Received: 23 April 2020 | Revised: 19 May 2021 | Accepted: 20 May 2021

DOI: 10.1111/hequ.12340

ARTICLE

Higher Education Quarterly WILEY

About job market outcomes: Assessing the performance of Colombian higher education institutions

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Abstract

One method for evaluating higher education performance is to conceptualize it as a production function represented as an input/output process. This paper proposes a performance evaluation of higher education institutions from the perspective of recent graduates taking as inputs students' cognitive abilities and tuition, and as outputs three we contend are relevant for recent graduates: starting salary, sectoral distinctiveness, and sectoral variety. Using a sample of recent Colombian higher-education graduates, we apply the DEA technique to analyze efficiency at the institutional level in the formal labor market. Our results highlight the importance of focusing on the student as the protagonist of the educational process and contribute to the debate about the selection of relevant inputs and outputs when measuring institution's efficiency.

Resumen

Un método para evaluar el desempeño de las instituciones de educación superior es a través de su conceptualización como una unidad de producción donde cada institución cuenta con insumos y productos. Este documento propone evaluar el desempeño de las instituciones de educación superior desde la perspectiva de los recién graduados tomando como insumos las habilidades cognitivas de los estudiantes y la matrícula pagada, y como productos tres que consideramos son relevantes para los recién graduados en el mercado laboral: el salario de enganche, la distinción sectorial, y la variedad sectorial. Utilizando una muestra de recién egresados de educación superior, aplicamos la técnica DEA para analizar la eficiencia a nivel institucional en el mercado laboral formal colombiano. Nuestros resultados resaltan al estudiante como el protagonista del proceso educativo además de contribuir al debate sobre la selección de insumos y productos relevantes a la hora de medir la eficiencia de las instituciones de educación superior a través de funciones de producción.

1 | INTRODUCTION

It is well-known that education plays an important role in a nation's economic development through its contribution to human capital formation. Academic research on this topic dates back four decades, with Becker (1964), Schultz (1968), and Mincer (1974) being seminal contributions, and has continued to examine this relationship from myriad of perspectives, centering on higher education in particular due to its close connection to the labor market.[1]

The conceptualization of higher education as an input/output process that can be represented through a production function enables the evaluation of specific outputs of higher education and the efficiency of higher education providers, given specific inputs.[2] However, as Vandenberghe (1999) states, the production-function research on education should go beyond the simple conception of the “educational black box” that focuses on ratios of outcomes to monetary inputs.

With this in mind, we evaluate the performance in the labor market of recent graduates from a sample of higher education institutions (HEIs) in Colombia that offer a five-year bachelor's degree, using tuition costs along with a nonmonetary input that has rarely been considered previously: students' cognitive abilities assessed prior to higher education. We linked this information with labor market outcomes providing a wide perspective of efficiency that includes information before and after higher education which is a characteristic not frequently seen for developing countries.

There is evidence that cognitive skills acquired previous to higher education are associated with higher labor market outcomes. As Lleras (2008) points out, cognitive skills affect earnings directly and indirectly through post-secondary education, given that more-skilled high school graduates are more likely to attend and complete higher education programs, which results in higher earnings as adults. Students' cognitive abilities can thus be considered some of the raw materials that institutions of higher education transform besides tuition costs, resulting in desirable job market outcomes.

Regarding outcomes, we will analyze three with which we expect recent graduates are concerned.[3] The first is starting salary, following the premise of Kong and Fu (2012) that college students are more concerned with getting a promising job after graduation rather than with test scores and because starting salaries reflects the use of education as a relatively inexpensive screening device by employers (Taubman & Wales, 1973). We believe employers infer recent graduates' productivity potential while recruiting, not only from interviews and tests (when applied), but also from the reputation of institutions and programs.

Given that recent graduates from different institutions of higher education are not evenly distributed across economic sectors of the labor market, our second and third outcomes are focused on depicting this distribution. The relevance of these outcomes lies in providing information to recent graduates about their potential performance in the labor market beyond wages given their cognitive abilities and the tuition paid.

The second outcome is "sectoral distinctiveness" (SD), a concept originally developed by Ransom and Phipps (2016) as "occupational distinctiveness" that we adapted and redefine as "the degree of distinctiveness that recent graduates from a given HEI have across the economic sectors of the labor market". Then, the SD of a given HEI is high when the interaction of its recent graduates with those of other HEIs is the lowest possible, meaning that this institution has certain dominance in terms of placement of its graduates in some economic sectors of the labor market.

Our third outcome is "sectoral variety" (SV), adapted from the concept of occupational variety from Ransom and Phipps (2016) that we redefine as "the degree of variety of economic sectors of the labor market where recent graduates from a specific HEI find placement". An HEI with a high SV could be understood as an institution that graduates students with more generic competencies that can be adapted to different employment requirements. This would allow graduates to choose their occupations based on their preferences, given that their skills are adaptable. Or, under an imbalanced labor market scenario where certain graduates are, on the basis of their abilities, in greater demand than others, a high SV would reflect an institution whose recent graduates are able to adapt to the labor market's lack of absorption capacity.

We cannot generalize optimum levels for SD and SV for all HEIs, because some institutions are specialized in certain fields of study and their recent graduates are expected to be concentrated on a specific economic sector. Therefore, we performed all our analysis and estimations by fields of study.[4] These two indicators provide information about how HEIs prepared students in a specific field of study for the labor market by comparing their performance with other HEIs' recent graduates. This is more evident when wages are combined with each one of these two outcomes because it will provide information about dominance of economic sectors or higher adaptability.

To construct the efficiency frontiers for evaluating the performance of HEIs, given the inputs and outputs mentioned above, we use the data envelopment analysis (DEA) approach. This has been widely used in the literature to analyze the efficiency of HEIs.

Most of these studies focus on public institutions and whether financial resources are used efficiently. Among the most important are Johnes (2006), Abbott and Doucouliagos (2003), Wolszczak-Derlacz (2014), Mikusova (2015), Nazarako and Sparauskas (2014), Cunha and Rocha (2012) and Agasisti et al. (2011). As far as we know, there is no research that uses students' cognitive skills assessed prior to entering an HEI as an input using this methodology. In fact, in the research cited above most of the inputs selected are focused on the institutions' characteristics rather than on those of the students. Our main objective is to fill this gap by evaluating the performance of HEIs focusing on the student as the protagonist of the educational process.

We hope our analysis will provide a new perspective for policy makers, especially those in developing and emerging countries where HEIs promote social mobility to a significant degree. This paper is organized as follows. In Section 2 we briefly describe the data used. In Section 3 we analyze the inputs and the performance indicators (outputs) of HEIs. In Section 4 we explain the methodology applied. Section 5 presents the results of our estimations. Finally, Section 6 summarizes the main findings and presents conclusions.

