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Evaluation of undergraduate academic programs through data envelopment analysis and time-to-degree estimates at Spanish public universities

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A B S T R A C T

This article proposes nonparametric and parametric methods for conducting meaningful evaluations of academic programs. In particular, it proposes the use of data envelopment analysis (DEA) along with regression analysis for the evaluation of Spanish public universities' undergraduate curricula. Unlike the radial DEA models, which assume an equiproportional expansion of all outputs to achieve efficiency, the current study also relies on the use of non-radial DEA models for assessing the efficiency of Spanish public universities. A non-radial DEA measure (the so-called Russell measure) allows for unlike proportional augmentations in each positive output. In this study, non-radial DEA measures allow us to identify different levels of inefficiency for each output considered (social sciences and non-social sciences degrees). Specifically, the results show that the inefficiency in the production of scientific and technical degrees is greater than that in the production of humanities and social sciences degrees, although there are differences among institutions. Bachelor's degree production time is also estimated, and a duration analysis explains the time to degree. A worrying result is the "excessive" time it takes for a university to produce four-year undergraduate degree programs. The mean graduation time is 5.7 years. The Cox proportional hazards regression shows that a shorter time to graduation is associated with higher teaching quality as well as a higher faculty-to-student ratio. Parametric survival analysis using a lognormal distribution with gamma frailty also verifies these latter results.

1. Introduction

The present study aims to measure the technical efficiency of the instructional component of undergraduate education at traditional Spanish public universities. The specific focus was on examining whether undergraduate students advance toward fulfilling their degree requirements within a specified timeframe. The rationale behind this choice is that the Spanish University System (*Sistema Universitario Español*, SUE) is mainly characterized by campus-based public universities that enroll primarily undergraduate students.[1] The SUE undertook a reform of its curricula in 2010, starting to offer new undergraduate degrees called *grados* (a four-year bachelor's degree). However, to date, no research studies have examined in depth the curricular reform of the Spanish higher education system in terms of efficiency and productivity. Moreover, public universities in Spain are funded mostly by the public budget and charge low tuition fees for undergraduate teaching. Performance evaluation is, therefore, desirable and necessary to show society the accomplishments that are achieved with the use of public resources.

Although accountability continues to be an important goal of program evaluation, the major goal should be to improve program performance [1]. Data envelopment analysis (DEA) is recommended in this article as the principal tool for performance evaluation of bachelor's degree programs. Primarily, we are interested in knowing the degree to which a university's output levels—such as passed academic credits—fall short of the highest levels that can be attained for its input levels—such as enrolled academic credits and teaching personnel. DEA is a nonparametric, linear programming-based technique that is suitable for this purpose since it does not require any specific functional form or assumptions about the production process for converting inputs into outputs, making it flexible and applicable to the evaluation of academic programs. DEA also provides action guidelines for inefficient

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[1] On average, for the 2014–2020 period, the joint demand of the system (SUE) was around 1.5 million bachelor's, master's, and doctorate students in public and private universities [60]. Of that figure, around 85% corresponds to enrollment in undergraduate programs (the vast majority, 90%, in public universities).

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decision-making units (DMUs) to improve their performance by emulating best-practice producers. Thus, the improvement of a DMU (a university) would be guided by the principle of relative efficiency. Here, efficiency is understood as the process of achieving the best possible results using existing resources.

The use of nonparametric methods in program evaluation has a long tradition in the DEA literature (e.g., Ref. [2–6]). In higher education, DEA has gained significant attention as a tool for assessing the efficiency of universities, departments, or individual programs (e.g., Ref. [7–30]). Nonetheless, these studies used standard DEA models (i.e., radial DEA models, which assume an equiproportional expansion of all outputs to achieve efficiency (or an equiproportional reduction in all inputs). In other words, radial DEA models result in a radial expansion of all outputs or a radial contraction of all inputs. In contrast, the current study relies on the use of non-radial DEA models for efficiency measurement of Spanish public universities, in particular the output-based non-radial technical efficiency (or the Russell measure).

Non-radial models have also been developed and used in the DEA literature, albeit as latecomers (e.g., Ref. [31–36]). However, non-radial measures of efficiency have not been exploited until now in the evaluation of programs in the public sector. Therefore, this article contributes to the enrichment of applications of non-radial DEA models. When the goal of assessment in higher education is to measure efficiency and the information is aggregated by higher education institutions (HEIs), non-radial DEA models are very valuable to solve the efficiency evaluation problem in the presence of output heterogeneity. Specifically, in the context of output shortfalls, the non-radial efficiency approach overcomes the drawback of the radial approach in that the non-radial approach does not assume a technically inefficient DMU has a shortfall in production to the same degree for all its outputs. In the current study, to make the results of the assessment relevant to university managers and policymakers, we propose that undergraduate programs be divided into scientific (health sciences and STEM degrees) and non-scientific (humanities, and social and legal studies degree programs). We assume that a university in one area may achieve better academic results than another. Non-radial DEA measures allow for identifying different levels of inefficiency for each output considered. Thus, one advantage of non-radial DEA models is the removal of the assumption that inefficiency occurs to the same degree in every university output. However, due to the limitations of the data set used, our understanding is limited regarding the environmental factors that explain the inefficiencies.[2]

In addition to DEA-based efficiency measurement, this article aims to estimate the time to graduation at traditional Spanish public universities. In the context of relatively low undergraduate students' academic productivity, it is expected that obtaining a bachelor's degree extends beyond four years, which can greatly increase the cost of producing that degree. In addition to an extra burden on university resources, university academic programs that take on average much longer than intended increase private costs for the students (especially opportunity costs) and delay their entry into the labor market, which creates a considerable social cost by reducing the labor supply of skilled workforce. This study proposes the use of duration models to explain undergraduate students' time to graduation. Hazard-based duration models are ideally suited to modeling duration data. We will limit ourselves to the Cox proportional hazards (PH) model and the accelerated failure time (AFT) model. The data allow us to control for several factors that may influence graduation times, such as teaching quality and the faculty-to-student ratio.

The rest of this article is organized as follows. We start in Section 2 with a description of the proposed methods to measure the technical efficiency of four-year undergraduate degree programs and models for explaining time to graduation. Section 3 shows the empirical results of the efficiency evaluation of the teaching provided by traditional Spanish public universities. The empirical results of the efficiency measurement in the production of undergraduates are presented in Section 4. Section 5 presents estimates of the average time it takes universities to produce bachelor's degree programs. Factors that explain time-to-degree at Spanish public universities are identified in Section 6 using duration or survival models. Section 7 presents a discussion and policy implications derived from the present study. Section 8 concludes.

2. Methods

2.1. Overview

Fig. 1 shows the main steps that we propose to evaluate bachelor's degree programs. The first step is to determine the evaluation criteria. The Office of the Provost, along with the university's academic and administrative leaders, should identify the criteria that will be used to evaluate the undergraduate degree programs. These criteria may include student learning outcomes, student feedback, faculty qualifications, student enrollment and retention rates, and other relevant measures. The primary goal of the current study is to measure undergraduate education efficiency and estimate time to degree and its determinants. A second step would be to identify the specific tools that will be used in the performance evaluation. The current study proposes the use of data envelopment analysis (DEA) for the efficiency measurement of universities' undergraduate curricula. DEA-based performance evaluation is useful for university policy and management purposes to have a measure of the university's teaching performance in relation to their peers. Duration analysis is proposed to explain the determinants of time to degree. A third step involves the identification of the decision-making units (DMUs) involved in the performance evaluation exercise. A fundamental assumption of DEA is that a set of DMUs should be homogenous in the sense that all DMUs are "alike" and therefore directly comparable. In this article, the focus is on the Spanish public university system. A crucial fourth step in evaluating university performance is deciding the inputs and outputs involved in the education production process. The fifth step involves running the proposed models to identify the efficient and inefficient academic programs of the different DMUs. Also, our purpose is to study the determinants of time to graduation. Finally, our goal is to do benchmarking to identify areas for improvement.

