to explain the variation in charter school effectiveness.

Second, our paper contributes to evidence on SCP returns. Most of this literature focuses either on a single US state[14] or a single country.[15] Our results extend the current literature by highlighting—within and across countries—the variance of a large set of program quality determinants, the association between these determinants and student outcomes, and the heterogeneity of these associations. We do not estimate SCP returns relative to a high school diploma (as in some of this literature) but rather compare SCPs among themselves.

Finally, this paper also relates to the literature that uses surveys to collect international data on practices to compare across countries. Some recent efforts of this kind include surveys on managerial practices in schools, firms, and health care (Bloom et al., 2015; 2016; 2020) as well as on universities' practices on governance and performance (Aghion et al., 2010; McCormack et al., 2014). While data from administrative sources and "big data" methods have become increasingly prevalent, survey data remains an attractive option for two reasons. First, granular data on program quality determinants is usually not collected administratively either in developed or developing countries. Even countries that collect general institution or program characteristics do not inquire about issues such as links with the productive sector, faculty, and infrastructure. Second, as Bloom et al. (2016) note, some practices rarely have comparable measures across countries. To our knowledge, this is the first paper to conduct a multi-country data collection initiative on higher education quality determinants and student outcomes for cross-country comparisons.

[14] See Bahr (2013; 2016) and Carrell and Kurlaender (2016) for California; De Vlieger, Jacob, and Stange (2017) for University of Phoenix; Kane et al. (2021) and Boatman and Long (2018) for Tennessee; Liu et al. (2015) for North Carolina; and Xu & Dadgar (2018) for Virginia.

[15] See Cellini and Turner (2019), Stange (2012), and Scott-Clayton and Rodriguez (2015) for the United States; Melguizo and Wainer (2016) for Brazil; Dinarte et al. (2022), Shavelson et al. (2016), Melguizo et al. (2016), Saavedra (2009), Barrera-Osorio and Bayona-Rodriguez (2019) for Colombia; and Rodriguez et al. (2016) for Chile.

The remainder of the paper is organized as follows. Section 2 describes the SCP landscape in the region. Section 3 presents the data and descriptive statistics. Section 4 describes our empirical approach and section 5 summarizes the main results. Section 6 concludes.

2 SCPs in Latin America and the Caribbean, and in Survey Countries

Higher education in LAC has recently experienced a large, rapid expansion, with gross enrollment rates rising from 23 to 52 percent between 2000 and 2017 (Ferreyra et al 2017). Quality remains a challenge, with average graduation rates of only 47 percent across countries. Program and field variety are an additional challenge, as only 9 percent of higher education students in LAC are enrolled in SCPs (relative to the world average of 24 percent), and the average share of STEM graduates is lower in the region than the world (18 vs. 25 percent, respectively). Perhaps as a result, the share of firms reporting serious difficulties in finding qualified workforce is higher in LAC (32 percent) than any other region in the world (Ferreyra et al 2017, Ferreyra et al 2021).

Across our five survey countries, the institutional landscape and popularity of SCPs shows great variation (see Table A1 and Ferreyra et al 2021).[16] Relative to total higher education enrollment, SCPs capture a share between 4 percent in the Dominican Republic and 32 percent in Colombia. On average, SCPs last two or three years and cover a variety of fields ranging from traditional (e.g., nursing and tourism) to innovative areas (e.g., cybersecurity and digital animation). The number of SCPs varies between 209 in the Dominican Republic and 2,388 in Brazil, and the number of HEIs ranges from 28 in the Dominican Republic to 467 in Brazil. SCP providers include universities and non-university HEIs or providers in all countries except Peru, where they only include non-university HEIs. A public national institution exists in Colombia

[16] In what follows, "Brazil" refers exclusively to the states of Ceará and São Paulo, and "Peru" to licensed programs.

(SENA), and a private one in Brazil (the S-System, including SENAI) and Peru (SENATI). Due to this institutional variety and lack of coordination among providers, there is usually no clear pathway from SCPs to bachelor's programs.

In our survey countries, SCPs are offered by public and private HEIs; the private share varies from 21 percent in Colombia to 97 percent in Peru. For-profit HEIs are permitted only in Brazil and Peru. While programs in public institutions are free or highly subsidized due to government financial support, private institutions depend almost entirely on tuition revenues. In some cases, governments provide scholarships, student loans, or guarantees for student loans; students can usually borrow from commercial banks. For the most part, however, students pay tuition out of their own pockets (Ferreyra et al., 2021). HEIs generally need a license to open a program and must undergo a periodic evaluation for license renewal.

As in the US, SCPs in LAC attract more disadvantaged and nontraditional students than bachelor's degree programs. Nonetheless, SCP students in LAC exhibit relatively favorable academic and labor market outcomes (Ferreyra et al. 2021). The SCP average completion rate is 57 percent, 11 percentage points higher than the average completion rate for bachelor's degrees. SCP graduates in LAC have lower unemployment rates, higher formal employment rates, and higher salaries not only than high school graduates but also than dropouts from bachelor's degree programs, even after controlling for observable characteristics. On average, *Mincerian* returns to SCPs relative to high school or an incomplete bachelor's program are equal to 60 and 25 percent, respectively. In other words, SCPs seem a promising option for postsecondary training.

3 Data and Descriptive Statistics

3.1 Program-Level Data

The World Bank Short-Cycle Programs Survey (WBSCPS). This novel and unique survey collects rich information at the program and institution levels about practices, inputs, and other characteristics typically not reported in administrative datasets. The WBSCPS was administered to SCP directors between September 2019 and October 2020 in five LAC countries: Brazil (states of Ceará and São Paulo), Colombia, the Dominican Republic, Ecuador, and Peru (licensed programs). These countries were chosen based on their availability of SCP sampling frames (see below), the interest of their educational authorities in participating in the study, and their research and policy relevance.

For the survey, the SCP universe (or sampling frame) is the set of all programs offered in a country as reported by official sources. Since the universe size varies greatly across countries, we surveyed all programs in the universe in the Dominican Republic, Ecuador, and Peru (including, for the latter, all licensed programs as of October 2019). For Colombia and Brazil, we applied a stratified random sampling procedure to obtain representative SCP samples at the national level in Colombia and the state level in Brazil. The total sample size is 3,656 programs relative to a universe of 5,657 programs over all five countries. Table A2 shows the sampling methodology by country as well as the assumptions used for power calculations.

We developed a survey instrument to gather comparable information across countries (available at instrument). The instrument was shared and validated with local authorities, piloted in subsample of programs, and adjusted based on pilots. The instrument is organized around the following topics: student demographics and readiness for the program; admission and graduation requirements; faculty characteristics, hiring, and evaluation; curriculum and practical training; infrastructure; online teaching; costs and financing; oversight and regulation; institutional governance; interaction with industry; job search assistance; competition; and academic and labor market outcomes. We mapped the information collected to program quality determinants, further grouped into six categories (T&C, LPS, faculty, infrastructure, costs and funding, and other practices); student, program, and HEI characteristics; and program-level outcomes.

Interviewers were trained in data-collection protocols. To assess training effectiveness, a practical exercise was carried out as in Bloom et al. (2020), during which trainees practiced how to read and complete the questionnaire. Interviewers contacted all program directors in the sample. Directors first received an email from the survey firm about the study (accompanied by a letter from the research team) announcing a forthcoming phone call or website link to complete the survey. Interviewers called each program director eight times on average and scheduled the interviews in advance for the directors' convenience, sometimes splitting the interview into two calls to suit the directors' schedule. These procedures helped us to obtain a response rate of 70 percent on average (Table A3) for a total of 2,103 interviews (67 percent online and 33 percent by phone). This is a high response rate, especially because the survey is relatively long and requests some information that the directors may have had to look up, and 48 percent of surveys were conducted under stay-at-home policies due to the COVID-19 pandemic.

Addressing threats to survey data quality. Two sources of bias can emerge with survey data: self-selection and self-reporting. Self-selection into responding the survey might have taken place, for instance, if the directors of higher-performing programs had been more motivated to answer. In addition, since some interviews took place while the HEIs were migrating from in-person to online delivery—when staff were hardly available—only the directors of programs with larger staff might have responded. To mitigate this potential bias, we followed two strategies. First, we verified that the share of programs declining to participate in the survey was low and similar across countries. Only 14 percent of program directors declined to participate in the survey (Table A3).

Second, we evaluated survey representativeness. For each country, we compared programs in the survey and others in the universe based on characteristics such as HEI governance (public / private; for-profit), tuition, enrollment, and institution type (university, non-university HEI, non-HEI). Although a few differences were statistically significant, they were small in magnitude (Table A4). We recalibrated the sampling weights used in the estimations to account for them. As a result, our results can be viewed as representative for the SCP universes.

Self-reporting could have biased our survey data if, for example, program directors had expected to receive some benefit from the educational authorities based on their responses, in which case they would have had incentives to misreport information. To mitigate this problem, we followed best practices for self-reported data collection and applied them to all programs. First, respondents received a letter from the research team indicating that all responses would remain confidential and anonymous and would be reported only in an aggregate fashion—thus favoring truthfulness—as in Bloom et al. (2020). Second, the letter informed respondents that the survey was being conducted exclusively by The World Bank for research purposes and made no mention of governmental units. Third, questions were designed to avoid common biases associated with self-reporting. For example, questions referred to specific time periods (such as the previous academic year) to avoid memory biases, and, where possible, included specific response options.

To address potential biases in self-reported program outcomes, we conducted an outcome validation exercise using country-specific administrative data and household surveys. On average, we found that directors' outcome reports did not differ substantially from outcomes obtained from these other sources. This result was more salient when we restricted the comparison of average labor market outcomes to the age group that was more likely to be enrolled in SCPs (Table A5).

We supplement the survey data with administrative information on program tuition and high-quality accreditation (above and beyond a regular license), and institution governance and type. Some of these variables are available in administrative sources such as higher education censuses, whereas we collected others from HEI and program websites.

3.2 Descriptive statistics of program-level data

Tables 1 and A6 show descriptive statistics of quality determinants (panel A) and student, program, and HEI characteristics (panel B) using program-level data from the WBSCPS and administrative sources. We begin with the description of quality determinants. On average, the programs have desirable traits but also substantial variation. In terms of *infrastructure*, most programs (72 percent) have enough equipment for practical training given enrollment. Online teaching was rare prior to the COVID-19 pandemic, suggesting that the adjustment to provide it must have been challenging. As for *T&C*, most programs (70 percent) teach a fixed curriculum with structured pathways (last updated, on average, about three years ago), with substantial emphasis on practical training. They tend to teach both cognitive (e.g., numerical) and socioemotional competencies (e.g., working under pressure), and about half of them provide remedial education, before and/or during the program. Most programs (86 percent) analyze student performance more than once a year to address problems. About 60 percent of the programs require an internship outside the institution, and less than half of the programs have special graduation requirements such as specific exams, theses, or second language tests. Regarding *costs and funding*, annual tuition is $2,244 on average; it varies between zero and $25,515 (note that all monetary variables are expressed in 2019 PPP dollars except where noted). Less than a third of the programs receive outside funding, and about 40 percent of programs report having some students who take on bank or government loans.

In terms of LPS, most programs (82 percent) have somebody in charge of industry relations. About half of the programs (52 percent) communicate with local firms to gauge their needs or collect data on graduates' employment or employers' satisfaction with the graduates. Less common (35-40 percent) are agreements with industry to hire program graduates or train faculty. Most programs support students' job search; for instance, they train students for job interviews (69 percent), run an employment center (60 percent), and, most often, provide job market information (81 percent). As for *faculty*, the average program has 20 instructors. On average, these are well-qualified (82 and 49 percent have bachelor's and graduate degrees, respectively) and experienced (56 percent have at least five years of industry experience) although less than half currently work in industry. They are mostly male and teach part-time. In most programs (85 percent), faculty are evaluated more than once a year, and about half of the programs provided professional training to most faculty the previous year. When hiring faculty, most programs (88 percent) seek practical experience. In terms of *other practice*s, two-thirds of programs frequently review and update their administrative records, and 50-70 percent rely on admission requirements such as exams, interviews, or test scores in mandatory national exams. In the average program, faculty members comprise the largest share of the HEI's governing board (40 percent of board members).

As panel B shows, in the average program most students are part-time, male, and younger than 25 years old. Most incoming students lack basic skills; the main deficiency is in numerical skills (reported by 82 percent of programs), followed by reading and writing. The average program has a theoretical duration of 5.2 semesters, is 11.5 years old, and enrolled 222 students the year prior to the survey. HEIs in our sample are mostly private (70 percent), are not universities, and lack high-quality accreditation. The average institution is 38 years old and offers 22 programs.

Program-level outcomes. We measure these based on the aggregate information on academic and labor market outcomes reported by program directors. Academic outcomes include dropout rate and time-to-degree. Dropout rate is the percentage of students who dropped out among those who were supposed to graduate the previous academic year. Our time-to-degree measure is the extra time to graduate (ETG), equal to the average percentage of additional time that students take to graduate relative to the program's theoretical duration, which is reported by the program director. Labor market outcomes include formal employment and wages. Formal employment is a binary variable that equals one when the director reports that almost all the program's graduates from the previous year are currently employed or self-employed in the formal sector, and zero otherwise. Wages correspond to the average annual salary earned by last year's graduates, whether they work in the formal or informal sector. Appendix I provides further detail on outcomes.

On average, dropout rate is 14 percent. Average dropout rates are similar in Brazil, Colombia, and the Dominican Republic and slightly lower in Ecuador and Peru (Figure 1 panel A). Average ETG is 19 percent, ranging from an average of 31 percent in the Dominican Republic to 9 percent in Peru (Figure 1 panel A). In terms of formal employment, 59 percent of directors reported that almost all their graduates were formally employed or self-employed. Formal employment is highest in Brazil and lowest in Ecuador (averages are 74 and 39 percent, respectively; see Figure 2 panel A). Wages vary greatly within and across countries (panel B Figure 2). The average ranges from $7,481 in Peru to $11,910 in Ecuador and is only 30- 40 percent above the minimum wages in all countries except Brazil, where it is more than twice as high (Table A7).

3.3 Individual-Level Data for Ecuador and Brazil

Despite its novelty and richness, our program-level data gives us limited ability to estimate the value-added contribution of quality determinants to student outcomes. To control for student and peer characteristics—including previous labor market outcomes—we merged in individual-level data from multiple administrative sources for Brazil and Ecuador.

Brazil

Higher Education Census (HEC). This is the universe of higher education students, programs, and HEIs in Brazil and comes from the Ministry of Education. For a given academic year, and for every student enrolled in higher education, the HEC provides demographics (age, gender, and race), initial enrollment date, and dropout or graduation status by year's end. Focusing on the programs in our sample of effective surveys (henceforth, surveyed programs), we selected the students who entered them in 2014, and used the 2015 and 2016 HECs to establish whether they had graduated. We define a student's peers as those who entered her same program in 2014.

National Educational Entrance Examination. The *Exame Nacional de Ensino Médio*, (ENEM) dataset comes from the Brazilian Ministry of Education and includes student demographic and family background variables. Although it includes individual ENEM test scores, we do not use these because they are missing for 60 percent of the sample.

Labor Market Outcomes. Their source is the Annual Reports of the Social Administration (*Relação Anual de Informações Sociais,* RAIS), a matched employer-employee dataset of all workers and firms in the Brazilian formal sector. It is constructed by the Brazilian Ministry of Labor based on a mandatory annual survey filled by all firms in the formal sector. RAIS contains information on earnings (gross monthly wages), employment, occupation, and demographics for all individuals who are employed by a formal firm in a particular year. For every individual selected from the 2014 HEC, we use RAIS to measure employment status and earnings in the 12-month period before she starts the program (namely, in 2013) and the 12-month period following her graduation (namely, in 2016 or 2017) provided she graduates within three years.

By merging these sources, we create an individual-level dataset for Brazil for students who entered our surveyed programs in 2014. It includes student gender, age, and mother's education level; graduation status as of 2016; and pre- and post-program labor market outcomes for graduates who were formally employed after graduation. We merge the individual-level dataset with information at the program- and HEI- levels from the WBSCPS and other administrative data. The resulting dataset includes 29,453 students and 401 programs (relative to 601 surveyed programs).[17]

Ecuador

2019 Higher Education Census (HEC). This is the universe of higher education graduates who obtained their degrees between January and December of 2019. It comes from the Science, Technology, and Innovation Secretariat (*Secretaria Nacional de Ciencia, Tecnologia e Innovacion*, SENESCYT), and contains information on approximately 29,000 SCP graduates, including field of study, institution, program name, and graduation date. Based on these data, we define a student's peers as those who also graduated from her program in 2019.

National Educational Entrance Examination. This dataset comes from the National Institute for Educational Assessment (*Instituto Nacional de Evaluacion*, INEVAL) at the Ministry of Education. It records test scores on the mandatory high school exit exam (*Ser Bachiller*) and self-reported student socioeconomic background at the time of the exam. We obtained access to a subset of this dataset through the Higher Education Access Unit (*Subsecretaria de Acceso a la Educacion Superior*) at SENESCYT, with information on students who took the test in 2017 and

[17] Some programs do not match because they did not yet exist in 2014, which is our cohort's entry year. Others did exist in 2014 but did not have graduates who were formally employed during our sample period. Table A8 presents descriptive statistics for the subsample of 401 programs matched to individual-level data. It also shows t-tests for mean differences between those programs and the remaining 200. A few means are statistically different. For example, matched programs are more likely to have sufficient infrastructure for practical training or coordinate job interviews with firms than unmatched programs. They also tend to be older, are taught by smaller institutions, and have higher shares of part-time students.

2018 (age, gender, whether the student has children of her own, family of origin's socioeconomic score, and mother's education level.) Note that the subset of students to which we were given access may not be a representative sample of all students who took the test. Further, the scores of the *Ser Bachiller* test were not shared with us.

Labor Market Outcomes. Their source are individual-level records from the Ecuadorian Social Security Institute (*Instituto Ecuatoriano de Seguridad Social,* IESS) and the Ecuadorian Internal Revenue Service Unit (*Servicio de Rentas Internas,* SRI), which together yield the universe of individuals formally employed or self-employed, with monthly records of individual employment status and earnings between January 2018 and December 2020. We use these to construct labor market outcomes for the 12-month periods before and after graduation.

The final dataset for Ecuador is a sample of 2019 SCP graduates. It includes individual characteristics (gender, age, whether the student has children), socioeconomic background (mother's education level and socioeconomic index), pre-graduation labor market outcomes, and post-graduation formal employment status and wages. We merge the individual-level dataset with information at the program and HEI levels from the WBSCPS and administrative sources. The resulting dataset includes 1,239 individuals and 92 programs (relative to the 245 programs with effective surveys in our sample).[18]

It is worth emphasizing that our individual-level datasets for Brazil and Ecuador are different in that, for Brazil, we have information on all students who entered our survey programs in 2014

[18] Some programs do not match to individual-level data for reasons similar to those in Brazil. In addition, some programs match but only have one student. Table A9 presents descriptive statistics for the subsample of the 92 surveyed programs that match to individual-level data and shows t-tests for mean differences between these programs and the 153 unmatched ones with 2+ students. Some differences are statistically significant. Matched programs are more likely to update the curriculum based on government standards and HEI labor market perceptions, require a professional test for graduation, or have agreements with firms to hire their graduates. They have more workshops for practice, charge a higher tuition, and have more faculty members. They are more likely to be taught by private, large HEIs, and have high-quality accreditation.

(whether they went on to graduate or not), whereas we only have information on graduates for Ecuador. Therefore, we will examine graduation outcomes only for Brazil, but will analyze the following labor market outcomes for graduates from both countries over the 12-month period following graduation: (i) whether the student was formally employed at least one month; (ii) what percent of those months she was formally employed; and average monthly wages (calculated as the average over her months of formal work, and equal to zero if she did not work formally at all). Further, we use individual-level data to construct average characteristics and previous labor market experience for peers.[19] Appendix I provides additional information on all variables.

3.4 Descriptive statistics of individual-level data

Table 2 presents descriptive statistics of program graduates in Ecuador and Brazil, for whom we study labor market outcomes. In both countries, the average student is about 25 years old and about 60 percent of students are female (panel A). Students in Ecuador have more educated mothers than in Brazil and 27 percent of them have children of their own. The average student in Brazil has accumulated more formal labor market experience before entering the program than the average graduate in Ecuador (panel C): 64 percent of students in Brazil worked at least one month before entering the program and worked for 46 percent of the time on average, whereas only 26 percent of graduates in Ecuador worked at least one month before graduation and worked for 19 percent of the time on average. Students in Brazil, therefore, have peers with more previous labor market experience than in Ecuador. After graduating (panel D), the average graduate in Brazil is more likely than that in Ecuador to be employed formally for at least one month (70 vs. 35 percent),

[19] For student *i*, peer characteristics are the average characteristics of the *other* students in her cohort (Sacerdote, 2011). Recall that a program's cohort is set of all 2019 program graduates in Ecuador (as information on entry cohort is not available) and all 2014 program entering students in Brazil. Interviews with local experts from Ecuador confirmed that graduation and entry cohorts usually have similar characteristics.

spends a greater fraction of the time in formal employment (53 vs. 24 percent), and has a higher monthly wage (US$1,031 vs. US$876) conditional on being formally employed. Finally, Table A10 describes the full set of students who started an SCP in 2014 in Brazil, of whom only 30 percent graduated within three years.

4 Empirical Strategy

4.1 Cross-Country Estimations Using Program-Level Data

Data-driven selection of quality determinants

The WBSCPS has the fascinating advantage of providing a large set of variables that proxy for program quality determinants. However, this large number of variables poses some challenges. The first is to select the "right" set of explanatory variables. Using too few controls—or the "wrong" ones—may create omitted variable biases while using too many may overfit the model. A second empirical challenge is the potential for researcher's confirmation bias—selecting the variables in a way that confirms her hypotheses. We address these issues with our two-stage estimation approach. First, we use a data-driven method to select the parsimonious set of quality determinants that best fit the outcome data. Second, we estimate the association between the selected program quality determinants and the outcomes of interest.