2 | DATA

To build our database, we drew on several different administrative sources in Colombia. We used information from a sample of graduates of five-year university programs who earned their degrees between the first semester of 2007 and the first semester of 2011, as reported by each tertiary educational institution to the National System of Higher Education (SNIES) and centralized by the Labor Observatory for Education (OLE) of Colombia. This database includes information at the individual level regarding the characteristics of the program attended, year of graduation, characteristics of the degree-awarding institution, the economic sector in which the individual works

(ISIC 3.1 classification aggregated into 14 categories), whether the individual contributes to social security, and, if so, the starting salary for the job the individual currently holds.

Income information was extracted by OLE from the official records used by the Ministry of Finance and Public Credit of Colombia to estimate individuals' social security contributions. For this reason, we consider graduates for which there is information about their salaries (they make social security contributions payments) as formal labor market workers. Wage's information is the monthly starting salary each individual up to one year after graduation from an HEI. Our wages are “base wage rate” for eight hours of work a day and do not include bonuses, tips, or commissions.

To incorporate each program's knowledge area (field of study), including tuition fees, we merged the OLE database with information on each academic program from the National System of Higher Education Information (SNIES) of Colombia. The fields of study are classified in eight categories. Fields of study are assigned by the Colombian Ministry of Education when each higher education program receives its license to operate in the country.

Finally, by using a unique code generated by the Colombian Institute for Educational Evaluation (ICFES) we merged OLE information with recent graduates' scores on the Saber11 standardized test. Through these scores we were able to capture each individual's cognitive abilities prior to enrolling in an HEI. To make Saber11 test scores comparable across years, we estimated the percentile position each student attained among all the students who took the test nationwide and then aggregated the information of our sample by institution.

It must be noted that we are using information just from a sample of recent graduates and not the population. Our information is limited to those recent graduates who provided information to OLE and that could be matched with their Saber11 test scores and also with their formal labor market starting salaries using a database translator developed by the Ministry of Education.[5] We excluded from our sample all recent graduates from online programs, since the experience of online training may not be comparable to classroom training.

Our data also shows that most of the recent graduates who earned degrees at HEIs in Bogotá started working in that city, and that flow of recent graduates to other cities across the country exists but is not comparable. This could be understood as Bogotá city being a single labor market separated from the rest of the country. Given that, the 9533 individuals included in our analysis (who will later be aggregated by institution) are recent graduates who earned at HEIs located in Bogotá and who entered the job market there as well. Even though our dataset intended to capture most of the students that obtained their degrees from each HEI, the linkage exercise might have cause bias in our results. From an approximate of 58,000 graduates[6] from the seven HEI selected between the first semester of 2007 and the first semester of 2011, we have information related to wages, the formal labor market sectors, besides the Saber11 test scores of only the 15.52% of the population. For this reason, this dataset should not be representative of the Colombian Higher Education System and our results should not be interpreted as representative of Colombian HEIs.

As our objective is to provide a new perspective from which to evaluate and analyze the efficiency of HEIs and to avoid any misinterpretation regarding the results, we have kept the names of the seven HEIs anonymous, using letters A through G to represent them.

3 | OUTPUTS AND INPUTS TO ASSESS THE PERFORMANCE OF HEIS

As Vandenberghe (1999) makes clear, using a production function perspective helps to understand the supply side of the educational process, which complements the traditional demand-sided analysis performed in line with human capital theory. However, the technology that each institution or program of higher education uses is still a black box into which researchers can see only dimly. For this reason, we analyze the efficiency of HEIs focusing on the benefits it provides to its recent graduates. We believe that even though a HEI might be efficient in transforming monetary inputs into outputs (e.g., government funding into doctoral graduates), the real challenge is to transform the student's abilities, prior to enrolling in a HEI, and the tuition charged (inputs) into labor market outputs that are desirable for the recent graduate.

3.1 | Outputs

3.1.1 | Starting salary

As mentioned earlier, our outputs are oriented to a student-based efficiency evaluation. We follow Kong and Fu (2012), who observe that students as higher education consumers are less concerned with the efficiency of the institution or program and more with the help the latter can provide when it comes to entering the labor market.

Also, it has been demonstrated in the literature that students are able to anticipate their starting salaries when making their higher education decisions (Betts, 1996; Dominitz & Manski, 1996; Webbink & Hartog, 2004) what is more, individuals who choose to enroll in school are those who expect favorable outcomes from it (Manski, 1993).

Also, the starting salary, represents the lowest financial compensation a worker will receive before acquiring expertise and job knowledge. Thus, in the absence of an appraisal of the worker's performance the starting salary is based on the information the employer has—the worker's education.

The starting salaries of the recent graduates in our study are full-time monthly wages expressed in Colombian pesos of 2011.[7] All the individuals started working in the formal labor market no longer than a year after earning their university degrees. Figure 1 shows the composition of wages across economic sectors of the labor market by institution and Figure 2 shows the average wages across fields of study, also by institution.

As can be seen in Figure 2, degrees in certain fields of study lead, on average, to higher wages than others, as is the case with F6. This is why the performance of the HEIs should be evaluated by field of study; doing so makes it possible to compare the opportunities that a particular HEI offers its recent graduates compared to the other HEIs that face the same conditions in the labor market.

3.1.2 | Sectoral distinctiveness

In this study, SD represents the degree of uniqueness that recent graduates from a given HEI have across economic sectors of the labor market. Table 1 illustrates the interaction of institutions by field of study across the economic sectors of the labor market. It can be seen that there are certain fields of study where the interaction

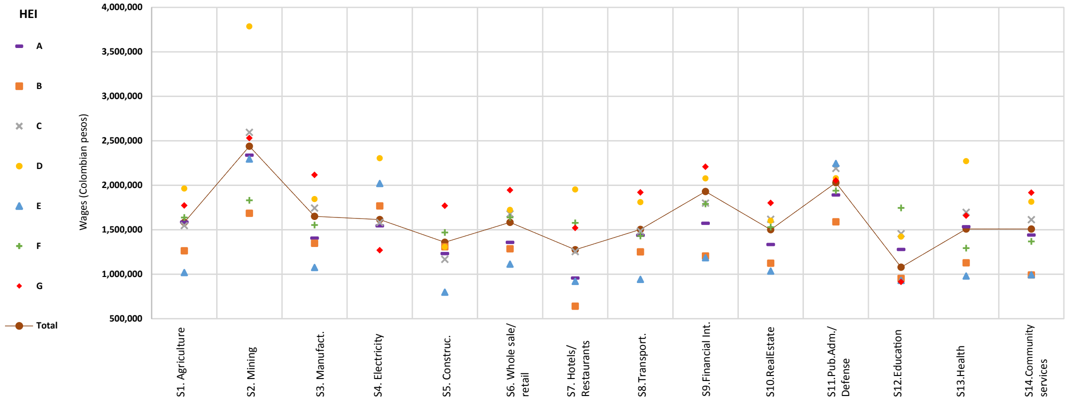

FIGURE 1 Average wages by higher education institution and labor market economic sectors (Colombian pesos of 2011)