2.2. Undergraduate education efficiency measurement

The microeconomic theory of production looks at the activity of a firm mainly as a production process that transforms inputs (such as capital and labor) into outputs, and technical efficiency reflects the ability of the firm to produce the maximum amount of output from a set of resource inputs, given the technology (output-orientation).[3] In higher education, it is assumed that universities want to maximize undergraduate students' academic productivity, that is, what percentage of the enrolled credits students are able to pass in an academic year. Note that productivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use [37]. Both the production achieved (numerator, O) and the resources used (denominator, I) must be measured in physical (technical) units. For example, labor productivity can be defined as the quantity of output produced with a given level of labor input, irrespective of the quantity of other inputs used. In the context of the provision of undergraduate education, the academic

[2] Our sample of institutions is relatively small, so it is not advisable to introduce a further distinction between academic programs since the model's ability to discriminate among DMUs (universities) decreases as the numbers of outputs and inputs increase.

[3] A production process is also efficient if a given amount of output cannot be produced with fewer inputs (input-orientation).

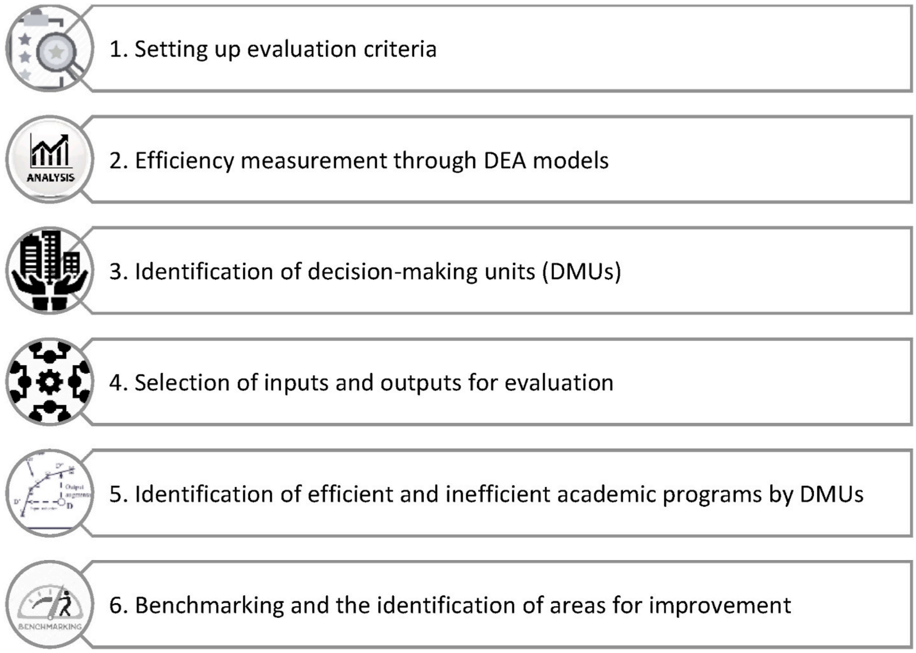

Fig. 1. Steps involved in undergraduate academic program evaluation.
Source: author's elaboration

productivity of undergraduate students can be defined as $\frac{y_t^i}{x_t^i}$, where y_t^i represents the total passed credits by students at university i in the academic year t (output), and x_t^i represents the total number of credits enrolled by those students at the same institution in that time period (input). In this analysis, it is also important to distinguish at least between two types of teaching outputs. On the one hand, the total passed credits in humanities and social sciences degrees (e.g., History, Sociology, Law, or Economics). On the other hand, the total passed credits in degrees in hard sciences, health sciences, and engineering (e.g., Physics, Pharmacy, or Computer Engineering). Both the difficulty of the studies and the types of students admitted to them differ between those two broad fields of knowledge. The quality and success of undergraduate academic programs depend upon the extent to which they attract students with the potential to succeed. We know that some degrees, such as STEM degrees (college programs in science, technology, engineering, and mathematics), attract students with higher average abilities. Among the inputs, in addition to considering the total number of credits enrolled in these two large groups of degrees, the total number of teaching staff should be used to reflect the academic labor input.

2.3. Nonparametric techniques for efficiency measurement

As already mentioned, DEA is a widely used technique for measuring the relative efficiency of DMUs that convert multiple inputs into multiple outputs. It compares the observed performance of each DMU with the best possible performance based on linear programming methods, allowing for the identification of inefficiencies. The ease with which DEA can manage several educational inputs and several educational outputs has made DEA an appropriate technique for measuring the technical efficiency of educational institutions. However, nonparametric efficiency measurement in higher education has typically used conventional models (i.e., radial DEA models) without exploiting the possibilities offered to university management by the use of non-parametric, non-radial models. Unlike the radial measures of efficiency, which assume that the efficiency can be improved by simultaneously increasing all the desirable outputs by the same proportion (output-oriented DEA models), non-radial efficiency measurements allow for non-equiproportional changes in university outputs (i.e., the various outputs are maximized by different proportions).

In order to assess undergraduate students' academic performance (also the production of undergraduate graduates), this study proposes a non-radial DEA model, which allows for different proportional augmentations in each positive output. A non-radial DEA measure (the Russell measure) allows us to determine which dimension (in particular, between non-scientific and scientific degree programs) presents more technical inefficiency for the universities under study. Following Zhu [38], the output-oriented non-radial DEA model under constant returns-to-scale (CRS) can be formulated as[4]

$$\max\left(\frac{1}{s}\sum_{r=1}^{s}\varphi_r+\varepsilon\sum_{i=1}^{m}s_i^-\right)$$

subject to

$$\sum_{j=1}^{n}\lambda_j y_{rj}=\varphi_r\, y_{rk}\quad r=1,2,\ldots,s; \tag{1}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^-=x_{ik}\quad i=1,2,\ldots,m;$$

$$\lambda_j\geq 0\ (j=1,2,\ldots,n);\ \varphi_r\geq 1\ (r=1,2,\ldots,s).$$

In (1), y_{rj} and x_{ij} (all positive) are the known outputs and inputs of the jth DMU, respectively, s_i^- represents input slacks,[5] and ε is the non-Archimedean infinitesimal value, which forestalls weights from being zero. Our evaluation includes n DMUs (universities in our analysis). By solving the linear programming problem associated with each university (k is the DMU under evaluation in (1)), we will be able to obtain relative efficiency scores for individual institutions. A DMU with an efficiency score of one is on the so-called "best-practice" frontier. Efficient universities are used as a benchmark to compare with inefficient universities. The degree of inefficiency is calculated as a distance from "best-practice" institutions. This methodology allows us to determine

[4] The mean of the efficiency indices of each output is maximized.

[5] The input excesses are represented by non-zero slacks. Note that output slacks do not exist in the output-oriented non-radial DEA models [38].

projection points on the frontier for each output without assuming that they should be equiproportional.

However, we also employ envelopment DEA models, in particular the output-oriented CRS model (the CCR-DEA model), to compare the efficiency scores obtained using non-radial DEA models with those obtained using radial DEA models. A general output maximization CCR-DEA model based on the developments of Charnes et al. [39] is presented in the Appendix. An output orientation is adequate for university efficiency measurement since the objective of universities is for students to pass as many credits as possible for those who enroll, given their teaching staff. "When one talks about the efficiency of a firm one usually means its success in producing as large as possible an output from a given set of inputs" ([40], p. 254). Note also that CRS technical efficiency (TE) scores evaluate the overall performance of each DMU (university in the current study) in relation to the rest of the DMUs used in the analysis.[6] An institution would be overall technically efficient if its CRS TE score was 1; otherwise, it would be overall technically inefficient (i.e., CRS TE score >1).[7]

2.4. Selection of homogeneous units to measure technical efficiency

DEA uses mathematical programming to measure the technical efficiency of a sample of producers, or DMUs. However, the concept of efficiency is relative, where the term "relative" means that each DMU is compared with any other homogeneous unit. The homogeneity assumption is based on the idea that the performance of a DMU can only be compared to other DMUs that operate under similar constraints, employ similar inputs for producing similar outputs, and share the same technology [41]. Based on this assumption, this study chose for the performance exercise only traditional Spanish public universities (campus-based universities), which are mainly fed by public money, share a common regulatory framework (Organic Law of the University System), and use similar educational production technology (distance/on-learning public universities and all private universities were excluded in this study). We chose the 2015–2016 academic year (AY), which is the first one with complete data once the Bologna reform was complete in Spain. The principal data source about Spanish public universities was the Spanish Association of University Rectors (*Conferencia de Rectores de las Universidades Españolas*, CRUE).

