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Unlocking university efficiency: a Bayesian stochastic frontier analysis

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Abstract

In this paper, we analyze the performance of the Spanish public university system over the 2010–2019 period, which was particularly turbulent due to the tight budget constraints imposed on universities. To disentangle the main sources of performance change, we adopt a dynamic approach by decomposing it into efficiency change (catching up) and technical change (shifts in the frontier). In contrast to many studies on higher education institutions (HEIs), we opt for stochastic frontier analysis, employing the ray production function proposed by Löthgren (1997) to account for the multiple-output nature of HEIs. Additionally, to offer a more detailed examination of uncertainty quantification, we conduct inference within the Bayesian paradigm. Broadly, results point to an overall positive performance change over the entire period, particularly for technical change during 2010–2014. However, there were notable discrepancies across universities, which could be unlocked with certain precision via the posterior distributions of performance and its components.

Keywords: Bayesian inference; efficiency; ray production function; stochastic frontier analysis; universities

1. Introduction

In the current knowledge economy, innovation has become a key driver of competitiveness, and labor or natural resources have been replaced by knowledge as the main source of wealth creation (Florida and Cohen, 1999; Uyarra, 2010b; Acs et al., 2017) at both regional and national levels. In such a context, universities, or higher education institutions (HEIs), have been acknowledged as key players whose increasingly varied activities impact regional economies in multiple ways (Uyarra, 2010a; Goddard et al., 2012). These activities have usually been synthesized in the three missions of universities, namely teaching (first mission), research (second mission), and, more recently, knowledge transfer through interaction in various ways with the socioeconomic environment (third mission) (Sánchez-Barrioluengo, 2014; Compagnucci and Spigarelli, 2020). Although all universities are concerned with these three missions in some degree, it has been argued that they are not homogeneous institutions because the balance between the three varies, which in turn changes their role in regional development processes (Uyarra, 2010a; Trippl et al., 2015).

Most of the literature on the functioning of universities and their impact on regional development has adopted "the more the better" principle, according to which the more output the various university activities produce, the higher they are ranked and the greater their societal and regional impact (Valero and Van Reenen, 2019), irrespective of the amount of resources used to carry out their actions. In fact, this same principle underlies many of the national or international university rankings (Johnes, 2018), such as, for example, the Academic Ranking of World Universities. However, the importance of the linkages between inputs and outputs, largely because of their implications for the public management of resources, has spawned a substantial literature analyzing a variety of questions related to the efficiency and productivity of HEIs, from a multiplicity of angles in terms of methodologies used, contexts examined, or measurement of what universities do. Specifically, many studies on HEIs efficiency have evaluated relevant factors such as (i) measuring, ranking, and comparing efficiency of universities across time and space (countries) (Guironnet and Peypoch, 2018; Johnes, 2018); (ii) identifying internal and environmental determinants of efficiency (Johnes and Salas-Velasco, 2007; Wolszczak-Derlacz, 2017; Rhaiem, 2017) and (iii) measuring how universities' efficiency influences regional economic development (Barra and Zotti, 2017; Agasisti et al., 2019; Crespo et al., 2022).

In the HEIs efficiency literature, the researcher is confronted with two critical issues, regardless of the particular objective of the study. The first refers to the definition and measurement of what universities do. This implies addressing the intricate task of identifying variables to measure university outputs for each of the university missions and the set of inputs used to produce them (Berbegal Mirabent and Solé Parellada, 2012). These decisions will define whether a technical or a cost-efficiency approach is used (Giménez and Martínez, 2006; Johnes and Salas-Velasco, 2007). The second critical issue concerns the methodology. Efficiency studies are usually based on frontier approaches, among them, data envelopment analysis (Charnes et al., 1978) and some of its variants—such as the nonconvex free disposal hull (Tulkens, 1993), and the partial frontier methods (Cazals et al., 2002; Aragon et al., 2005)—which are very popular options. Parametric methods such as stochastic frontiers (Kumbhakar and Lovell, 2000) are less commonly used, but relevant applications considering them are published regularly (such as the recent study by Johnes et al., 2022). As Agasisti (2023) rightly notes, both families of methods have strengths and weaknesses that complement each other, making the definitive preference for one over the other a challenge. In this study, we choose to work within the broad category of parametric techniques, particularly stochastic frontier analysis (SFA). This choice is motivated by the ability of these methods to directly provide efficiency scores in a statistically robust manner, allowing for the application of statistical inference to explore factors potentially associated with (in)efficiency.

