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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 gather 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. We show that specific quality determinants may favor academic and labor market outcomes. 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. These findings have implications for the design and replication of high-quality SCPs, their regulation, and the development of information systems.

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. As such, they can play a central role in adjusting to rapidly changing market needs, expanding higher education to non-traditional students, and providing lifelong learning opportunities.

However, despite their promise, SCPs have shortcomings. Crucially, the international evidence indicates that students academic and labor market outcomes vary greatly across these programs, suggesting that high- and low-quality SCPs coexist in higher education (HE) systems worldwide.[3] This might explain why previous

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[1] For bachelor's enrollment rates worldwide, see UNESCO (https://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, Hupkau, & Ruiz-Valenzuela (2022) for the UK; and Ferreyra et al. (2021) for Latin America and the Caribbean.

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efforts to explore what constitutes a high-quality HE program have led to mixed or inconclusive findings.[4] As a result, SCP quality remains a "black box."

This paper represents a first attempt to open the SCP quality "black box". It seeks to identify program practices (e.g., how programs relate to local employers) and inputs (e.g., facilities for practical training)—henceforth, quality determinants—positively associated with students' outcomes.[5] To this end, we adopt two complementary approaches: an aggregate regional analysis of program-level information for five countries in Latin America and the Caribbean (LAC), and a country-level analysis using rich individual-level data for two of those countries.[6]

Underpinning both approaches is a new and unique survey, the World Bank Short-Cycle Program Survey (WBSCPS), which we designed and implemented in 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, 2015). We group them in six categories: training and curriculum (T&C), 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, extra time to graduation, formal employment, and wages) and quality determinants for the five survey countries. For the country-level approach, we supplement 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.

The sheer amount of information 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.[7] 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 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. Differences in selected quality determinants are not surprising given the large variation in program outcomes and quality determinants across countries.

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 that are relevant for the labor market. Providing labor market information, in turn, is quite rare in Latin America. 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's contribution to the literature is three-fold. First, it links to work on the role of higher education program quality on graduates' outcomes. This literature includes contribution from multiple disciplines and usually focuses on bachelor's programs and yields mixed results., perhaps because those studies have typically used data from a single country and examined a single deter-

[4] For instance, the research in education and economics documents positive associations between firms' internship agreements in HE programs and employment, yet the impact on wages is weak (Di Meglio et al., 2022; Jaeger et al., 2020; Wesley Routon & Walker, 2019; Yi, 2018). Similarly, some studies find positive effects of offering online training in programs (Deming et al., 2016; Jaggar & Xu, 2016), whereas others report negative or no effects (Bettinger et al., 2017; Cellini & Grueso, 2021; Krieg & Henson, 2016; Figlio et al., 2013). Only a few papers examine the benefits of industry engagement in curriculum design (Plewa et al., 2015). Appendix I presents a comprehensive literature review on the associations between higher education programs' quality determinants and academic or labor market outcomes.

[5] 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.

[6] We initially set out to collect individual-level data for 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 complex information systems and facilitating data access remains a key task in developed and developing countries alike.

[7] 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.

minant such as availability or use of funding options; curriculum structure, training, and academic remediation; availability of infrastructure for practical training; practices on faculty assessment, training, and hiring; practices to promote student employability and industry engagement; and other institution characteristics such as governance.[8] Our paper is novel in that we collect evidence and simultaneously analyze associations between multiple program determinants and academic and labor market outcomes for several countries, and focus specifically on SCPs.

Second, our paper contributes to the evidence on SCP returns. Most of this literature focuses either on a single US state[9] or a single country.[10] For the US, the most comprehensive study on practices of successful SCPs (at community colleges) is Bailey (2015). This study, however, does not provide systematic, quantitative evidence. Other studies use data from the US and document substantial heterogeneity in returns across fields of study (Jepsen et al., 2014) and significant variation in their quality (Carrell & Kurlaender, 2016). For Colombia, Dinarte et al. (2022) finds that SCPs vary greatly in their contributions to student-level outcomes, across and especially within fields of study. 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.[11]

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. 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 HE quality determinants and student outcomes for cross-country comparisons.

Of course, as in any empirical paper exploiting a non-experimental design, we caution against over-interpreting our findings. First, a negative association between a specific determinant and an outcome does not necessarily mean the determinant is undesirable. Instead, it indicates the need to understand how it fits the program's goals. Second, our point estimates represent empirical associations, which might inform high-quality program design and regulatory settings. They cannot be directly interpreted as causal effects as might be potentially subject to selection and omitted variable biases.

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).[12] 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 (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 non-traditional 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.

[8] See Appendix I for a review of the evidence from multiple disciplines.

[9] See Bahr (2013; 2016) and Carrell and Kurlaender (2016) for California; De Vlieger et al. (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 and Dadgar (2018) for Virginia.

[10] 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-Rodríguez (2019) for Colombia; and Rodriguez et al. (2016) for Chile.

[11] We do not estimate SCP returns relative to a high school diploma (as in some of this literature) but rather compare SCPs among themselves.

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

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 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 across 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 in each country. We mapped the information collected to potential 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 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. 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 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 due to COVID-19 restrictions, 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 comparing programs in the survey and those 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, and were small in magnitude (Table A4), we recalibrated the sampling weights for the estimations accordingly.

Self-reporting could have biased our survey data if, for example, program directors 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 were assured that all responses would remain confidential and anonymous, would be reported only in an aggregate fashion, and would be used exclusively by the World Bank for research purposes. Second, questions were designed to avoid common biases associated with self-reporting, for example referring to specific time periods (such as the previous academic year) to avoid memory biases, and, where possible, including specific response options.

We conduct an outcome validation exercise to address potential biases in self-reported program outcomes using country-specific administrative data and household surveys. On average, we find that directors' outcome reports do not differ substantially from outcomes obtained from these alternative sources. For example, the average employment rate estimated using WBSCPS is 42 percent, and between 38 and 44 percent when computed using household surveys or administrative sources. This result is more salient when restricting the comparison of average labor market outcomes to the age group most likely to be enrolled in SCPs. For example, the average employment rate for those aged 21–25 was 38 percent. See further details in Table A5 in the Appendix, which includes the sources of information used for this exercise.

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. On average, the programs have desirable characteristics 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. As for *T&C*, most programs (70 percent) teach a fixed curriculum with structured pathways (last updated, on average, about three years ago), with 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. 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 (in 2019 PPP dollars). 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, mostly 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. In terms of *other practices*, 50–70 percent rely on admission requirements such as exams, interviews, or test scores in mandatory national exams.

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 an official 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 official 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 II 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 (Fig. 1 panel A). Average ETG is 19 percent, ranging from an average of 31 percent in the Dominican Republic to 9 percent in Peru (Fig. 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 Fig. 2 panel A). Wages vary greatly within and across countries (Fig. 2 panel B). 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.