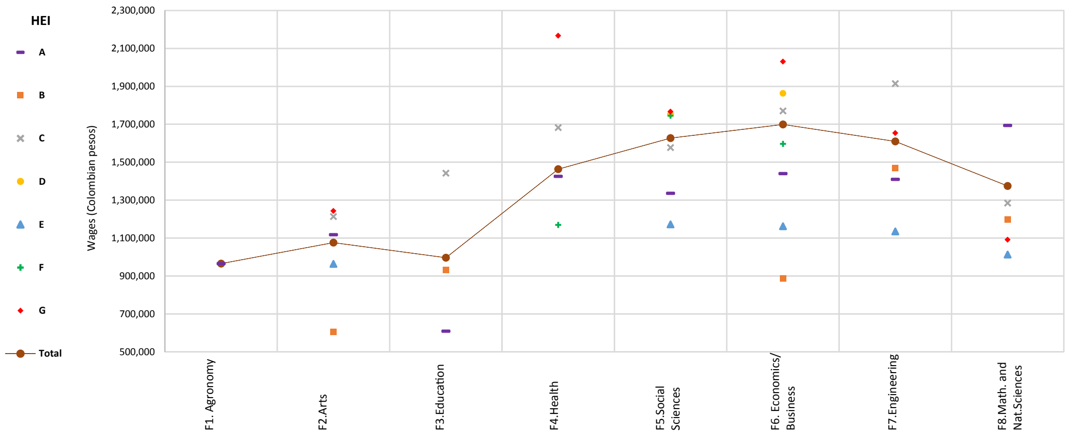

FIGURE 2 Average wages by higher education institution and field of study (Colombian pesos of 2011)

TABLE 1 Distribution of fields of study across economic sectors (number of institutions)

Fields of Study	S1.Agriculture	S2.Mining	S3.Manufaturing	S4.Electricity	S5.Construction	S6.WholeSale/ Retail	S7.Hotels/ Restaurants	S8.Transportation	S9.Financial Intermediation	S10.Real Estate	S11.Pub.Adm/ Defense	S12.Education	S13.Health	S14.Community Services	*Max*
	Economic Sectors														
F1.Agronomy	1	0	1	0	1	1	0	1	1	1	1	0	0	1	*1*
F2.Arts	4	3	5	0	4	4	4	4	4	5	3	5	5	5	*5*
F3.Education	0	2	2	0	1	2	1	2	3	3	1	3	2	2	*3*
F4.Health	1	2	4	0	2	3	2	3	2	3	3	4	4	3	*4*
F5.Social Sciences	5	5	6	3	5	6	5	6	6	6	6	6	6	6	*6*
F6.Economics/Bus.Adm.	6	7	7	2	7	7	7	7	7	7	7	7	7	7	*7*
F7.Engineering	5	5	5	5	5	5	5	5	5	5	5	5	5	5	*5*
F8.Mathematics/Nat.Sc.	3	3	3	3	4	4	2	3	3	5	2	5	5	4	*5*

of institutions is higher (darker cells) such as F6and F5 showing higher rivalry between recent graduates. On the other hand, fields of study with the lowest interaction, such as F3and F4, reflect the dominance of some institutions over certain economic sectors which could be read as a niche market.[8]

To estimate the degree of distinctiveness, we made use of a well-known concept in economics: segregation. The less interaction recent graduates from a given HEI have with recent graduates from other institutions across economic sectors of the labor market, the higher the institution's distinctiveness.

We estimate our SD index through the Alonso-Villar and Del Rio (2010) "D^g" index, which is an adaptation of the dissimilarity index, developed originally for a two-group scenario by Duncan and Duncan (1955), to a multi-group context. The intuition behind our SD index is to estimate the local segregation of each HEI, which is the segregation of each HEI (target population's subgroup) across the economic sectors of the labor market (organizational units) by field of study.

Following Alonso-Villar and Del Rio (2010) notation, our population, represented by $T = \sum_j t_j$, are all recent graduates from all HEIs that are distributed across a formal labor market with $J > 1$ economic sectors following $t \equiv (t_1, t_2, \ldots, t_J)$, where $t_j > 0$, representing the number of recent graduates in economic sector j ($j = 1, \ldots, J$).[9]

The formal labor market can thus be represented by a Matrix E where rows correspond to HEIs and columns to economic sectors. The segregation of each HEI can be estimated by comparing the distribution of each HEI expressed in proportions $\left(\frac{c_1^g}{C^g}, \ldots, \frac{c_j^g}{C^g}\right)$, with the distribution of economic sectors, also expressed in proportions $\left(\frac{t_1}{T}, \ldots, \frac{t_J}{T}\right)$.

To accomplish this, the SD index (called D^g in Alonso-Villar & Del Rio, 2010) is estimated, as the maximum distance between the equality line and a segregation curve[10] through the following equation:

$$\mathrm{SD} = \frac{1}{2}\sum_j \left|\frac{c_j^g}{C^g} - \frac{t_j}{T}\right| \quad (1)$$

The SD index is bounded between 0 and 1, where 1 indicates total segregation (total distinctiveness). Alonso-Villar and Del Rio (2010) demonstrates this index is a segregation index that satisfies the following properties: scale invariance, symmetry in groups, movement between groups, insensitivity to proportional divisions, aggregation, symmetry in types, range between zero, and one size invariance.[11] Figure 3 shows the SD index for each institution by field of study.

An interpretation for a high SD such as the reported by institution A in field of study F3. Education (SD index of 0.48) is that the recent graduates from institution A are working in economic sectors where other institutions' recent graduates with degrees in education are not.

3.1.3 | Sectoral variety

The objective of SV is to measure the flexibility recent graduates from a specific institution have across the economic sectors of the labor market. Any recent graduate who found a job faced two possible scenarios: (a) the graduate had some alternatives and choose between them according to selection criteria (wages, learning possibilities, future opportunities, no commuting required, family-related reasons, etc.), or (b) the graduate had only one