To select quality determinants in the first stage, we use a supervised machine learning approach: the Least Absolute Shrinkage and Selection Operator (LASSO) technique. LASSO chooses a parsimonious set of controls that provide the best possible fit of the data and discards those that contribute little to the fit. For a given outcome in program *j* and country *c*, we estimate the following linear specification using LASSO:

$$y_{jc} = \alpha_0 + \sum_{d=1}^{6} \boldsymbol{Q}_{jc}^{d}{}' \boldsymbol{\alpha_1^d} + \boldsymbol{C}_{jc}' \boldsymbol{\alpha_2} + \boldsymbol{N}_{jc}' \boldsymbol{\alpha_3} + \phi_c + \phi_f + \epsilon_{jc} \,, \tag{1}$$

where y_{jc} represents one of the four program-level outcomes reported by program directors (dropout rate, ETG, formal employment, and wages). The vector $\boldsymbol{Q}_{jc}^{d}$ includes all the survey variables for category d of quality determinants (recall the six categories: infrastructure, costs, T&C, LPS, faculty, and other practices; see Table 1 panel A.). We use $\boldsymbol{Q}_{jc}$ and $\boldsymbol{\alpha_1}$ to refer to the full set (over all categories) of quality determinants and their coefficients, respectively.

A potential concern from regressing y_{jc} on $\boldsymbol{Q}_{jc}$ alone is omitted variable bias, as other program or institution characteristics might determine y_{jc} and be correlated with the determinants. Therefore, we control for observable characteristics at the program or institution level, $\boldsymbol{C}_{jc}$ (see Table 1 panel B). To avoid model oversaturation due to these additional variables, we use a data reduction strategy—principal components analysis (PCA)—and build indexes for student body, program, and HEI characteristics (Appendix I). We also include country and field fixed effects in all specifications (ϕ_c and ϕ_f, respectively) to account for systematic differences in program-level outcomes across countries and fields. Moreover, we add the statistical noise controls for survey measurement error (Table 1 panel C), $\boldsymbol{N_{jc}}$, including number of attempts to complete the survey, whether the interview was conducted during lockdown policies, and interview mode (phone or online). Finally, ϵ_{jc} is the error term.

We use the adaptive LASSO (Belloni et al., 2014 and 2015), which selects the tuning parameters (weights) used by LASSO to discard or keep determinants in order to minimize the out-of-sample mean squared error (MSE) of the predictions.[20] To ensure that we control for $\boldsymbol{C}_{jc}$ and $\boldsymbol{N_{jc}}$, LASSO includes them in every model it estimates, holding them "fixed" while it finds

[20] Adaptive LASSO is more conservative than the cross-validation (CV) method, which tends to include extra covariates whose coefficients are zero. See Zou (2006), Bühlmann and Van de Geer (2011), and Chetverikov, Liao, and Chernozhukov (2019).

the best combination of quality determinants in $\boldsymbol{Q}_{jc}$. In other words, LASSO tries combinations of quality determinants (which are therefore "floating" variables) conditional on the "fixed" variables. The selected subset of determinants for category d, $\boldsymbol{Q}_{jc}^{*d}$, is an input for the second estimation stage.

Associations between quality determinants and outcomes

LASSO's ability to work as a covariate-selection method makes it a nonstandard estimator and prevents the estimation of standard errors. Therefore, we implement a second stage that predicts a given outcome as a function of its selected determinants through the following OLS regression:

$$y_{jc} = \beta_0 + \sum_{d=1}^{6} \boldsymbol{Q}_{jc}^{*d\prime} \boldsymbol{\beta}_1^d + \boldsymbol{C}_{jc}' \boldsymbol{\beta_2} + \boldsymbol{N}_{jc}' \boldsymbol{\beta_3} + \gamma_c + \gamma_f + \omega_{jc} \,. \qquad (2)$$

The estimated parameters of interest are in the $\widehat{\boldsymbol{\beta}_1^d}$ vectors, reflecting the association between the selected quality determinants and the outcome. Standard errors are clustered at the HEI level.

4.2 Country-Specific Estimations Using Individual-Level Data

Program-level data does not allow us to satisfactorily address student self-selection into programs. To address this limitation, we use the individual-level administrative data for Brazil and Ecuador and follow Dinarte et al. (2022), Melguizo et al. (2016), and Smith and Stange (2016) to estimate the following model for a given outcome and country (Brazil or Ecuador):

$$y_{ijt} = \sum_{d=1}^{6} \boldsymbol{Q}_j^{d\prime} \boldsymbol{\delta_1^d} + \mathbf{R}_i' \boldsymbol{\delta_2} + \boldsymbol{Z}_{ij}' \boldsymbol{\delta_3} + \boldsymbol{C}_j' \boldsymbol{\delta_4} + \boldsymbol{N}_j' \boldsymbol{\delta_5} + \phi_f + \epsilon_{ij}^k, \qquad (3)$$

where y_{ij} is an outcome for student *i* in program j; $\boldsymbol{R}_i$ is an index of individual characteristics (e.g., gender, age, socioeconomic status, parental education) and previous labor market experience; and $\boldsymbol{Z}_{ij}$ is an index of peer characteristics and previous labor market experience. These indexes were created (via PCA) to reduce the dimensionality of the corresponding variables (see Appendix I).

For Brazil estimations we also include state fixed effects (São Paulo and Ceará) and graduation year (2015 and 2016) fixed effects. Standard errors are clustered at the program level.

We estimate this equation following the same two-stage approach described above. Throughout, all regressors except for those in the $\boldsymbol{Q}^d$ vectors are held fixed**.** Estimates of the second-stage coefficients on the LASSO-selected quality determinants measure these determinants' contributions to student outcomes, net of the contributions from the student, her peers, or other program and institution characteristics.

4.3 Variance decompositions

We conduct a Shapley–Owen R-squared decomposition of the second-stage regressions (Shapley 1953; Owen 1977; Huettner and Sunder 2012). For the program-level regressions, we quantify the fraction of explained variation attributable to the following sets of variables: quality determinants (overall and per category); student, program, and HEI characteristics (as captured by the corresponding PCA scores), field fixed effects, and country fixed effects. For the individual-level regressions, we additionally quantify the fraction of explained variation attributable to student and peer administrative variables (as captured by the PCA scores) as well as, for Brazil, state and graduation-year fixed effects.

5 Estimation results

5.1 SCP Quality Determinants

Using program-level data

Academic Outcomes

Dropout rates. Several determinants are associated with reductions in dropout rates of about 1.5-2 pp, relative to a sample average of 14% (Figure 3 panel a; Table A11 column 1).[21] The largest reductions are associated with one T&C determinant—having a fixed curriculum—and two LPS determinants—providing job market information and obtaining equipment from industry for student training. The fixed curriculum finding is consistent with the US community college evidence in Bailey et al (2015) that structured pathways promote graduation. Industry connections and job search assistance, in turn, might show students their labor market prospects and motivate them to graduate. Some determinants are associated with higher dropout rates (e.g., receiving outside funding, which might come with conditions that limit the program's margin of action).

Estimated Time to Degree (ETG). The determinants associated with the greatest ETG reductions (3 to 7 pp, relative to an average ETG of 18.6%) come from multiple categories (Figure 3 panel b; Table A11 column 2). Unsurprisingly, programs that teach students to work under hardship or pressure have lower ETGs, presumably by teaching them to persevere and work efficiently, as do programs that evaluate faculty more than once per year (promoting frequent teaching adjustments), engage with industry for student evaluation or curriculum design (perhaps yielding a more efficient and engaging curriculum), or have higher tuition (as students would seek to graduate fast to avoid paying it). Programs with a higher ETG (by about 3 to 5 pp) are those whose curriculum updates rely heavily on the HEI's perception of the labor market (which might make the program unnecessarily long or involved) or that require a thesis or research project for graduation. Anecdotal evidence indicates that such projects become a hindrance to students who do not have

[21] Figures 3-6 presents the estimated association between student outcomes and quality determinants, focusing on significant coefficients (at the 1, 5 or 10 percent level). For binary determinants (e.g., whether the program provides job market information), the figure presents the coefficient estimate. For non-binary determinants (e.g., percent of female faculty), it presents the coefficient estimate multiplied by the determinant's standard deviation. The full regressions of the corresponding outcome on the variables selected by LASSO (including those whose coefficients are not statistically significant) are in tables A11-A14.

the preparation or support necessary to complete the projects on time. Some determinants may improve one outcome but hurt others. For example, programs with a higher proportion of faculty working in industry have lower ETG but higher dropout rates. Such instructors may design engaging curricula (lowering ETG) but deviate students away from the program and into industry (raising dropout rates).

Labor Market Outcomes

Formal employment. Teaching numerical competencies is associated with a 15-pp increase in formal employment, relative to an average formal employment of 59 percent (Figure 4 panel a; Table A12 column 1). While intrinsically valuable, these competencies may also capture related skills such as logical reasoning and critical thinking. Further, programs that provide remediation during the program also have higher formal employment—by providing a context for the remediation, they may be more effective at raising employability-related skills. Some LPS practices are associated with higher (4-9 pp) formal employment, such as running an employment center (9 pp), assigning staff to collect graduates' employment data, and collecting data frequently on graduates' employment or employers' satisfaction with graduates. Further, graduates from programs with a higher proportion of experienced faculty or that have enough equipment for practice also have higher formal employment. On the other hand, formal employment is lower in programs with a higher proportion of young faculty, who may have little experience working in industry or teaching these programs.

Wages. Higher wages (by 3-7 percent) accrue to graduates from programs with specific T&C practices such as teaching numerical competencies, providing remediation during the program, granting credits for longer degrees, and relying heavily on the HEI's perception of the labor market for curriculum updates (Figure 4 panel b; Table A12 column 2). Further, graduates from programs with a higher faculty-student ratio[22] and a higher share of faculty with bachelor's degrees also have higher wages. Unsurprisingly, graduates from programs that use knowledge tests as admission requirements (and are therefore more selective) have higher wages. Wages are lower in HEIs with a higher representation of students in the governing body since student demands may not be driven by concerns over future earnings.

Program-level analysis—taking stock

The program-level analysis shows that, across countries, T&C, LPS, and faculty determinants are associated to academic and labor market outcomes. Cost and infrastructure determinants, in contrast, are associated only to academic or labor market outcomes, respectively. The main determinants, based on the size of their association with academic and labor market outcomes, are those from T&C; they include teaching a fixed curriculum, training students to work under pressure, teaching numerical competencies, and providing credits for longer degrees.

In a theme of our findings, a few determinants favor some outcomes but hinder others. For example, relying on the HEI's perception of the labor market for curriculum updates favors wages but hinders ETG. Although our estimates do not imply causality, these results may indicate the need to weigh these trade-offs when deploying the corresponding practices.

Using individual-level data for Brazil

By using individual-level for Brazil and Ecuador, we gain variation in the outcomes and augment sample sizes relative to our program-level analysis. This gives the adaptive LASSO the ability to select a higher number of determinants in the first stage, and our second stage gains statistical power to find significant coefficients. Further, controlling for student and peer characteristics helps

[22] Since we control for program enrollment, the coefficient on number of faculty can be interpreted in terms of faculty-student ratio.

us address student self-selection into the program and provides an approximation to the value-added contributions from program determinants to student outcomes.

Academic outcomes (graduation). Given our short graduation window (three years), the graduation outcome is practically a measure of on-time graduation and is therefore related to the two academic outcomes measured in the survey. Consistent with our program-level findings, graduation in Brazil is sensitive to determinants from all categories (Figure 5 panel a; Table A13 column 1). The largest associations (6-9 pp, relative to a sample average graduation of 30.3 percent) correspond to two T&C practices, namely frequent analysis of student performance (to solve academic problems in real time) and the use of tests as graduation requirements (which may operate as a commitment device or may be a professional requirement akin to US bar exams). Graduation is also higher (by about 5 pp) in programs that offer at least one online class (providing students with greater coursework flexibility) or maintain their main labs periodically (ensuring that the equipment can be used when needed). External financing through bank loans is associated with higher graduation rates, perhaps by allowing students to focus on their studies rather than having to work. Programs with industry agreements to train faculty have higher graduation rates, likely by helping faculty stay current and connected with industry. HEIs with greater student representation in the governing board also have higher graduation rates, as students may negotiate either for laxer graduation requirements or for teaching practices that promote persistence. A few determinants are negatively associated with graduation rate, such as providing professional training for all or almost all of the faculty (consistent with program-level findings on ETG and suggestive that the professional training may detract from time with the students), having internships agreements with industry (as students may take longer to finish or be poached by industry before they graduate), and updating the curriculum based on regulatory norms or student feedback, which may not reflect labor market needs.

Labor market outcomes. Recall that we focus on graduates' labor market outcomes during the twelve months following graduation, including two formal employment measures—whether the student is ever employed, and percent of the time employed (sample means are 70 and 53 percent, respectively)—and average monthly wage (sample mean is $716 including zeros).

Several determinants have a positive and relatively large association to these three outcomes (Figure 5 panels b-d; Table A13 columns 2-4). From T&C, programs that analyze student performance frequently and those that teach numerical competencies have better outcomes for the two employment measures (by 4-6 pp) and higher wages (by about 30 percent). Programs that require a graduation test also have better labor market outcomes. From LPS, providing job market information is associated with better employment outcomes (by 4-6 pp) and wages (by about 40 percent), likely because it facilitates and kickstarts students' job search. The positive association of labor market outcomes with practices related to faculty (frequent faculty evaluation) and administration (frequent review of administrative data) shows the usefulness of real-time reviews. Admission interviews have a positive association to labor market outcomes, likely by ensuring a student's good fit to the program. Interestingly, the use of bank loans also has a positive association with labor market outcomes, perhaps by allowing students to choose high-return programs, and online provision helps students graduate and work a greater fraction of the time, perhaps by allowing them to work during the program and therefore improve labor market prospects. On the other hand, two practices are negatively associated to all labor market outcomes, namely training students for job interviews, and collecting data on employment or employers' satisfaction more than once a year. While seemingly good, these practices may detract from other productive uses of time or be interpreted by potential employers as an attempt to remediate other weaknesses.

All in all, three practices are associated with an improvement both in academic and labor market outcomes in Brazil: frequent analysis of student performance, use of tests as a graduation requirement, and students' access to bank loans. These practices may allow students to choose high-return programs, may help the program identify academic problems in real time, and may constitute a commitment device for students to graduate. Programs with online provision of classes also perform better in several outcomes, likely because they are more flexible. In addition, numerical competencies are associated with better labor market outcomes.

Using individual-level data for Ecuador

Since we do not observe academic outcomes for Ecuador, we discuss the same labor market outcomes as for Brazil during the twelve months following graduation: whether the student is ever employed formally and percent of the time employed formally (sample means are 35 and 24 percent, respectively), and average monthly wage (sample mean is $300 including zeros).

Several determinants from the T&C and LPS categories have a positive and large association to the three outcomes (Figure 6 panels a-c; Table A14 columns 1-3). From T&C, teaching numerical competencies is associated with a 20-pp improvement in the employment measures and a doubling of wages. Programs that collect student satisfaction information frequently also have better labor market outcomes, perhaps because they improve job placement based on the feedback. Updating the curriculum based on government standards also delivers better outcomes, perhaps because firms prefer to hire graduates from compliant programs. From LPS, programs that provide labor market information have better employment outcomes (as in Brazil), as do programs that train students for job interviews (unlike Brazil). Job interview training is associated with a 20-pp improvement in the employment measures and more than a threefold-increase in wages. In Ecuador, students might need this training more than in Brazil because they have less previous labor market experience (section 3.4). At the same time, a couple of faculty determinants are negatively associated to both labor market outcomes. The main one is hiring faculty based on research skills, which are not necessarily desirable for SCP teaching.

Given Ecuador's low formal employment, we further examine which variables contribute exclusively to formal employment (but not wages). These include having sufficient infrastructure for practical training (consistent with program-level findings), borrowing equipment from industry for practical training, and having agreements with industry to hire graduates. In contrast with Brazil, programs that require a graduation test have worse labor market outcomes.

Taking stock. Overall, the set of quality determinants associated with program outcomes is different in Brazil and Ecuador. This is not surprising given the large variation in program characteristics, practices, and outcomes across countries. Further, some practices (such as requiring a graduation test or training students for job interviews) have opposite-sign associations with labor market outcomes in Brazil and Ecuador. This might indicate that how these practices are implemented (e.g., how much they take away from other activities) and in which context (e.g., how much students need them) likely affects their usefulness.

What makes a program good?

We return to our original question of what makes a program good. Based on our estimates, the answer depends on the type of data used and the country of interest. This is not surprising given that the outcomes are not strictly comparable between program- and individual-level data; country-specific contexts are different for Brazil and Ecuador and, of course, sample sizes and data variation are remarkably different across all our samples. Nonetheless, all our estimations tell a consistent story: outcomes are indeed associated with program quality determinants; labor market outcomes, in particular, are strongly associated with T&C and LPS determinants.

We find two practices that contribute to *all* labor market outcomes in Brazil and Ecuador—teaching numerical competencies and providing labor market information. One of these—teaching numerical competencies—is positively associated to *all* labor market outcomes in the regional analysis for the five countries. Besides their intrinsic importance, numerical competencies may also proxy for related skills such as logical reasoning, problem solving, and critical thinking (World Bank 2019). Further, programs that teach these skills may contribute much to student outcomes given the serious mathematical deficiencies of incoming students. Providing labor market information, in turn, is quite rare in LAC, where HEIs do not view it as their responsibility to assist students in their job search. By providing that information, HEIs take a first step towards placing their graduates and engaging with this process.

5.2 Variance decompositions

Program-level regressions

Despite the rich set of explanatory variables in our LASSO regressions, we explain little of the observed variation in outcomes: about 8-9 percent for academic outcomes and 13-18 percent for labor market outcomes (see R-squared values in Table 3). This is consistent with recent work by Filmer et al. (2021) using machine-learning techniques to explore teacher value added and with Dinarte et al. (2022) on SCP value added in Colombia.

We now focus on the explained variation of outcomes based on Shapley-Owen decompositions (Table 3 and Figure A1). Taken together, quality determinants account for a sizable 50-60 percent of the explained variation in dropout rate, ETG and formal employment but only 15 percent for wages, for which 71 percent of the explained variation is accounted for by country fixed effects.

Quality determinants explain much of the variance in academic outcomes (determined mostly within the institution) and of formal employment (since institutions may vary in their ability to place students). However, they explain little of the variance in wages, which are monetary outcomes and therefore sensitive to the national context. Field of study accounts for a substantive share of explained outcome variation (6 to 21 percent, depending on the outcome), consistent with the documented cross-field variation in dropout rates, net returns, and SCP value added (Ferreyra et al. 2017, Dinarte et al. 2022, Ferreyra et al. 2021).

Among quality determinant categories, T&C accounts for the largest share of explained variation of ETG (25%), formal employment (22%) and wages (8%), and LPS accounts for the largest share of explained variation of dropout rates (18 percent). Costs, in turn, explain a non-negligible share (13 percent) of the explained variation of academic outcomes but nothing of labor market outcomes. Student and program characteristics account for very little of the explained outcome variation but HEI characteristics account for more, particularly in the case of the academic outcomes (10 percent for dropout rates and 5 percent for ETG).

Individual-level regressions

Brazil. Despite having student and peer administrative data in addition to survey-level data, we explain relatively little (12-15 percent) of the variation in graduation and labor market outcomes (Table 4). Nonetheless, the role of student and peer administrative variables is considerable for labor market outcomes: together they account for 30-40 percent of their explained variation (Table 4 and Figure A2). In contrast, they explain little of the variation in graduation, much of which is explained by field of study (24 percent) and HEI characteristics (32 percent), consistent with program-level findings. As in the latter, field of study explains much variation in graduation, while the geographic unit (state, in this case) accounts for most (26-37%) of the variation in labor market outcomes. The role of quality determinants is non-negligible: overall, they account for a sizable 20 percent of the explained variation in labor market outcomes and 40 percent for graduation, mostly through T&C determinants.

Ecuador. Our regressions for Ecuador explain a higher share (between 27 and 37 percent) of variation in labor market outcomes than for Brazil or survey data (Table 5). The specification is not exactly comparable to that of Brazil because it does not include geographic unit fixed effects (due to small sample sizes). Still, individual and peer administrative variables account for about 40 percent of explained variation, as in Brazil (Table 5 and Figure A3). Consistent with previous results, field accounts for 10-15 percent of the explained variation and, overall, quality determinants account for 32-28 percent of it, mostly due to T&C and faculty, each of which captures about 10-15 percent of explained variation.

Program- and individual-level data—taking stock. Overall, we do not explain much of the observed variation in student- or program-level outcomes. Nonetheless, quality determinants in the program-level regressions account for about 50-60 percent of the observed variation in dropout rates, ETG and formal employment, and about 20-40 percent of the individual-level regressions for academic and labor market outcomes, with the largest explanatory power generally accruing to T&C practices. Especially for academic outcomes, field and HEI characteristics are highly explanatory. Geography, in turn, is highly explanatory for labor-market outcomes. The salient role of quality determinants—together with our previous findings on the association of specific determinants to outcomes—suggests that adopting certain practices might improve outcomes for some programs and shrink their worrisome variation.

6 Conclusions

Little is known about what determines higher education programs' quality—namely, the program practices and inputs that contribute to good student outcomes. The rich data collected by the WBSCPS provides a unique opportunity to make inroads into this issue for a specific type of higher-education program, SCPs. We collected program-level data on quality determinants; HEI, student body, and program characteristics; and aggregate outcomes for 2,103 SCPs in five countries in LAC. We complemented this novel dataset with individual-level information on academic and labor market outcomes from Brazil and Ecuador. We document a large variation in program quality determinants and outcomes and exploit it to identify the practices and inputs associated with better outcomes after controlling for student, program, and HEI characteristics.

We find that outcomes are generally associated with quality determinants from multiple categories. While the specific outcome predictors vary by outcome and across analyses, two practices are positively associated to *all* labor market outcomes based on individual-level data from Brazil and Ecuador—teaching numerical competencies and providing labor market information—and one of these—teaching numerical competencies—is positively associated with labor market outcomes in the survey countries based on program-level data. Besides their intrinsic importance, numerical competencies may proxy for related skills such as logical reasoning, problem solving, and critical thinking and may remediate students' cognitive deficiencies at entry. By providing labor market information, programs take a first step towards placing their graduates and break with the LAC tradition of not assisting graduates in their job search. Further, we find that program quality determinants account for a substantial share (15-60 percent depending on the regression and outcome) of the explained variation in academic and labor market outcomes. Taken together, these findings suggest that the adoption of the quality determinants identified as outcome predictors—shrinking the gap in quality determinants—might also shrink the gap in outcomes.