2.5. Selection of input and output variables

Universities are multi-product organizations that produce different outputs using multiple inputs. A critical issue to be addressed when working with DEA models is the selection of outputs and inputs to be included. There is no consensus on which input and output measures to use in efficiency measurement in higher education, and, in many cases, variable selection is driven by data availability.[8] As already said, this study uses primarily as input the total number of credits that undergraduate students were registered for the 2015–2016 AY at each university (i.e., the total students' academic load). Across the European Higher Education Area, bachelor's degrees are typically 4 years in length, and undergraduate students need to have earned 240 academic credits (the so-called ECTS) before graduation (4 years full-time). In Spain, the planned load for an undergraduate student is five courses (or subjects) per semester, so the typical number of credits each academic year is 60 credits.[9] As we also anticipated, we distinguish between degrees in the humanities and social sciences, on the one hand, and degrees in the hard sciences, health sciences, and engineering, on the other hand.[10] In addition, the total number of teaching staff was used to reflect the academic labor input. The data included tenured (Full Professors and Associate Professors) and non-tenured faculty counts by university. This division may be relevant to take into account the greater teaching experience of the former. Since the article focuses on students' academic performance, non-academic personnel were not included since they do not participate in the direct process of converting educational inputs into the educational outputs that we are describing. Only faculty hold key roles as the implementers of all curriculum and instruction. As an output variable of the instructional component of higher education, our analysis primarily uses for each institution the total number of passed credits by its undergraduate students in the 2015–2016 AY according to the two broad fields of study (teaching outputs).

Our choice of input and output variables implies innovation in comparison with previous papers that have appeared in the DEA literature. Among other advantages, we avoid the problem of having full-time and part-time students; also, the efficiency of teaching can be assessed more accurately considering the same time dimension of inputs and outputs. Additionally, we used the number of teaching staff members and enrolled undergraduate students as inputs and the number of bachelor's degree graduates as outputs in order to perform a sensitivity analysis.[11] It is also worth pointing out that total volume measures (strictly positive continuous variables) were used for all inputs and outputs, avoiding the use of variables measured in the form of ratios, percentages, and indices. Indeed, there is an ongoing scholarly discussion regarding the appropriateness of ratio data in DEA models (e.g., Ref. [42]). Moreover, our approach defines all inputs and outputs without using monetary units, measuring technical efficiency in the engineering sense of microeconomic analysis.

2.6. Bachelor's degree production time and its determinants

Another goal of this study is to estimate the average time it takes for Spanish face-to-face public universities to award bachelor's degrees. Based on academic credits enrolled and passed, we propose the following steps.

1. Determine the total number of credits required for graduation. In Spain, the total number of academic credits needed to complete a bachelor's degree program is 240.
2. Identify the average number of credits taken by students each academic year.
3. Calculate the academic performance rate, that is, the average percentage of credits that students successfully complete each academic year. For instance, if the academic performance rate (the pass rate) is around 80%, it means that students generally pass 80% of the credits they enroll in.

[6] In the measurement of HEIs' performance, the DEA CCR model provides a measure of the overall (global) performance of each university.

[7] The concept of "scale" is typical of the microeconomic analysis of firms that produce cars, furniture, etc. For example, firms experiencing increasing returns to scale (IRS) could optimize their production process by moving to a larger dimension. However, in the production of knowledge, whether in the form of courses taught or degrees awarded, the concept of "scale" does not have an easy interpretation or direct applicability. Therefore, the breakdown of global technical efficiency (i.e., CRS efficiency) into scale efficiency and "pure" technical efficiency (i.e., variable returns-to-scale efficiency) is difficult to apply in the current study.

[8] See Cui et al. [14], who present a recent summary table with the main inputs and outputs used in published DEA studies that measure university efficiency.

[9] Undergraduate students take courses in two semesters, and each course or subject has, on average, 6 credits (about 4 h of in-person classes per week). Part-time students are not considered in Spain. There are also no courses during the summer.

[10] Given our degrees-of-freedom constraints, the inclusion in the DEA models of more disaggregation of fields of study would not be wise in any case.

[11] Applications of DEA to assess performance in higher education have traditionally used (under)graduate enrollment in colleges and universities as inputs and the number of (under)graduates as outputs [14].

4. Calculate the average number of credits passed per academic year. For example, if students take an average of 55 credits per academic year and have a pass rate of 80%, the average number of credits passed per academic year would be 44 credits.
5. Divide the total number of credits required for graduation by the average number of credits passed per academic year to estimate the number of years required to graduate. If the total required credits are 240 and the average credits passed per academic year is 44, the estimated number of years to graduate would be about 5.5 years.

Finally, we propose survival models, also known as duration or hazard models, to identify the explanatory variables that significantly explain time to degree. Survival analysis concerns analyzing the time to the occurrence of an event. The length of time T, until someone earns an undergraduate degree (failure time $T = t$), is the time-to-event measure of interest in our study. Basically, a duration measures the length of time spent by an individual in a given state [43].[12] Duration data is typically non-normal and often right-skewed, meaning that ordinary least squares (OLS) regression might not be appropriate for modeling such data [44]. Instead, duration models (typically either a Cox proportional hazards regression model or a parametric survival model) are more suitable for analyzing duration data.[13] The Cox proportional hazards regression model [45] is one of the most widely used duration models. It is a semi-parametric model that does not require assumptions about the underlying distribution of the duration.[14] Instead, it estimates the hazard ratio, which measures the relative risk of the event happening at any given time. The Cox model is useful for studying the effect of various covariates on the duration of an event. Nevertheless, to take into account unobserved factors that could influence bachelor's degree production time, we also estimate a parametric duration model. In parametric survival models (accelerated failure time (AFT) models), however, one is required to make specific assumptions about the form of the hazard function. Commonly used parametric survival models include the exponential survival model, the Weibull distribution, and lognormal regression. More details can be found in the Appendix.

3. Technical efficiency in the provision of undergraduate teaching

3.1. Descriptive statistics

Table 1 displays the descriptive statistics of the four inputs and two outputs used in the first DEA exercise.[15] A preliminary exploratory analysis shows that academic performance rates—what percentage of the credits enrolled a student is able to pass in one academic year—are relatively low at traditional Spanish public universities (last column of Table 1). On average, for the public higher education system, the rate of academic performance is about 80 percent in humanities and social sciences degrees and 75 percent in hard sciences, health sciences, and engineering degrees. However, it is essential to differentiate between student academic performance and university efficiency, two connected but dissimilar notions. The concept of efficiency is related to the way in which resources are used in production. In this study, we examine to what extent university inputs are being used in an optimal manner to produce educational outputs. The meaning of "optimal" determines the meaning of "efficiency."

3.2. How has each university performed in providing undergraduate teaching?

The output orientation does not concern itself with the efficient use of the educational inputs but rather with the maximization of the teaching outputs. The estimates of technical efficiencies (CRS TE scores) are shown in Table 2 (second column). The average efficiency of the Spanish public system of higher education is 1.061 (about 94%), meaning that universities, as an industry, should simultaneously expand their teaching outputs by around 6%, given their inputs, to operate efficiently (see bottom of the second column). However, the percentage increase in teaching outputs varies according to the institution analyzed. Some universities, such as Universitat Pompeu Fabra in Barcelona or Universidad Pablo de Olavide in Seville, are (relatively) efficient; they got a CRS TE score equal to 1 and no slacks (slack values are not displayed here). On the contrary, relatively inefficient institutions obtained a CRS TE score greater than 1. For example, Universitat Autònoma de Barcelona obtained a CRS TE score equal to 1.012, so it should simultaneously increase its two outputs by about 1.2% (i.e., a 1.2% increase in both passed credits in social sciences degrees and non-social sciences degrees) to become efficient (all input and output slacks were null).[16] Likewise, for example, the University of the Basque Country (Euskal Herriko Unibertsitatea) should simultaneously increase its two teaching outputs by 11.6% to become efficient.[17] As noted, only 11 out of the 46 universities are globally efficient.