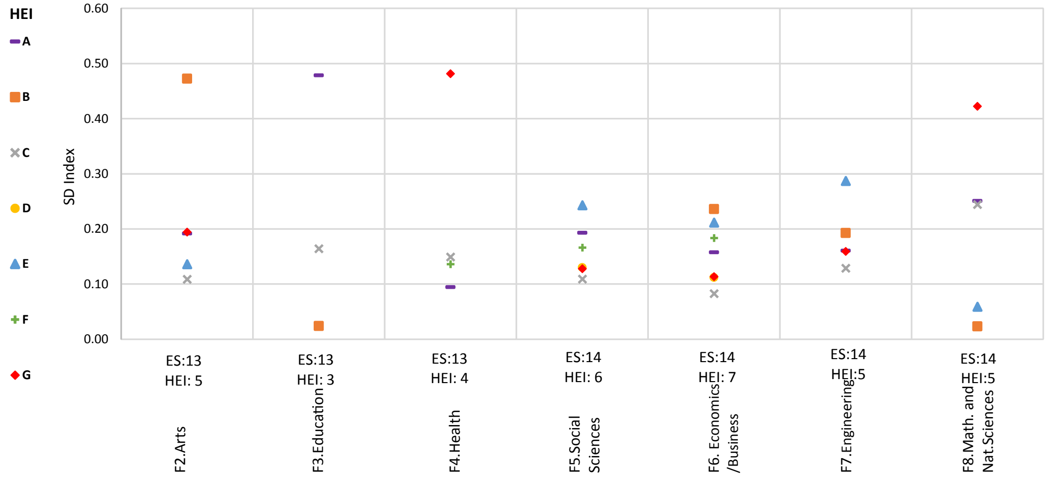

FIGURE 3 Sectoral distinctiveness (SD Index) by institution and field of study. ES: Number of economic sectors where newly graduates in that field of study work. HEI: Number of higher education institutions that have newly graduates from that field of study

job choice. Yet this availability of jobs depends not only on the institution or the individual, but also on the labor market itself, its capacity of absorption and its valuation of certain fields of study at the time the recent graduate decided to join the labor market. It has been found that the demand for graduates from certain fields of study reflects the labor market's appetite under current economic conditions (Altonji et al., 2014; Reimer et al., 2008); however, under these circumstances, HEIs that provide better adaptability would be more desirable.

Table 2 shows the variance of the distribution of recent graduates by field of study across economic sectors of the labor market. Even though most fields of study show a higher concentration of recent graduates (highlighted by darker cells) in economic sector S10. Real estate, Renting and Business Activities, the distribution is still not homogeneous. There are also fields of study that show a higher concentration in specific economic sectors, such as F3. Education in economic sector S12. Education (45.2% of recent graduates from this field of study work in the education economic sector); and F4. Health in economic sector S13. Health and Social Work (37.7% of recent graduates work on the health economic sector).

Our database does not include the reason why each individual chose a particular job; however, by aggregating individual information at the institutional level we have an approximation of the options (flexibility/variety) an institution provides to its recent graduates.

According to Ransom and Phipps (2016), the statistical concept that reflects what the SV index intends to capture is the inverse of concentration and is expressed through the following equation:

$$SV = \left[\sum_j \left(\frac{c_j^g}{C^g} \right)^2 \right]^{-1} \tag{2}$$

Equation 2 is the reciprocal of Simpson's Diversity Index also known as the Herfindahl-Hirschman Index. By using the reciprocal of Simpson's Diversity Index, the SV index can be interpreted as the number of "effective" economic sectors in which individuals from a specific HEI work. Here "effective" means the number of equally sized economic sectors.

By using Equation 2, we estimate the SV index for each institution by field of study and then rescale it from 0 to 1 as the percentage of the total number of economic sectors in which all HEIs in that field of study have recent graduates working. Given that our SV index goes from 0 to 1, a HEI with an SV index of 1 should be interpreted as one whose recent graduates are working in all the economic sectors that recent graduates from the rest of HEIs in the same field of study are. Figure 4 depicts our estimations of the SV index for each HEI by field of study.

TABLE 2 Distribution of fields of study across economic sectors (number of newly graduates)

Fields of Study	Economic Sectors: S1.Agriculture	S2.Mining	S3.Manufaturing	S4.Electricity	S5.Construction	S6.WholeSale/ Retail	S7.Hotels/ Restaurants	S8.Transportation	S9.Financial Intermediation	S10.Real Estate	S11.Pub.Adm/ Defense	S12.Education	S13.Health	S14.Communitary Services	*Total*
F1.Agronomy	4	0	3	0	2	7	0	3	1	12	2	0	0	2	*36*
F2.Arts	11	3	108	0	11	93	9	34	18	304	7	55	13	49	*715*
F3.Education	0	3	13	0	3	24	6	18	17	84	1	170	5	32	*376*
F4.Health	1	2	35	0	6	48	2	41	3	126	28	49	224	29	*594*
F5.Social Sciences	16	17	130	5	22	141	14	113	116	659	140	269	56	131	*1829*
F6.Economics/Bs.Adm.	21	36	222	2	29	256	40	188	634	743	44	112	42	93	*2462*
F7.Engineering	43	102	367	15	166	298	25	173	277	967	22	378	24	58	*2915*
F8.Mathematics/Nat.Sc.	11	15	85	3	11	63	6	19	10	148	3	183	40	9	*606*
Total	*107*	*178*	*963*	*25*	*250*	*930*	*102*	*589*	*1076*	*3043*	*247*	*1216*	*404*	*403*	9533

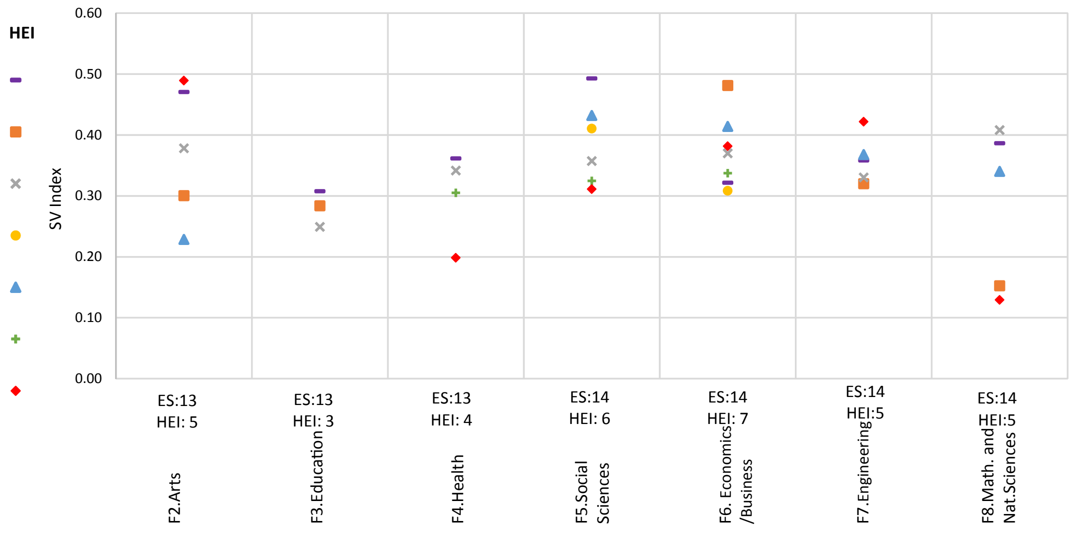

FIGURE 4 Sectoral variety (SV Index) by institution and field of study

By applying our SV index, we make the presence of recent graduates across economic sectors comparable and equivalent. As can be seen in Figure 4, for field of study F2. Arts, institution G has recent graduates working across 49% of equivalent economic sectors (highest variety) and institution E has recent graduates working in only 23% of equivalent economic sectors (lowest variety). The higher the SV index for an institution in a field of study, the more diversity/variety across economic sectors it has.