Some final caveats are in order. First, a negative association between a determinant and an outcome does not indicate that the determinant is undesirable. Nonetheless, it indicates the need to focus on that specific determinant and assess how it fits with the program's goals. For example, our estimates do not imply that training students for job interviews is undesirable but indicate the need to understand why this practice might detract from student outcomes in some settings or how it might be interpreted by employers. Second, we do not claim to have identified the program determinants that causally make one program better than another (the individual-level regressions, however, bring us closer to that point than the program-level ones). Nonetheless, our findings—the first of their kind—are of great interest for any country seeking to promote SCPs. They can inform the design and replication of high-quality programs as well as the regulatory mechanisms to ensure the adoption of good practices on the part of programs and institutions. They can also inspire more detailed, nuanced data collection on programs and institutions and encourage the development of effective individual-level information systems, an endeavor that would yield much deeper insights on what makes higher education good.

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Tables and Figures

Table 1. Descriptive Statistics
Using Program-Level Data from the WBSCPS and Administrative Sources

Variable	Mean	Std. Dev.	Min.	Median	Max.	Obs.
Panel A. Program quality determinants						
Infrastructure						
Has enough equipment or tools for practice	0.72	0.45	0	1	1	2,103
Program offers at least one online class	0.35	0.48	0	0	1	2,103
Training and curriculum						
Teaches numerical competencies	0.80	0.40	0	1	1	2,103
Promotes work under hardship or pressure	0.84	0.36	0	1	1	2,103
Curriculum is fixed	0.70	0.46	0	1	1	2,103
Time assigned to practical training (%)	46.45	16.56	4	50	80	2,072
Graduation requirement						
Test	0.40	0.49	0	0	1	2,103
Thesis or research project	0.37	0.48	0	0	1	2,103
Internships outside institution are mandatory	0.58	0.49	0	1	1	2,103
Remediation support						
Remediation classes before starting the program	0.51	0.50	0	1	1	2,103
Remediation classes during the program	0.57	0.50	0	1	1	2,103
Years since last update to curriculum	2.91	2.69	0	2	25	1,946
More than once per year:						
Analyze student performance to solve problems	0.86	0.35	0	1	1	2,103
Collect student satisfaction data	0.69	0.46	0	1	1	2,103
Costs						
Annual tuition (2019 PPP USD)	2,244	1,762	0	2,367	25,515	2,103
HEI has received funding from						
Private sector	0.20	0.40	0	0	1	2,103
Government	0.34	0.47	0	0	1	2,103
Link with productive sector						
Engagement with firms						
Somebody in charge of industry relations	0.82	0.38	0	1	1	2,103
Industry has agreements with HEI to hire program grads	0.39	0.49	0	0	1	2,103
Industry has agreements to train faculty	0.35	0.48	0	0	1	2,103
Collect data on employment or employers' satisfaction	0.56	0.50	0	1	1	2,103
Communicate with local firms about their needs	0.52	0.50	0	1	1	2,103
Job search assistance						
HEI trains students for job interviews	0.69	0.46	0	1	1	2,103
HEI provides job market information	0.81	0.40	0	1	1	2,103
HEI has an employment center	0.60	0.49	0	1	1	2,103
Faculty						
Number of faculty	20.00	18.70	1	15	200	2,076
Percent of faculty						
with BA degree	82.20	29.40	0	100	100	2,043
with graduate degree	48.60	32.60	0	43	100	1,998
working full-time	38.40	30.30	0	31	100	1,987
with 5yrs+ industry experience	55.70	33.10	0	56	100	1,988
<40 years old	40.00	29.20	0	34	100	1,961

that are women	34.00	23.50	0	30	100	2,021
Faculty are evaluated more than once per year	0.85	0.360	0	1	1	2,103
Almost all or all faculty participated in professional training last year	0.55	0.50	0	1	1	2,103
Other Practices						
Update or review admin data more than once per year	0.66	0.47	0	1	1	2,103
Admission requirements						
General or specific knowledge test	0.59	0.49	0	1	1	2,103
Interview	0.50	0.50	0	1	1	2,103
Min. score in HS GPA or national entry test	0.66	0.47	0	1	1	2,103
Percent of governing body that belongs to:						
Private sector	18.90	21.20	0	12	100	2,103
Government	11.90	16.40	0	1	100	2,103
Faculty	39.00	27.80	0	33	100	2,103
Panel B. Student body, program, and institution characteristics						
Student body characteristics						
Academic deficiencies						
Mathematics is lacking in incoming students	0.82	0.39	0	1	1	2,103
Reading is lacking in incoming students	0.70	0.46	0	1	1	2,103
Writing is lacking in incoming student	0.68	0.47	0	1	1	2,103
Percent of students that are						
25+ years old	28.94	29.30	0	20	100	2,103
full-time	43.89	39.00	0	33	100	2,103
Women	38.19	29.20	0	40	100	2,103
Student body characteristics (PCA score)	-0.02	1.40	-2.78	-0.31	4.88	2,103
Program characteristics						
Program duration (semesters)	5.20	0.97	2	6	8	2,101
Program has high quality accreditation	0.19	0.39	0	0	1	2,103
Total number of students in the program last year	221.60	332.80	1	125	4,321	2,030
Program age (years)	11.50	9.46	0	10	70	2,103
Program characteristics (PCA score)	0.02	1.25	-7.59	0.20	2.43	2,082
Institution characteristics						
HEI is public	0.30	0.46	0	0	1	2,103
HEI is a university	0.21	0.41	0	0	1	2,103
HEI is for profit	0.20	0.40	0	0	1	2,103
HEI age	37.84	30.80	1	32	481	2,094
Number of programs in the HEI	21.59	36.30	1	10	268	2,103
HEI characteristics (PCA score)	0.08	1.16	-1.84	-0.21	9.57	2,094
Panel C. Noise controls						
Survey conducted during COVID	0.48	0.50	0	0	1	2,103
Number of attempts to complete the survey	8.36	3.16	1	9	17	2,103
Survey completed by phone	0.33	0.47	0	0	1	2,103

Sources: Own calculations using WBSCPS and administrative data.
Notes: This table shows the descriptive statistics of the main variables used in the analysis. An observation corresponds to a program. Dummy variables included in the list are those with means between 0.1 and 0.9. Statistics are weighted by WBSCPS sampling weights. Panel A refers to quality determinants, presented by category. Panel B refers to characteristics of the student body, program, and higher education institution (HEI); Panel C refers to survey noise controls. Total number of surveys completed is 2,103. Values in the "Obs." column vary depending on the number of valid responses. Tuition is presented in dollars but transformed in logs for estimation. Mean of PCA Scores are different than zero due to the use of sampling weights. All variables in panel B are included in the corresponding indexes (PCA Scores), except for "HEI is public," which is included separately in the corresponding regressions as a "fixed" control.

Table 2. Descriptive Statistics for Students in Brazil and Ecuador
Based on Individual-Level Data for Students Matched to Surveyed Programs

Variable	Brazil		Ecuador	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Panel A. Student characteristics				
Age	24.53	5.65	24.66	3.40
Female	0.59	0.49	0.62	0.49
Mother's education:				
Less than primary	0.12	0.32	-	-
Primary school	0.16	0.36	0.15	0.36
High school	0.19	0.39	0.28	0.45
Higher education	0.07	0.26	0.52	0.50
Unknown	0.46	0.49	0.05	0.22
Student has children	-	-	0.27	0.44
Socioeconomic index (std)	-	-	0.01	0.97
Student administrative variables (PCA Score)	0.01	1.25	0.07	1.32
Panel B. Peer (average) characteristics				
Age	24.59	1.70	24.66	1.81
Percentage of female peers	0.56	0.27	0.62	0.30
Percentage of peers by mother's education:				
Less than primary	0.12	0.06	-	-
Primary school	0.15	0.06	0.15	0.14
High school	0.18	0.07	0.28	0.19
Higher education	0.06	0.06	0.52	0.24
Unknown	0.49	0.13	0.05	0.06
Percentage of peers with children	-	-	0.27	0.18
Peers' socioeconomic index (std)	-	-	0.01	0.37
Peers' administrative variables (PCA Score)	-0.22	1.57	0.14	1.36
Panel C. Own and peers' previous labor market outcomes				
Percent of time employed before graduation/entry	46.32	43.50	19.02	36.24
Average peers' percent of time employed before graduation/entry	49.13	13.50	19.02	21.26
Employed at least one month before graduation/entry	0.64	0.48	0.26	0.44
Pct. of peers employed at least one month before graduation/entry	0.65	0.18	0.26	0.25
Panel D. Outcomes				
Average monthly wage conditional on working (USD, PPP)	1,031.40	577.56	876.06	381.36
Average monthly wage (USD, PPP)	715.62	678.84	300.29	472.02
Percent of time employed after graduation	53.37	43.97	24.01	38.23
Employed at least one month after graduation	0.70	0.46	0.35	0.48
Number of observations	7,843		1,239	

Sources: Own calculations using individual-level administrative data for Brazil and Ecuador. For more details on data sources and variable definitions, see Section 3.3 and Appendix 1.
Notes: In this table, the unit of observation is a program graduate. Statistics are weighted using WBSCPS sampling weights. A higher value of the socioeconomic index indicates a higher socioeconomic status. For a given student, her peers are the other students in her program and cohort; cohorts are defined in Section 3. Means of PCA scores are different than zero due to the use of sampling weights. In Panel C, previous labor market outcomes are pre-graduation (Ecuador) and pre-enrollment (Brazil). Average monthly wage conditional on working corresponds to individuals who are employed at least one month after graduation. For the remaining individuals, average monthly wage equals zero; therefore, the "Average monthly wage" row shows unconditional average monthly wages (which equal zero for individuals who do not work formally at all). Wage statistics trim off the 1st and 99th percentile. Purchasing power parity (PPP) adjustment of wages uses the 2019 (Ecuador) or 2017 (Brazil) PPP conversion factor.

Table 3. R-Squared Shapley-Owen Decomposition
Estimations using Program-Level Data

	(1)	(2)	(3)	(4)
Outcome:	**Dropout Rate**	**Extra Time to Graduate**	**Formal Employment**	**Wages**
Percent of explained variation attributable to:				
All quality determinants	60.22	51.95	50.51	15.48
Infrastructure	-	-	6.54	0.25
Costs	12.85	12.92	-	-
Training and curriculum	11.45	24.59	22.36	7.68
Faculty	17.22	12.47	12.41	4.03
Link with productive sector	18.46	1.97	6.99	0.84
Other practices	0.23	-	2.21	2.68
Student characteristics (PCA Score)	0.24	0.25	2.15	0.04
Program characteristics (PCA Score)	0.60	0.31	0.23	1.84
HEI characteristics (PCA Score)	10.48	4.93	2.30	3.32
Country fixed effects	7.37	31.57	38.58	71.19
Field of study fixed effects	21.08	10.99	6.21	8.13
R-squared	0.080	0.087	0.134	0.178
Obs.	1,526	1,693	1,270	1,752

Source: Own estimations using WBSCPS data. For variable definitions, see Section 3 and Appendix 1.
Notes: This table present results from the R-squared Shapley-Owen decomposition for the regressions reported in Tables A11 (dropout rate and extra time-to-graduate) and A12 (formal employment and wages), estimated with WBSCPS program-level data. For each regression, the table shows R-squared (net of the variation explained by survey noise variables) and the percent of the (net) explained variation attributable to each set of variables. "Obs." indicates number of programs (equal to the number of observations in the underlying regression).

Table 4. R-Squared Shapley-Owen Decomposition for Brazil
Estimations Using Individual-Level Data

	(1)	(2)	(3)	(4)
Outcomes:	**Graduation**	**Ever employed after graduation**	**Percent of time employed**	**Wages**
Percent of explained variation attributable to:				
All quality determinants	39.98	19.54	24.62	18.89
Infrastructure	4.19	-	0.99	-
Costs	7.34	0.45	1.02	0.47
Training and curriculum	10.81	7.90	8.30	7.51
Faculty	5.49	3.32	2.82	3.48
Link with productive sector	8.05	2.37	4.73	2.16
Other Practices	4.11	5.50	6.77	5.27
Student characteristics (PCA Score)	0.25	1.30	1.63	1.32
Program characteristics (PCA Score)	1.03	1.51	1.18	1.51
HEI characteristics (PCA Score)	32.42	0.81	0.63	0.73
Student administrative variables (PCA Score)	0.41	14.33	24.23	18.09
Peer administrative variables (PCA Score)	1.83	18.17	15.36	18.03
Field of study fixed effects	23.92	7.34	5.67	7.64
State fixed effects	0.16	36.71	25.79	33.51
Graduation year fixed effects	-	0.29	0.90	0.27
R-squared	0.134	0.135	0.122	0.149
Obs.	22,663	7,177	6,827	7,089

Source: Own estimations using data from the WBSCPS and Brazil individual-level data. For variable definitions, see Section 3 and Appendix 1.

Notes: This table present results from the R-squared Shapley-Owen decomposition for the regressions reported in Table A13, estimated with individual- and program-level data for Brazil (states of Ceara and Sao Paulo). For each regression, the table shows R-squared (net of the variation explained by survey noise variables) and the percent of the (net) explained variation attributable to each set of variables. “Obs.” indicates number of students (equal to the number of observations in the underlying regression).

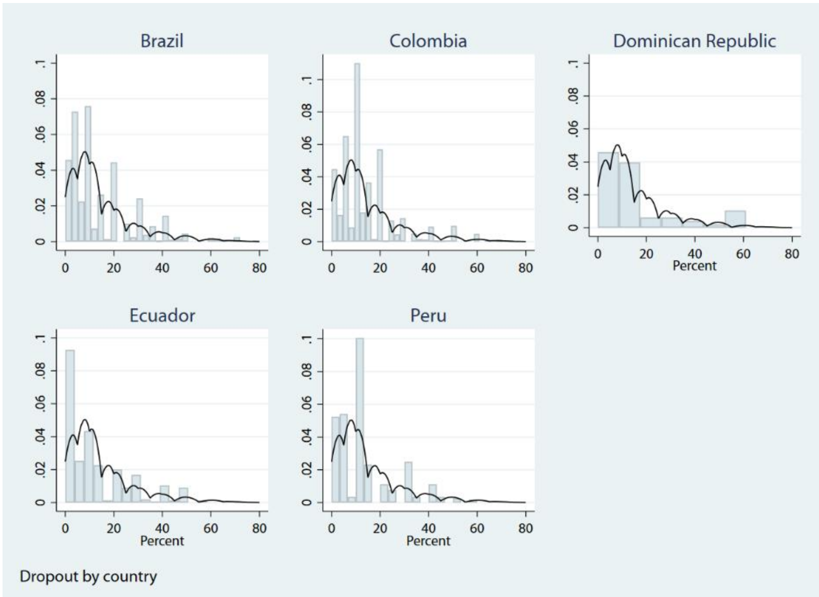
Table 5. R-Squared Shapley-Owen Decomposition for Ecuador
Estimations Using Individual-Level Data

	(1)	(2)	(3)
Outcomes:	**Ever employed after graduation**	**Percent of time employed**	**Wages**
Percent of explained variation attributable to:			
All quality determinants	35.00	37.64	32.06
Infrastructure	-	1.98	-
Costs	-	0.84	-
Training and curriculum	15.53	12.39	12.45
Faculty	9.46	15.81	10.08
Link with productive sector	8.78	5.83	8.09
Other Practices	1.23	0.80	1.44
Student characteristics (PCA Score)	1.71	1.42	1.52
Program characteristics (PCA Score)	2.27	3.65	2.49
HEI characteristics (PCA Score)	6.52	2.75	6.32
Student administrative variables (PCA Score)	19.90	27.60	22.99
Peer administrative variables (PCA Score)	20.01	17.48	21.04
Field of study fixed effects	14.59	9.47	13.59
R-squared	0.265	0.354	0.282
Obs.	1,214	1,201	1,206

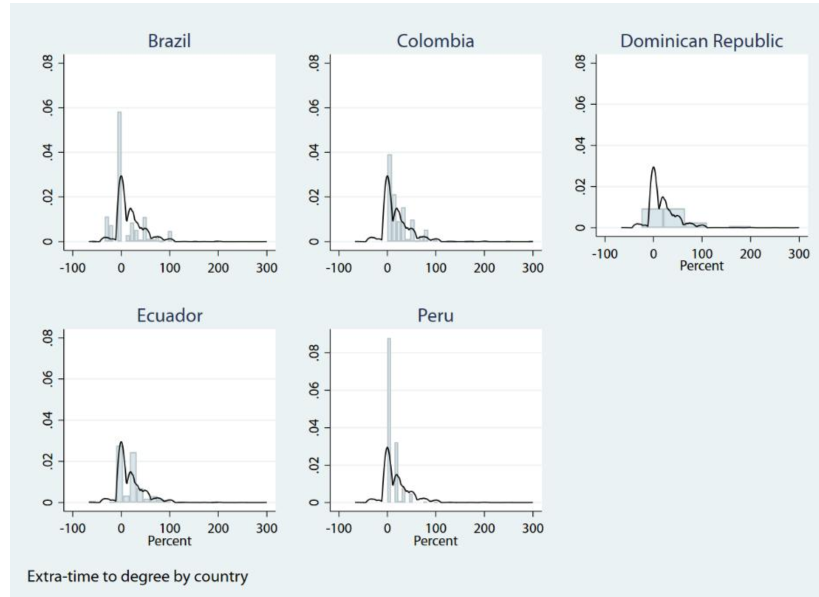
Source: Own estimations using data from the WBSCPS and Ecuador individual-level data. For variable definitions, see Section 3 and Appendix 1.

Notes: This table present results from the R-squared Shapley-Owen decomposition for the regressions reported in Table A14, estimated with individual- and program-level data for Ecuador. For each regression, the table shows R-squared (net of the variation explained by survey noise variables) and the percent of the (net) explained variation attributable to each set of variables. "Obs." indicates number of students (equal to the number of observations in the underlying regression).

Figure 1. Academic Outcomes Across Countries
Based on Program-Level Data



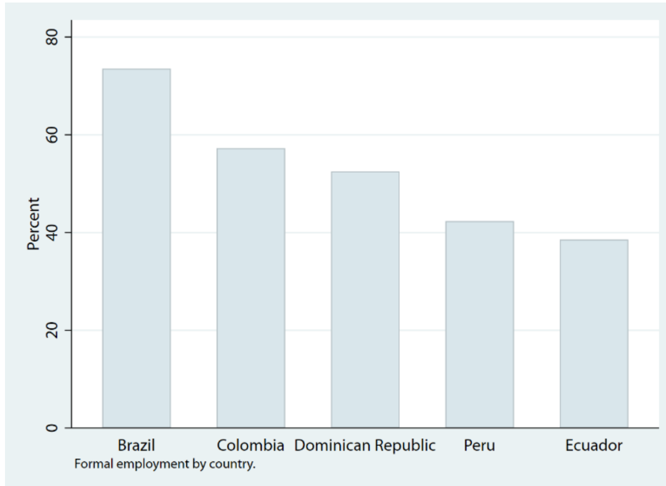
Panel A. Dropout rates



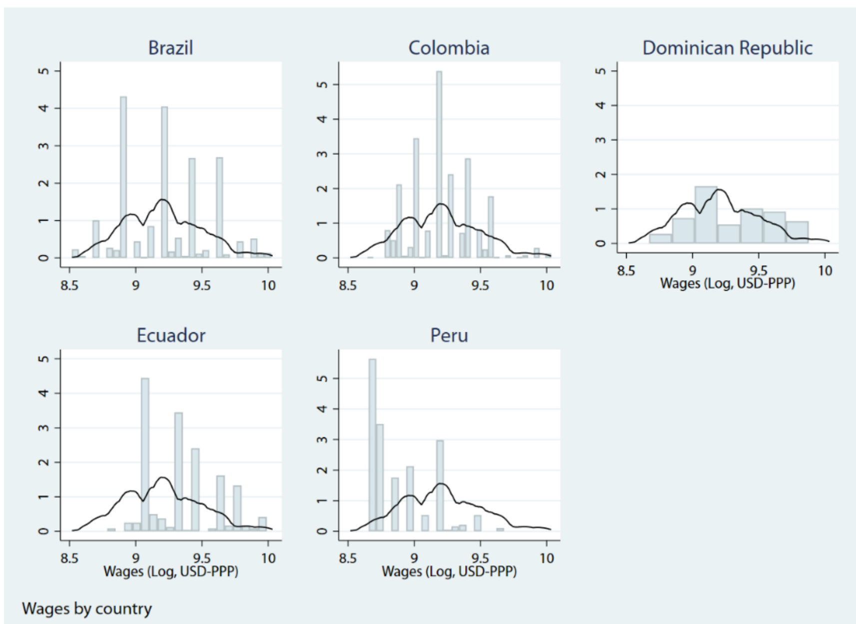
Panel B. Extra time to degree

Source: Own calculations based on the WBSCPS.
Notes: This figure shows the distribution of program academic outcomes (as reported by program directors) by country. For Brazil, Panel A shows the histogram of dropout rates as well as the (superimposed) smoothed kernel distribution of dropout rates for all five countries, and similarly for every country and panel. Only São Paulo and Ceara are included for Brazil, and licensed programs for Peru. Outcomes are defined in Section 3.2 and Appendix I.