3.3.1. 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 (*Relacão Anual de Informacões 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, 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).[13]

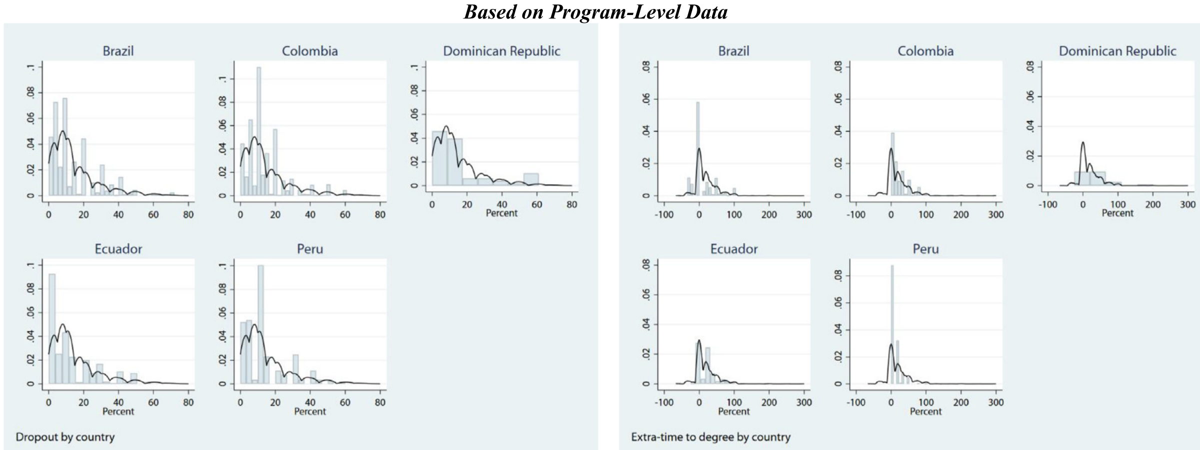
3.3.2. Ecuador

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 2018 (age, gender,

[13] 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.

Based on Program-Level Data



Panel A. Dropout rates *Panel B. Extra time to degree*

Fig. 1. Academic outcomes across countries. *Based on program-level data. 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 II.

whether the student has children of her own, family of origin's socioeconomic score, and mother's education level.) Yet, 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).[14]

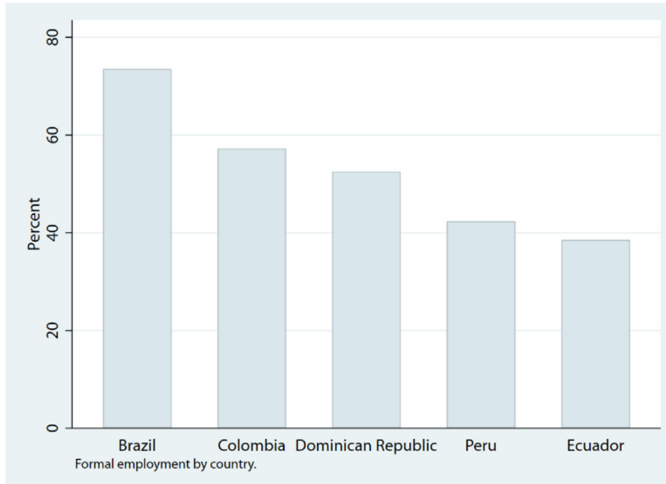
Our individual-level datasets for Brazil and Ecuador are different in that, for Brazil, we have information on all students who entered our survey programs in 2014 (whether they went on to graduate or not), whereas we only have information on graduates for Ecuador. Therefore, we examine graduation outcomes only for Brazil, but 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.[15] Appendix II provides additional information on all variables.

3.4. Descriptive statistics of individual-level data

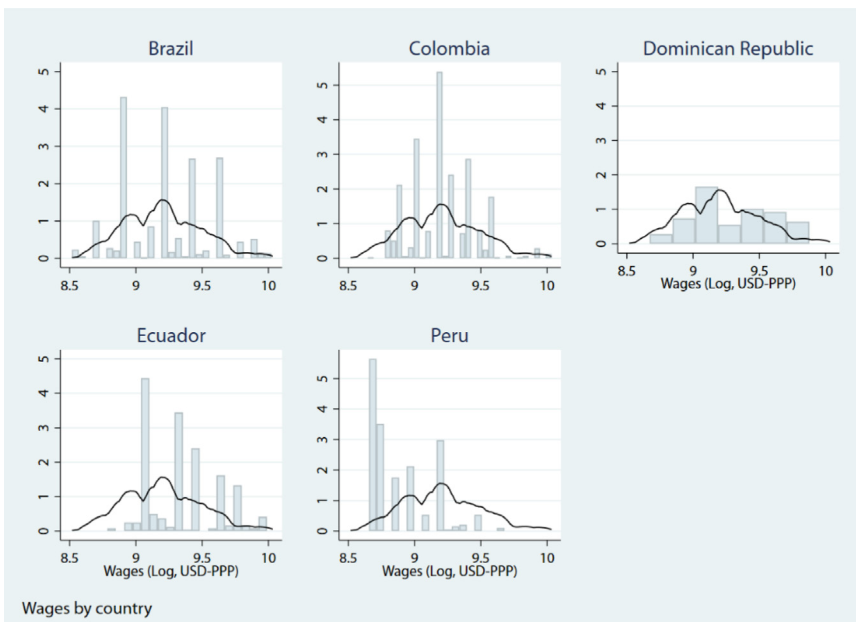
Table 2 presents descriptive statistics of program graduates in Ecuador and Brazil, for whom we study labor market outcomes. In both countries, the average student is about 25 years old and about 60 percent of students are female (panel A). Students in Ecuador have more educated mothers than in Brazil 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), spends a greater fraction of

[14] 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.

[15] 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.



Panel A. Formal employment



Panel B. Wages

Fig. 2. Labor market outcomes across countries. *Based on program-level data. 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 II. Only São Paulo and Ceara are included for Brazil, and licensed programs for Peru.

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

4.1.1. 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[16]. For a given outcome in program j and country c, we estimate the following linear specification using LASSO:

$$y_{jc} = \alpha_0 + \sum_{d=1}^{6} \boldsymbol{Q}_{jc}^{d}{}' \boldsymbol{\alpha}_1^{\boldsymbol{d}} + \boldsymbol{C}_{jc}' \boldsymbol{\alpha}_2 + \boldsymbol{N}_{\boldsymbol{jc}}' \boldsymbol{\alpha}_3 + \phi_c + \phi_f + \epsilon_{jc}, \tag{1}$$

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 II). 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), $\boldsymbol{N}_{\boldsymbol{jc}}$, 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, 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.[17] To ensure that we control for $\boldsymbol{C}_{jc}$ and $\boldsymbol{N}_{\boldsymbol{jc}}$, LASSO includes them in every model it estimates, holding them "fixed" while it finds 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.