We are aware that there are additional outputs that could be considered when assessing the performance of HEIs; however, for most countries, data restrictions prevent a deeper evaluation. An example to be followed is the evaluation performed by the Teaching Excellence and Student Outcomes Framework (TEF) administered by the Office for Students in the United Kingdom who created its own ranking to assess each higher education provider (university and college level) in terms of graduate-level employment, further study and even student satisfaction of recent graduates from undergraduate programs. However, TEF is a national exercise that requires government coordination that unfortunately most developing countries do not have. Our intention is to provide an alternative HEI performance evaluation that includes outcomes that are already available, and that could be extended nation-wide with the authorization of data release. Nevertheless, TEF framework should be considered as inspiration for developing countries that are looking for improvement in their higher education sectors.

3.2 | Inputs

3.2.1 | Standardized test scores

To measure students' cognitive abilities prior to enrolling in an HEI, we used Saber11 test scores. Saber11 is a standardized test that all high school students in Colombia are required to take during their senior year in order to graduate. Saber11 results can thus be considered the raw materials (inputs) that are transformed through the higher education process.

Using Saber11 scores as an input helps us to control for some potential problems in the analysis of higher education efficiency. For example, given that HEIs are so heterogenous, the best students may self-select into what they consider are the best institutions. This could distort the concept of efficiency, because institutions or programs that produce the best outputs are good only because they had the best inputs from the beginning. Then, a highly efficient institution or program is that which takes students with the lowest Saber11 scores (as a proxy of initial cognitive abilities) and "transforms" them into desirable labor market outputs.

With regard to the "transformation" of students, it should be noted that we are still talking about a black box. We assume that students gain not only through a (positive) change in cognitive abilities (though we are not measuring whether the student performs better or worse academically upon graduation) but also through an increase in potentially helpful social ties, (via social networks and interactions with professors and peers, signaling, partnerships, and so forth) and signaling that the HEIs facilitate directly or indirectly to make each of their students desirable in the labor market.

Given that Saber11 test scores are divided by subject, we estimated the mean of Saber11 subjects by institution and by field of study, based on individual data, and used that information as input.[12] To make individual scores comparable so that we could later aggregate them by institution, we standardized them by semester, which gave us the percentile in which a particular student was located, compared to all the students who took the test nationwide by Saber11 subject. Because of this, Saber11 test scores present an advantage when compared with specific university entry tests because they reflect a standardized measure of cognitive abilities that makes possible to compare students from different high schools.[13] As Chetty et al. (2017) highlights, students admitted to selective colleges tend to have similar observable measures of ability (proxied trough standardized test scores) independently from their background as shown in Espenshade et al. (2004), and Hoxby and Avery (2013).

3.2.2 | Tuition fees

Given that a student may consider higher education to be an investment, tuition fees might be a factor when choosing a degree and institution. We have therefore included a monetary input that is the average semi-annual tuition fee charged by each HEI by field of study. Tuition fee is expressed in Colombian pesos of 2011.

3.2.3 | Input selection

Because Saber11 results might be affected by students' characteristics, we regressed each one of the six different subjects[14] on available demographic characteristics of recent graduates such as sex and parents' education and found that they are statistically significantly related to Saber11 test scores... Appendix 1 summarizes these Ordinary Least Square regressions using each of Saber11 scores as dependent variables.

We also run OLS regressions to test which subject(s) should be selected to be used as input. In our estimations we used wages, SD and SV as dependent variables and Saber11 scores as independent variables in addition to tuition. Table 3 reports these results.

Table 3 shows[15] the only combination of independent variables that is statistically significant for all three of our labor market outcomes given that we will combine outcomes in our estimations. Because of that, we will use Saber11 test scores of chemistry besides tuition (which is also statistically significant in all our regressions) as inputs for our performance evaluation through DEA.

TABLE 3 Input selection—OLS regressions

All Saber11 subjects	Dependent variable: Wages		Dependent variable: Sectoral distinctiveness		Dependent variable: Sectoral variety	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
mathematics	683.243	419.3177	0.0000858***	0.0000286	0.0000574***	0.0000286
physics	543.874	388.0201	0.0000614	0.0000409	0.0000556	0.0000404
chemistry	1475.140***	567.7176	0.0000503**	0.0000281	0.0000573***	0.0000283
biology	732.621	568.2578	0.0000674**	0.0000402	0.0000533	0.0000415
language	−510.874	688.3309	−0.0000147	0.0000436	0.0000198	0.0000434
philosophy	1340.027***	384.8852	−0.000069***	0.0000265	−0.0000616**	0.0000261
tuition	0.050***	0.0030	1.71E−09***	2.72E−10	3.48E−09***	2.35E−10
_cons	852,872.500***	49,818.2900	0.1233287***	0.0038756	0.3171373***	0.0038177
Obs.		9533		9533		9533
Saber11 subjects that were statistically significative for all outcomes	**Dependent variable: Wages**		**Dependent variable: Sectoral distinctiveness**		**Dependent variable: Sectoral variety**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
chemistry	2240.507***	463.2137	0.0001562***	0.0000319	0.000147***	0.0000333
philosophy	1457.784***	358.4997	−0.0000506***	0.0000253	−0.0000412	0.0000251
tuition	0.051***	0.0030	1.84E−09***	2.70E−10	3.60E−09***	2.33E−10
_cons	882,256.700***	42,745.8200	0.1277588***	0.0034338	0.3218832***	0.0032841
Obs.		9533		9533		9533
Final selection	**Dependent variable: Wages**		**Dependent variable: Sectoral distinctiveness**		**Dependent variable: Sectoral variety**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
chemistry	2744.298***	455.1679	0.0001387***	0.0000308	0.0001328***	0.0000324
tuition	0.053***	0.0030	1.78E−09***	2.69E−10	3.55E−09***	2.32E−10
_cons	934,794.300***	39,938.2900	0.1259504***	0.0033056	0.3204137***	0.0031426
Obs.		9533		9533		9533

***1% statistically significant; **5% statistically significant; *10% statistically significant.

4 | EMPIRICAL METHODOLOGY: DEA

DEA is an analytical technique used mainly in operational research to identify the best performance in the use of inputs between a group of similar decision-making units (DMUs). Initially proposed by Charnes et al. (1978) and later modified by Banker et al. (1984), DEA uses a measure of efficiency of any DMU as the maximum ratio of weighted output to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity. Each DMU is charge of the inputs into outputs transformation, and its performance is evaluated on the basis of its efficiency, understood as the ratio of outputs to inputs (Ji & Lee, 2010).

A remarkable characteristic of DEA is that it enables the efficiency evaluation of DMUs over different outputs. We can therefore set each HEI as a DMU and measure the efficiency of each in transforming students' cognitive abilities and tuition into starting salaries, SD and SV. Some studies that have applied DEA in research on higher education using different inputs and outputs are reviewed in Nazarako and Sparauskas (2014).