Figure 2. Labor Market Outcomes Across Countries
Based on Program-Level Data



Panel A. Formal employment

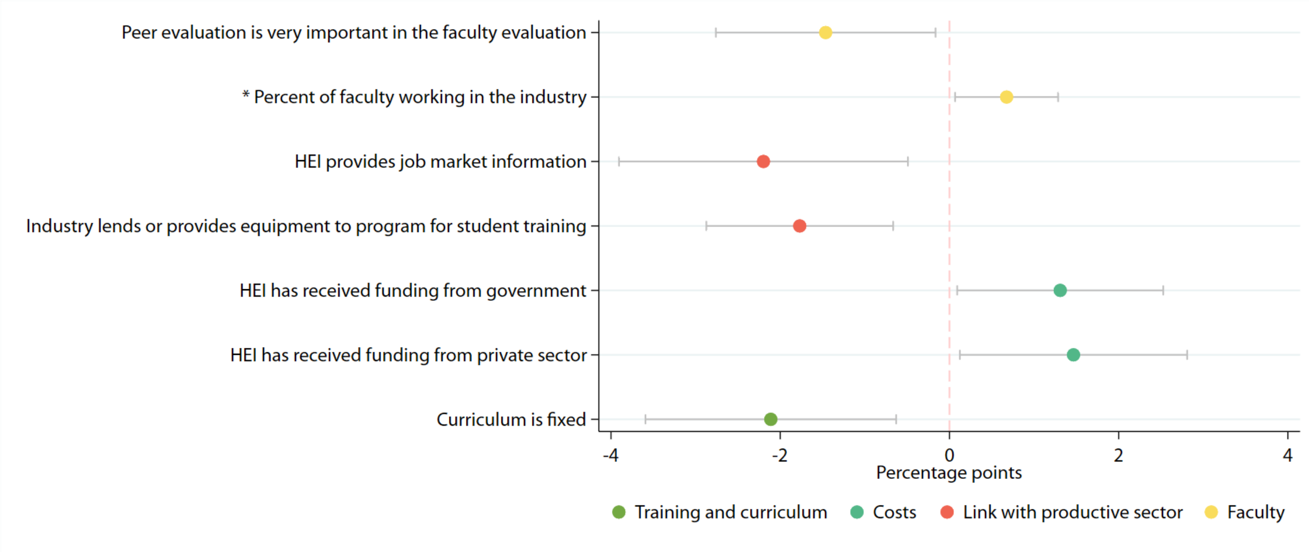


Panel B. Wages

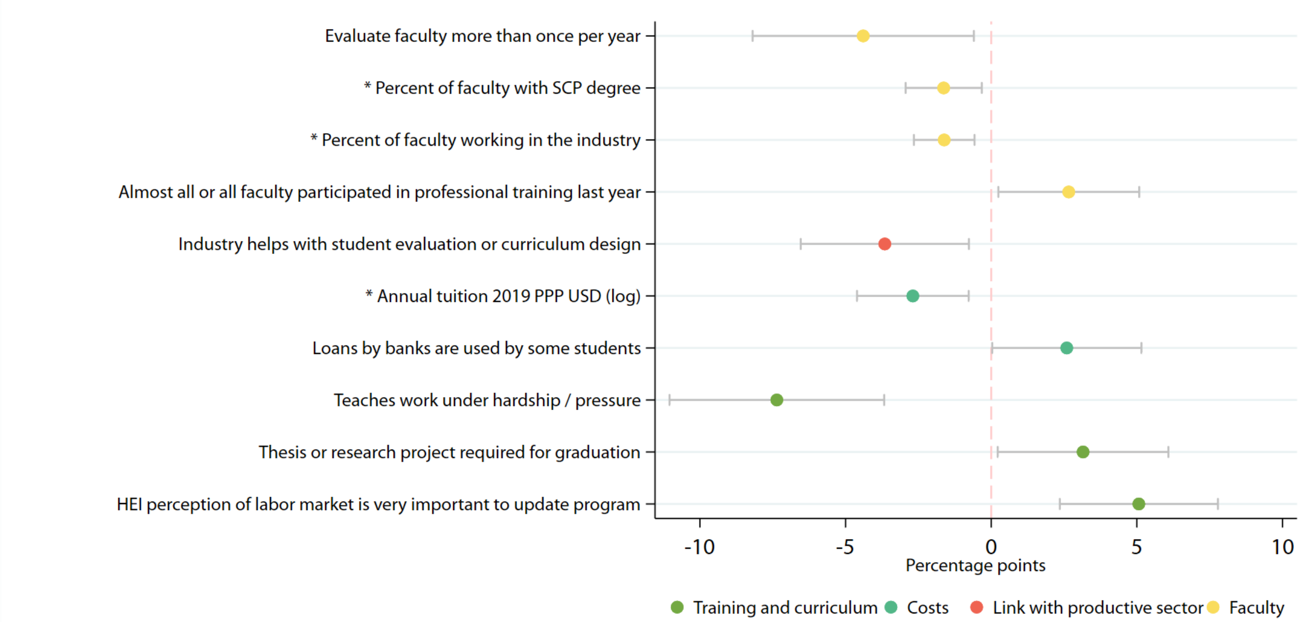
Source: Own calculations using data from the WBSCPS.
Notes: This figure shows the distribution of program labor market outcomes (as reported by program directors) by country. Panel A shows, for every country, the percentage of program directors that report that almost all their graduates from the previous year are employed or self-employed in the formal sector. Panel B reports the distribution of annual wages in 2019 PPP dollars by country. The smoothed kernel distribution of wages for all five countries (black line) is superimposed on the histogram for the corresponding country. Wage percentiles 1 and 99 are not included. Outcomes are defined in Section 3.2 and Appendix I. Only São Paulo and Ceara are included for Brazil, and licensed programs for Peru.

Figure 3. Associations between Program Quality Determinants and Academic Outcomes
Based on Program-Level Data

Panel A. Dropout Rates



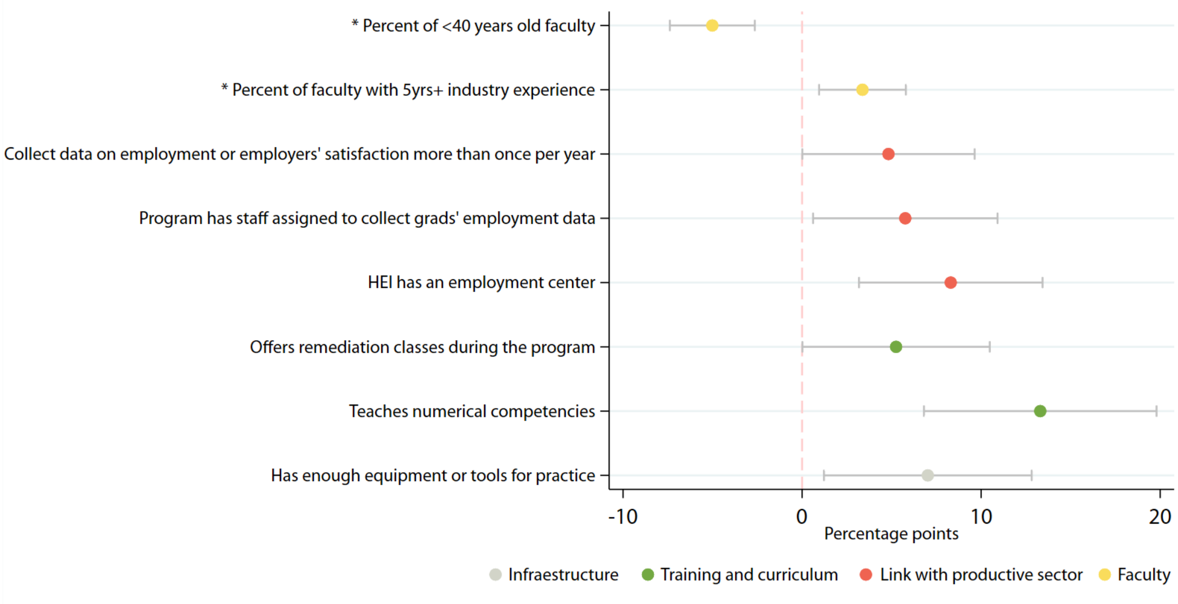
Panel B. Extra Time to Graduate



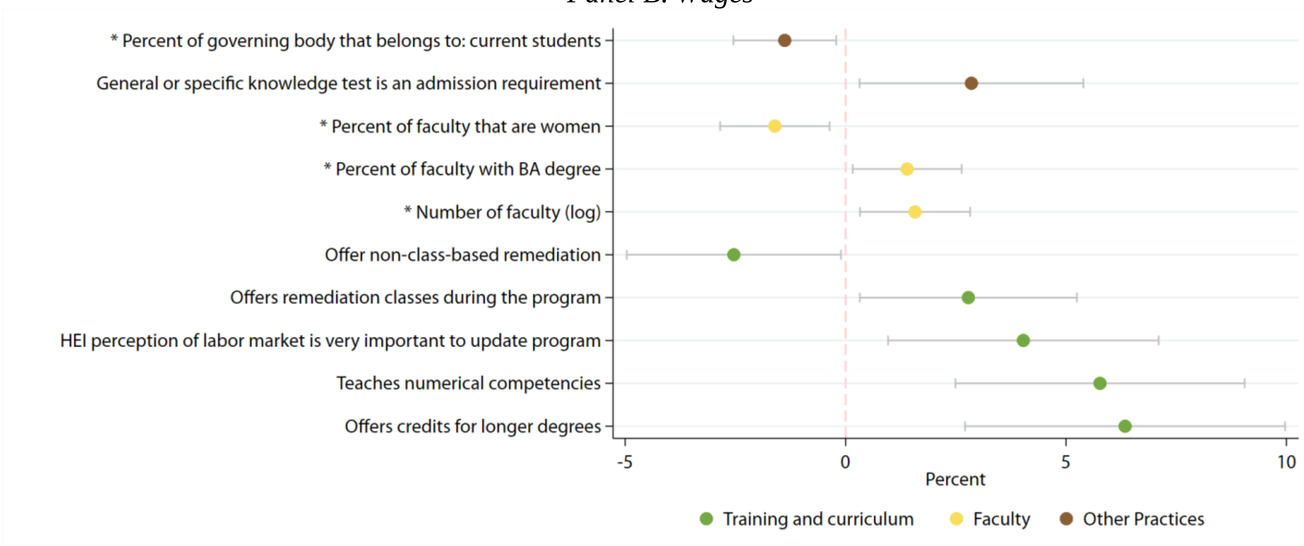
Source: Own estimations using WBSCPS data for all survey countries.
Notes: The figure shows the estimated changes in average dropout rate (Panel A) and extra time-to-graduate (Panel B) associated with quality determinants. Dropout rate is the percentage of students who dropped out of the program among those who should have graduated the previous year. Extra time to graduate is the average additional time taken to graduate as a percent of the theoretical duration of the program. Changes in these outcomes are expressed in percentage points. The figure focuses on coefficient estimates that are statistically significant at 10% or less, based on estimates presented in Table A11; 90% confidence intervals are also shown. The average dropout rate and ETG for the estimation sample are 14.0 and 18.6 percent, respectively. For dummy variables, the estimated change is equal to the variable coefficient. For non-dummy variables, which are noted with *, the estimated change is reported as the corresponding coefficient times the variable's standard deviation. A positive change denotes a deterioration of the outcome; a negative change indicates an improvement.

Figure 4. Associations between Program Quality Determinants and Labor Market Outcomes
Based on Program-Level Data

Panel A. Formal Employment



Panel B. Wages

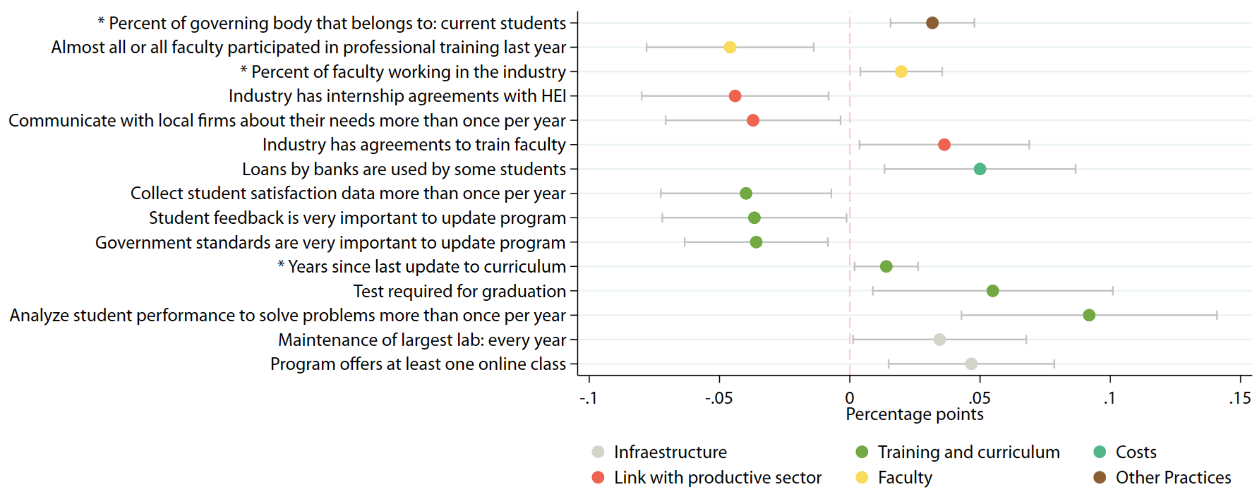


Source: Own estimations using WBSCPS data for all survey countries.
Notes: Panel A shows the estimated change in the average probability that almost all graduates from a program are employed or self-employed in the formal sector that is associated with quality determinants, expressed in percentage points. Panel B shows the estimated change in average wages (in percent) that is associated with the quality determinants. For dummy variables, the estimated change is equal to the variable coefficient. For non-dummy variables, which are noted with *, the estimated change is equal to the corresponding coefficient times the variable's standard deviation. In Panel B, the estimated change in wages associated with variable X is equal to *(exp(estimated change from X)-1)*100*. The two panels are based on estimates shown in Table A12 (only for coefficients significant at 10% or lower levels) and show 90% confidence intervals. Percentiles 1 and 99 from the wage distribution are excluded. In the estimation sample, on average 59 percent of directors within this subset of programs report that almost all their graduates are employed or self-employed in the formal sector, and the average annual wage of graduates is $10,424 (2019 PPP). In these panels, a positive change denotes an outcome improvement; a negative change indicates a deterioration.

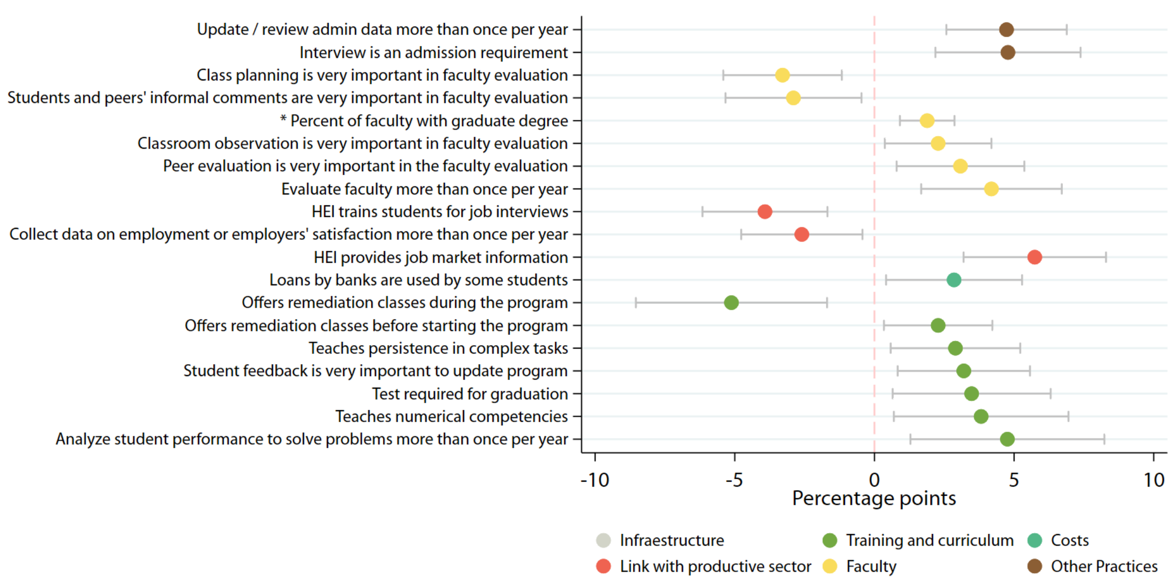
Figure 5. Contributions of Program Quality Determinants to Graduation and Labor Market Outcomes in Brazil

Based on Individual-Level Data

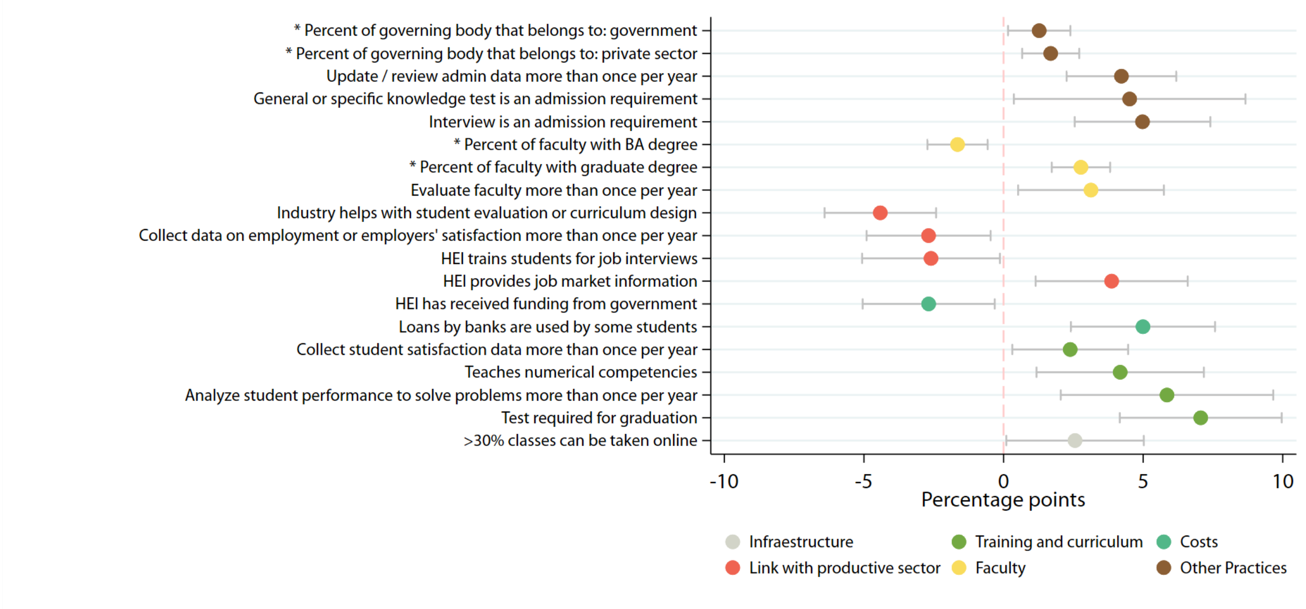
Panel A. Graduation



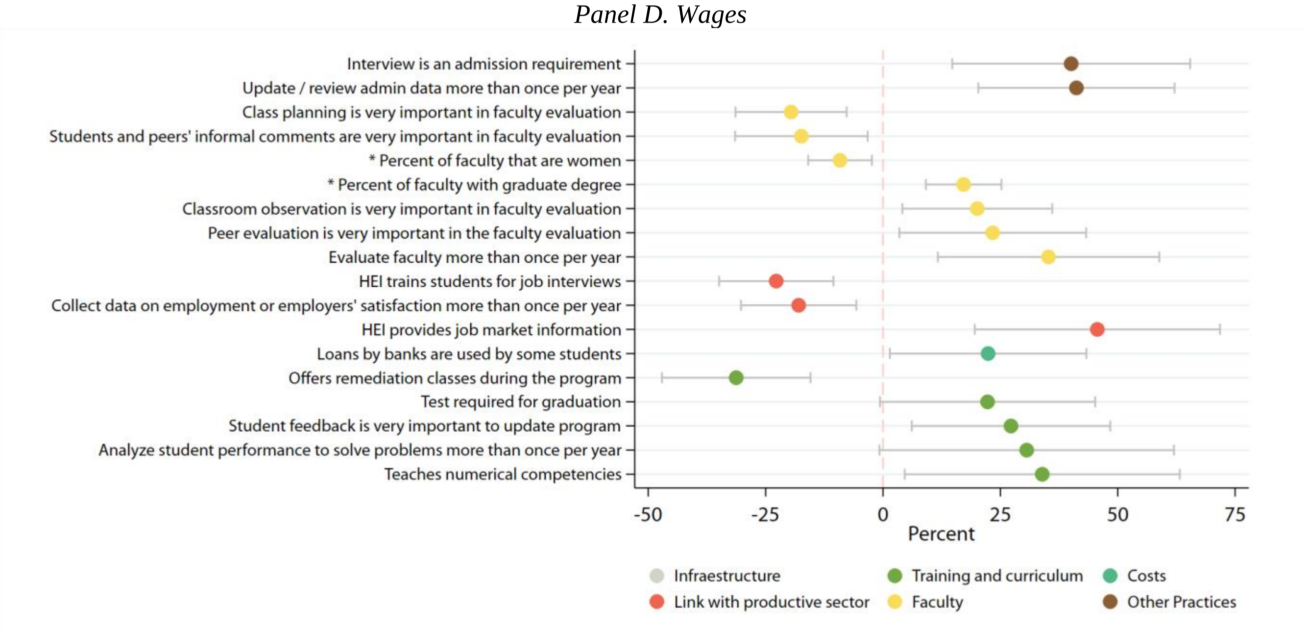
Panel B. Ever Employed After Graduation



Panel C. Percent of Time Employed



Panel D. Wages

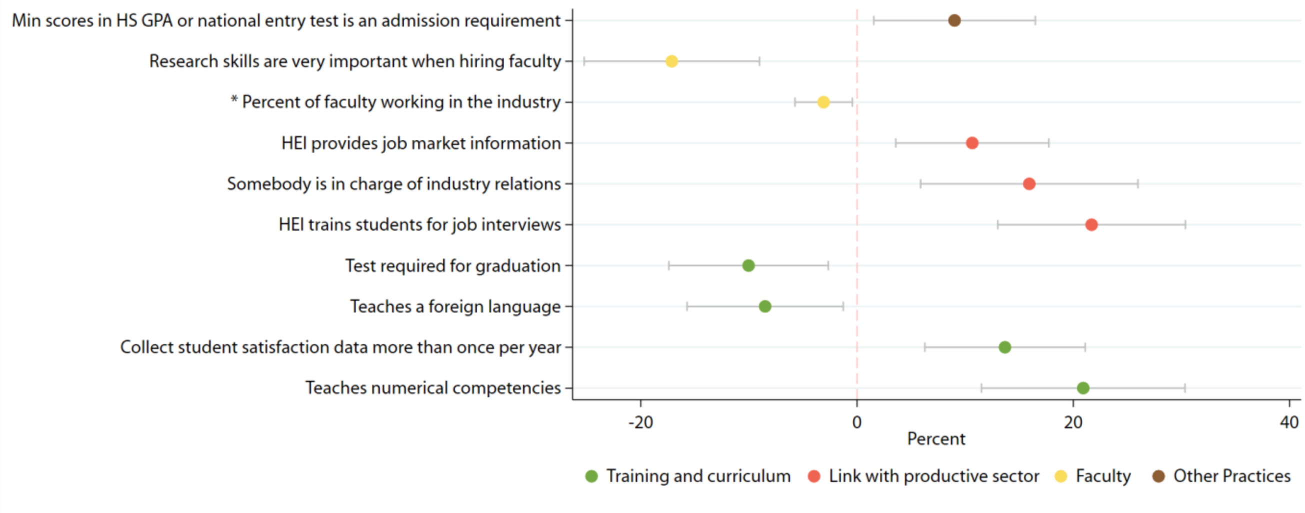


Source: Own estimations using individual-level and WBSCPS data for Brazil.
Notes: The figure shows the estimated change in graduation and labor market outcomes that are associated with program quality determinants in Brazil. Outcomes are the following: graduating within three years of enrollment (Panel A); working in the formal sector at least one month during the 12-month period following graduation (Panel B); percent of months that the graduate works in the formal sector in the 12 months following graduation (Panel C); average formal wage in the 12 months following graduation (Panel D—average is over the months that the student works formally; it equals zero if the student does not work formally at all over that period). In panels A-C, changes are shown in percentage points; in Panel D, in percent. For dummy variables, the estimated change is equal to the variable coefficient. For non-dummy variables, which are noted with *, the estimated change is equal to the corresponding coefficient times the variable's standard deviation. In Panel D, the estimated change in wages associated with variable X is equal to *(exp(estimated change from X)-1)*100*. Panels are based on estimates shown in Table A13 (only for coefficients significant at 10% or lower levels) and show 90% confidence intervals. Percentiles 1 and 99 from the wage distribution are excluded. In the estimation sample, the average graduation rate, percentage of students ever employed, and average percent of time employed are 30.3%, 70%, and 53.5%, respectively; average monthly wage of graduates (2017 PPP) is $716. In these panels, a positive change denotes an outcome improvement; a negative change indicates a deterioration.