3.3. Non-radial DEA model: output-oriented CRS model

Although the analysis carried out so far using radial efficiency measures yields interesting information on university performance,[18] from the point of view of university policy and management, it would be more relevant to have information on the specific percentage increase in each of the teaching outputs. In other words, the standard envelopment DEA models assume a proportional expansion of the outputs. Nonetheless, in some instances, these assumptions might be too restrictive. This has led to the development of non-radial models. A non-radial DEA measure (i.e., the Russell measure) allows for unlike proportional augmentations in each positive output. Table 2 also shows in its last two columns the results of the proposed non-radial DEA model to improve the efficiency of inefficient institutions by focusing on the output side and allowing for different proportional augmentations in each positive teaching output.[19] For example, the Universitat Autònoma de Barcelona is efficient in the production of humanities and social sciences degrees, and this institution should only increase its teaching output in hard sciences degrees, health sciences degrees, and engineering degrees by 2.4% (all input and output slacks were null). Hence, the Russell measure

[12] The duration outcome measures the length of time from the beginning of a state until it ends (failure time). The analysis of unemployment duration data continues to be the primary application field for duration models in economics. There is abundant literature analyzing factors that affect the duration of unemployment spells [61].

[13] At its core, survival analysis concerns nothing more than making a substitution for the normality assumption characterized by OLS with something more appropriate for the problem at hand [44].

[14] When using a Cox proportional hazards model, one is freed from the necessity of specifying the distribution of the hazard function or, equivalently, from specifying the distribution of event times [62].

[15] There are 47 on-site universities within the Spanish public university system. We finally work with 46 of them (DMUs), excluding the Universitat Politècnica de Catalunya because it only offers engineering degrees. One of the central assumptions of DEA is that all DMUs in the sample are functionally alike in the sense that all DMUs obtain (use) similar outputs (inputs) (e.g., Ref. [63]).

[16] In fact, all output slacks were zero for all DMUs in this analysis, and some (very few) DMUs presented positive input slacks. Slack details can be requested from the author upon request.

[17] For this university, an input slack was also obtained for hired faculty, implying an additional reduction of 296 academics to become efficient in teaching provision.

[18] The "Farrellian" radial efficiency measurement.

[19] In this analysis, some (very few) DMUs got positive input slacks for the teaching staff only. The rest of the input slacks and all the output slacks were null.

Table 1
Assessing the efficiency of Spanish public universities in the provision of undergraduate teaching, 2015–2016: descriptive statistics.

	Obs.	Mean	Std. Dev.	Min.	Max.	Rate (%) of academic performance
Input variables						
Tenured faculty (FTE)	46	919.3	598.9	210.3	2706.5	
Non-tenured faculty (FTE)	46	748.0	477.7	135.3	2082.8	
Total credits enrolled in arts and humanities, social sciences, and law programs	46	630,070.5	456,180.8	32,596.0	1,938,274.0	
Total credits enrolled in hard sciences, health sciences, and engineering and architecture programs	46	432,937.1	299,156.1	59,032.5	1,358,185.0	
Output variables						
Total passed credits in arts and humanities, social sciences, and law programs	46	508,162.5	372,757.7	21,908.5	1,566,471.0	80.3
Total passed credits in hard sciences, health sciences, and engineering and architecture programs	46	326,725.9	222,666.4	39,963.0	938,432.3	75.2

Source: author's elaboration

helps to identify the specific output that is driving the inefficiency of a DMU. It provides insights into the potential improvements that can be made to enhance efficiency by increasing the amount of a particular output. In this new analysis, the University of the Basque Country (Euskal Herriko Unibertsitatea) should increase the passed academic credits in humanities and social sciences degrees by 6.7% but should increase the passed academic credits in hard sciences degrees, health sciences degrees, and engineering degrees by 16.9%.[20] Since non-radial efficiency measures can identify specific areas of inefficiency for each DMU, non-radial DEA models seem to be more suitable for program evaluation in the public sector.[21] In the case of public universities, non-radial DEA models can identify specific undergraduate programs that require improvement.

4. Technical efficiency in the production of undergraduates

We just measured universities' efficiency based on student credit load, a novel approach to the evaluation of university performance. However, DEA models that employ typical inputs and outputs in the assessment of university performance are run in this section as a sensitivity analysis. As we have already mentioned, applications of DEA to evaluate performance in higher education have usually used the number of (under)graduates as an output and the enrollment of (under)graduates students in colleges and universities as an input. As seen in Table 3, in the academic year 2015–2016, on average, about 11,400 (8000) students were enrolled for social sciences undergraduate degrees (non-social sciences degrees) at on-site public universities in Spain, and around 1900 (1500) students graduated on average from undergraduate programs.[22]

Table 4 shows the results of the envelopment (radial) and non-radial DEA models. The analysis used as input variables the number of students enrolled in social sciences and non-social sciences degrees, in addition to tenured and non-tenured academic staff. As one of the outputs, the number of undergraduate graduates was incorporated into the model run, differentiating between social sciences and non-social sciences graduates.[23] As can be seen in the lower part of Table 4, the mean efficiency of the public system of higher education in undergraduate degree production is 1.206 (around 84%). To operate efficiently, higher education institutions (HEIs) as an industry should simultaneously expand their outputs by 21% (radial DEA measure) while keeping their inputs fixed. Nonetheless, non-radial DEA measures indicated that the inefficiency in the production of scientific and technical degrees was greater than that in the production of humanities and social sciences degrees. Specifically, the average efficiency in the production of social sciences degrees was around 87%, and around 79% for the production of non-social sciences degrees. As seen in the last row and last two columns of Table 4, the production of social sciences degrees should increase by 17.2%, while the increase in non-social sciences degrees should be 31%.

If we focus on specific institutions, the results reveal that Spanish universities such as Universitat Pompeu Fabra and Universidad Pablo de Olavide are technically efficient in producing undergraduates (an efficiency score equal to 1 and all input and output slacks equal to 0).[24] On the contrary, Universidad de Salamanca, for instance, is inefficient, indicating by its radial DEA measure that it should increase both outputs simultaneously by 4.7% to become efficient.[25] However, the non-radial DEA measures indicated that this institution is efficient in the production of social sciences undergraduates but not in non-social sciences degree production since it should increase its production of undergraduates by 13.2%.[26]

Finally, if we compare the results of Table 2 and those of Table 4, we observe that of the 11 universities that are efficient in maximizing academic performance (Table 2), six of them are also efficient in producing undergraduates (Table 4). However, if we consider the public higher education system as a whole, it is more inefficient in the production of undergraduates (Table 4) than in the delivery of undergraduate teaching (Table 2). For validating the results, we used rankings of the efficiencies and applied nonparametric statistical tests. As we will see below, students enroll, on average, in fewer credits than the theoretical load of an academic year. This fact, together with student academic underperformance, translates into an average production time for undergraduates greater than the theoretical four years.

5. Bachelor's degree production time

To test the robustness of the results obtained so far in the performance evaluation of teaching activities and undergraduate degree production, we computed Spearman's rank correlations between DEA (CRS) TE scores shown in Tables 2 and 4 (second column in both cases). Spearman's rank correlation coefficient assesses the statistical dependence between the rankings of two variables, which measures the strength and direction of the association between two ranked variables. In the current study, Spearman's rho was 0.481 ($p < 0.001$). The null hypothesis is rejected, and we have solid evidence to believe H_1 (i.e.,

[20] Also, a reduction of 207 hired academics.

[21] Many other real-world evaluations in the public sector might require non-radial measures of technical efficiency to be used. For example, the evaluation of the efficiency of teaching hospitals, which offer a wide range of medical services but also provide medical education and training to future healthcare professionals.

[22] In Spain, postgraduate students represent a very small percentage of the total student body and are not included in the analysis. They were also not included in the analysis in the previous section.

[23] Descriptive statistics are also displayed in Table 3.

[24] Slacks result is not displayed.

[25] In addition to a reduction in 2 non-tenured academics (result not displayed).

[26] In addition to a reduction in 39 non-tenured academics (result not displayed).

Table 2
Efficiency measurement of Spanish public universities in their provision of undergraduate teaching, 2015–2016 academic year.