4.1.2. 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:

$$y_{jc} = \beta_0 + \sum_{d=1}^{6} \boldsymbol{Q}_{jc}^{*d}{}' \boldsymbol{\beta}_1^{d} + \boldsymbol{C}_{jc}' \boldsymbol{\beta}_2 + \boldsymbol{N}_{\boldsymbol{jc}}' \boldsymbol{\beta}_3 + \gamma_c + \gamma_f + \omega_{jc} \tag{2}$$

The estimated parameters of interest are in the $\widehat{\boldsymbol{\beta}_1^{\boldsymbol{d}}}$ 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):

$$y_{ijt} = \sum_{d=1}^{6} Q_j^{d'} \delta_1^d + R_i' \delta_2 + Z_{ij}' \delta_3 + C_j' \delta_4 + N_j' \delta_5 + \phi_f + \in_{ij}^{k}, \tag{3}$$

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 II). 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 & 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

5.1.1. Using program-level data

5.1.1.1. 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% (Fig. 3 panel A; Table A11 column 1).[18] 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

[16] The LASSO method is a regression analysis technique that adds a penalty term to the OLS regression equation. The penalty term restricts the size of the coefficients, forcing some of them to shrink toward zero, which can help with model specification and prevent overfitting. As in our setting, this methodology is used when dealing with high-dimensional data. The LASSO method helps to select the determinants of the outcome of interest and discard the irrelevant or redundant variables.

[17] 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 et al. (2019).

[18] Figs. 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.

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

(*continued on next page*)

Table 1 (*continued*)

Variable	Mean	Std. Dev.	Min.	Median	Max.	Obs.
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.

finding is consistent with the US community college evidence in Bailey (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 (Fig. 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 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).

5.1.1.2. 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 (Fig. 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 (Fig. 4 panel B; Table A12 column 2). Further, graduates from programs with a higher faculty-student ratio[19] and a higher share of faculty with bachelor's degrees also have higher wages. On the other hand, graduates from programs who use knowledge tests as admission requirements (and are therefore more selective) tend to report higher wages. Of course, this result demands a careful interpretation as testing might account for unobservable variables (e.g., ability). Wages are lower in HEIs with a higher representation of students in the governing body, another result allowing for multiple interpretations.

5.1.1.3. 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

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

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 II.
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.

hinders ETG. Our estimates do not imply causality, so they may suggest the need to better assess and capture critical information available to students as well as their interests and perceptions about HEI programs.[20]

5.1.2. 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 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 (Fig. 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

[20] To assess LASSO's potential limitations, we implement an alternative empirical strategy: elastic nets, which is suitable when the model contains highly correlated independent variables. These results are reported in Figs. A1 and A2 in the Appendix. They confirm the robustness of the quality determinants selected under LASSO. In particular, the elastic net method selects the same determinants selected using LASSO for academic outcomes (reported in Fig. 3). This is also the case for Wages (Fig. 4, panel B). For Formal Employment (Fig. 4, panel A), six of the eight original quality determinants are selected under the alternative method. The unselected ones are "Collect data on employment or employer's satisfaction more than once per year" and "Program has staff assigned to collect grads' employment data." However, the larger point estimate associated with "HEI has an employer center" under elastic nets (Fig. A2, panel A) relative to LASSO's (Fig. 4, panel A) captures the effect of those two unselected determinants. All in all, these similarities alleviate potential concerns surrounding LASSO's limitations.Since the elastic net approach is less conservative than LASSO, a few extra significant quality determinants emerge under the alternative method: two new determinants for Dropout Rates, Extra Time to Graduate, and Formal Employment. Since we prefer the more conservative approach, we feature LASSO as our preferred empirical strategy.