Furthermore, we consider DEA appropriate for our research from the perspective of economic theory, given the reconciliation of DEA with the economics production function proposed by Nakamura (2017).

By estimating an efficiency frontier constructed with the most efficient DMUs, DEA results enable the ranking of DMUs according to their proximity to that frontier (proximity is represented by θ where $0 \leq \theta \leq 1$). The most efficient DMUs are above the efficiency frontier ($\theta = 1$) and the rest are below ($0 \leq \theta < 1$).

We performed our estimations using an output-oriented approach. Doing so enables us to evaluate HEIs by the maximum level of output they can produce (wages, SD, and SV), given the cognitive abilities of the students they enroll and the tuition those students pay (inputs).[16]

With regard to scale assumptions, even though our sample includes only the top HEIs in Colombia, we cannot assume that all HEIs are operating at their optimal scale (constant returns to scale), as does the original model proposed by Charnes et al. (1978) does. This is especially true when analyzing institutional efficiency by field of study. Because of that, we adopted the modification of DEA by Banker et al. (1984), who introduced variable returns to scale in DEA and through this the possibility of analyzing efficiency from the technical and scale perspectives (Ji & Lee, 2010).

In order to formulate our output-oriented DEA model with variable returns to scale, we assume that k HEIs are evaluated from a student's perspective, based on m inputs that are used to produce z outputs, with y_{rk} being the amount of output r produced by HEI_k and x_{ik} the amount of input i used by HEI_k. Regarding s_r and s_i, they represent the output and input slacks, respectively. It must be noted that the HEI under evaluation is represented in the following equations using "0" as subindex.

Following Johnes (2006b), we define the Technical Efficiency of HEI_k as $\frac{1}{\phi_k}$, and then we determine the efficiency of each HEI by solving the following linear programming problem:

$$\text{Maximize} \quad \phi_k + \varepsilon \sum_{i=1}^{m} s_i + \varepsilon \sum_{r=1}^{z} s_r \tag{3}$$

$$\text{Subject to} \quad \phi_k y_{r0} = \sum_{k=1}^{n} \lambda_k y_{rk} - s_r \tag{4}$$

$$x_{i0} = \sum_{k=1}^{n} \lambda_k x_{ik} + s_i \tag{5}$$

$$\sum_{k=1}^{n} \lambda_k = 1 \tag{6}$$

where $\lambda_k, s_r, s_i \geq 0 \quad \forall\, k = 1, \ldots, n; r = 1, \ldots, z; i = 1, \ldots, m.$

HEI_k will be efficient if its efficiency score is 1 and all the slacks are 0 (slacks represent the additional improvement through an increase in outputs that would be needed to make an HEI efficient). The efficiency scores, as mentioned before, are represented in our results through θ where $0 \leq \theta \leq 1$.

5 | RESULTS

The efficiency scores (represented by θ) and also the ranking based on these scores are presented in Table 4 including all fields of study. The estimations were performed at the institutional level, using as inputs the average of each institution's Chemistry Saber11 test scores by field of study and the semi-annual average tuition of each HEI by field of study expressed in Colombian pesos of 2011. Regarding outputs, we included the average wage, SD index, and SV index, respectively, of each institution by field of study.[17]

We initially performed our DEA estimations using each of the outputs separately, since SD and SV reflect opposite opportunities in the labor market (they show an inverse correlation of −0.0216 across our entire sample). Columns 6, 7, and 8 show the results using starting salaries (wages) as an output; columns 9, 10, and 11 report results using the SD index as an output; and columns 12, 13, and 14 exhibit the results using the SV index as output.

Finally, we combined outputs to evaluate the performance of HEIs. Columns 15, 16, and 17 show the results using wages and the SD index together and columns 18, 19, and 20 show the results using wages and the SV index together as outputs.

Regarding returns to scale (RTS), they are represented in columns 8, 11, 14, 17, and 20 next to the θ of each estimation where—represents decreasing returns to scale, * represents constant returns to scale, and + represents increasing returns to scale.

It must be noted that DEA rankings do not provide results regarding which HEI registers the highest output; instead, it ranks institutions based on which institution with a given input (cognitive abilities and tuition costs) produced the maximum possible output or combination of outputs.

When the whole sample is used (Table 4) without considering fields of study, HEI D not only registers the highest average wage, but is also one of most efficient HEI at transforming inputs into the combinations of wages and SD and wages and SV. Even though this institution does not charge the highest tuition, nor do its students have the highest saber11 test scores, when in the labor market its recent graduates enjoy better labor market opportunities than the rest because it provides better dominance and wages and even better flexibility and wages than other HEI that required higher tuition cost or higher initial cognitive abilities.

Figure 5, Panels A to H are intended to show the heterogeneity of HEIs by fields of study. This enables the comparison of institutions by the same criterion, which is mandatory when evaluating institutions using rankings. However, for visual simplicity in Figure 5 we included saber11 test scores only as inputs and the efficiency scores for two outputs: the combination of wages and SD index, and the combination of wages with SV index.[18]

Field 2. Arts: When using all our outputs separately and combined, most of institutions in this field of study show to be efficient. Only HEI E performs below the rest of institutions when efficiency scores are translated into a ranking; this might be caused by charging the second highest tuition yet registering average wages, SD and SV indices below its competitors in this field of study.

Field 3. Education: The three institutions that have recent graduates in this field of study are located on the frontier (maximum efficiency) when the outputs are combined. However, when focusing on specific outputs such as SD and SV, HEI C is shown to be underperforming. Along these lines, when wages are evaluated, HEI A is inefficient because has the best inputs of the three institutions (highest Saber11 scores and tuition), yet its recent graduates register the lowest average wage when in the labor market.

Regarding Field 4. Health, there are considerable differences between the inputs of HEI G and the rest of HEIs. HEI G tuition is more than three times the tuition of other institutions and the cognitive abilities of its students are more than 18 percentiles higher than the rest. With these inputs, HEI G registers the highest average wage