		Output-Oriented CRS Non-Radial Efficiency	
DMU	Output-Oriented CRS Radial Efficiency[a]	Percentage increase in teaching output 1[b]	Percentage increase in teaching output 2[c]
Universidad Autonoma de Madrid	1.000	0.0	0.0
Universidad de Granada	1.000	0.0	0.0
Universidad de Leon	1.000	0.0	0.0
Universidad Miguel Hernandez de Elche	1.000	0.0	0.0
Universidad Pablo de Olavide	1.000	0.0	0.0
Universidad Politecnica de Madrid	1.000	0.0	0.0
Universidad Rey Juan Carlos	1.000	0.0	0.0
Universitat de Barcelona	1.000	0.0	0.0
Universitat de Lleida	1.000	0.0	0.0
Universitat Politecnica de Valencia	1.000	0.0	0.0
Universitat Pompeu Fabra	1.000	0.0	0.0
Universitat Autonoma de Barcelona	1.012	0.0	2.4
Universitat de Girona	1.017	1.1	2.6
Universitat de Valencia	1.020	2.0	2.3
Universidad Carlos III de Madrid	1.022	0.0	8.1
Universidade de Santiago de Compostela	1.039	9.3	3.0
Universidad de Jaen	1.040	3.1	13.2
Universidad de Salamanca	1.040	3.4	6.9
Universidad de Malaga	1.045	3.7	14.7
Universitat Rovira i Virgili	1.045	4.2	5.0
Universidad de Almeria	1.052	4.6	11.7
Universidad Publica de Navarra	1.060	0.5	14.4
Universidad de Burgos	1.062	2.6	11.1
Universidad de Murcia	1.066	11.3	6.1
Universidad de Extremadura	1.067	7.2	6.2
Universidad de Castilla-La Mancha	1.067	9.1	4.6
Universidad Complutense de Madrid	1.069	6.8	7.7
Universidad de Alcala	1.069	9.1	5.5
Universidad de Cordoba	1.070	4.4	11.1
Universidad de Alicante	1.072	6.8	10.3
Universidad de Valladolid	1.072	6.4	10.8
Universidad de La Laguna	1.073	12.7	6.3
Universidad de La Rioja	1.083	6.9	24.6
Universidad de Zaragoza	1.094	11.1	8.9
Universidad de Las Palmas de Gran Canaria	1.099	12.0	9.6
Universidad de Cadiz	1.103	12.7	8.0
Universitat Jaume I	1.105	9.8	15.8
Universidad de Oviedo	1.107	10.6	11.0
Euskal Herriko Unibertsitatea	1.116	6.7	16.9
Universidad de Sevilla	1.116	10.2	13.9
Universidade de Vigo	1.121	10.6	31.4
Universitat de les Illes Balears	1.128	14.5	12.5
Universidad de Huelva	1.132	12.7	19.1
Universidad de Cantabria	1.139	13.7	14.0
Universidade da Coruña	1.191	18.7	22.4
Universidad Politecnica de Cartagena	1.208	32.6	18.4
Average	1.061	6.3	8.5

All computations were done using DEA-Frontier software [38].
[a] DEA technical efficiency score under constant returns to scale (output-oriented). Universities achieving a score of 1 are efficient, while a university is inefficient if the score is > 1.
[b] Passed academic credits in humanities and social sciences degrees.
[c] Passed academic credits in hard sciences degrees, health sciences degrees, and engineering degrees.
Source: author's calculations

Table 3
The efficiency of Spanish public universities in the production of undergraduates, 2015–2016: descriptive statistics.

	Obs.	Mean	Std. Dev.	Min.	Max.
Input variables					
Tenured faculty (FTE)	46	919.3	598.9	210.3	2706.5
Non-tenured faculty (FTE)	46	748.0	477.7	135.3	2082.8
Total number of undergraduates enrolled in social sciences degree programs[a]	46	11,359.6	7947.7	669.0	34,407.0
Total number of undergraduates enrolled for non-social sciences degrees[b]	46	7918.2	5428.2	1062.0	26,061.0
Output variables					
Total number of social sciences undergraduates[a]	46	1884.4	1313.4	74.0	6021.0
Total number of non-social sciences undergraduates[b]	46	1486.8	1060.8	202.0	4576.0

[a] Arts and humanities, and social sciences and law programs.
[b] Hard sciences, health sciences, and engineering and architecture programs.
Source: author's elaboration

Table 4
Efficiency measurement of undergraduate degree production at Spanish public institutions of higher education, 2015–2016 academic year.

DMU	Output-Oriented CRS Radial Efficiency	Output-Oriented CRS Non-Radial Efficiency	
		Percentage increase in the production of social sciences undergraduates	Percentage increase in the production of non-social sciences undergraduates
Universidad de Almeria	1.000	0.0	0.0
Universidad de Extremadura	1.000	0.0	0.0
Universidad de La Rioja	1.000	0.0	0.0
Universidad de Leon	1.000	0.0	0.0
Universidad Pablo de Olavide	1.000	0.0	0.0
Universidad Politecnica de Madrid	1.000	0.0	0.0
Universidad Rey Juan Carlos	1.000	0.0	0.0
Universitat Politecnica de Valencia	1.000	0.0	0.0
Universitat Pompeu Fabra	1.000	0.0	0.0
Universidad de Malaga	1.023	0.0	17.2
Universidad de Salamanca	1.047	0.0	13.2
Universidad de Alicante	1.068	0.0	21.5
Universidad de Granada	1.093	3.0	24.7
Universidad Miguel Hernandez de Elche	1.116	40.0	0.0
Universidad de Jaen	1.136	11.2	16.2
Universitat de Valencia	1.151	8.7	23.6
Universidad de Huelva	1.155	0.0	31.2
Universidad de Valladolid	1.163	0.0	49.5
Universitat Rovira i Virgili	1.167	9.6	28.7
Universidad de La Laguna	1.171	16.9	20.3
Universidad Publica de Navarra	1.176	10.8	25.2
Universidad de Burgos	1.184	0.0	50.7
Universidade da Coruña	1.197	9.1	31.2
Universidad Autonoma de Madrid	1.201	18.8	22.0
Universitat de Girona	1.228	13.6	38.5
Universitat Autonoma de Barcelona	1.234	14.6	37.6
Universidad Complutense de Madrid	1.234	11.7	45.7
Euskal Herriko Unibertsitatea	1.242	30.8	18.1
Universidad de Sevilla	1.254	17.7	34.6
Universitat Jaume I	1.258	11.0	56.4
Universidade de Vigo	1.270	27.6	26.4
Universidad de Alcala	1.278	28.9	26.7
Universidad de Oviedo	1.304	53.2	19.5
Universitat de Lleida	1.310	10.9	62.7
Universitat de Barcelona	1.329	33.1	32.9
Universidad de Castilla-La Mancha	1.340	23.4	50.5
Universidad de Murcia	1.352	33.3	37.8
Universidade de Santiago de Compostela	1.360	35.1	46.9
Universidad Politecnica de Cartagena	1.364	118.4	23.8
Universitat de les Illes Balears	1.378	20.0	60.7
Universidad de Cantabria	1.380	15.2	67.1
Universidad de Zaragoza	1.399	27.5	54.9
Universidad Carlos III de Madrid	1.430	28.6	69.3
Universidad de Cadiz	1.471	36.8	62.4
Universidad de Las Palmas de Gran Canaria	1.479	32.2	101.0
Universidad de Cordoba	1.549	39.4	73.3
Average	1.206	17.2	30.9

All computations were done using DEA-Frontier software [38].
Source: author's calculations

rankings from DEA scores are directly related). Thus, as expected, the greater the efficiency of the undergraduate teaching process, the greater the efficiency in the production of undergraduate degrees. However, for the public higher education system, the median value of the efficiency in the production of undergraduates (1.199) was significantly higher than the median value of the efficiency in the provision of teaching (1.064).[27] In other words, Spanish public universities are more inefficient at producing undergraduate academic degrees than at providing undergraduate teaching. This can be explained "by the reduction suffered in the number of credits that the students of public universities enroll annually (55 annually) as a result of the increase in tuition fees (the average price of a credit) in the second and successive enrollments" ([46], p. 88). For the sample of universities used in this article, the average number of credits enrolled was also about 55 in the 2015–2016 academic year, and undergraduate students passed on average around 78% of the credits of those enrolled in that academic year (Table 5). What are the consequences of "low" enrollment intensity and "low" student performance? If students take on average 55 college credits instead of 60 credits,[28] of

[27] The efficiency scores did not appear to be normally distributed. We used the non-parametric test in Stata software; *signtest* tests that the median of differences between matched pairs is 0 (the null hypothesis). The null hypothesis was rejected at the 5% level. The difference was statistically significant.