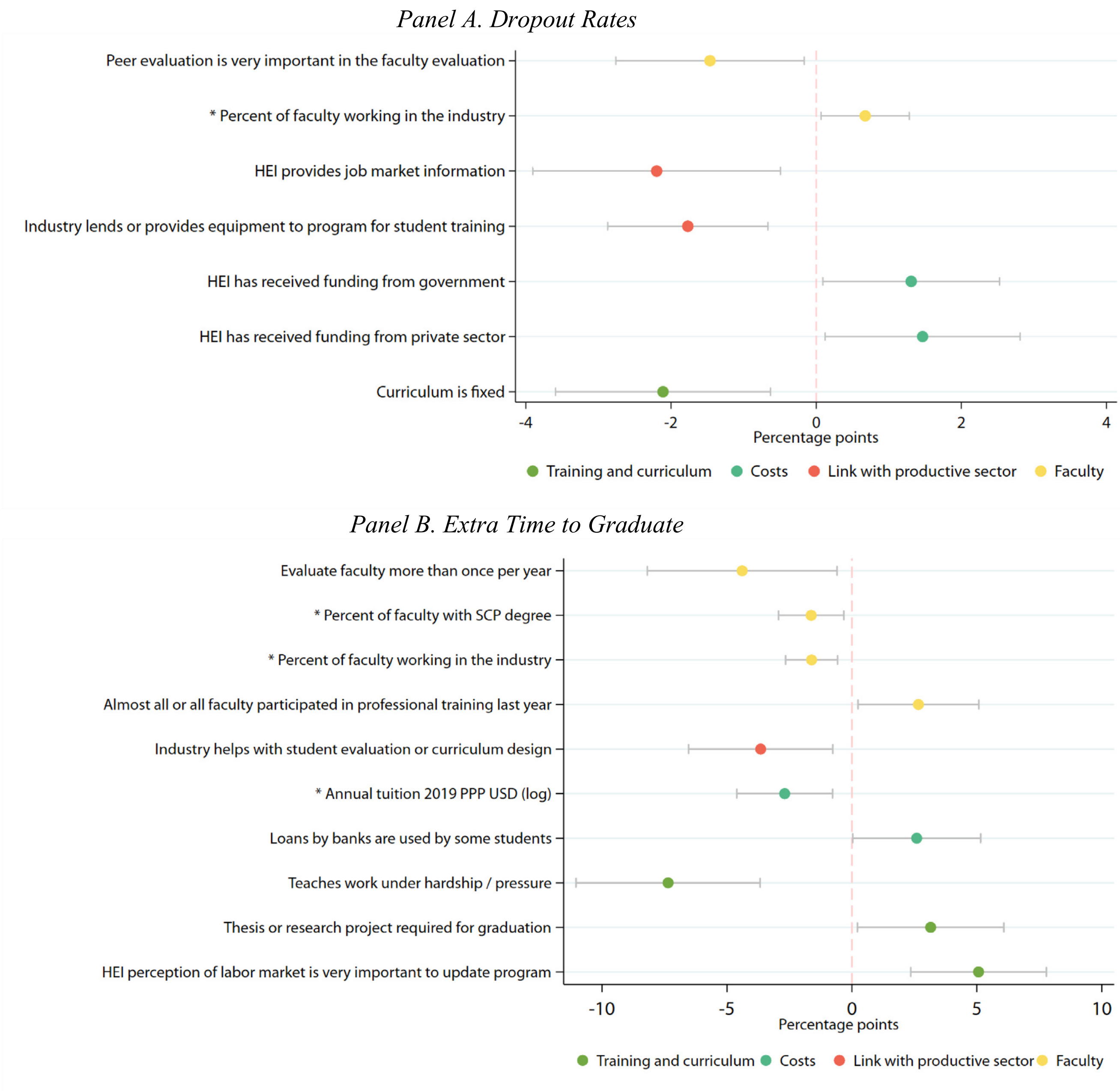


Fig. 3. Associations between program quality determinants and academic outcomes. *Based on program-level data. Source*: Own estimations using WBSCPS data for all survey countries. *Notes*: The figure shows the estimated changes in average dropout rate (Panel A) and extra time-to-graduate (Panel B) associated 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.

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.

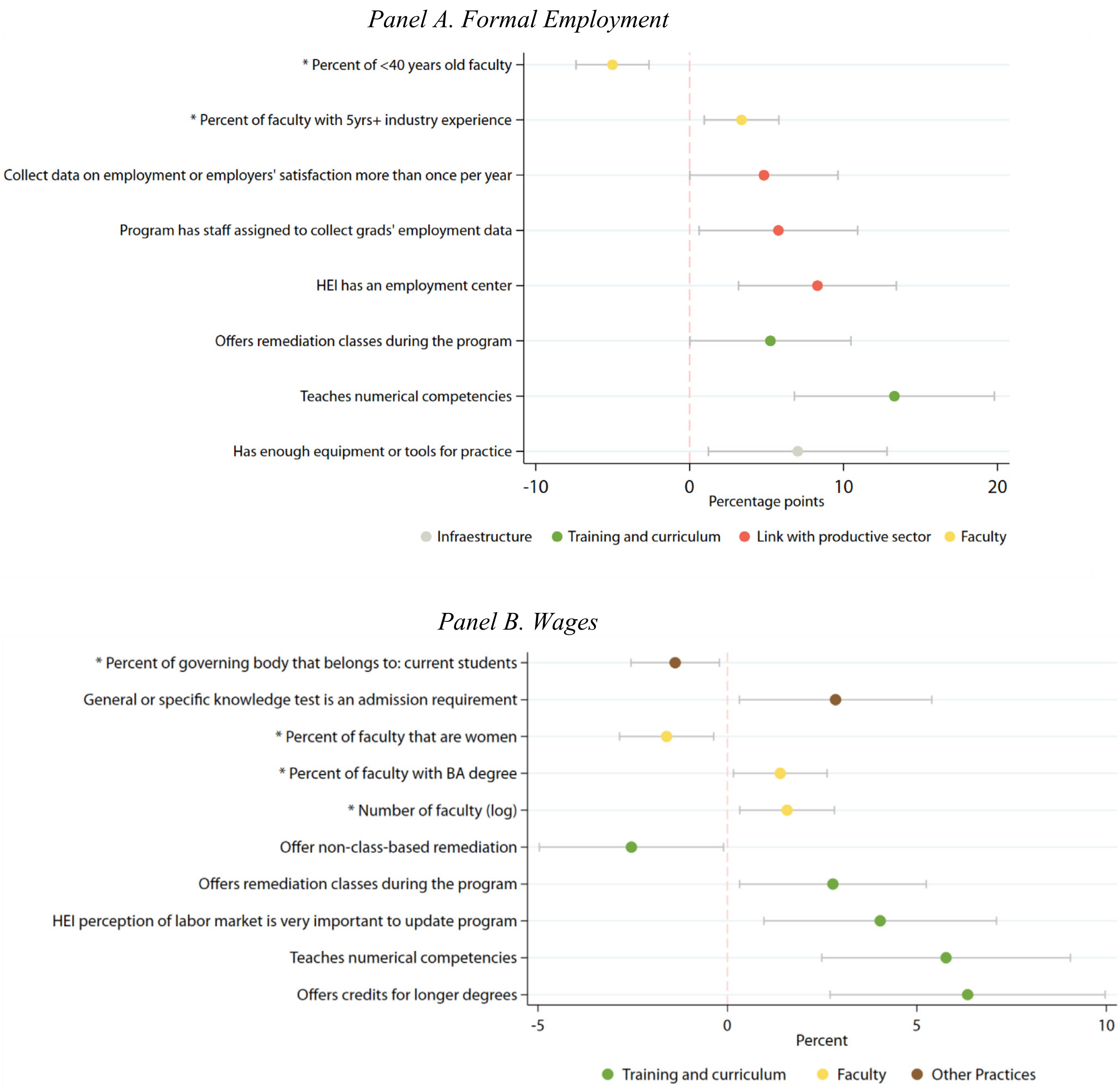


Fig. 4. Associations between program quality determinants and labor market outcomes. *Based on program-level data. Source*: Own estimations using WBSCPS data for all survey countries. *Notes*: Panel A shows the estimated change in the average probability that almost all graduates from a program are employed 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.

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 (Fig. 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