TABLE 4 DEA results (output oriented) field of study: Total

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	TUITION	S11	WAGE	SD	SV	o_WAGE			o_SD			o_SV			o_WAGE_SD			o_WAGE_SV		
HEI	mean	mean	mean	index	index	rank	theta	RTS	rank	theta	RTS	rank	theta	RTS	rank	theta	RTS	rank	theta	RTS
A	54,62,247	89.37	14,18,369.5	0.11	0.44	6	0.84	(+)	6	0.51	(+)	1	1.00	(–)	7	0.84	(+)	1	1.00	(–)
B	2,19,688	79.51	11,38,637.5	0.15	0.39	1	1.00	(*)	1	1.00	(*)	1	1.00	(*)	1	1.00	(*)	1	1.00	(*)
C	67,26,590	82.79	16,52,463.8	0.06	0.42	4	0.91	(+)	7	0.29	(+)	4	0.94	(–)	6	0.91	(+)	5	1.00	(–)
D	68,34,039	82.75	18,27,060.4	0.19	0.38	1	1.00	(*)	4	0.89	(–)	6	0.83	(+)	1	1.00	(*)	1	1.00	(*)
E	52,38,243	68.46	10,59,698.6	0.22	0.31	7	0.72	(*)	2	1.00	(*)	7	0.83	(*)	1	1.00	(*)	7	0.83	(*)
F	72,35,455	80.44	15,78,732.0	0.21	0.45	5	0.89	(*)	3	0.94	(–)	3	1.00	(*)	1	1.00	(–)	6	1.00	(*)
G	1,12,92,326	89.94	17,08,574.2	0.15	0.41	3	0.94	(+)	5	0.70	(+)	5	0.91	(–)	5	0.94	(+)	1	1.00	(+)

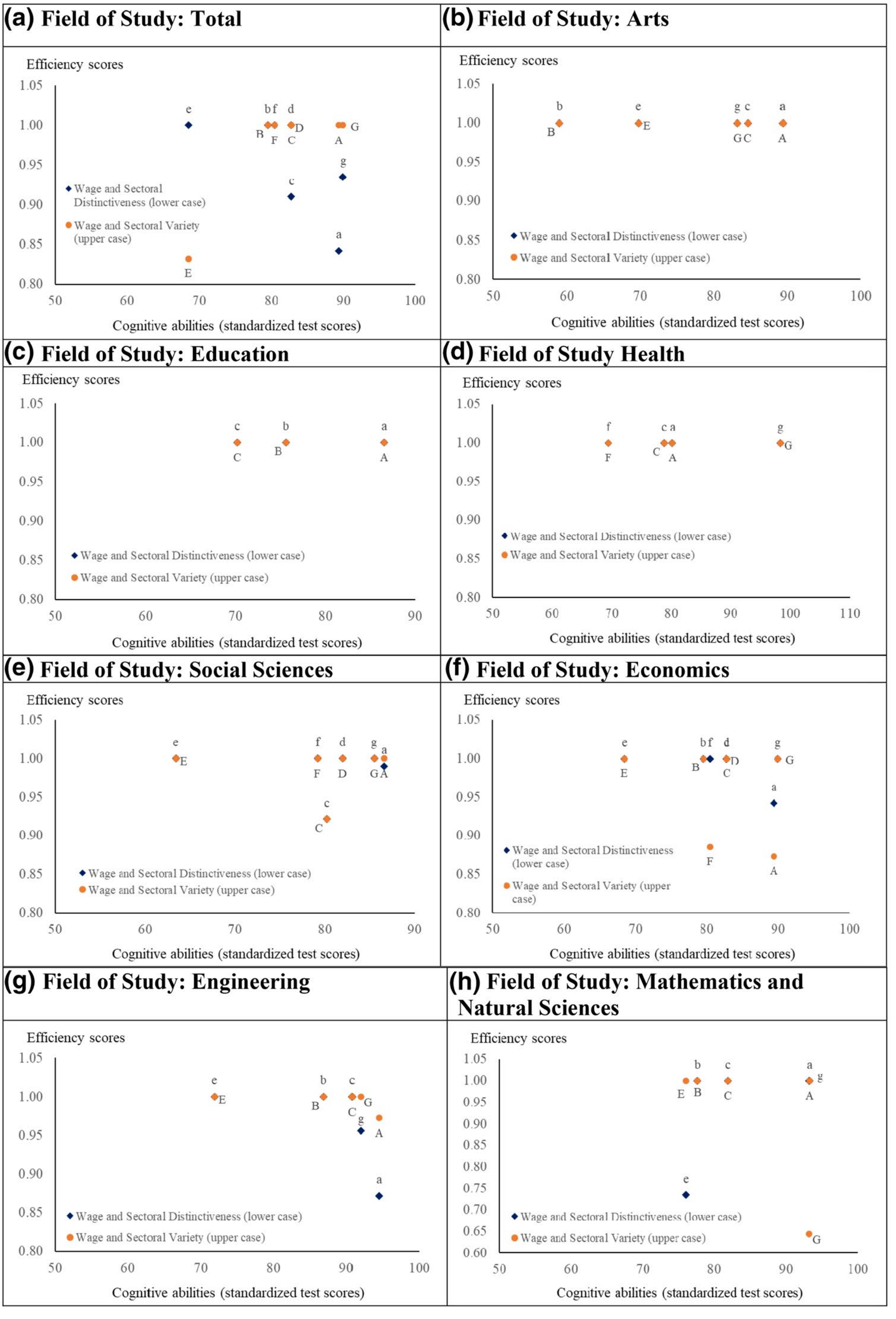

FIGURE 5 DEA results (output oriented) by field of study

and the highest SD in the labor market. This institution is also the most efficient when transforming its inputs into wages and SD as outcomes and the combination of both. This could be read as HEI G having a niche market for the field of study of Health where its newly graduates are segregated and have higher wages than their competitors.

For Field 5. Social Sciences, HEI F and G show only a minimal difference in terms of average wages (around 1%) and both institutions are efficient in terms of transforming their inputs into wages. However, the tuition and Saber11 test scores required by HEI G are much higher. Furthermore, when it comes to distinctiveness and flexibility in the labor market, HEI F turns out to be more efficient and registers higher SD and SV indices in the labor market. This could indicate that even though both institutions are comparable in terms of wages, HEI F is more efficient, when other labor market opportunities besides salary are considered.

About the results for Field 6: Economics, Business Administration, and Accounting. Highlighting the relevance of efficiency evaluation, HEI G registers the highest average wage in the labor market, and if this were the sole criterion, we could say that this institution is “the best” in this field of study. However, this institution charges the highest tuition, and its students also report the highest cognitive abilities (Saber11 test scores). HEI G is indeed efficient at transforming high-quality inputs into wages, but there are other institutions that achieve comparable efficiency in terms of producing wages, yet with lower inputs, such as HEIs C, D, and B. Furthermore, when the other outputs are considered, HEI G is not as efficient as other HEIs in terms of flexibility and distinctiveness in the labor market.

For Field 7. Engineering, Architecture, and Urbanism, HEI B is the most efficient institution whether the outputs of wages, SD, and SV are measured separately or combined. However, HEI A and HEI E present an interesting comparison. Both institutions charge nearly the same tuition, but HEI A's recent graduates register cognitive abilities more than 20 percentiles higher than those of HEI E. HEI A registers a higher average wage for recent graduates than HEI E and is also more efficient regarding this output; yet with regard to flexibility and distinctiveness, HEI E registers higher SD and SV indexes and is also more efficient in terms of these outcomes. In fact, when the SD and SV indexes are combined with wages, HEI E is far more efficient than HEI A even though the latter registers higher average wages. This could indicate that HEI E is better at transforming a lower level of cognitive abilities into better labor market opportunities, such as distinctiveness and flexibility, than HEI A.