[28] Scheduled academic load for one school year.

Table 5
Academic information and student outcomes at Spanish public universities, 2015–2016 academic year.

	Obs.	Mean		Std. Dev.	Min	Max
Credits enrolled per student[a]						
	Obs.	Mean	(median)	Std. Dev.	Min	Max
All bachelor's degree programs	46	54.71	(55.05)	2.92	49.40	65.81
Social sciences degrees	46	54.78	(55.16)	3.49	48.37	68.96
Non-social sciences degrees	46	54.39	(54.62)	2.45	49.25	60.63
Student academic performance[b]						
	Obs.	Mean	(performance rate)[c]	Std. Dev.	Min	Max
All bachelor's degree programs	46	0.78	(78%)	0.05	0.60	0.89
Social sciences degrees	46	0.80	(80%)	0.05	0.67	0.91
Non-social sciences degrees	46	0.75	(75%)	0.06	0.59	0.87
The average time to complete a four-year degree[d]						
	Obs.	Mean	(median)	Std. Dev.	Min	Max
All bachelor's degree programs	46	5.66	(5.60)	0.58	4.55	8.01
Social sciences degrees	46	5.50	(5.47)	0.54	4.19	7.33
Non-social sciences degrees	46	5.92	(5.90)	0.62	4.88	8.14

[a] For each university, it is calculated as a ratio between the total number of credits enrolled and the total number of undergraduate students registered.
[b] For each university, it is calculated as a ratio between the total number of passed academic credits and the total number of credits enrolled.
[c] What percentage of the credits enrolled a student is able to pass in one academic year.
[d] Since "the study plans [curriculum] will have 240 credits" (Royal Decree 1393/2007, October 29), the duration (in years) has been estimated for each institution by dividing 240 by the product of the average number of credits enrolled per student and the academic performance rate. Table 5 shows the average for the higher education system. Detailed information is displayed in Fig. 2 (all bachelor's degree programs were included).
Source: author's calculations

which only 78% are passed, undergraduate students will obviously need more than four years to complete a four-year bachelor's degree. According to our estimates, the average time enrolled for bachelor's degree completion is 5.7 years in public institutions (Table 5).[29]

Therefore, an evident inefficiency of the Spanish public higher education sector is the "excessive" time it takes to produce undergraduate degrees, especially if we keep in mind that these are highly subsidized programs. We use quotation marks because everything depends on the extra time that academics (or taxpayers) assume is reasonable to complete a 4-year bachelor's degree. Even in the United States, although its higher education system is different, the average time to complete a bachelor's degree was 5.2 years in public institutions and 4.8 years in private, not-for-profit institutions between July 2014 and June 2015 [47].[30] Hence, the DEA models in Section 3 might be overestimating (underestimating) the technical efficiency (inefficiency) of Spanish public universities.

Time-to-degree estimates by university are displayed in Fig. 2. All undergraduate programs were considered jointly without distinguishing by fields of knowledge. The intended completion time for a bachelor's degree is four years in Spain, but the actual time to get a four-year degree is 5.7 years on average. Nonetheless, there are differences among institutions. "Small-sized" universities such as Universitat Pompeu Fabra and Universidad Pablo de Olavide, along with other "medium-large-sized" universities such as Universidad de Granada and Universidad Autónoma de Madrid, are able to produce undergraduate education degrees in less than 5 years; nonetheless, for the vast majority of universities, it takes at least 5 years to produce these qualifications.

6. Explaining time-to-degree at Spanish public universities

6.1. Descriptive statistics

Since the measure of time-to-graduation has become a benchmark of university success (e.g., Ref. [48]), this section aims to identify those factors that explain time-to-degree at Spanish public universities. Thus, the dependent variable in regressions (duration models) was the average time it took each university to produce its undergraduate degree programs (estimates of duration outcomes shown in Fig. 2).[31] As explanatory variables, we considered those relevant ones for which we had information in our database. Table 6 shows the descriptive statistics. First, a teaching quality index by the university was used in the regressions. The U-Ranking project by the Valencian Institute of Economic Research (IVIE) offers the ranking of Spanish universities according to their performance indices [49]. The U-Ranking Teaching Index (performance ranking) considers spending per student, university entry cut-off marks, dropout rate, and percentage of foreign students, among other indicators (the higher the value, the higher the teaching quality). Second, faculty per hundred students was calculated for each institution. A higher faculty-to-student ratio would be associated with institutions whose courses, on average, have fewer students. Third, we considered the weight of the degrees in health sciences since these programs attract the best high school students in Spain, but not all universities offer them. For each university, we divided the credits enrolled in health sciences undergraduate programs in 2015–2016 by the total number of credits enrolled. Finally, for each university, we considered the weight of technical degrees to take into account the difficulty involved in technical university studies (e.g., computer engineering) and also that there are universities more specialized in this type of program than others (e.g., tech universities). It was defined for each institution as the quotient between the credits enrolled in technical degrees and the total number of credits enrolled.

6.2. Time to degree for undergraduate programs: a duration analysis

As we already mentioned in the second section, the fact that the dependent variable of interest (time-to-degree) was measured in years means that hazard-based duration models are also suitable for modeling the duration of time until graduation. Table 7 displays the regression

[29] In Table 5, the mean values of academic performance rates—as well as average degree completion times—differed significantly from a statistical point of view between social sciences and non-social sciences degrees.

[30] Previous research also confirmed that the length of time it takes college graduates to attain degrees has increased, pointing to a reduction in the pace at which relatively continuously enrolled students complete college credits; that is, students are accumulating the same number of college credits more slowly [64].

[31] Since we use aggregated information for the different institutions as explanatory variables, we do not distinguish between social sciences degrees and non-social sciences degrees.

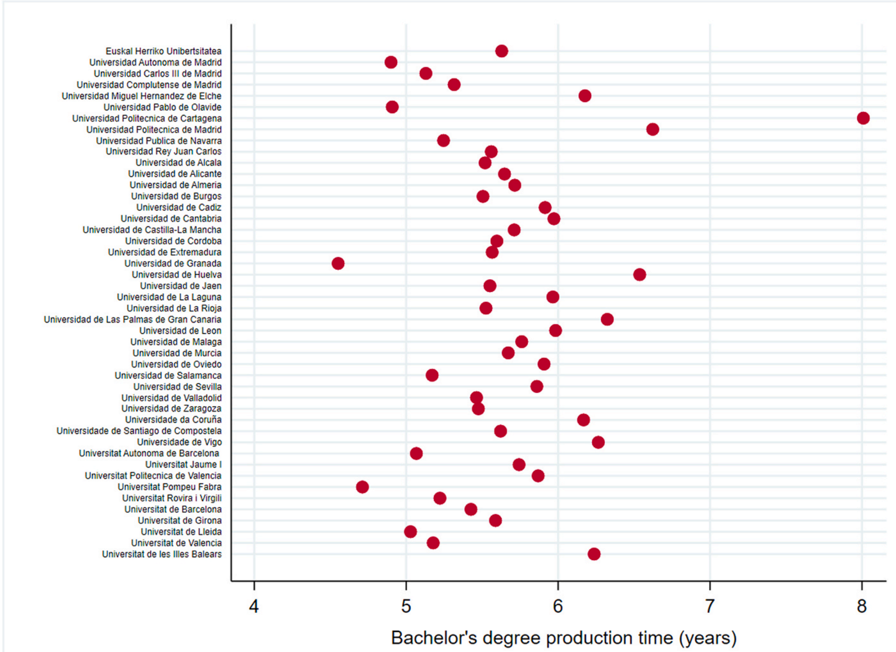

Fig. 2. Undergraduate production at Spanish public universities.
Average time-to-degree estimates in years on the horizontal axis.
Source: author's elaboration

Table 6
Explanatory variables of time to graduation.