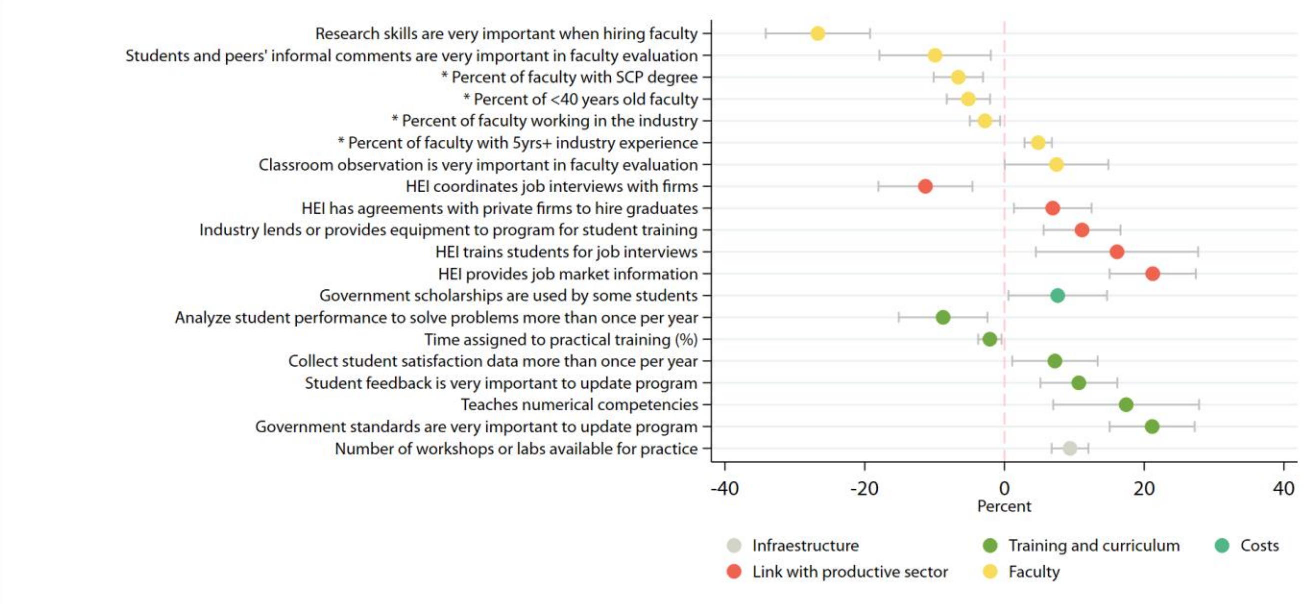
Figure 6. Contributions of Program Quality Determinants to Labor Market Outcomes in Ecuador

Based on Individual-Level Data

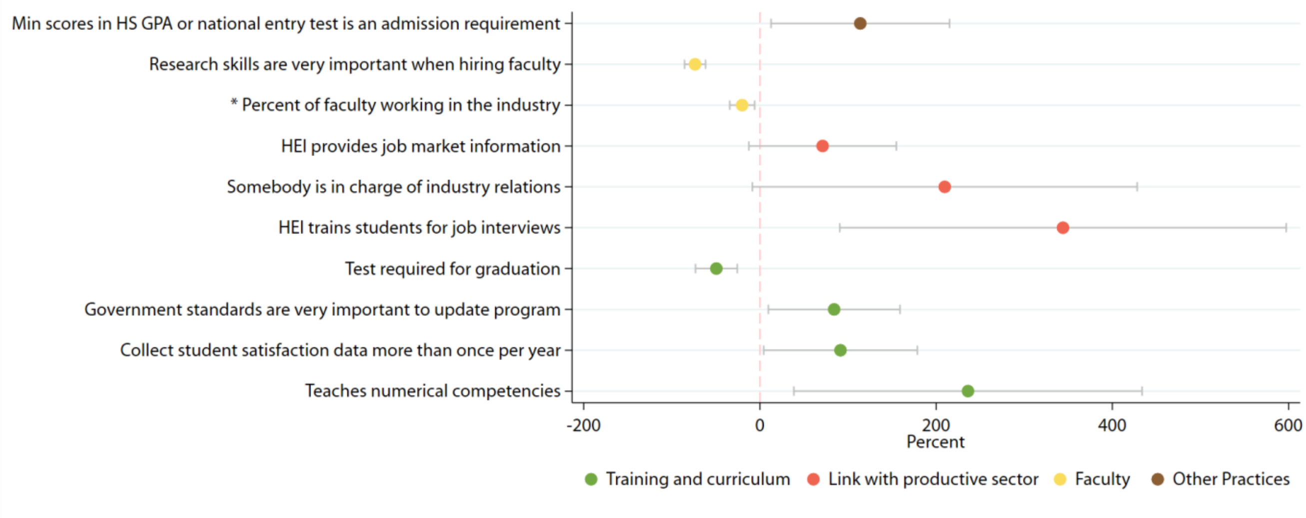
Panel A. Ever Employed After Graduation



Panel B. Percent of Time Employed



Panel C. Wages



Source: Own estimations using individual-level and WBSCPS data for Ecuador.

Notes: The figure shows the estimated change in graduation and labor market outcomes that are associated with program quality determinants in Brazil. Outcomes are the following: working in the formal sector at least one month during the 12-month period following graduation (Panel A); percent of months that the graduate works in the formal sector in the 12 months following graduation (Panel B); average formal wage in the 12 months following graduation (Panel C—average is over the months that the student works formally; it equals zero if the student does not work formally at all over that period). In panels A and B, changes are shown in percentage points; in Panel C, in percent. For dummy variables, the estimated change is equal to the variable coefficient. For non-dummy variables, which are noted with *, the estimated change is equal to the corresponding coefficient times the variable's standard deviation. In Panel D, the estimated change in wages associated with variable X is equal to *(exp(estimated change from X)-1)*100*. Panels are based on estimates shown in Table A14 (only for coefficients significant at 10% or lower levels) and show 90% confidence intervals. Percentiles 1 and 99 from the wage distribution are excluded. In the estimation sample, the percentage of ever employed and average percent of time employed are 35% and 24% respectively; average monthly wage of graduates (2017 PPP) is $300.3. In these panels, a positive change denotes an outcome improvement; a negative change indicates a deterioration.

Data Appendix

Appendix I. Description of Outcomes and Other Variables

Outcomes from individual-level administrative data

A. Previous labor market experience

These variables refer to the 12-month period before graduation (Ecuador) or entry into the program (Brazil). For a given student, her peers are those who graduated from the same program as her in the same year (Ecuador) or who entered the same program as her in the same year (Brazil). Previous labor market experience outcomes include the following:

Percent of time employed before graduation/entry is the number of months the individual was employed during that 12-month period divided by 12.

Peer average percent of time employed before graduation/entry is the average of the previous variable for the student's peers.

Employed at least one month before graduation/entry is a dummy that takes the value of one if the individual was employed for at least one month within the corresponding 12-month period.

Percent of peers employed at least one month before graduation/entry is the average of the previous variable for the student's peers.

B. Graduation

Graduation (only for Brazil) is a dummy that takes the value of one if the individual graduated within three years of entering the program.

C. Labor Market Outcomes

These variables (for Ecuador and Brazil) refer to the 12-month period following graduation. They include the following:

Employed at least one month after graduation is a dummy that takes the value of one if the individual was employed for at least one month during that period.

Percent of time employed after graduation is the number of months the individual was employed during that 12-month period divided by 12

Average monthly wage (USD, PPP) is the average monthly wage received by the individual during that 12-month period. If the student worked at least one month, average wage is equal to total wages divided by the number of months he worked (i.e., it is equal to her average monthly wage conditional on working). If she did not work at all, average wage is zero. Purchasing power parity (PPP) adjustment of wages was done using the 2019 (Ecuador) or 2017 (Brazil) PPP conversion factor.

Other variables based on individual-level administrative data

Student administrative variables (PCA score) consist of an index created for Brazil and Ecuador through a Principal Component Approach with the goal of reducing the dimensionality of the student characteristics included in estimation. The index includes the following student characteristics: age, gender, mother's education level (less than primary, primary, high school, higher education, unknown), whether the student has children (Ecuador), and socioeconomic status index (Ecuador).

Peer administrative variables (PCA score) follows the same logic, but for peers' (average) characteristics. The variables included in the calculation of the index were average characteristics at the student's cohort level, which is defined as all students (excluding the student herself) who entered (for Brazil) or graduate in (for Ecuador) the same program in the same year. Thus, the calculation of the index includes peers' average age, percentage of peers who are women, percentage of peers with each level of mother's education, percentage of peers with children (Ecuador), and peers' average socioeconomic index (Ecuador).

Outcomes from survey data

Dropout rate is the percentage of students that dropped out among those who were supposed to graduate the academic year before the survey.

Extra time to graduate (ETG) is the average percentage of additional time that students take to graduate relative to the theoretical duration of the program. For example, if a program is supposed to last two years and students take, on average, three years to graduate, then ETG=50% (=1 extra year *100 / 2 years). To calculate ETG, we asked directors (i) the average time it took the last cohort to graduate from the program and (ii) the theoretical duration of the program.

Formal employment is a binary variable that equals one when the director reports that almost all the program graduates from the previous year are employed or self-employed in the formal sector. Directors were given three possible options regarding how many of the past year's graduates found employment or self-employment in the formal sector: almost all; some; almost none or none.

Wages is the average salary of the graduates from last year, whether they work in the formal or informal sector. Purchasing power parity (PPP) adjustment of wages was done using the 2019 PPP conversion factor.

Other variables based on survey data

Student characteristics (PCA Score) consist of an index created to reduce the dimensionality of the average student characteristics at the program level available in the survey data. It was built using a Principal Component Analysis approach and includes the following student characteristics (see Panel B in Table 1): percent of full-time students, percent of female students, percent of students that are 25+ years old, academic deficiencies in incoming students. The latter are indicators of whether program directors reported that missing skills among incoming students in math, oral expression, reading, writing or other competencies.

Program characteristics (PCA Score) follows a similar logic and includes the following program characteristics (see Panel B in Table 1): program duration (semesters), number of cities where the HEI offers the program, whether the program has high quality accreditation, total number of students in the program last year, and program age (years).

HEI characteristics (PCA Score) also follows a similar logic and includes the following institution characteristics (see Panel B in Table 1): HEI age, whether the HEI is a university, whether the HEI is for profit, and number of programs in the HEI. Note that whether the HEI is public is not included in this index; it is included as a separate "fixed" control in our estimation strategy.

Appendix Tables and Figures

Table A1. Institutional Framework for WBSCPS Countries

Indicator	Brazil	Colombia	Dominican Republic	Ecuador	Peru
1. SCP enrollment share (%)	12	32	4	14	25
2. Program types	Technological (2-3 yrs.)	Technical (2 yrs.) Technological (3 yrs.)	Technical (2 yrs.) Prof. technical (*tecnico superior*; 2-3 years)	Technical Technological (mostly 2 yrs.)	Technical (2 yrs.) Prof. technical (3-4 yrs.) Tech. bachelor's (3-4 yrs.)
3. Number of HEIs offering SCPs	HEI in Brazil: 1,700 HEI in SP + Ceará: 467	217	28	182	HEIs w/ licensed prog.: 75 Other HEIs: 747
4. Private enrollment (%)	Brazil: 84 SP + Ceará: 77	21	49	53	HEIs w/ licensed prog.: 97 Other HEIs: 50
5. HEI types and enrollment shares (%)	SP + Ceará: Universities 41 Univ. Centers 17 Schools 38 IF and CEFET 3	Universities 9 Univ. Institutes 13 Technol. Inst. 7 Technical Inst. 6 SENA 65	Universities 47 Tech. Institutes 53	Tech. & Technol. Inst.: 95 Univ. and Polytechnic Schools: 5	HEIs w/ licensed programs: Higher Education Institutes: 100
6. Number of SCPs	SP + Ceará: 2,388	2,130	209	543	Licensed programs: 392
7. Public funding to students at public HEIs	Zero tuition	Zero tuition at SENA Public HEIs: government scholarships; loans from public institution (ICETEX)	Zero tuition, but "academic fees."	Zero tuition	Zero tuition
8. Funding for students at private HEIs	ProUni (government scholarship for low-income, high ability students) FIES (government and state-guaranteed student loans banks) FUNDACRED (loans)	Government scholarships Loans from public institution (ICETEX)	Government scholarships Loans from public institution (FUNDAPEC)	Loans from public bank (*Banco del Pacifico*)	Public loans and scholarships (PRONABEC) for low-income, high-ability students
9. Public funding to public HEIs	Yes. Sources: federal, state, municipality	For SENA: yes (dedicated taxes) For other public HEIs: yes	Yes	Yes	Yes
10. Public funding to private HEIs	No	No	n/a	Partial for some private HEIs (*cofinanciadas*)	No

11. National mandatory entry exam	ENEM (high school graduation exam) required by public HEIs Vestibular (HE entry exam) required by some HEIs	Saber 11 (mandatory for high school graduation)	POMA or PAA (mandatory for HE entry)	Ser Bachiller (mandatory for high school graduation)	Only for students applying to PRONABEC scholarship
12. National mandatory exit exam	ENADE (mandatory for HE graduation; only some majors tested in a given year)	Saber T&T (mandatory for SCP graduation)	n/a	No	No
13. Operating license	Mandatory (initial accreditation) by HEI and program.	Mandatory by HEI and program; must be renewed periodically	Mandatory; evaluation required to renew license every 5 years.	Mandatory by HEI	Mandatory by HEI and program; lasts 5 years.
14. Accreditation	At private HEIs, accreditation must be renewed, generally every 3 years.	High-quality accreditation is voluntary for HEIs and programs, mandatory for teaching programs. Lasts 4 years.	HEIs can voluntarily pursue international accreditation.	Periodic mandatory accreditation is needed to remain open.	Voluntary for HEIs and programs; mandatory for education, law and health programs.
15. For-profit HEIs	Allowed (36% of SCPs in Brazil; 39% in SP+ Ceará)	Not allowed	Not allowed	Not allowed	Allowed (75% of licensed SCPs)

Sources: Ferreyra et al. (2021).
Notes: HEIs in Brazil's S-System count as university centers or schools. For Colombia, *Servicio Nacional de Aprendizaje* (SENA) is not counted as an HEI in row (3) but its students are counted as part of public enrollment in row (4). For Ecuador, private share includes enrollment in private institutions with public funding (*cofinanciadas*). When an HEI has branches in multiple cities, each branch is counted separately. CEFET = Federal Centers for Technological Education (*Centros Federais de Educação Tecnológica*) (Brazil); ENADE = National Exam of Student Achievement (*Exame Nacional de Desempenho dos Estudantes*) (Brazil); ENEM = National Assessment of Secondary Education (*Exame Nacional de Ensino Médio*) (Brazil); FIES = Student Financing Fund (*Fundo de Finaciamiento Estudantil*) (Brazil); FUNDAPEC = Pro-Education and Culture Action Educational Credit Foundation (*Fundación Acción Pro Educación y Cultura [APEC] de Crédito Educativo*) (Dominican Republic); HEI = higher education institution; HE= higher education; IF = Federal institute (Instituto Federal) (Brazil); ICETEX = Colombian Institute of Educational Credit and Technical Training Abroad (*Instituto Colombiano de Crédito Educativo y Estudios Técnicos en el Exterior*) (Colombia); PAA = Academic Aptitude Test (*Prueba de Aptitud Académica*) (Dominican Republic); POMA = (*Prueba de Orientación y Medición Académica*) (Dominican Republic); PRONABEC = National Program of Scholarships and Educational Credit (*Programa Nacional de Becas y Crédito Educativo*) (Peru); Prof. = professional; SCP = short-cycle program; Tech. = technical. WBSCPS = data from the World Bank Short-Cycle Program Survey.

Table A2. Sampling frame and survey structure, by country

Country	Sampling Procedure (1)	SCPs universe (2)	Replace-ment rate (3)	Assumptions for power calc. (4)	Stratification levels (5)	Sampling Frame (Universe) Source (6)
Brazil	Represen-tative sample	2,388	50%	Effect size: 0.08 Power: 80% Alpha: 0.05 Formal employment at baseline: 9.23%	*State*: Ceara, Sao Paulo *HEI Administration*: Public, private *HEI academic organization*: Universidade, Centro Universitário, Faculdade, Instituto Federal de Educação, Ciência e Tecnologia	Higher Education Census (*Censo da Educação Superior*), 2017.
Colombia	Represen-tative sample	2,130	50%	Effect size: 0.08 Power: 80% Alpha: 0.05 Formal employment at baseline: 10%	*Region:* Caribe, Centro-Oriente, Centro-Sur, Cafetero-Antioquia, Pacifico *HEI Administration*: Public, private *HEI academic organization*: University, technical center, technological center.	National Information System of Higher Education (*Sistema Nacional de Información de la Educación Superior*), 2017
Dominican Republic	Census	209	n.a.	n.a.	All programs	Ministry of Economics, Planning, and Development, 2019
Ecuador	Census	543	n.a.	n.a.	All programs	Secretariat of Higher Education, Science, Technology, and Innovation, 2019
Peru	Census	387	n.a.	n.a.	All licensed programs	Ministry of Education, 2019

Notes: For each country included in the WBSCPS, this table shows the sampling procedure (whether using the universe of programs or a representative sample) in column (1), size of program universes in column (2), replacement rate in column (3), and assumptions for power calculations in column (4). To determine the sample size, details on stratification levels used to calculate the number of programs to be included Colombia and Brazil samples and the source of sampling frame (universe or initial list of programs) are in columns (5) and (6). The assumptions to estimate sample size for Brazil were based on Almeida et al (2015). “n.a.” = not applicable.

Table A3. Universes, Samples, and Response Rates, by country

Country	Universe size (1)	Sample size (2)	Survey status				Closed Programs (7)	Adjusted response rate (8)
			Effective Surveys (3)	Declined to answer (4)	Not effective due to COVID (5)	Not effective due to other reasons (6)		
Brazil	2,388	1,203	601	162	0	174	266	64%
Colombia	2,130	1,314	900	93	15	99	207	81%
Dominican Republic	209	209	80	13	0	0	116	86%
Ecuador	543	543	294	66	0	124	59	61%
Peru	387	387	228	83	0	67	9	60%
Total	5,657	3,656	2,103	417	15	464	657	70%

Source: Own calculations using WBSCPS.
Notes: This table shows the universe, sample size, and effectiveness measures for the WBSCPS. For Dominican Republic and Ecuador, the universe of programs was included in the survey. For Peru, the universe of licensed programs was included. For Brazil and Colombia, representative samples were drawn from the States of Sao Paulo and Ceara and at the national level, respectively. Columns (1) and (2) show the number of programs in the universe and sample sizes for each country in the study, respectively. Columns (3) through (6) indicate the number of surveys by status for each country: column (3) indicates completed surveys; columns (4) and (5) indicate the number of surveys that SCP directors declined to answer or that did not answer because they were preparing for distance learning, respectively; and column (6) indicates surveys not answered for other reasons, such as lack of provost authorization. Column (7) shows the number of programs that were closed at the time of the survey but that were reported as open in the sampling frames. Columns (3) through (7) add up to total sample size (column 2). Adjusted response rate is the share of effective surveys (column 3) relative to all active programs in our sample (i.e., Sample size (2) – Closed programs (7)). For example, for Brazil, adjusted response rate = 601/ (1,203 – 266) = 64%.