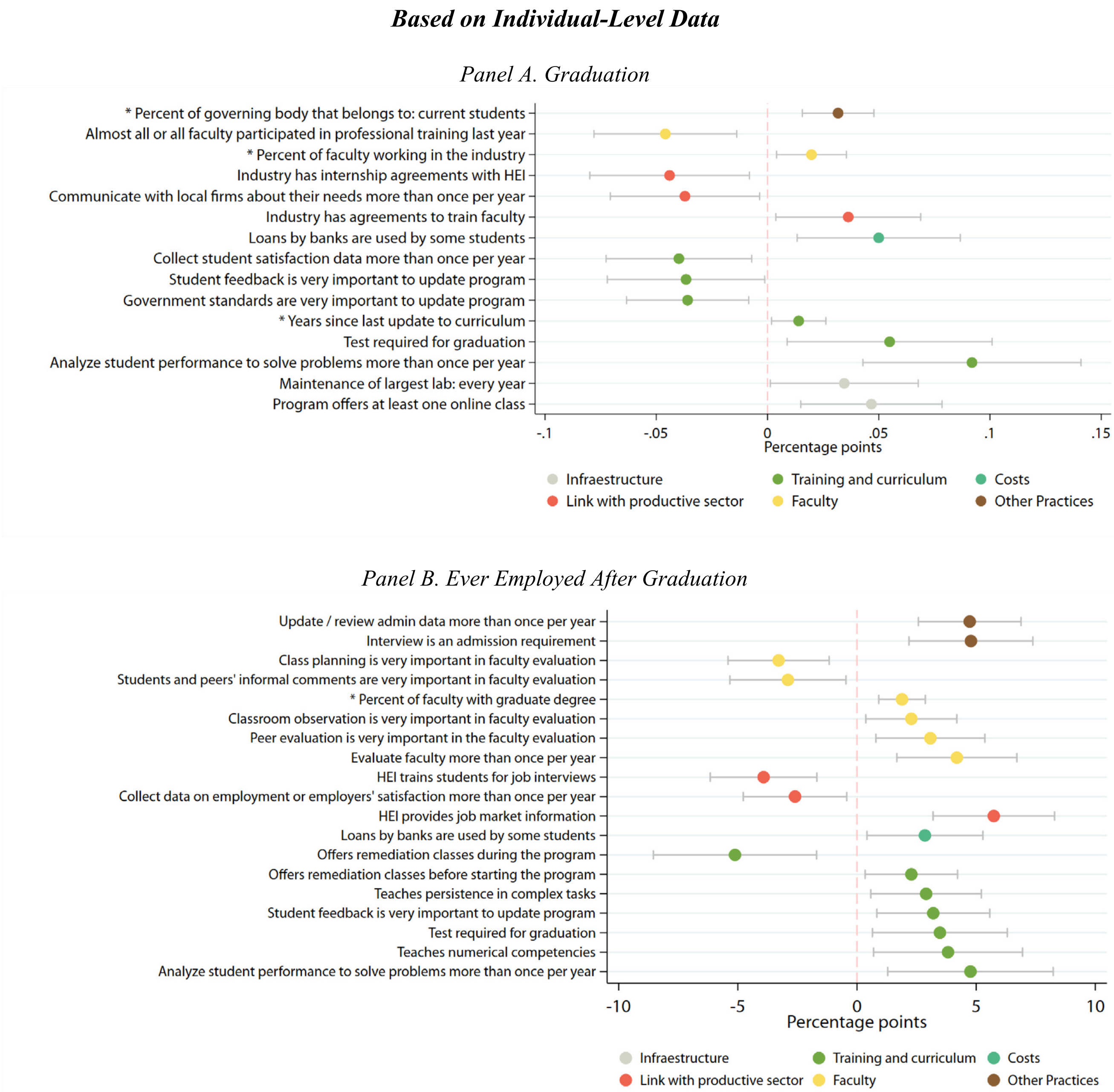
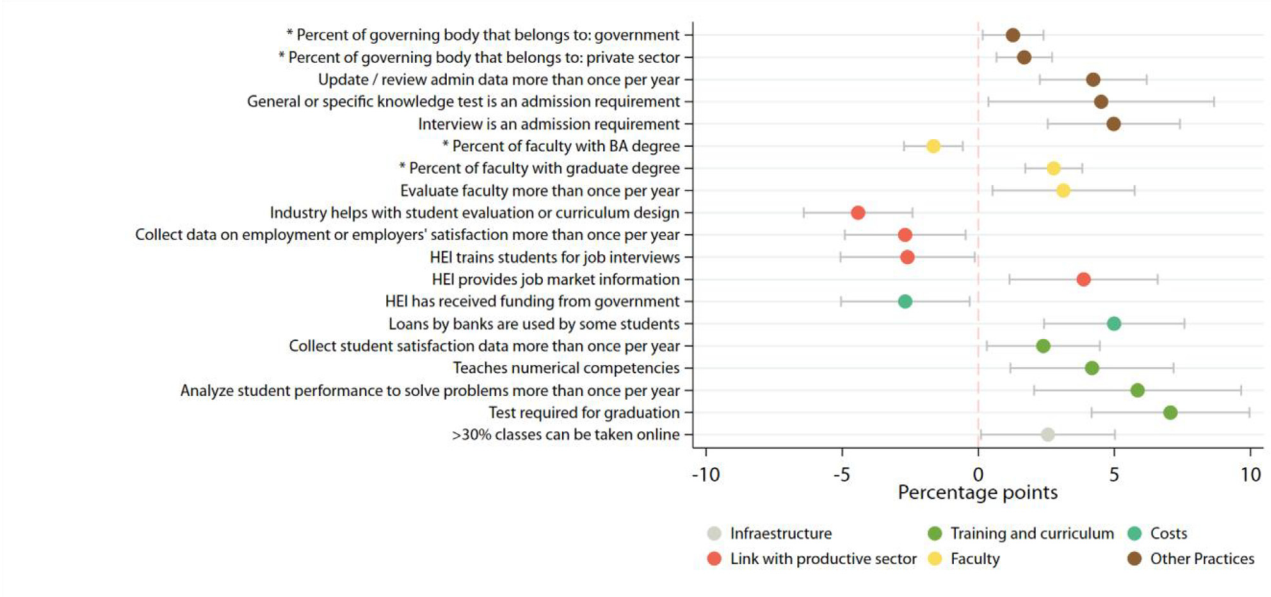


Fig. 5. Contributions of program quality determinants to graduation and labor market outcomes in Brazil. *Source*: Own estimations using individual-level and WBSCPS data for Brazil. *Notes*: The figure shows the estimated change in graduation and labor market outcomes that are associated with program 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.