	Mean	Std. Dev.	Min	Max
U-Ranking Teaching Index 2018	1.03	0.12	0.8	1.4
Faculty per hundred students	8.85	1.53	3.54	12.14
Weight of health sciences undergraduate programs	0.12	0.07	0.00	0.30
Weight of technical degrees	0.22	0.19	0.02	0.93

Source: author's elaboration

results. We begin our analysis by using the Cox proportional hazards regression model [45], which makes no assumptions about the shape of the hazard over time. Table 7 reports the hazard ratios (HRs) for the explanatory variables (regressors) included in the analysis. Note that we assume no time-varying covariates. A hazard ratio greater than 1 is associated with a "higher risk of failure." In this study, a greater risk means a shorter survival time and, thus, a shorter period of time until graduation. In summary, if the HR is above one, the effect of the regressor is to shorten the time-to-degree. On the contrary, if the hazard ratio is below one, the corresponding regressor lengthens that period. The estimated hazard ratios of the teaching quality and faculty-to-student ratio are greater than 1 and statistically significant. Thus, a shorter time to graduation is associated with higher teaching quality as well as a higher faculty-to-student ratio. However, HR is less than 1 for the weight of technical degrees, meaning that, all else being equal, the average time it takes to produce a university degree increases as the range of technical degrees offered by a university increases. At the bottom of Table 7, we performed a formal test based on Schoenfeld residuals for evaluating the proportional hazards (PH) assumption of the Cox model (the null hypothesis). We failed to reject the null hypothesis at the 5% significance level.

Additionally, to take into account unobserved factors that could in-

Table 7
Duration analysis to explain the time-to-degree.

	Cox regression			Lognormal AFT regression (gamma frailty)			
	Hazard ratio		Robust Std. Err.	Coefficient		Robust Std. Err.	Time ratio
U-Ranking Teaching Index 2018	70.355	***	109.512	−0.251	***	0.061	0.778
Faculty per hundred students	1.370	**	0.197	−0.012	**	0.006	0.988
Weight of health sciences undergraduate programs	0.058		0.132	0.201		0.154	1.223
Weight of technical degrees	1.19E-03	***	1.54E-03	0.401	***	0.107	1.493
Constant				1.984	***	0.087	7.271
	Number of obs. = 46			Number of obs. = 46			
	Wald chi2(4) = 36.62			Wald chi2(4) = 41.52			
	Prob > chi2 = $p < 0.001$			Prob > chi2 = $p < 0.001$			
	Log pseudolikelihood = −118.32458			Log pseudolikelihood = 60.225569			
					Point estimate	[95% conf. interval]	
	Test of proportional-hazards assumption			sigma	0.061	0.033	0.113
	chi2 = 3.81			theta	0.109	3.80E-04	31.055
	Prob > chi2 = 0.432						

** $p < 0.05$ *** $p < 0.01$.
The analysis was performed using Stata® 18 statistical software [50].
Source: author's elaboration

fluence bachelor's degree production time, we estimate a parametric duration model. Specifically, Table 7 shows the results of the lognormal regression (accelerated failure-time (AFT) form), which accounts for unobserved heterogeneity (also termed "frailty" in survival analysis).[32] We first fit a generalized gamma model to test the following hypotheses [44]: H_0: $\kappa = 0$, in which case if H_0 is true then the model is lognormal; H_0: $\kappa = 1$, in which case if H_0 is true then the model is Weibull. We could not reject the null "H_0: $\kappa = 0$" at the 5% significance level. Therefore, the lognormal model is an appropriate parametric model for the data (full details are available upon request). However, with the AFT formulation, a negative (positive) coefficient indicates that the regressor accelerates (decelerates) the time to failure, and time ratios will be lower than 1 (greater than 1). The results shown in the last columns of Table 7 confirm that higher teaching quality as well as a higher faculty-to-student ratio shorten the time to graduation (negative coefficients and statistically significant). Time ratios (exponentiated coefficients) are lower than 1, making teaching quality a crucial factor that explains bachelor's degree production times (the time ratio was the lowest). The results shown in the last columns of Table 7 also confirm that the time to produce undergraduate degrees lengthens when the university increases its specialization in technical degrees (the estimated coefficient associated with the regressor is positive and the time ratio is greater than 1).[33]

7. Discussion

Measuring performance in public-sector organizations has many benefits. It allows managers to set up mechanisms to evaluate, control, budget, motivate, promote, and improve their strategic decision-making [51]. Policymakers and managers of higher education institutions also need to know how well their universities are operating. The exercises to evaluate the results of universities in many countries increasingly use rankings that order institutions from different perspectives and with different criteria. In reality, rankings are a particular way of approaching the evaluation of university results, and their attractiveness stems from the fact that they offer information in a simple and synthetic way. Nonetheless, data envelopment analysis provides wealthier managerial information for university performance evaluation since it captures performance in a multi-output, multi-input production framework. For example, how much output universities could produce from given inputs (known as an output-oriented radial approach). In higher education, non-parametric, non-radial measures of efficiency have not been exploited until now, however, and constitute the main contribution of this article to the empirical literature. For instance, a crucial advantage of non-radial DEA models is the removal of the assumption that inefficiency occurs to the same degree in every university output. Based on these models, the results shown allow us to affirm that some Spanish universities should perhaps specialize in the production of degrees in the humanities and social sciences, in which they are efficient, and abandon scientific and technical degree programs in which they show high inefficiency (e.g., Universidad de Valladolid and Universidad de Huelva, Table 4). Others, on the contrary, show much less inefficiency in the production of technical degrees than in social sciences programs such as the Tech University of Cartagena. Does the latter really need to offer a Bachelor's Degree in Business Administration and Management when the results of our analysis (Tables 2 and 4) and the information provided by its own website reflect a high level of inefficiency in this social sciences program?[34] Offering public university education to citizens does not necessarily mean having to offer all kinds of degrees. It is more efficient to move students with grants to universities located in other cities than to offer them all kinds of degrees in their "neighborhoods." Studies appearing in the literature have shown that Spanish public universities with a greater percentage of grant recipients tend to be less inefficient because a greater percentage of grantees has positive effects on stimulating effort and academic performance (e.g., Ref. [28]).

Additionally, using information on student enrollment and academic performance, the amount of time undergraduate students needed to finish a four-year degree was estimated. A casual inspection of Fig. 2 confirms the "excessive" length of time it takes for universities to produce undergraduates. We were able to identify very few institutions that could function as benchmarks in the higher education sector, such as Universidad Pablo de Olavide, Universidad de Granada, Universidad Autónoma de Madrid, and Universitat Pompeu Fabra. In program evaluation, the word "benchmark" is often used to refer to a standard; the standards are the targets for program performance [52]. University performance evaluation has meaning only when goals have been set. Most undergraduate academic programs are designed so that they can be completed in four years. If the 2010 curriculum reform was designed correctly, Spanish universities should aim for students to finish their studies on time or need at most an extra year. Yet, the mean graduation time is much longer, 5.7 years. Taking more than 5 years to produce 4-year degrees tells us that something is wrong. Several reforms that were aimed at increasing the efficiency of Spanish universities were carried out in the early 2010s, such as the entry into force of Royal Decree-Law 14/2012 (the so-called Decreto Wert). This law granted public universities in each region the freedom to set the price of university tuition. While some studies showed that student performance improved after a change in the level of tuition fees (e.g., Ref. [53]), much remains to be learned about how student behavior in terms of the likelihood of course completion impacts course enrollment and time to graduation. That is, how tuition fee hikes and penalties for course repetition effect taking a reduced course load if students enroll only in those subjects that they believe they will pass. This enrollment behavior of undergraduate students reduces inefficiency in terms of academic productivity but increases it in terms of the time to graduation. By rethinking the theoretical student academic load (and courses) foreseen in the curricula, the requirements for access to universities, teacher training, and teaching strategies, among other actions, institutions should achieve their goals of producing undergraduates on time. Some researchers also claim that in order to modify this behavior, students should be informed about the negative consequences on future employment outcomes of postponing graduation, such as reduced employment probability and the starting salary penalty [54].