The results for Field 8. Mathematics and Natural Sciences show that HEI B is the most efficient at transforming the given cognitive abilities of its students and tuition into wages, SD, and SV. However, this could reflect the low tuition HEI B charges and the low Saber11 test scores its students register. What is more, when outputs are combined (wages and SD) HEI B underperforms showing the relevance of using multiple outputs when considering the efficiency evaluation.

One curious finding was that HEI G charges the highest tuition and also has the students with one of the highest Saber11 test scores, yet their newly graduates do not have the highest average wage and its SV index is the lowest for this field of study. This reflects HEI G's poor performance in terms of wage and SV efficiency (the lowest position for both outputs).

6 | CONCLUSIONS

Our intention with these results is to provide a different perspective on efficiency in higher education. We propose to evaluate HEIs using outputs that are relevant for recent graduates rather than for the institutions. For this reason, we use SD and SV as outputs that complement the traditional wage analysis.

Even though our results are derived from just a sample of well-known top universities in Bogotá, Colombia, the performance analysis helped us evaluate HEIs as producers of labor market opportunities from angles that had not been considered before. We believe we all (researchers and policy makers) can learn from institutions that are not ranked among the best, when only monetary inputs are considered, but are successful in transforming students with lower cognitive skills into graduates who have access to competitive wages and opportunities across the labor market. We also highlight the differences between HEIs in terms of how they educate students in different fields of study.

One limitation of the present study is that we do not have information about the future of our sample of recent graduates. We cannot track the evolution of their wages, the length of time these recent graduates will be paid their starting salaries, or whether they will be promoted or move to a different company. The information we provide is intended to be used as reference about the relevance of heterogeneity of HEIs and also as a proposal that cognitive inputs be considered in the educational process. Our intention is that HEIs will be evaluated not only with regard to their financial efficiency, but also with regard to their equalizing effect in the labor market and the opportunities they provide for their students.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study was derived from the following resources openly available: Colombian Institute for Educational Evaluation – ICFES (www.icfes.gov.co), National System of Higher Education Information – SNIES (www.snies.mineducacion.gov.co) and Labor Observatory for Education – OLE (www.ole.mineducacion.gov.co).

CONFLICT OF INTEREST

No conflicts of interest have been declared by the authors.

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ENDNOTES

[1] For a complete review, see AWPA (2013) and Devadas (2015).

[2] For a complete review of the literature on efficiency in education, refer to De Witte and Lopez-Torres (2005).

[3] Another important line of research that is not included in this study are the outcomes that are relevant for Higher Education Institutions' academics and stakeholders which reflect another objective of HEIs different than the preparation of students for the labor market such as the production of research and industry engagement. Taylor (2001), Pugh et al. (2005) and Nasim et al. (2020) provide evidence about these topics.

[4] Higher education programs in Colombia are classified by "knowledge areas," which are similar to fields of study.

[5] It should be noted that we worked with a sample of recent graduates for whom we were able to find Saber11 test scores and who took the Saber11 test from 2002 on. Due to data protection laws in Colombia, in order to merge OLE information with Saber11 test scores we relied on a translator of identification codes provided by the Ministry of Education; this meant the building of a complete database was possible for only a limited number of individuals.

[6] Approximation estimated using data from the Labor Observatory for Education for the HEIs selected for this study between the first semester of 2007 until the first semester of 2011. We included only those graduates that attended in person programs in Bogota.

[7] In order to make wages comparable, we used starting salaries in real prices of 2011.

[8] Here "niche market" refers to a space in the labor market in which recent graduates from a specific institution and field of study are working, and there are few or no workers from that same field of study but who have graduated from different HEIs.

[9] All equations were extracted and adapted from Alonso-Villar and Del Rio (2010).

[10] In order to plot the segregation curve for group "g" (S^g), the economic sectors need to be arranged in ascending order according to c_j^g/t_j and then plot the cumulative distribution of economic sectors ($\sum_{i\leq j} t_i/T$) on the x-axis and the cumulative proportion of individuals of the higher education institution ($\sum_{i\leq j} c_i^g/C^g$) on the y-axis should be plotted.

[11] We compared our SD index developed by Alonso-Villar and Del Rio (2010) with a well-known segregation index: the square root segregation index of Hutchens (2004). Both indexes rank the same institutions by field of study as the most segregated in most of the cases, which validates our sectoral distinctiveness results. This comparison is available upon request to the corresponding author.

[12] As will be noted later, the one Saber11 subject that has a statistically significative relationship with all our output variables is chemistry.

[13] Britton et al. (2019) for example, groups universities based on average entry scores based on standardized test scores and found that male students from universities with more demanding entry requirements have higher income, which corroborates a relationship between cognitive abilities and students' outcomes.

[14] The six Saber11 subjects are: Mathematics, Language (Spanish), Philosophy, Chemistry, Physics and Biology.

[15] Table 3 also shows the sensitivity analysis based upon different selections of input variables that lead to the selection of our input variables.

[16] We used the Stata software DEA module of Ji and Lee (2010) to perform our estimations.

[17] Given that only one HEI had recent graduates from field of study 1: Agriculture and Veterinary, we excluded that field of study from our estimations and analysis.

[18] The complete tables for each one of the economic sectors are available upon request to the corresponding author.

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How to cite this article: Saavedra-Caballero F, Van Bellegem S. About job market outcomes: Assessing the performance of Colombian higher education institutions. *Higher Educ Q*. 2021;00:1–20. https://doi.org/10.1111/hequ.12340

APPENDIX 1

Variable	Dependent variable: Saber11—Mathematics		Dependent variable: Saber11—Physics		Dependent variable: Saber11—Chemistry		Dependent variable: Saber11—Biology	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
sex	9.412***	0.63742	9.454***	0.6275	4.207***	0.4588	4.572***	0.45243
edu_dad	0.870***	0.27378	1.604***	0.2795	1.148***	0.2159	1.016***	0.21034
edu_mom	1.256***	0.27800	0.897***	0.2780	0.938***	0.2110	0.963***	0.21042
_cons	91.100***	6.82756	58.872***	1.2908	73.633***	1.0307	72.414***	1.00456
Obs.	5966		5966		5966		5966	
	Dependent variable: Saber11—Language		Dependent variable: Saber11—Philosophy		Dependent variable: Saber11—Foreign Language			
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.		
sex	0.544***	0.4154	−1.225**	0.6566	2.669***	0.4832		
edu_dad	1.190***	0.1989	1.608***	0.2898	2.946***	0.2402		
edu_mom	0.866***	0.1914	1.023***	0.2940	2.122***	0.2364		
_cons	75.294***	0.9184	60.338***	1.3026	59.796***	1.2461		
Obs.	5966		5966		5966			

*** 1% statistically significant; **5% statistically significant; *10% statistically significant.