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

Panel C. Percent of Time Employed



Panel D. Wages

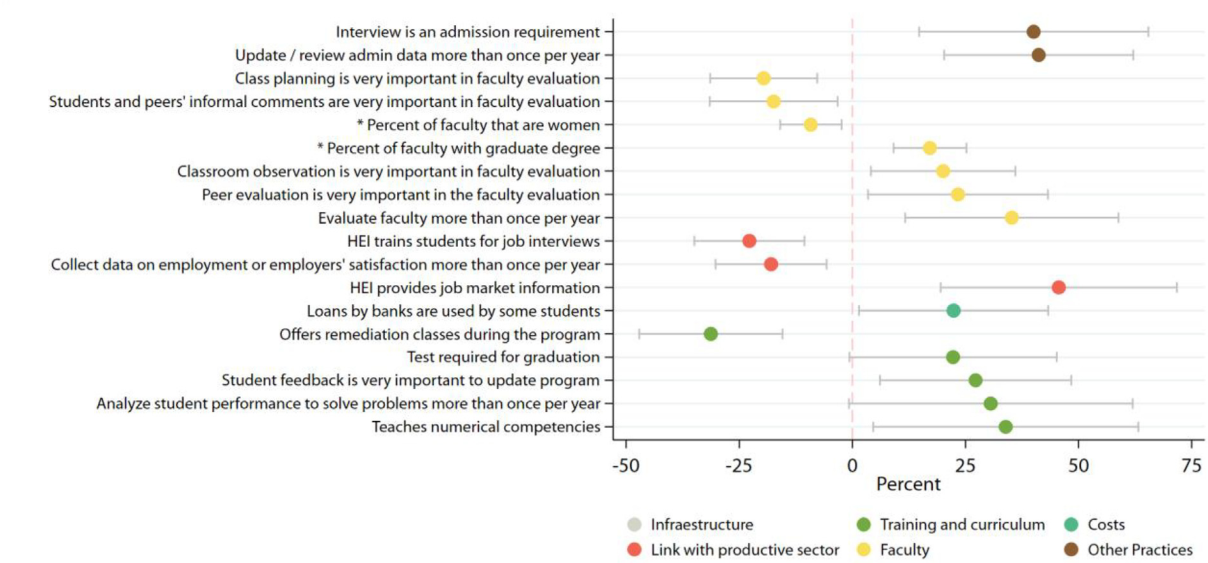


Fig. 5 (*continued*)

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.

5.1.3. 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 (Fig. 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.

5.1.4. 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 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

5.2.1. 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 Fig. A3). 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).

5.2.2. Individual-level regressions

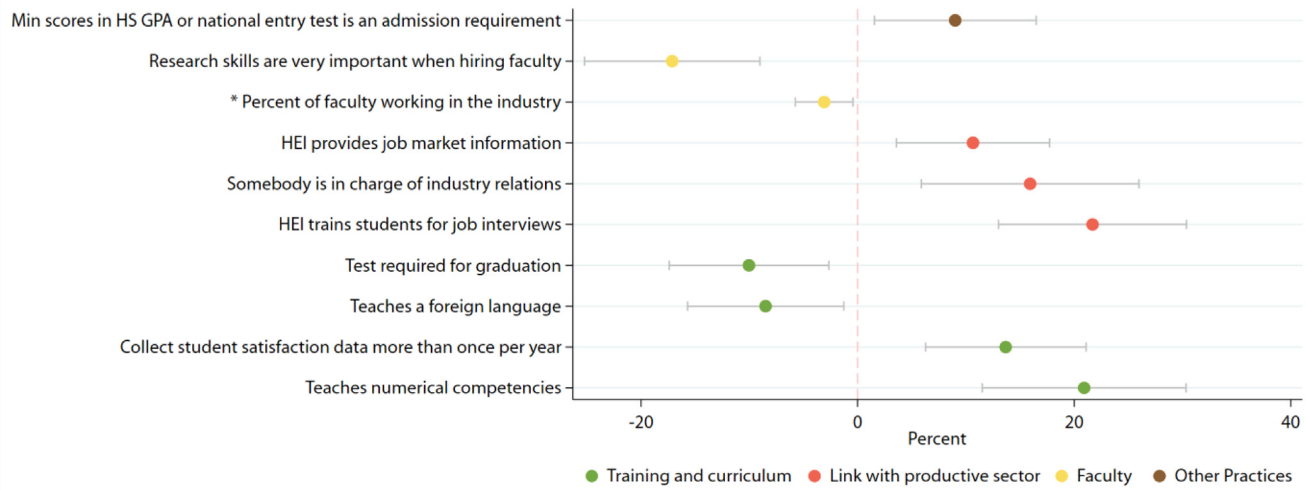
Brazil. Despite having student and peer administrative data in addition to survey-level data, we explain relatively little (12–15 percent) of the variation in graduation and labor market outcomes (Table 4). Nonetheless, the role of student and peer administrative variables is considerable for labor market outcomes: together they account for 30–40 percent of their explained variation (Table 4 and Fig. A4). 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, as in Brazil, individual and peer administrative variables account for about 40 percent of explained variation in Ecuador (Table 5 and Fig. A5). 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.

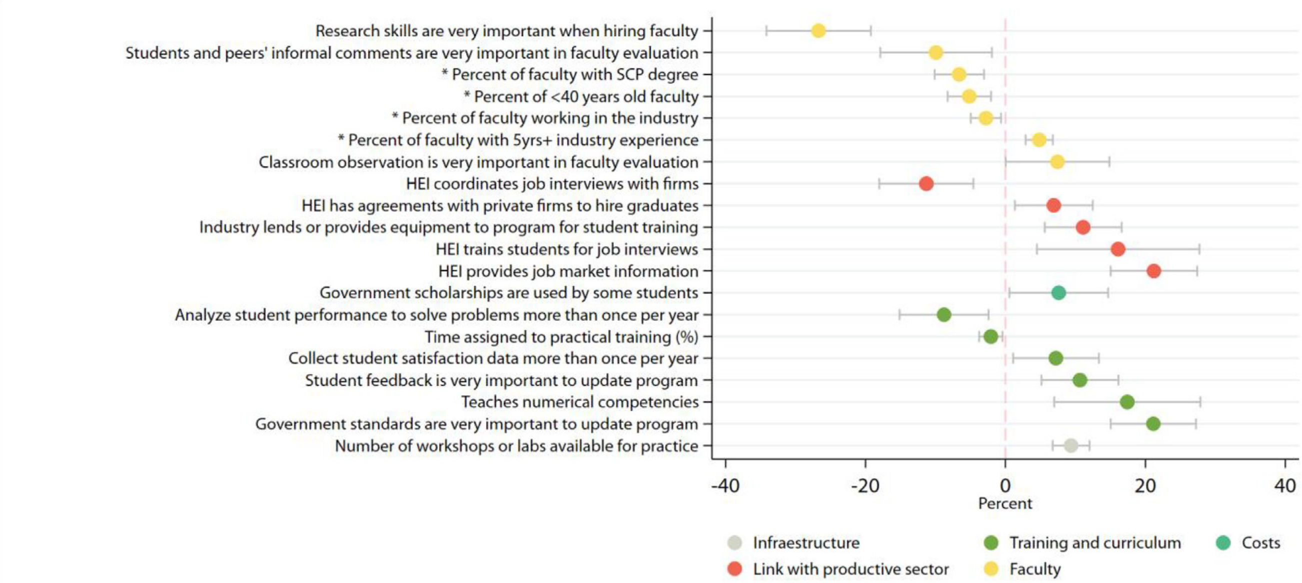
Program- and individual-level data—taking stock. Overall, we do not explain much of the observed variation in student- or program-level outcomes. Nonetheless, quality determinants in the program-level regressions account for about 50–60 percent of the observed variation in dropout rates, ETG and formal employment, and about 20–40 percent of the individual-level regressions for academic and labor market outcomes, with the largest explana-