Taking an international comparative perspective, a growing concern in higher education is also the prolonged duration of degree completion, as it leads to decreased institutional efficiency and increased direct and opportunity costs for students [55]. Some remedies have been suggested, such as matching policies that aim to improve the match between (prospective) students and their degree programs, helping them make conscious and deliberate study choices [55]. However, cross-country overviews of completion rates and the average time to complete a degree are barely available [55], and a few papers have devoted their attention to the determinants of academic match [56]. Thus, more data is required, and more research about effective interventions is needed to further develop this area of policy analysis.

8. Conclusion

This article proposes the use of data envelopment analysis (DEA) for evaluating the technical efficiency performance of bachelor's degree programs within a public system of higher education. We ran different envelopment (radial) and non-radial DEA models to measure the relative efficiency of traditional Spanish public universities once the Bologna reform was complete. Since university inputs are more or less fixed (both teaching staff and places offered), we apply an output-based measure of efficiency. Thus, inefficiency is interpreted as the potential increase in university outputs given the inputs.

[32] The gamma distribution is frequently used for this purpose.
[33] No issues with multicollinearity were found.
[34] https://estudios.upct.es/grado/5101/resultados.

In evaluating the efficiency of teaching, the results of the standard DEA models point to an inefficiency in undergraduate teaching provision. The average efficiency of the Spanish public system of higher education is 1.061 (about 94%), meaning that universities, as an industry, should simultaneously expand their teaching outputs (credits exceeded by students) by around 6%, given their inputs, to operate efficiently. However, the main inefficiency is associated with the production of undergraduates. To operate efficiently, institutions of higher education, as an industry, should simultaneously expand the number of undergraduate degrees awarded by 21% (radial DEA measure), keeping their inputs fixed.

Along with conventional models for efficiency measurement (i.e., radial DEA models), this article has also exploited the possibilities offered to university management by the use of non-parametric, non-radial DEA models. The key advantage of the latter is the removal of the assumption that inefficiency occurs to the same degree in every university output. For inefficient institutions, we will no longer be required to increase all outputs by the same proportion to achieve efficiency. For example, the production of social sciences degrees should increase by 17.2%, while the increase in non-social sciences degrees should be 31%. The results allow us to affirm that some universities should specialize, perhaps, in the production of degrees in humanities and social sciences in which they are efficient and abandon scientific and technical degree programs in which they show high inefficiency. Others, on the other hand, show much less inefficiency in the production of technical degrees than in social sciences programs.

The main consequence of the observed inefficiencies in our study is the "excessive" time (5.7 years on average) that it takes Spanish universities to produce four-year undergraduate programs. Many factors can influence the production time for four-year bachelor's degrees. The Cox proportional hazards regression shows that a shorter time to graduation is associated with higher teaching quality as well as a higher faculty-to-student ratio. Parametric survival analysis using a lognormal distribution with gamma frailty also verifies these latter results. The consequences of these inefficiencies extend beyond the individual student experience and have broader implications for Spanish society and its economy. Firstly, prolonged study durations lead to delayed entry into the workforce. This delay translates into a loss of potential aggregate output. Moreover, it places an additional burden on the public education system, as longer program durations require increased financial resources and institutional support.

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Manuel Salas-Velasco: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

APPENDIX

The standard envelopment DEA model: output-oriented CRS model[35]

Let us consider a sample of n DMUs, DMU_j ($j = 1,2,\ldots,n$), for which a common set of "m" inputs, $\{x_{ij}\}_{i=1}^{i=m}\ x \in \mathbb{R}_{+}^{m}$, are converted into a common set of "s" outputs, $\{y_{rj}\}_{r=1}^{r=s}\ y \in \mathbb{R}_{+}^{s}$.[36] The technology that models the conversion of inputs into outputs is represented by: $\mathrm{T} = [(x,y) \mid x \text{ can produce } y]$. A constant returns-to-scale (CRS) DEA technology for output-oriented technical efficiency measurement involves the solution of the following linear programming (LP) problems, in which we labeled the DMU evaluated by the subscript k. Specifically, the output-oriented CRS envelopment model can be expressed as [38]

$$\begin{aligned} & \max \varphi \\ & \text{subject to} \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq \varphi\, y_{rk} \quad r = 1,2,\ldots,s; \\ & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik} \quad i = 1,2,\ldots,m; \\ & \lambda_j \geq 0 \quad \forall j = 1,2,\ldots,n. \end{aligned} \tag{2}$$

$$\begin{aligned} & \max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \\ & \text{subject to} \\ & \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \varphi^*\, y_{rk} \quad r = 1,2,\ldots,s; \\ & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik} \quad i = 1,2,\ldots,m; \\ & \lambda_j \geq 0 \quad \forall j = 1,2,\ldots,n. \end{aligned} \tag{3}$$

First, we calculate φ^* in (2) by ignoring the slacks. Then we optimize the slacks by fixing the φ^* in the linear programming problem (3), where s_i^-

[35] We would like to avoid the exposition of the technical details involved since DEA is well-established in the literature. See, among others, Amirteimoori et al. [65], Banker et al. [66], Charnes et al. [39,67], Cooper et al. [68,69], Liu et al. [4], Ramanathan [70], Ray [71], Seiford [6,72], and Zhu [38,73].

[36] For the units under evaluation, inputs and outputs must be greater than 0.

and s_r^+ represent input and output slacks, respectively.[37] DMU_k is efficient if and only if $\varphi^* = 1$ and $s_i^{-*} = s_r^{+*} = 0$ for all i and r, where the asterisk represents optimal values [38]. A technically efficient DMU cannot produce any additional output from its existing input mix. Otherwise, if $\varphi^* > 1$, the decision unit under evaluation is inefficient. In this case, $[(\varphi^* - 1)\ 100]$ is the percentage increase in all outputs—the maximum possible radial expansion—that could be achieved by the technically inefficient DMU under analysis to become efficient with input quantities held constant. Efficiency in the standard CCR DEA model is measured radially; that is, it requires equiproportional increases in all outputs. In some cases, achieving efficiency may also require further decreases in inputs and/or further increases in outputs (non-zero input/output slacks, respectively).[38] The above LP problems (i.e., the CCR model) should be solved n times (once for each DMU in the sample).

Time to graduation: survival analysis[39]

Hazard-based duration models are ideally suited to modeling duration data. Such models focus on an end-of-duration occurrence, given that the duration has lasted until some specified time [57]. This concept of the conditional probability of termination of duration recognizes the dynamics of duration, i.e., it recognizes that the likelihood of ending the duration depends on the length of elapsed time since the start of the duration.

A key concept in survival analysis is that of the hazard function. Let's consider a non-negative random variable, T, which describes the length of time until an event of interest occurs. The length of time it takes for a university to produce four-year undergraduate degree programs is the time-to-event measure of interest in our study. The hazard function (or hazard rate) specifies the instantaneous rate of failure at $T = t$, conditional upon survival to time t, and it is defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{Prob(t \le T \le t + \Delta t \mid T \ge t)}{\Delta t} \tag{4}$$

In our study, the hazard function represents the probability of awarding a degree at $T = t$, conditional upon survival to time t.

Let's suppose that a vector of basic covariates X is available for each institution, and aspects of X are expected to be predictive of subsequent failure time. The hazard function depends on the covariates X: $h(t|X)$.

The Cox proportional hazards regression model [45] states the hazard function as a function of two components following a multiplicative specification:

$$h(t|\mathrm{X}) = h_0(t)\exp(X\beta) \tag{5}$$

where the baseline hazard $h_0(.)$ involves t but not X; the second component involves X but not t. It provides hazard ratios (HR) for each predictor variable, indicating the change in the hazard rate for a unit change in the predictor variable, all else being equal. A HR greater than 1 suggests an increased hazard, while a HR less than 1 suggests a decreased hazard.

The Cox model does not make any assumptions about the shape of the baseline hazard function. By not making any assumptions about the distributional form of the baseline hazard, the Cox model avoids estimation bias derived from assuming a misleading parametric distribution [58]. In this sense, it is a "safe" choice of model.

Alternatively, we can estimate parametric duration models (accelerated failure time models) where we make assumptions about the shape of the baseline hazard $h_0(.)$.[40] Here, a covariate accelerates (or decelerates) the time to failure. Although we must do statistical tests to decide the regression model (Weibull, etc.), unlike the Cox model, they account for unobserved heterogeneity, also termed "frailty" in survival analysis (e.g., Ref. [59]).

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