Table A4. Survey representativeness checks, by country

Dependent variable:	Program is included in the survey	Program is an effective survey	Program is an effective survey, excluding closed programs
	(1)	(2)	(3)
Panel A. Brazil			
HEI is public	0.028**	0.042*	0.042*
Obs.	2,367	2,367	2,101
HEI is for-profit	0.039	0.032	0.042
Obs.	2,362	2,362	2,096
Total enrollment	-4.953	-2.232	-5.738
Obs.	2,362	2,362	2,097
Total graduates	-1.249	-0.506	-1.504
Obs.	2,359	2,359	2,094
Annual tuition cost	419.1*	288.3	305.0
Obs.	2,388	2,388	2,122
Panel B. Colombia			
Technical program	0.008	0.011	0.009
Obs.	2,130	2,130	2,015
Distance (virtual) program	0.011	-0.003	-0.001
Obs.	2,130	2,130	2,015
Annual tuition cost (in COP)	-28,285.2	80,234.1	87,502.3
Obs.	2,130	2,130	2,015
Total enrollment in 2017	66.7	-65.3	-88.9
Obs.	2,130	2,130	2,015
HEI is SENA	0.003	-0.014	-0.019
Obs.	2,130	2,130	2,015
Program has high quality accreditation	-0.006	-0.003	-0.002
Obs.	2,130	2,130	2,015
Panel C. Dominican Republic			
HEI is a university		-0.376**	-0.038
Obs.		209	93
HEI is public		0.073	-0.039

Obs.	156	86
Panel D. Ecuador		
HEI is public	0.346***	0.372***
Obs.	543	483
Total graduates	20.2**	19.9**
Obs.	465	405
Annual tuition cost	-387.2	-107.4
Obs.	333	291
Program is taught online	0.058*	0.052
Obs.	543	484
Panel E. Peru		
Technical program	-0.027	-0.026
Obs.	387	383
Professional program	0.027	0.026
Obs.	387	383
Annual tuition cost (in SOL)	1061.9	1460.4
Obs.	387	383
Program has high quality accreditation	-0.002	-0.007
Obs.	387	383
Face-to-face program	0.033	0.030
Obs.	387	383

Source: Own estimations using WBSCPS.

Notes: This table summarizes the results from representativeness checks performed using available program-level administrative data, by country. In each column, we present estimated coefficients from the following model: $y_p = \alpha_0 + \beta D_p + S + \epsilon_p$ for Brazil and Colombia and $y_p = \alpha_0 + \beta D_p + \epsilon_p$ for the rest of countries. In this model, y_p is the characteristic of program *p* (e.g., whether the program has high quality accreditation). We estimate a model for each characteristic available in the country's administrative data. *S* is the sampling strata variable, and D_p indicates a dummy that varies by model depending on the comparison. Column (1) presents the comparison of programs selected for the survey relative to the rest of non-selected programs within the universe of programs for which we have administrative information ($D_p = 1$ if the program was selected for the survey, and 0 otherwise). This check only applies to Brazil and Colombia, the countries for which we drew samples. Column (2) shows results from testing for differences between programs with an effective survey and all other programs in the universe. Column (3) is similar to column (2) but compares effective surveys with all other programs in the universe *that have not closed*. All regressions estimate robust standard errors clustered at the HEI level. Significance levels: * p<0.1, ** p< 0.05, *** p<0.01.

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Table A5. Validation of Outcomes Reported by Principals Using Administrative Data and Household Surveys

	Outcome data source	Survey Data (WBSCPS)	Survey Data, employment rate	Administrative Data	HH Survey (21-25 years old)	HH Survey (25-29 years old)	HH Survey (21-29 years old)
		(1)	(2)	(3)	(4)	(5)	(6)
Brazil	Graduation rate (%)	62.19		30.30			
	Dropout rate (%)	14.90					
	Extra time to graduate (%)	11.99					
	Employment rate (%)	73.52	69.65	65.6	76.00	82.00	80.00
	Wages (USD, PPP 2019)	10,730.00		10,006.40*	10,155.00	13,440.00	12,472.00
Colombia	Graduation rate (%)	58.41		61.00			
	Dropout rate (%)	14.25		23.00			
	Extra time to graduate (%)	24.04		25.00			
	Employment rate (%)	57.25	65.42	63.00	75.00	78.00	77.00
	Wages (USD, PPP 2019)	10,313.00		12,192.00	8,892.00	10,212.00	9,684.00
Dominican Republic	Graduation rate (%)	58.49					
	Dropout rate (%)	14.95					
	Extra time to graduate (%)	30.97					
	Employment rate (%)	52.50	65.42				
	Wages (USD, PPP 2019)	11,275.00					
Ecuador	Graduation rate (%)	54.71					
	Dropout rate (%)	12.45					
	Extra time to graduate (%)	18.52					
	Employment rate (%)	38.56	53.40	40.18	48.00	63.00	57.00
	Wages (USD, PPP 2019)	11,910.00		10,900.00	10,222.00	13,689.00	12,511.00
Peru	Graduation rate (%)	64.06					
	Dropout rate (%)	12.82					
	Extra time to graduate (%)	8.95					
	Employment rate (%)	42.32	56.40	40.00	38.00	46.00	43.00
	Wages (USD, PPP 2019)	7,481.00		12,167.00	7,545.00	8,829.00	8,229.00

Source: Own calculations using WBSCPS, administrative data, and households' surveys. The administrative data sources are the following: Annual Reports of the Social Security Institution (*Relação Anual de Informações Sociais,* RAIS) for Brazil for 2017, Social Security and Taxes database for 2019-2020 for Ecuador, *Observatorio Laboral para la Educacion (*OLE) for Colombia for 2016, and *Ponte en Carrera* for Peru for 2018. The household surveys are the original (unharmonized) surveys from these sources: Brazil: PNADC (*Pesquisa Nacional por Amosta de Domicílios Contínua*) for 2018; Colombia: GEIH (*Gran Encuesta Integrada de Hogares*) for 2018; Ecuador: ENEMDU (*Encuesta Nacional Empleo, Desempleo y Subempleo*) for 2018; Peru: ENAHO (*Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza*) for 2017.

Notes: This table presents a validation exercise for the outcomes reported in the survey data. Graduation, dropout, time to degree, and employment are expressed as percentages. * indicates that wages are expressed in annual USD PPP (2017) for Brazil when using administrative data (column 3). Column 1 presents outcome averages as reported by program directors in the WBSCPS; means are weighted by the WBSCPS sampling weights (see definitions of outcomes from survey data in Appendix 1). In column (2), we impute a formal employment rate based on the following survey questions: "Regarding the graduates of the program in recent years, how many were employed by a firm in the formal sector?" and "Regarding the graduates of the program in recent years, how many were self-employed in the formal sector?" Directors had to choose among three possible answers: almost all, some; almost none or none. We assume the following formal employment rates for those answers: 80, 40, and 10% respectively. Column (2) shows the resulting formal employment rate imputation. In column (3) we show average outcomes calculated using individual-level administrative data; wages refer to individuals working in the formal sector and the formal employment rate is the percentage of SCP graduates who work formally. Formal workers include the following: employed and self-employed in Colombia, Peru, and Ecuador; and employed in Brazil. Columns 4-6 report validation outcomes using household survey data for different age groups; wages refer both to formal and informal employees.

Table A6. Descriptive Statistics

Using Program-Level Data from the WBSCPS and Administrative Sources

Variable	Mean	Std. Dev.	Min.	Median	Max.	Obs.
Panel A. Program quality determinants						
Infrastructure						
Maintenance of largest lab: every year	0.57	0.49	0	1	1	2,103
Has enough equipment or tools for practice	0.72	0.45	0	1	1	2,103
Number of workshops or labs available for practice	6.12	6.15	0	4	65	2,031
>30% classes can be taken online	0.15	0.36	0	0	1	2,103
Program offers at least one online class	0.35	0.48	0	0	1	2,103
Training and curriculum						
Teaches numerical competencies	0.80	0.40	0	1	1	2,103
Teaches a foreign language	0.60	0.49	0	1	1	2,103
Teaches persistence in complex tasks	0.76	0.42	0	1	1	2,103
Promotes work under hardship or pressure	0.84	0.36	0	1	1	2,103
Offers credits for longer degrees	0.89	0.31	0	1	1	2,103
Curriculum is fixed	0.70	0.46	0	1	1	2,103
Time assigned to practical training (%)	46.45	16.56	4	50	80	2,072
Graduation requirement						
Test	0.40	0.49	0	0	1	2,103
Thesis or research project	0.37	0.48	0	0	1	2,103
Second language	0.11	0.31	0	0	1	2,103
Internships outside institution are mandatory	0.58	0.49	0	1	1	2,103
Mandatory internships during the program+	0.16	0.37	0	0	1	2,103
Mandatory internships at the end of the program+	0.22	0.41	0	0	1	2,103
Remediation support						
Remediation classes before starting the program	0.51	0.50	0	1	1	2,103
Remediation classes during the program	0.57	0.50	0	1	1	2,103
Non-class-based remediation	0.43	0.50	0	0	1	2,103
Years since last update to curriculum	2.91	2.69	0	2	25	1,946
Important reasons to update program:						
Government standards+	0.70	0.46	0	1	1	2,103
Employment outcomes or employers' requests+	0.87	0.34	0	1	1	2,103
HEI perception of labor market+	0.83	0.38	0	1	1	2,103
Enrollment trends+	0.56	0.50	0	1	1	2,103
Student feedback+	0.78	0.41	0	1	1	2,103
More than once per year:						
Analyze student performance to solve problems	0.86	0.35	0	1	1	2,103
Collect student satisfaction data	0.69	0.46	0	1	1	2,103
Costs						
Annual tuition (2019 PPP USD)	2,244	1,762	0	2,367	25,515	2,103
HEI has received funding from						
Private sector	0.20	0.40	0	0	1	2,103
Government	0.34	0.47	0	0	1	2,103
Funding options used by some students						
Loans by banks	0.41	0.49	0	0	1	2,103

Loans by government program	0.45	0.50	0	0	1	2,103
Loans by HEI	0.29	0.46	0	0	1	2,103
Other loans	0.34	0.47	0	0	1	2,103
Government scholarships	0.66	0.48	0	1	1	2,103
HEI scholarships	0.77	0.42	0	1	1	2,103
Link with productive sector						
Engagement with firms						
Somebody in charge of industry relations	0.82	0.38	0	1	1	2,103
Industry helps with student evaluation or curriculum design	0.70	0.46	0	1	1	2,103
Industry has agreements with HEI to hire program grads	0.39	0.49	0	0	1	2,103
Industry has agreements to train faculty	0.35	0.48	0	0	1	2,103
Industry lends or provides equipment to program for student training	0.50	0.50	0	1	1	2,103
Collect data on employment or employers' satisfaction	0.56	0.50	0	1	1	2,103
Communicate with local firms about their needs	0.52	0.50	0	1	1	2,103
Program has staff assigned to collect grads' employment data	0.68	0.47	0	1	1	2,103
Job search assistance						
HEI coordinates job interviews with firms	0.60	0.49	0	1	1	2,103
HEI trains students for job interviews	0.69	0.46	0	1	1	2,103
HEI provides job market information	0.81	0.40	0	1	1	2,103
HEI has an employment center	0.60	0.49	0	1	1	2,103
Faculty						
Number of faculty	20.00	18.70	1	15	200	2,076
Percent of faculty						
with BA degree	82.20	29.40	0	100	100	2,043
with graduate degree	48.60	32.60	0	43	100	1,998
with SCP degree	20.00	30.00	0	6	100	1,916
working full-time	38.40	30.30	0	31	100	1,987
working in the industry	42.10	30.90	0	37	100	2,008
with 5yrs+ industry experience	55.70	33.10	0	56	100	1,988
<40 years old	40.00	29.20	0	34	100	1,961
that are women	34.00	23.50	0	30	100	2,021
Faculty are evaluated more than once per year	0.85	0.360	0	1	1	2,103
Important for faculty evaluation						
Classroom observation+	0.60	0.49	0	1	1	2,103
Class planning+	0.61	0.49	0	1	1	2,103
Student evaluation+	0.70	0.46	0	1	1	2,103
Students and peers' informal comments+	0.32	0.47	0	0	1	2,103
Peer evaluation+	0.31	0.46	0	0	1	2,103
Almost all or all faculty participated in professional training last year	0.55	0.50	0	1	1	2,103
Important for faculty hiring						
Practical experience	0.88	0.32	0	1	1	2,103
Research skills	0.62	0.48	0	1	1	2,103
Other Practices						
Update or review admin data more than once per year	0.66	0.47	0	1	1	2,103
Admission requirements						
General or specific knowledge test	0.59	0.49	0	1	1	2,103
Interview	0.50	0.50	0	1	1	2,103

Min. score in HS GPA or national entry test	0.66	0.47	0	1	1	2,103
Percent of governing body that belongs to:						
Private sector	18.90	21.20	0	12	100	2,103
Government	11.90	16.40	0	1	100	2,103
Faculty*	39.00	27.80	0	33	100	2,103
Current students or other sectors	25.60	22.30	0	21.5	100	2,103
Panel B. Student body, program, and institution characteristics						
Student body characteristics						
Academic deficiencies						
Mathematics is lacking in incoming students	0.82	0.39	0	1	1	2,103
Oral expression is lacking in incoming students	0.57	0.49	0	1	1	2,103
Reading is lacking in incoming students	0.70	0.46	0	1	1	2,103
Writing is lacking in incoming student	0.68	0.47	0	1	1	2,103
Other competencies are lacking in incoming students	0.15	0.36	0	0	1	2,103
Percent of students that are						
25+ years old	28.94	29.30	0	20	100	2,103
full-time	43.89	39.00	0	33	100	2,103
Women	38.19	29.20	0	40	100	2,103
Student body characteristics (PCA score)	-0.02	1.40	-2.78	-0.31	4.88	2,103
Program characteristics						
Program duration (semesters)	5.20	0.97	2	6	8	2,101
Number of cities where the HEI offers the program	3.55	8.32	1	1	151	2,083
Program has high quality accreditation	0.19	0.39	0	0	1	2,103
Total number of students in the program last year	221.60	332.80	1	125	4,321	2,030
Program age (years)	11.50	9.46	0	10	70	2,103
Program characteristics (PCA score)	0.02	1.25	-7.59	0.20	2.43	2,082
Institution characteristics						
HEI is public	0.30	0.46	0	0	1	2,103
HEI is a university	0.21	0.41	0	0	1	2,103
HEI is for profit	0.20	0.40	0	0	1	2,103
HEI age	37.84	30.80	1	32	481	2,094
Number of programs in the HEI	21.59	36.30	1	10	268	2,103
HEI characteristics (PCA score)	0.08	1.16	-1.84	-0.21	9.57	2,094
Panel C. Noise controls						
Survey conducted during COVID	0.48	0.50	0	0	1	2,103
Number of attempts to complete the survey	8.36	3.16	1	9	17	2,103
Survey completed by phone	0.33	0.47	0	0	1	2,103

Sources: Own calculations using WBSCPS and administrative data.
Notes: This table shows the descriptive statistics of the main variables used in the analysis (Table 1 presents an abridged version). An observation corresponds to a program. Dummy variables included in the list are those with means between 0.1 and 0.9. Statistics are weighted by WBSCPS sampling weights. Panel A refers to quality determinants, presented by category. Panel B refers to characteristics of the student body, program, and higher education institution (HEI); Panel C refers to survey noise controls. Total number of surveys completed is 2,103. Values in the "Obs." column vary depending on the number of valid responses. * indicates the omitted category in the analysis. + indicates that the variable is conditional on another. For example, "Mandatory internships during the program" is conditional on "Internships outside institution are mandatory" = 1; therefore, its coefficient is relative to not having mandatory internships outside the institution or having them but not during the program. Tuition is

presented in dollars but transformed in logs for estimation. “Test as graduation requirement” includes professional, industry, and national exit tests. Mean of PCA Scores are different than zero due to the use of sampling weights. All variables in panel B are included in the corresponding indexes (PCA Scores), except for “HEI is public,” which is included separately in the corresponding regressions as a “fixed” control. “HS” = high school.

Table A7. Average Annual Wages of SCP Graduates, by Country

Average wage	Brazil	Colombia	Dominican Republic	Ecuador	Peru
	(1)	(2)	(3)	(4)	(5)
In dollars (USD PPP 2019)	$10,730	$10,313	$11,275	$11,910	$7,481
In terms of the minimum wage	2.2	1.3	1.3	1.4	1.3

Source: Own calculations using WBSCPS and administrative data.
Note: This table reports the average annual wage per country, expressed in purchasing power parity (PPP) dollars or as a multiple of the country's annual minimum wage. Average wage in terms of the minimum wage (MW) is calculated using each country's MW in 2019 (Brazil, Ecuador, and Peru) and 2020 (Colombia and Dominican Republic). Average annual wage in terms of minimum wages = average annual wage / annual MW, where annual MW = monthly MW * 12. Percentiles 1 and 99 are excluded from these calculations. Statistics are weighted by WBSCPS sampling weights. Only São Paulo and Ceará are included for Brazil, and licensed programs for Peru.

Table A8. Descriptive Statistics for Programs in Brazil
Using Program-Level Data from the WBSCPS and Administrative Sources

Variable	Programs not matched with individual data		Programs matched with individual data		P-value diff. (1) – (3) (5)
	Mean (1)	**Std.Dev. (2)**	**Mean (3)**	**Std.Dev. (4)**	
Panel A. Program quality determinants					
Infrastructure					
Program offers at least one online class	0.34	0.47	0.33	0.47	0.74
>30% classes can be taken online	0.13	0.34	0.10	0.30	0.19
Number of workshops or labs available for practice	4.57	4.09	5.72	5.61	**0.01**
Has enough equipment or tools for practice	0.80	0.40	0.88	0.33	**0.01**
Maintenance of largest lab: every year	0.67	0.47	0.70	0.46	0.56
Training and curriculum					
Curriculum is fixed	0.75	0.43	0.80	0.40	0.23
Teaches numerical competencies	0.83	0.38	0.80	0.40	0.47
Teaches a foreign language	0.30	0.46	0.34	0.47	0.32
Teaches persistence in complex tasks	0.64	0.48	0.70	0.46	0.13
Remediation support					
Remediation classes before starting the program	0.46	0.50	0.46	0.50	0.84
Remediation classes during the program	0.87	0.34	0.89	0.31	0.47
Non-class-based remediation	0.44	0.50	0.45	0.50	0.83
Graduation requirements					
Professional association test	0.17	0.37	0.17	0.37	0.99
Thesis or research project	0.13	0.34	0.14	0.35	0.81
Years since last update to curriculum	1.63	1.66	1.97	2.01	**0.04**
Important reasons to update program:					
Government standards	0.48	0.50	0.53	0.50	0.22
Employment outcomes or employers' requests	0.85	0.35	0.88	0.32	0.29
HEI perception of labor market	0.86	0.35	0.88	0.32	0.42

Enrollment trends	0.50	0.50	0.47	0.50	0.48
Student feedback	0.85	0.36	0.83	0.38	0.53
More than once per year:					
Analyze student performance to solve problems	0.85	0.36	0.89	0.31	0.13
Collect student satisfaction data	0.71	0.45	0.67	0.47	0.30
Time assigned to practical training (%)	44.79	16.38	46.13	15.86	0.34
Internships outside institution are mandatory	0.25	0.44	0.30	0.46	0.20
Mandatory internships at the end of the program	0.10	0.30	0.11	0.31	0.77
Costs					
Funding options used by some students					
HEI scholarships	0.78	0.42	0.69	0.46	**0.02**
Government scholarships	0.80	0.40	0.74	0.44	**0.09**
Loans by HEI	0.26	0.44	0.27	0.45	0.70
Loans by banks	0.18	0.38	0.19	0.39	0.75
Other loans	0.24	0.43	0.31	0.46	**0.08**
HEI has received funding from					
Government	0.30	0.46	0.31	0.46	0.91
Private sector	0.14	0.35	0.19	0.39	0.21
Annual tuition (2019 PPP USD)	2,735.20	1,748.13	2,728.69	2,061.10	0.97
Link with productive sector					
Engagement with firms					
Collect employment data for graduates more than once per year	0.51	0.50	0.50	0.50	0.76
Communicate with local firms about their needs more than once per year	0.55	0.50	0.59	0.49	0.30
Industry helps with student evaluation or curriculum design	0.45	0.50	0.49	0.50	0.27
Industry has internship agreements with HEI	0.82	0.38	0.83	0.38	0.80
Industry has agreements with HEI to hire program grads	0.36	0.48	0.37	0.48	0.79
Industry has agreements to train faculty	0.27	0.44	0.26	0.44	0.84
Industry lends or provides equipment to program for student training	0.40	0.49	0.41	0.49	0.81
Somebody in charge of industry relations	0.83	0.38	0.80	0.40	0.45
Program has staff assigned to collect grads' employment data	0.42	0.49	0.39	0.49	0.45

Job search assistance					
HEI coordinates job interviews with firms	0.56	0.50	0.65	0.48	**0.04**
HEI trains students for job interviews	0.68	0.47	0.63	0.48	0.29
HEI provides job market information	0.75	0.43	0.81	0.39	**0.07**
HEI has an employment center	0.35	0.48	0.34	0.47	0.80
Faculty					
Number of faculty	15.45	9.17	16.08	8.61	0.41
Percent of faculty					
<40 years old faculty	38.44	27.25	34.86	26.25	0.14
that are women	40.95	25.21	38.83	23.31	0.32
with BA degree	85.89	25.91	84.41	26.62	0.52
with graduate degree	70.12	28.25	65.40	29.85	**0.07**
with 5yrs+ industry experience	63.32	27.65	62.17	28.59	0.65
working in the industry	46.39	29.79	41.84	27.82	**0.07**
Important for faculty hiring					
Practical experience	0.87	0.34	0.88	0.33	0.75
Research skills	0.37	0.48	0.44	0.50	0.13
Important for faculty evaluation					
Classroom observation	0.53	0.50	0.49	0.50	0.26
Class planning	0.49	0.50	0.44	0.50	0.26
Student evaluation	0.79	0.41	0.70	0.46	**0.03**
Students and peers' informal comments	0.24	0.43	0.24	0.43	0.86
Peer evaluation	0.26	0.44	0.24	0.43	0.52
Almost all or all faculty participated in professional training last year	0.65	0.48	0.67	0.47	0.68
Faculty are evaluated more than once per year	0.77	0.42	0.77	0.42	0.97
Other Practices					
Update or review admin data more than once per year	0.62	0.49	0.55	0.50	0.13
Percent of governing body that belongs to:					
Private sector	17.47	19.70	14.12	16.96	**0.03**
Government	5.47	11.29	7.78	13.92	**0.04**

Current students	15.34	14.51	16.42	15.64	0.42
Admission requirements					
General or specific knowledge test	0.83	0.37	0.90	0.30	**0.02**
Interview	0.23	0.43	0.18	0.39	0.12
Min. scores in HS GPA or national entry test	0.87	0.33	0.88	0.33	0.84
Panel B. Student body, program, field of study, and institution characteristics					
Student body characteristics					
Percent of students that are full-time	18.74	27.64	14.11	22.90	**0.03**
Academic deficiencies					
Mathematics is lacking in incoming students	0.79	0.41	0.83	0.37	0.15
Reading is lacking in incoming students	0.64	0.48	0.61	0.49	0.47
Writing is lacking in incoming students	0.67	0.47	0.69	0.46	0.57
Oral expression is lacking in incoming students	0.50	0.50	0.47	0.50	0.58
Program characteristics					
Program duration (semesters)	4.81	0.96	4.81	0.91	0.99
Program age (years)	8.71	5.19	10.55	5.41	**0.00**
Total number of students in the program last year	151.55	275.94	144.11	163.48	0.69
Program has high quality accreditation	0.23	0.42	0.21	0.41	0.65
Institution characteristics					
HEI is for profit	0.48	0.50	0.45	0.50	0.45
HEI is a university	0.29	0.45	0.33	0.47	0.30
Number of programs in the HEI	36.60	75.98	9.86	7.87	**0.00**
HEI is public	0.16	0.37	0.19	0.39	0.44
Field of study					
Education, Arts, Humanities, and Social	0.14	0.34	0.07	0.25	**0.01**
Economics, Management and Accounting	0.55	0.50	0.64	0.48	**0.04**
Health, Agronomy, Vet, Engineering and Architecture	0.31	0.46	0.29	0.45	0.60
Panel C. Noise controls					
Number of attempts to complete the survey	9.17	2.91	9.33	2.66	0.51
Survey completed by phone	0.45	0.50	0.42	0.49	0.47

Observations	200		401		

Source: Own calculations using WBSCPS and administrative data.