Based on Individual-Level Data

Panel A. Ever Employed After Graduation



Panel B. Percent of Time Employed



Panel C. Wages

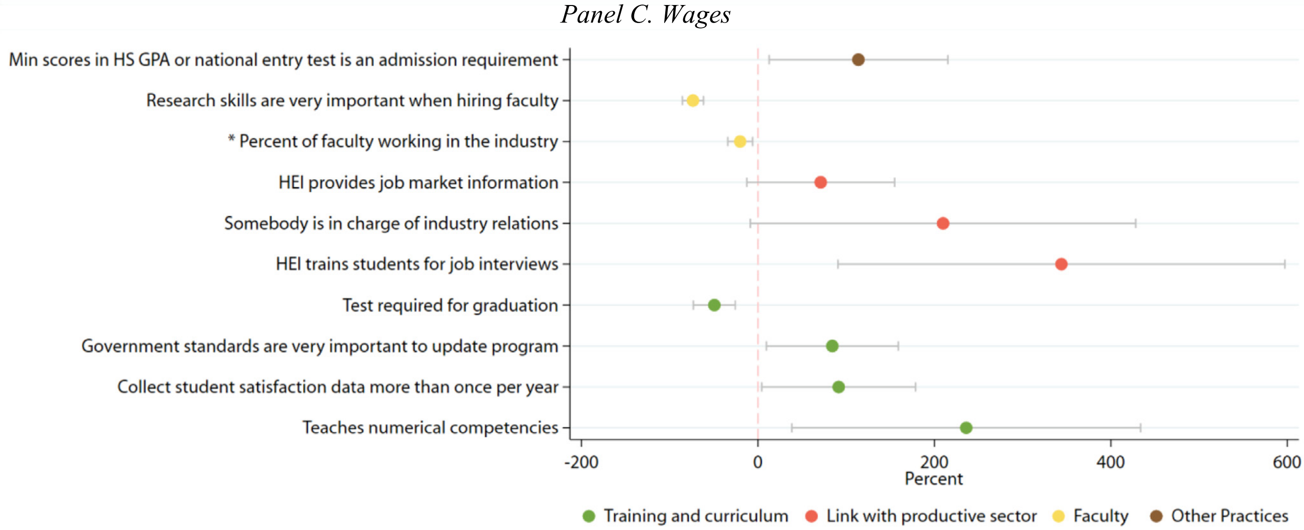


Table 3
R-squared Shapley-Owen decomposition. *Estimations using program-level data.*

Outcome:	**(1) Dropout Rate**	**(2) Extra Time to Graduate**	**(3) Formal Employment**	**(4) 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 II.
Notes: This table present results from the R-squared Shapley-Owen decomposition for the regressions reported in Table 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).

tory 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

Fig. 6. Contributions of program quality determinants to labor market outcomes in Ecuador. *Based on individual-level data. 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.

Table 4
R-squared Shapley-Owen decomposition for Brazil. *Estimations using individual-level data.*

Outcomes:	**(1) Graduation**	**(2) Ever employed after graduation**	**(3) Percent of time employed**	**(4) 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 II.
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.*

Outcomes:	**(1) Ever employed after graduation**	**(2) Percent of time employed**	**(3) 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 II.
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).

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.

CRediT authorship contribution statement

Lelys Dinarte-Diaz: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing - original draft, Writing – review & editing. **Maria Marta Ferreyra:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. **Sergio Urzua:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Marina Bassi:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Data availability

All codes used for the analyses and publicly available datasets. Researchers interested in accessing the survey data can contact us. Administrative records from Brazil and Ecuador are confidential

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2023.106294.

References

Aghion, P., Dewatripont, M., Hoxby, C., Mas-Colell, A., Sapir, A., & Jacobs, B. (2010). The governance and performance of universities: Evidence from Europe and the US. *Economic Policy, 25*(61), 7–59.

Barrera-Osorio, F., & Bayona-Rodríguez, H. (2019). Signaling or better human capital: Evidence from Colombia. *Economics of Education Review, 70*, 20–34.

Aucejo, E. M., Hupkau, C., & Ruiz-Valenzuela, J. (2022). Where versus what: College value-added and returns to field of study in further education. *Journal of Human Resources*, 0620–10978R1.

Bahr, P. R. (2013). Classifying community colleges based on students' patterns of use. *Res High Educ, 54*, 433–460.

Bahr, P. R. (2016). *The earnings of community college graduates in California*. Center for Analysis of Postsecondary Education and Employment Working Paper.

Bailey, T. R. (2015). *Redesigning America's Community Colleges: A clearer path to student success*. Harvard University Press.

Belloni, A., Chernozhukov, V., & Hansen, C. (2014). High-dimensional methods and inference on structural and treatment effects. *Journal of Economic Perspectives, 28*(2), 29–50.

Belloni, A., Chernozhukov, V., Chetverikov, D., & Kato, K. (2015). Some new asymptotic theory for least squares series: Pointwise and uniform results. *Journal of Econometrics, 186*(2), 345–366.

Bettinger, E. P., Fox, L., Loeb, S., & Taylor, E. S. (2017). Virtual classrooms: How online college courses affect student success. *The American Economic Review, 107*(9), 2855–2875.

Bloom, N., Lemos, R., Sadun, R., & Van Reenen, J. (2015). Does management matter in schools? *The Economic Journal, 125*, 647–674.

Bloom, N., Draca, M., & van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *Review of Economic Studies, 83*, p87–p.

Bloom, N., Lemos, R., Sadun, R., & Van Reenen, J. (2020). Healthy business? Managerial education and management in health care. *The Review of Economics and Statistics, 102*(3), 506–517.

Boatman, A., & Long, B. T. (2018). Does remediation work for all students? How the effects of postsecondary remedial and developmental courses vary by level of academic preparation. *Educational Evaluation and Policy Analysis, 40*(1), 29–58.

Bühlmann P., & van de Geer S. (2011). Lasso for linear models. In Statistics for high-dimensional data. Springer Series in Statistics. Springer, Berlin, Heidelberg.

Carrell, S. E., & Kurlaender, M. (2016). Estimating the productivity of community colleges in paving the road to four-year success, *NBER Working Paper*, w22904.

Cellini, S. R., & Turner, N. (2019). Gainfully employed?: Assessing the employment and earnings of for-profit college students using administrative data. *Journal of Human Resources, 54*(2), 342–370.

Cellini, S. R., & Grueso, H. (2021). Student learning in online college programs. *AERA Open, 7*(1), 1–18.