However, in contrast to nonparametric approaches to efficiency measurement, extending the basic stochastic frontier model to accommodate the multiple-output nature of HEIs activities is not straightforward, and so they have been less frequently used in this field. Among various approaches to address this issue, such as copula-based models (Carta and Steel, 2012; Schmidt and Kneib, 2023) and the transformation of the vector of outputs to construct an aggregate output (Fernández et al., 2000), we focus on a multiple-output generalization of the single-output stochastic frontier production model proposed by Löthgren (1997) and more recently improved by Henningsen et al. (2017). This model, known as the stochastic ray production frontier (SRPF), has been successfully applied in various fields (Gerdtham et al., 1999; Löthgren, 2000; Bhattacharyya and Pal, 2013). It defines the Euclidean norm of the vector of output quantities as a function of input quantities and polar coordinate angles of the output quantities. Furthermore, as noted by Tsionas et al. (2022), "the issues of endogeneity and inconsistency, prevalent in stochastic distance functions, are less profound in the SRPF as the error terms affect outputs radially given the exogenous output mix."

Once the model has been selected, the researcher still has to decide how to carry out inference and prediction. In our case, we propose to work within the Bayesian approach as it allows a detailed study of parameter uncertainty during model estimation and prediction of (in)efficiency (see, for instance, Van den Broeck et al., 1994; Koop et al., 1994; Fernández et al., 2000; Tsionas, 2000). In a different way to the one proposed by Tsionas et al. (2022), we implement the approximation of the posterior distributions of the parameters of the SRPF model using the software package `JAGS` (Plummer, 2003), which offers a more user-friendly implementation of the Markov chain Monte Carlo approximation (of the posteriors) for nonexperts in the Bayesian approach.

The aim of this paper is therefore threefold. First, we provide a user-friendly Bayesian approximation of the SRPF models, thus contributing to the scarce literature on this methodology. Second, and more importantly, we fill the gap of the scarcity of empirical applications of this methodology by applying it in the context of HEIs efficiency. Finally, the proposed method allows us not only to measure static efficiency with a specific frontier for each of the years (cross section) but also to adopt a dynamic approach and to obtain a Malmquist productivity index in which efficiency shifts over time are decomposed into (i) shifts towards the best practice frontier (catching up) and (ii) shifts of the efficiency frontier itself. Indeed, our analysis of the Spanish university system is one of the few that adopt both a static and a dynamic perspective. This is of particular interest since the years analyzed (2010–2019) were highly turbulent due to the severe budgetary constraints imposed on universities in this decade.

The remainder of the paper is organized as follows. Section 2 reviews the literature on HEIs efficiency and the particularities of the Spanish context. Section 3 discusses how inputs and outputs for each of the universities' missions were measured and presents the dataset used in the paper. Section 4 describes how the ray production function method was adapted to measure the efficiency of universities using stochastic frontier models estimated with Bayesian techniques. Section 5 presents the results for the case of Spanish universities, and Section 6 concludes.

2. A sketch of the literature on the efficiency of HEIs and its applications in the Spanish case

As indicated by Agasisti (2023), universities (like other economic agents) operate efficiently when they produce as many outputs (in terms of teaching, research, and knowledge transfer) as possible while keeping the costs (either in terms of physical units or monetary quantities) to a minimum. In practice, inefficiencies can arise in this production process, due to the overuse of resources for developing the universities' missions. This overuse implies a waste of resources—which are public resources since in most, countries public universities predominate (Fox, 2001; Kalb, 2010; Afonso et al., 2023).

The public finance literature illustrates the relevance of the issue, as it is closely connected to how public spending, and its efficient use, can contribute to economic growth and development. The available theoretical and empirical evidence exists not only for different levels of government—whether national (Giménez et al., 2018), regional (Chen, 2006; Afonso and Furceri, 2010), or local (Balaguer-Coll et al., 2022; Perugini, 2023)—but also for other relevant public administrations and institutions such as universities. In the latter case, an inefficient use of public resources by HEIs would lead to lower levels of education, research, and knowledge transfer, eroding the economic impact of universities on the economic growth of their home regions (Agasisti et al., 2019, 2021; Crespo et al., 2022), in particular via reduced gains from innovation (Agasisti, 2023). The mechanisms at work behind these results are multiple and can be classified as output, resource, and reputation effects (Agasisti et al., 2021). Furthermore, suboptimal spending can negatively impact other positive externalities associated with higher education, such as improving the populations' civic, democratic, and cultural skills (see also Glaeser et al., 2007).

Hence, measuring the efficiency and productivity of HEIs is an issue of paramount importance, from both theoretical and empirical perspectives (Hanushek and Ettema, 2017), and the related literature is still evolving (see the recent bibliometric study by Arias-Ciro, 2020). In such analyses, a bundle of inputs and outputs, along with a given technology, define a "frontier" of efficient units (universities). These units produce the highest level of output with the available resources (under an output orientation) or minimize the use of resources for producing a given level of output (under an input orientation).