Notes: This table shows descriptive statistics for the 601 surveyed programs in Brazil. The unit of observation is a program. Columns (1) and (2) refer to the 200 programs that do not match to students in the individual-level dataset; columns (3) and (4) refer to the 401 programs that match (with 2+ students per program); and column (5) presents the p-value for the t-test of the difference in means between columns (1) and (3). P-value is in boldface when the difference is significant at the 1, 5 or 10% level. Panel A refers to program quality determinants, classified by category. Panel B refers to student body, program, and HEI characteristics, and Panel C to noise controls. In the case of dummy variables, only those with a mean between 0.10 and 0.9 are included in this table and in the estimation. Statistics are weighted by the WBSCPS sampling weights.

Table A9. Descriptive Statistics for Programs in Ecuador
Using Program-Level Data from the WBSCPS and Administrative Sources

Variable	Programs not matched with individual data: Mean (1)	Std.Dev. (2)	Programs matched with individual data: Mean (3)	Std.Dev. (4)	P-value diff. (1) – (3) (5)
Panel A. Program quality determinants					
Infrastructure					
Program offers at least one online class	0.37	0.48	0.35	0.48	0.78
>30% classes can be taken online	0.25	0.44	0.32	0.47	0.27
Number of workshops or labs available for practice	3.14	2.64	3.99	3.63	**0.03**
Has enough equipment or tools for practice	0.56	0.50	0.64	0.48	0.22
Maintenance of largest lab: every year	0.52	0.50	0.58	0.50	0.41
Training and curriculum					
More than once per year					
Analyze student performance to solve problems	0.86	0.35	0.85	0.36	0.88
Collect student satisfaction data	0.67	0.47	0.60	0.49	0.27
Important reasons to update program					
Government standards	0.61	0.49	0.73	0.45	**0.05**
Employment outcomes or employers' requests	0.76	0.43	0.75	0.44	0.85
HEI perception of labor market	0.69	0.46	0.83	0.37	**0.01**
Enrollment trends	0.55	0.50	0.63	0.49	0.21
Student feedback	0.68	0.47	0.65	0.48	0.61
Teaches numerical competencies	0.80	0.40	0.80	0.40	0.88
Teaches a foreign language	0.62	0.49	0.68	0.47	0.28
Graduation requirements					
Professional association test	0.52	0.50	0.71	0.45	**0.00**
Thesis or research project	0.95	0.22	0.91	0.28	0.26
Second language	0.13	0.33	0.11	0.32	0.76

Internships outside institution are mandatory	0.94	0.24	0.94	0.24	0.90
Mandatory internships during the program	0.54	0.50	0.36	0.48	**0.01**
Time assigned to practical training (%)	52.37	13.78	51.06	13.14	0.47
Remediation support					
Remediation classes before starting the program	0.54	0.50	0.65	0.48	0.11
Remediation classes during the program	0.30	0.46	0.41	0.49	**0.08**
Non-class-based remediation	0.30	0.46	0.37	0.49	0.21
Years since last update to curriculum	2.26	2.09	2.08	2.16	0.53
Costs					
Annual tuition (2019 PPP USD)	1,049.59	1,389.20	1,546.45	1,701.53	**0.01**
Funding options used by some students					
Loans by banks	0.25	0.43	0.30	0.46	0.35
Loans by government program	0.36	0.48	0.38	0.49	0.80
Other loans	0.22	0.42	0.37	0.49	**0.01**
Government scholarships	0.45	0.50	0.38	0.49	0.26
HEI scholarships	0.64	0.48	0.75	0.44	**0.07**
Link with productive sector					
Engagement with firms					
Collect employment data for graduates more than once per year	0.44	0.50	0.52	0.50	0.22
Communicate with local firms about their needs more than once per year	0.38	0.49	0.39	0.49	0.79
Program has staff assigned to collect grads' employment data	0.71	0.46	0.76	0.43	0.33
Industry helps with student evaluation or curriculum design	0.68	0.47	0.61	0.49	0.24
Industry has agreements with HEI to hire program grads	0.30	0.46	0.45	0.50	**0.02**
Industry has agreements to train faculty	0.32	0.47	0.40	0.49	0.22
Industry lends or provides equipment to program for student training	0.54	0.50	0.50	0.50	0.53
Somebody in charge of industry relations	0.85	0.36	0.89	0.31	0.29
Job search assistance					
HEI coordinates job interviews with firms	0.42	0.50	0.46	0.50	0.57
HEI trains students for job interviews	0.48	0.50	0.58	0.50	0.11

HEI provides job market information	0.78	0.42	0.81	0.39	0.54
HEI has an employment center	0.72	0.45	0.74	0.44	0.66
Faculty					
Important for faculty evaluation					
Classroom observation	0.78	0.42	0.76	0.43	0.79
Class planning	0.76	0.43	0.75	0.43	0.92
Students and peers' informal comments	0.41	0.49	0.40	0.49	0.89
Peer evaluation	0.60	0.49	0.53	0.50	0.27
Almost all or all faculty participated in professional training last year	0.71	0.46	0.69	0.47	0.77
Research skills are very important when hiring faculty	0.58	0.50	0.69	0.46	**0.08**
Number of faculty	12.18	8.55	18.69	17.91	**0.00**
Percent of faculty					
with BA degree	84.12	26.93	86.20	23.55	0.54
with 5yrs+ industry experience	61.88	33.41	58.43	38.12	0.47
working full-time	55.01	35.17	57.45	32.05	0.59
with graduate degree	34.68	23.98	38.56	24.70	0.23
working in the industry	43.58	37.50	38.46	35.76	0.30
with SCP degree	18.00	28.94	14.02	24.20	0.28
<40 years old	55.39	33.48	51.42	29.92	0.35
that are women	38.64	23.30	38.56	21.85	0.98
Other Practices					
Update or review admin data more than once per year	0.70	0.46	0.75	0.43	0.39
Percent of governing body that belongs to:					
Private sector	12.85	22.49	6.76	16.16	**0.02**
Current students	13.57	13.38	11.93	9.38	0.29
Other sector	9.57	18.82	20.21	26.19	**0.00**
Admission requirements					
General or specific knowledge test	0.65	0.48	0.65	0.48	0.91
Interview	0.44	0.50	0.35	0.48	0.15

Min. score in HS GPA or national entry test is an admission requirement	0.50	0.50	0.46	0.50	0.60
Panel B. Student, program, field of study, and institution characteristics					
Student body characteristics					
Percent of students that are full-time	61.01	40.41	65.47	39.01	0.39
Academic deficiencies					
Mathematics is lacking in incoming students	0.67	0.47	0.81	0.40	**0.02**
Reading is lacking in incoming students	0.50	0.50	0.51	0.50	0.96
Writing is lacking in incoming students	0.68	0.47	0.54	0.50	**0.02**
Oral expression is lacking in incoming students	0.71	0.45	0.58	0.50	**0.03**
Program characteristics					
Program duration (semesters)	5.05	0.60	5.06	0.73	0.85
Program age (years)	10.54	9.28	12.80	9.27	**0.06**
Total number of students in the program last year	162.88	291.68	393.95	613.07	**0.00**
Institution characteristics					
HEI is public	0.40	0.49	0.25	0.44	**0.01**
Program has high quality accreditation	0.26	0.44	0.45	0.50	**0.00**
Number of programs in the HEI	4.96	3.31	6.18	4.56	**0.02**
Field of study					
Health	0.04	0.19	0.08	0.27	0.17
Education, Arts, Humanities, and Social	0.49	0.50	0.27	0.44	**0.00**
Economics, Management and Accounting	0.22	0.42	0.27	0.45	0.41
Agronomy and Vet, Engineering and Architecture	0.24	0.43	0.38	0.49	**0.02**
Panel C. Noise controls					
Number of attempts to complete the survey	9.85	3.46	9.39	3.95	0.34
Survey completed by phone	0.22	0.42	0.18	0.39	0.42
Observations	153		92		

Source: Own calculations using WBSCPS and administrative data.
Notes: This table shows descriptive statistics for the 245 surveyed programs in Ecuador. The unit of observation is a program. Columns (1) and (2) refer to the 153 programs that do not match to students in the individual-level dataset and have at least two students; columns (3) and (4) refer to the 92 programs that match (with 2+ students per program); and column (5) presents the p-value for the t-test of the difference in means between columns (1) and (3). P-value is in boldface

when the difference is significant at the 1, 5 or 10% level. Some programs match but have only one student; they are not included in this table or in the estimation using individual-level data. Panel A refers to program quality determinants, classified by category. Panel B refers to student body, program, and HEI characteristics, and Panel C to noise controls. For dummy variables, this list and the corresponding estimations only include those with a mean between 0.1 and 0.9 Statistics are weighted by WBSCPS sampling weights.

Table A10. Descriptive Statistics for Students in Brazil

Based on Individual-Level Data for Students Matched to Surveyed Programs

Variable	Mean	Std. Dev.
Panel A. Student characteristics		
Age	24.60	5.57
Female	0.47	0.50
Mother's education:		
Less than primary	0.11	0.31
Primary school	0.14	0.35
High school	0.19	0.39
Higher education	0.07	0.26
Unknown	0.49	0.50
Student administrative variables (PCA Score)	0.00	1.15
Panel B. Peer (average) characteristics		
Age	24.65	1.77
Percentage of female peers	0.47	0.28
Percentage of peers by mother's education:		
Less than primary	0.11	0.05
Primary school	0.14	0.06
High school	0.19	0.07
Higher education	0.07	0.06
Unknown	0.48	0.14
Peers' administrative variables (PCA Score)	-0.07	1.45
Panel C. Outcomes		
Graduated	0.30	0.46

Sources: Own calculations using individual-level administrative data for Brazil. For more details on data sources and variable definitions, see Section 3.3 and Appendix 1.

Notes: In this table, the unit of observation is a student. Statistics are weighted using WBSCPS sampling weights. For a given student, her peers are the other students who started her program in 2014. Means of PCA scores are different than zero due to the use of sampling weights. Number of observations is 29,453.

Table A11. Associations between SCP Quality Determinants and Academic Outcomes

Using Program-Level Data for all Survey Countries

Dependent variable:	*Dropout Rates*	*Extra time-to-graduate*
	(1)	(2)
Costs		
HEI scholarships are used by some students	1.438 (0.876)	
Loans by banks are used by some students	-1.284 (0.834)	2.595* (1.555)
HEI has received funding from government	1.309* (0.739)	
HEI has received funding from private sector	1.466* (0.815)	
Annual tuition (2019 PPP USD, log)		-0.987** (0.427)
Training and curriculum		
Curriculum is fixed	-2.111** (0.899)	
Offers remediation classes during the program	-1.003 (0.782)	
Years since last update to curriculum	-0.0439 (0.111)	
Enrollment trends are very important to update program	-1.122 (0.703)	
Promotes work under hardship or pressure		-7.358*** (2.236)
Test required for graduation		1.988 (1.623)
Thesis or research project required for graduation		3.153* (1.778)
HEI perception of labor market is very important to update program		5.069*** (1.646)
Analyze student performance to solve problems more than once per year		-2.547 (2.358)
Collect student satisfaction data more than once per year		-1.135 (1.582)
Link with productive sector		
Industry helps with student evaluation or curriculum design	-0.667 (0.790)	-3.652** (1.752)
Industry lends or provides equipment to program for student training	-1.769*** (0.670)	
Somebody in charge of industry relations	-1.507 (1.198)	
HEI trains students for job interviews	-0.817 (0.876)	
HEI provides job market information	-2.198** (1.036)	
HEI has an employment center		1.289 (1.485)
Faculty		
Number of faculty (log)		
Percent of faculty working in the industry		-0.0524** (0.0205)
Percent of faculty with SCP degree	-0.0132 (0.0126)	-0.0546** (0.0266)
Percent of faculty with graduate degree	0.00629 (0.0127)	
Percent of faculty working in the industry	0.0217* (0.0118)	
Research skills are very important when hiring faculty	-1.096 (0.801)	

Students’ and peers' informal comments are very important in faculty evaluation	-0.320	
	(0.705)	
Peer evaluation is very important in the faculty evaluation	-1.463*	
	(0.788)	
Practical experience is very important when hiring faculty		-3.417
		(2.234)
Almost all or all faculty participated in professional training last year		2.663*
		(1.467)
Faculty are evaluated more than once per year		-4.393*
		(2.305)
Other Practices		
Update or review admin data more than once per year	-0.274	
	(0.725)	
Student body, program, and HEI characteristics (PCA scores)	✓	✓
Noise controls, country-and field-fixed effects	✓	✓
Observations	1,525	1,692
Mean of dependent variable	14.03	18.58
R-squared	0.085	0.107
Adj. R squared	0.0613	0.0890

Source: Own estimations using WBSCPS data.
Notes: This table shows coefficients from the (second stage) OLS regressions of dropout rate and extra time to graduation (ETG) on the determinants selected by LASSO in the first stage. The unit of observation is a program. Regressions are weighted using WBSCPS sampling weights. See definitions of outcomes and PCA scores in Appendix 1. Specifications control for PCA scores of characteristics of the student body, program, and HEI as well as for survey noise controls, country fixed effects, and field fixed effects. Standard errors clustered at HEI level are in parenthesis. Significance levels: * p<0.1, ** p< 0.05, *** p<0.01.

Table A12. Associations between SCP Quality Determinants and Labor Market Outcomes

Using Program-Level Data for all Survey Countries

Dependent variable:	*Formal employment*	*Log Wages*
	(1)	(2)
Infrastructure		
Has enough equipment or tools for practice	0.0702**	0.0200
	(0.0352)	(0.0167)
Training and curriculum		
Teaches numerical competencies	0.133***	0.0561***
	(0.0394)	(0.0189)
Offers remediation classes during the program	0.0525*	0.0275*
	(0.0317)	(0.0146)
Offer non-class-based remediation		-0.0257*
		(0.0152)
Employment outcomes or employers' requests are very important to update program	0.0678	
	(0.0425)	
HEI perception of labor market is very important to update program	0.0400	0.0395**
	(0.0356)	(0.0179)
Enrollment trends are very important to update program		-0.0169
		(0.0130)
Offers credits for longer degrees		0.0615***
		(0.0207)
Link with productive sector		
Collect data on employment or employers' satisfaction more than once per year	0.0483*	
	(0.0292)	
Industry has agreements to train faculty	-0.0488	
	(0.0320)	
Industry lends or provides equipment to program for student training	-0.0266	
	(0.0286)	
Program has staff assigned to collect grads' employment data	0.0576*	
	(0.0313)	
HEI provides job market information		0.0126
		(0.0188)
HEI has an employment center	0.0830***	0.0252
	(0.0311)	(0.0161)
Faculty		
Percent of <40 years old faculty	-0.00175***	
	(0.000501)	
Percent of faculty with 5yrs+ industry experience	0.00101**	
	(0.000441)	
Percent of faculty that are women		-0.000683**
		(0.000324)
Percent of faculty with BA degree		0.000469*
		(0.000250)
Class planning is very important in faculty evaluation	0.0470	
	(0.0293)	
Classroom observation is very important in faculty evaluation		0.0157
		(0.0137)
Number of faculty (log)		0.0229**
		(0.0109)
Research skills are very important when hiring faculty		0.0207
		(0.0160)
Other Practices		
Update or review admin data more than once per year	0.0468	
	(0.0302)	
Percent of governing body that belongs to current students	-0.000798	-0.000614*
	(0.000678)	(0.000318)
Percent of governing body that belongs to private sector		0.000367
		(0.000349)

Interview is an admission requirement		0.0235
		(0.0168)
General or specific knowledge test is an admission requirement		0.0281*
		(0.0150)
Student body, program, and HEI characteristics (PCA scores)	✓	✓
Noise controls, country- and field-fixed effects	✓	✓
Observations	1,270	1,751
Mean of dependent variable	0.591	9.209
Average wage (USD 2019 PPP)		10,424.17
R-squared	0.136	0.175
Adj R squared	0.113	0.158

Source: Own estimations using WBSCPS data.
Notes: This table shows coefficients from the (second stage) OLS regressions of formal employment and log wages on the determinants selected by LASSO in the first stage. The unit of observation is a program. Formal employment equals one if the director reports that almost all of the program graduates are employed or self-employed in the formal sector. Regressions are weighted using sampling weights from the WBSCPS. See definitions of outcomes and PCA scores in Appendix 1. Number of observations vary across variables due to differences in share of missing values. Specifications control for PCA scores of characteristics of the student body, program, and HEI as well as for survey noise controls, country fixed effects, and field fixed effects. See Appendix 1 for the list of the variables included in the PCA indexes. Standard errors clustered at HEI level are in parenthesis. Significance levels: * p<0.1, ** p< 0.05, *** p<0.01.