Chetverikov, D., Liao, Z., & Chernozhukov, V. (2019). On cross-validated lasso. *The Annals of Statistics*. forthcoming.

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

De Vlieger, P., Jacob, B. & Stange, K. (2017). Measuring instructor effectiveness in higher education, *NBER Working Paper*, w22998.

Deming, D. J., Lovenheim, M., & Patterson, R. W. (2016). The competitive effects of online education. NBER Working Paper, no. w22749.

Di Meglio, G., Barge-Gil, A., Camiña, E., & Moreno, L. (2022). Knocking on employment's door: Internships and job attainment. *Higher Education, 83*(1), 137–161.

Ferreyra, M., Avitabile, C., Botero, J., Haimovich, F., & Urzúa, S. (2017). *At a crossroads: Higher education in Latin America and the Caribbean*. Washington, DC: World Bank Group.

Dinarte, Lelys; Ferreyra, M. M., Melguizo, T., & Sanchez, A. (2022). The contribution of short-cycle programs to student outcomes: Evidence from Colombia. *Policy Research Working Paper* 9424, World Bank, Washington, DC.

Ferreyra, M.M, Dinarte, L., Urzúa, S., & Bassi, M. (2021). The fast track to new skills: Short-cycle higher education programs in Latin America and the Caribbean. *Forthcoming*. World Bank, Washington, DC.

Figlio, D., Rush, M., & Yin, L. (2013). Is it live or is it internet? Experimental estimates of the effects of online instruction on student learning. *Journal of Labor Economics, 31*(4), 763–784.

Filmer, D., Nahata, V., & Sabarwal, S. (2021). Preparation, practice, and beliefs: A machine learning approach to understanding teacher effectiveness, *Policy Research Working Paper,* WPS 9847. Washington, D.C.: World Bank Group.

Grosz, M. (2020). The returns to a large community college program: Evidence from admissions lotteries. *American Economic Journal: Economic Policy, 12*(1), 226–325.

Hoxby, C. M., & Stange, K. (Eds.). (2019). *Productivity in higher education*. Chicago, IL: University of Chicago Press.

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

Jaeger, D. A., Nunley, J. M., Seals, A., & Wilbrandt, E. J. (2020). The demand for interns. *NBER Working Paper*, w26729.

Jaggar, S. S., & Xu, D. (2016). How do online course design features influence student performance? *Computers & Education, 95*, 270–284.

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

Kane, T. J., Boatman, A., Kozakowski, W., Bennett, C., Hitch, R., & Weisenfeld, D. (2021). Is college remediation a barrier or a boost? Evidence from the Tennessee SAILS program. *Journal of Policy Analysis and Management, 40*(3), 1–31.

Krieg, J. M., & Henson, S. E. (2016). The educational impact of online learning: How do university students perform in subsequent courses? *Education Finance and Policy, 11*(4), 426–448.

Liu, V. Y. T., Belfield, C. R., & Trimble, M. J. (2015). The medium-term labor market returns to community college awards: Evidence from North Carolina. *Economics of Education Review, 44*, 42–55.

Lovenheim, M. F., & Smith, J. (2022). Returns to different postsecondary investments: Institution type, academic programs, and credentials, *NBER Working Paper*, w29933.

McCormack, J., Propper, C., & Smith, S. (2014). Herding cats? Management and university performance. *The Economic Journal, 124*(578), F534–F564.

Melguizo, T., & Wainer, J. (2016). Toward a set of measures of student learning outcomes in higher education: Evidence from Brazil. *High Education, 72*, 381–401.

Melguizo, T., Sanchez, F., & Velasco, T. (2016). Credit for low-income students and access to and academic performance in higher education in Colombia: A Regression Discontinuity Approach. *World Development, 80*, 61–77.

Mountjoy, J. (2021). Community colleges and upward mobility, *NBER Working Paper*, w29254.

Owen, G. (1977). Values of games with a priori unions. In R. Henn & O. Moeschlin (Eds.), *Essays in mathematical economics & game theory* (pp. 76–88). Berlin: Springer.

Plewa, C., Galán-Muros, V., & Davey, T. (2015). Engaging business in curriculum design and delivery: A higher education institution perspective. *Higher Education, 70*(1), 35–53.

Saavedra, J. E. (2009). *The returns to college quality: A regression discontinuity analysis*. Cambridge, MA: Harvard University.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? In *Handbook of the Economics of Education* (Vol. 3, pp. 249-277). Elsevier.

Stange, K. (2012). Ability sorting and the importance of college quality to student achievement: Evidence from community colleges. *Education Finance and Policy, 7*(1), 74–105.

Scott-Clayton, J., & Rodriguez, O. (2015). Development, discouragement, or diversion? New evidence on the effects of college remediation policy. *Education Finance and Policy, 10*(1), 4–45.

Shapley, L. S. (1953). A value for n-person games. In *Contributions to the theory of games*, H. W. Kuhn, A. W. Tucker, (Eds.) II 307–317. Princeton University Press, Princeton.

Shavelson, R. J., Domingue, B. W., Mariño, J. P., Mantilla, A. M., Forero, A. M., & Wiley, E. E. (2016). On the practices and challenges of measuring higher education value added: The case of Colombia. *Assessment & Evaluation in Higher Education, 41*(5), 695–720.

Smith, J., & Stange, K. (2016). A new measure of college quality to study the effects of college sector and peers on degree attainment. *Education Finance and Policy, 11*(4), 369–403.

Stevens, A. H., Kurlaender, M., & Grosz, M. (2019). Career technical education and labor market outcomes evidence from California community colleges. *Journal of Human Resources, 54*(4), 986–1036.

Rodriguez, J., Reyes, L., & Urzua, S. (2016). Heterogenous economic returns to post-secondary degrees: Evidence from Chile. *The Journal of Human Resources, Spring, 51*(2), 416–460.

Wesley Routon, P., & Walker, J. K. (2019). College internships, tenure gaps, and student outcomes: A multiple-treatment matching approach. *Education Economics, 27*(4), 383–400.

World Bank. (2019). *World Development Report 2019: The changing nature of work*. Washington, DC: World Bank. doi:10.1596/978-1-4648-1328-3.

Xu, D., & Dadgar, M. (2018). How effective are community college remedial math courses for students with the lowest math skills? *Community College Review, 46*(1), 62–68.

Yi, G. (2018). Impact of internship quality on entrepreneurial intentions among graduating engineering students of research universities in China. *International Entrepreneurship and Management Journal, 14*(4), 1071–1087.

Zou, H. (2006). The adaptive LASSO and its oracle properties. *Journal of the American Statistical Association, 101*(476), 1418–1429.