Table A13. Associations between SCP Quality Determinants and Labor Market Outcomes

Using Individual- and Program-Level Data for Brazil

	Graduation	**Ever employed the year after graduation**	**Percent of time employed after graduation**	**Log average monthly wage**
	(1)	(2)	(3)	(4)
Infrastructure				
Program offers at least one online class	0.0467** (0.0193)			
>30% classes can be taken online			2.560* (1.497)	
Number of workshops or labs available for practice	0.00149 (0.00236)			
Has enough equipment or tools for practice	-0.0211 (0.0240)		-1.506 (1.893)	
Maintenance of largest lab: every year	0.0345* (0.0202)		0.0472 (1.369)	
Costs				
HEI scholarships are used by some students	0.00990 (0.0197)			
Loans by HEI are used by some students	0.0173 (0.0207)			
Loans by banks are used by some students	0.0500** (0.0223)	0.0285* (0.0148)	4.994*** (1.569)	0.202* (0.104)
Other loans are used by some students	0.0136 (0.0190)			
HEI has received funding from government	-0.0290 (0.0211)		-2.682* (1.438)	
HEI has received funding from private sector	0.0342 (0.0221)			
Training and curriculum				
Curriculum is fixed			-1.558 (1.459)	
Teaches numerical competencies	-0.0285 (0.0255)	0.0382** (0.0190)	4.177** (1.822)	0.292** (0.133)
Teaches a foreign language	0.0177 (0.0210)			
Teaches persistence in complex tasks	0.00888 (0.0199)	0.0290** (0.0141)	1.654 (1.400)	0.158 (0.0996)
Offers remediation classes before starting the program	0.0171 (0.0165)	0.0228* (0.0118)		0.132 (0.0820)
Offers remediation classes during the program		-0.0512** (0.0208)	-0.614 (2.026)	-0.375*** (0.140)
Offer non-class-based remediation	-0.0232 (0.0180)			
Professional association test required for graduation	0.0549* (0.0280)	0.0348** (0.0172)	7.062*** (1.763)	0.201* (0.114)
Thesis or research project required for graduation	0.0259 (0.0235)	0.0166 (0.0200)	1.941 (1.773)	0.104 (0.133)
Years since last update to curriculum	0.00675* (0.00357)			
Government standards are very important to update program	-0.0359** (0.0167)			
Employment outcomes or employers' requests are very important to update program	-0.0152 (0.0295)		-2.561 (2.007)	
Enrollment trends are very important to update program			-1.152 (1.153)	
Student feedback is very important to update program	-0.0366* (0.0215)	0.0320** (0.0144)		0.241** (0.101)
Analyze student performance to solve problems more than once per year	0.0919*** (0.0298)	0.0476** (0.0211)	5.854** (2.313)	0.267* (0.146)
Collect student satisfaction data more than once per year	-0.0398** (0.0199)		2.386* (1.261)	

Time assigned to practical training (%)	-0.000699			
	(0.000557)			
Internships outside institution are mandatory	0.0169			
	(0.0205)			
Mandatory internships at the end of the program	-0.0448			
	(0.0294)			
Link with productive sector				
Collect employment data for graduates more than once per year	-0.0186	-0.0260*	-2.686**	-0.198**
	(0.0187)	(0.0132)	(1.350)	(0.0910)
Communicate with local firms about their needs more than once per year	-0.0371*			
	(0.0204)			
Industry helps with student evaluation or curriculum design	-0.0137		-4.414***	
	(0.0169)		(1.214)	
Industry has internship agreements with HEI	-0.0440**		-1.799	
	(0.0218)		(1.492)	
Industry has agreements to train faculty	0.0363*			
	(0.0198)			
Industry lends or provides equipment to program for student training	-0.0174			
	(0.0188)			
Somebody (from board or staff) is in charge of industry relations	-0.0271		1.680	
	(0.0202)		(1.506)	
Program has staff assigned to collect grads' employment data	0.0320			
	(0.0201)			
HEI trains students for job interviews		-0.0392***	-2.599*	-0.258***
		(0.0136)	(1.500)	(0.0958)
HEI coordinates job interviews with firms	0.0121			
	(0.0179)			
HEI provides job market information	-0.0199	0.0574***	3.871**	0.376***
	(0.0228)	(0.0155)	(1.656)	(0.109)
HEI has an employment center	-0.0212			
	(0.0192)			
Faculty				
Faculty are evaluated more than once per year		0.0419***	3.131**	0.302***
		(0.0153)	(1.587)	(0.106)
Percent of <40 years old faculty	0.000567			
	(0.000351)			
Percent of faculty that are women		-0.000444	-0.0276	-0.00425**
		(0.000287)	(0.0271)	(0.00201)
Percent of faculty with BA degree	0.000433		-0.0636**	
	(0.000344)		(0.0253)	
Percent of faculty with graduate degree		0.000633***	0.0929***	0.00531***
		(0.000199)	(0.0213)	(0.00140)
Percent of faculty with 5yrs+ industry experience	-0.000571			
	(0.000399)			
Percent of faculty working in the industry	0.000721**		-0.0287	
	(0.000348)		(0.0227)	
Practical experience is very important when hiring faculty	0.0207			
	(0.0265)			
Classroom observation is very important in faculty evaluation	0.00654	0.0228*		0.183**
	(0.0189)	(0.0116)		(0.0808)
Class planning is very important in faculty evaluation	0.0171	-0.0329**	-1.345	-0.218**
	(0.0185)	(0.0129)	(1.284)	(0.0895)
Students and peers' informal comments are very important in faculty evaluation	-0.0134	-0.0290*		-0.191*
	(0.0189)	(0.0148)		(0.104)
Peer evaluation is very important in the faculty evaluation	0.0199	0.0308**		0.210**
	(0.0184)	(0.0139)		(0.0980)
Almost all or all faculty participated in professional training last year	-0.0459**		-1.955	
	(0.0195)		(1.228)	
Other practices				
Update or review admin data more than once per year	0.0130	0.0473***	4.222***	0.345***
	(0.0169)	(0.0131)	(1.194)	(0.0900)
Percent of governing body that belongs to: private sector		0.000412	0.107***	0.00334
		(0.000368)	(0.0394)	(0.00261)
Percent of governing body that belongs to: government or other sector			0.0744*	

	(1)	(2)	(3)	(4)
			(0.0396)	
Percent of governing body that belongs to: current students	0.00206***			
	(0.000635)			
General or specific knowledge test is an admission requirement	0.0339	0.0249	4.516*	0.163
	(0.0260)	(0.0253)	(2.521)	(0.178)
Interview is an admission requirement		0.0478***	4.977***	0.337***
		(0.0158)	(1.477)	(0.110)
Min. scores in HS GPA or national entry test is an admission requirement	-0.0141			
	(0.0251)			
Student body, program, and HEI characteristics (PCA scores)	✓	✓	✓	✓
Noise controls, state- and field-fixed effects	✓	✓	✓	✓
Graduation year fixed effect		✓	✓	✓
Observations	22,663	7,177	6,827	7,089
R-squared	0.126	0.122	0.109	0.135
Mean dependent variable	0.303	0.707	53.52	4.791
Average wage (USD 2017 PPP)				715.62
Adj R squared	0.124	0.117	0.103	0.131

Source: Own estimations using individual-level data from administrative sources and program-level data from the WBSCPS for Brazil. *Notes*: This table shows coefficients from the (second stage) OLS regressions of student outcomes on the quality determinants selected by LASSO in the first stage. The unit of observation is an individual. Outcomes (dependent variables) are graduation within three years of starting the program (col. 1), and the following labor market outcomes pertaining to the 12-month period following graduation: whether the student is formally employed at least one month (col. 2); percent of months she is formally employed (col. 3); and average monthly wage (col. 4). Average monthly wage is computed over the months worked; it is zero if the individual does not work formally at all. Regressions are weighted using WBSCPS sampling weights. All specifications include noise controls as well as fixed effects for graduation year, state, and field. They also control for PCA scores for the following: student body characteristics (based on survey data), student characteristics (based on individual-level data, including proxies for previous labor market experience), program characteristics (based on survey data), HEI characteristics (based on survey data), and peer characteristics (based on individual-level data, including proxies of peers' previous labor market experience). See Appendix 1 for the list of the variables included in each index. Standard errors clustered at program level are in parenthesis. Significance levels: * p<0.1, ** p< 0.05, *** p<0.0

Table A14. Associations between SCP Quality Determinants and Labor Market Outcomes

Using Individual- and Program-Level Data for Ecuador

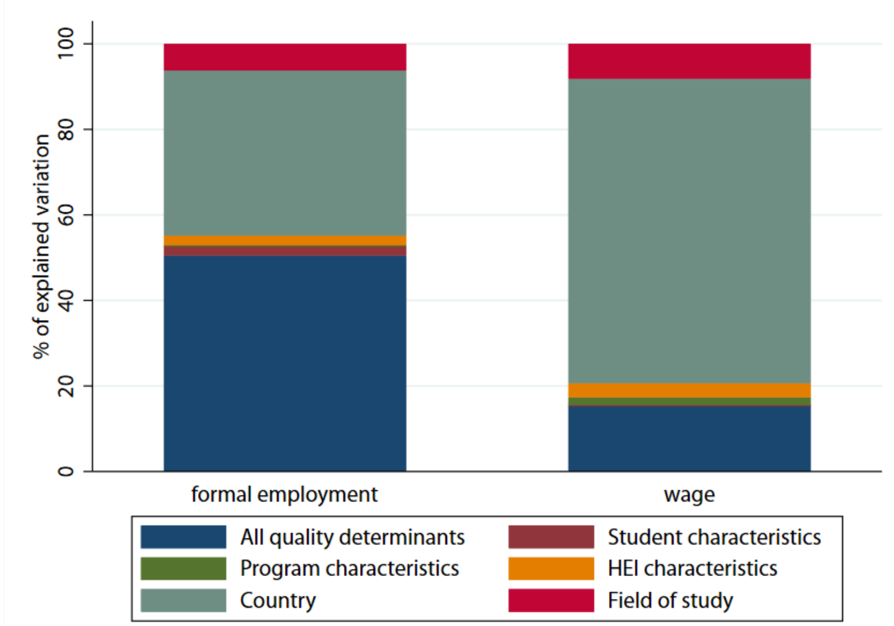
	Ever employed the year after graduation	**Percent of time employed after graduation**	**Average monthly wage (log)**
	(1)	(2)	(3)
Infrastructure			
Number of workshops or labs available for practice		2.645***	
		(0.445)	
Costs			
Government scholarships are used by some students		7.623*	
		(4.241)	
Training and curriculum			
Analyze student performance to solve problems more than once per year		-8.775**	
		(3.818)	
Collect student satisfaction data more than once per year	0.137***	7.221*	0.650**
	(0.0446)	(3.678)	(0.277)
Government standards are very important to update program	0.0546	21.14***	0.611**
	(0.0402)	(3.658)	(0.246)
Enrollment trends are very important to update program		-5.478	
		(4.142)	
Student feedback is very important to update program		10.65***	
		(3.310)	
Teaches numerical competencies	0.209***	17.42***	1.212***
	(0.0566)	(6.273)	(0.357)
Teaches a foreign language	-0.0850*		
	(0.0434)		
Professional association test required for graduation	-0.100**		-0.682**
	(0.0443)		(0.285)
Time assigned to practical training (%)		-0.253**	
		(0.122)	
Offers remediation classes before starting the program		-6.298	
		(3.821)	
Link with productive sector			
Industry lends or provides equipment to program for student training		11.11***	
		(3.309)	
HEI trains students for job interviews	0.217***	16.11**	1.491***
	(0.0522)	(6.982)	(0.347)
HEI coordinates job interviews with firms		-11.31***	
		(4.048)	
HEI provides job market information	0.107**	21.23***	0.537*
	(0.0425)	(3.710)	(0.297)
HEI has agreements with private firms to hire graduates		6.911**	
		(3.341)	
Somebody (from board or staff) is in charge of industry relations	0.159***	7.536	1.131***
	(0.0604)	(4.980)	(0.429)
Faculty			
Classroom observation is very important in faculty evaluation		7.454*	
		(4.460)	
Students and peers' informal comments are very important in faculty evaluation		-9.928**	
		(4.793)	
Research skills are very important when hiring faculty	-0.171***	-26.70***	-1.331***
	(0.0488)	(4.485)	(0.275)
Number of faculty (log)	-0.0628	-3.187	-0.363
	(0.0379)	(2.836)	(0.261)
Percent of faculty with 5yrs+ industry experience		0.177***	
		(0.0431)	
Percent of faculty working in the industry	-0.00122*	-0.110**	-0.00887**
	(0.000631)	(0.0514)	(0.00423)
Percent of faculty with SCP degree		-0.212***	
		(0.0680)	
Percent of <40 years old faculty		-0.218***	
		(0.0785)	

	(1)	(2)	(3)
Percent of faculty that are women	-0.000868 (0.000789)	-0.0655 (0.0965)	-0.00500 (0.00517)
Other practices			
Percent of governing body that belongs to current students		0.0112 (0.210)	
Min. scores in HS GPA or national entry test is an admission requirement	0.0902** (0.0449)		0.761*** (0.288)
Student body, program, and HEI characteristics (indexes)	✓	✓	✓
Noise controls, and field-fixed effects	✓	✓	✓
Observations	1,214	1,201	1,206
R-squared	0.230	0.325	0.247
Mean of dependent variable	0.348	23.81	2.294
Average wage (USD 2019 PPP)			300.6
Adj R squared	0.214	0.303	0.232

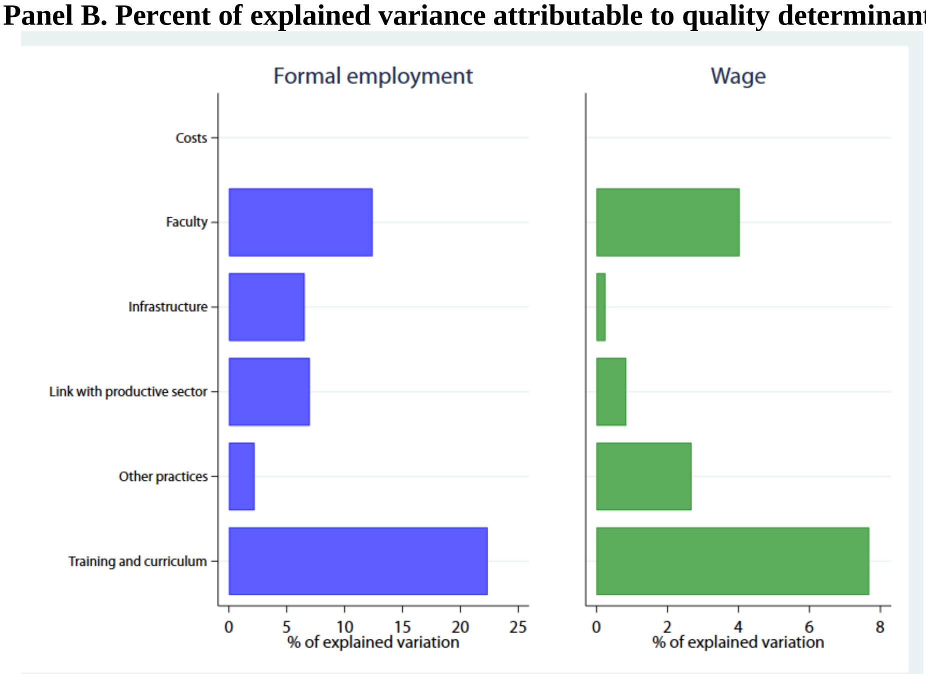
Source: Own estimations using individual-level data from administrative sources and program-level data from the WBSCPS for Ecuador. *Notes*: This table shows coefficients from the (second stage) OLS regressions of student outcomes on the quality determinants selected by LASSO in the first stage. The unit of observation is an individual. Outcomes (dependent variables) are the following labor market outcomes pertaining to the 12-month period following graduation: whether the student is formally employed at least one month (col. 1); percent of months she is formally employed (col. 2); and average monthly wage (col. 3). Average monthly wage is computed over the months worked; it is zero if the individual does not work formally at all. Regressions are weighted using WBSCPS sampling weights. All specifications include noise controls as well as fixed effects for graduation year, state, and field. They also control for PCA scores for the following: student body characteristics (based on survey data), student characteristics (based on individual-level data, including proxies for previous labor market experience), program characteristics (based on survey data), HEI characteristics (based on survey data), and peer characteristics (based on individual-level data, including proxies of peers' previous labor market experience). See Appendix 1 for the list of the variables included in each index. Standard errors clustered at program level are in parenthesis. Significance levels: * p<0.1, ** p< 0.05, *** p<0.0

Figure A1. R-Squared Shapley-Owen Decomposition
Using Program-Level Data

Panel A. Percent of explained variance attributable to each set of variables



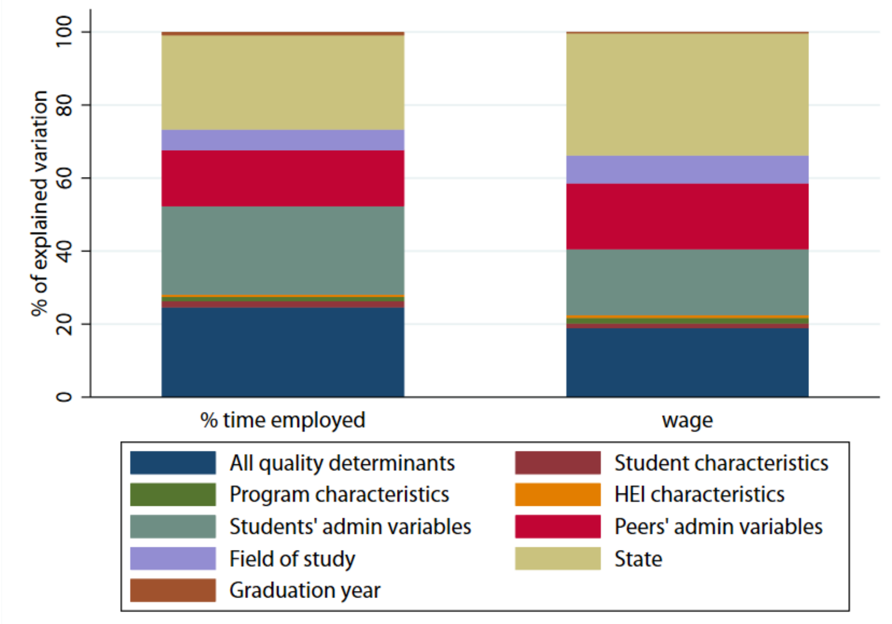
Panel B. Percent of explained variance attributable to quality determinants



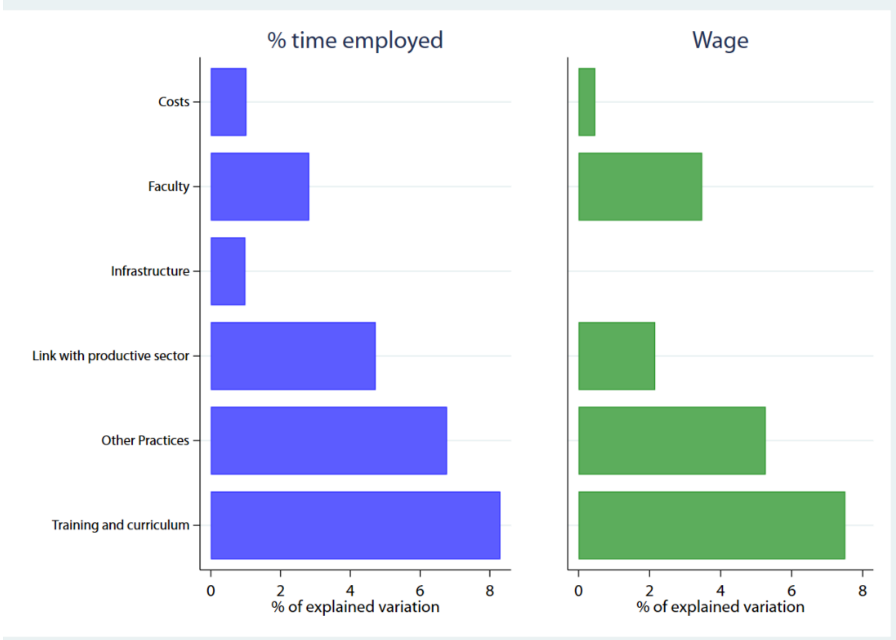
Source: Own estimations using WBSCPS program-level data.
Notes: This figure illustrates the Shapley-Owen decomposition presented in Table 3. It focuses on two labor market outcomes: formal employment and log wages.

Figure A2. R-Squared Shapley-Owen Decomposition
Using Individual- and Program-Level Data for Brazil

Panel A. Percent of explained variance attributable to each set of variables



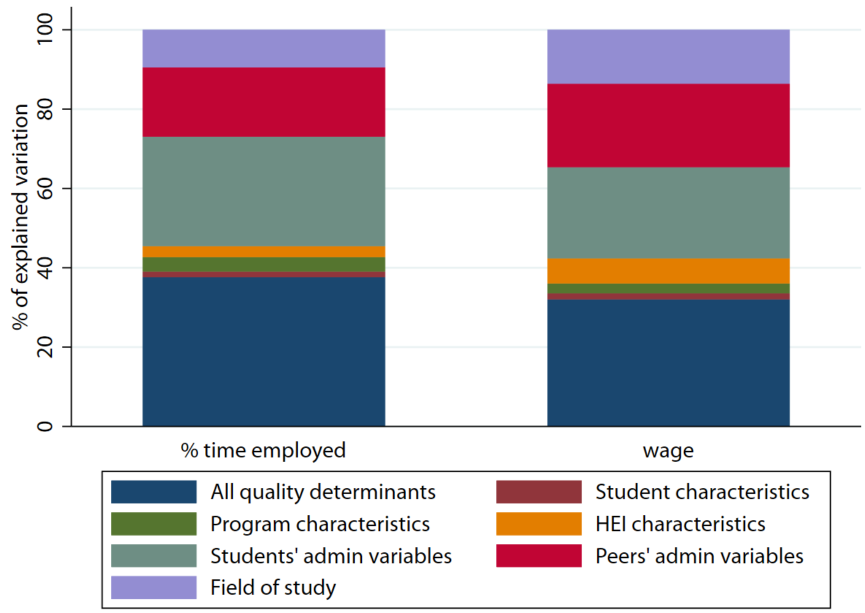
Panel B. Percent of explained variance attributable to quality determinants



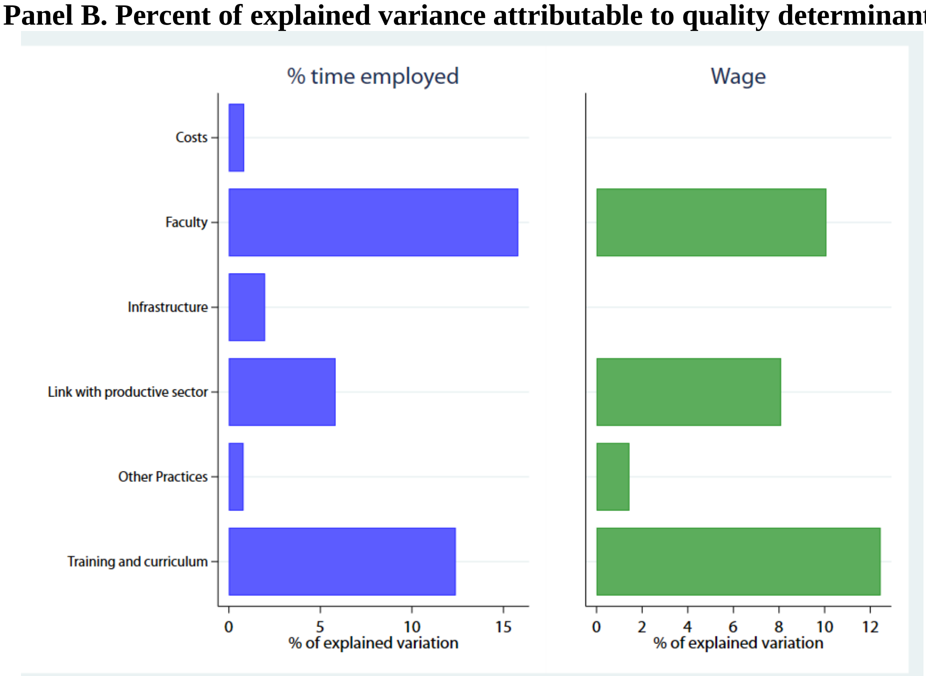
Source: Own estimations using WBSCPS program-level data and individual-level data from administrative sources for Brazil.
Notes: This figure illustrates the Shapley-Owen decomposition presented in Table 4. It focuses on two (labor market) outcomes: percent of time employed and log average wages.

Figure A3. R-Squared Shapley-Owen Decomposition
Using Individual- and Program-Level Data for Ecuador

Panel A. Percent of explained variance attributable to each set of variables



Panel B. Percent of explained variance attributable to quality determinants



Source: Own estimations using WBSCPS program-level data and individual-level data from administrative sources for Ecuador.
Notes: This figure illustrates the Shapley-Owen decomposition presented in Table 5. It focuses on two (labor market) outcomes: percent of time employed and log average wages.