The bulk of these studies have conducted country-specific analyses (partly due to the difficulties in comparing information from different university systems), focusing mostly on Europe, Canada, the United States, and, to a lesser extent, China (Johnes and Yu, 2008). The recent bibliometric study by Arias-Ciro (2020) reviews most of this literature. As Agasisti (2023) points out, the overall picture emerging suggests, first, that the average efficiency of universities is relatively high (in the vicinity of 10–15%), and second, that it is possible to identify explanatory factors for the inefficiencies found (e.g., faculty composition, mix between humanities, social sciences and technology schools, the sources of revenue, size). In contrast, fewer studies have adopted a more global perspective, in which entire university systems are the units of analysis (Agasisti, 2011), or which compare the efficiency of single universities across more than one country (Joumady and Ris, 2005; Bolli et al., 2016; Veiderpass and McKelvey, 2016; Wolszczak-Derlacz, 2017).

In Spain, as in many European countries, the first universities were founded several centuries ago, yet by the early 20th century the country still *only* had 10 public universities. It was not until the 1970s that the Spanish system embarked on a profound quantitative and qualitative transformation following, first, the democratic transition that ushered in a decentralized state in 1978, and second, the University Reform Law (LRU) of 1983, which set out to modernize Spanish universities.

Regarding quantity, although the number of public universities had already begun to rise in the last years of the dictatorship, the arrival of the democratic system reinforced that trend. Regional governments (Autonomous Regions, NUTS2), as the main decision-makers on the financing and management of universities and guided by an unwritten criterion of "one province, one university" (or at least one university campus), were instrumental in the creation of new universities and campuses. However, different strategies were followed; for instance, the Madrid region has several

Table 1
Budget evolution. Averages for public universities (in millions of euros)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Fees	40.9	39.9	43.8	44.6	44.1	44.9	45.1	43.7	43.2	42.8
Current transfers	164.5	147.1	132.0	124.1	121.6	127.5	131.2	129.7	132.4	138.4
Capital transfers	33.7	33.9	29.0	29.0	25.3	26.6	31.1	30.4	28.9	31.4
Overall expenditure	240.3	226.2	204.3	193.0	190.1	199.1	197.7	198.2	202.4	209.1

independent universities, the Basque Country has a single university with campuses in its three provinces, and Catalonia has at least one university in each of its four provinces.

About quality, the LRU set the base of the university system in terms of autonomy, departmental structure, and governance. Subsequent law reforms in 2001 (LOU) and 2007 (LOMLOU) did not affect the foundations of that system but involved significant transformations in its functioning in order to adapt Spanish universities to the Bologna Declaration by 2010 as well as to improve their internationalization, research relevance, and knowledge transfer activities, all of which are crucial in the current knowledge-intensive economy, as has been recognized in the triple helix (Etzkowitz and Leydesdorff, 2000) and regional innovation models (Cooke, 2001). Accordingly, university degrees were redefined in consonance with the three-cycle system (undergraduate, master, doctoral studies), a national agency for quality evaluation Agencia Nacional de Evaluación y Acreditación (ANECA, dsfad) was created, and changes to the career promotion and salary system for the academic staff were implemented to link them more closely with their performance in research and knowledge transfer activities.

Some of these changes were introduced during the Great Recession years. The ensuing debt crisis forced regional governments to impose budget cuts (see Table 1). In the period 2009–2014, public funds were reduced by about 20% (on average). However, these reductions were applied in different ways across regions due to differences in the degradation of their financial situations and in how each region identified priority areas to apply the budget cuts. For instance, the cut in current transfers to Castilla-La Mancha reached 50% (with a strong rebound after 2014), while for universities in Navarra or Galicia it was *only* about 10%. In some cases, such as in Andalusia, the cut in current transfers was partially offset by a larger amount of capital transfers. Since 2012, these cuts have been partially compensated by a gradual increase in tuition fees, which are also set by regional authorities. While the revenues from fees have risen on average, not all autonomous regions followed the same pattern. Thus, while the revenues from fees for universities in Catalonia and the Madrid region increased by 18% and 25%, respectively, in Galicia or Cantabria these revenues decreased. All these changes have altered students' incentives to enroll and pursue their studies in Spanish HEIs.

Relatively few studies have adopted an explicit approach to measure the efficiency of Spanish universities from a global perspective. Some studies provide an overview of the efficiency of Spanish HEIs. For example, Johnes and Salas-Velasco (2007), among others, analyze the determinants of costs and efficiencies for these institutions. However, despite its general interest, their analysis is too brief to draw substantive conclusions and is constrained to one year only. A more detailed analysis is provided by García-Aracil (2013), focusing mostly on understanding productivity, although her meticulous modeling of universities' activities is remarkable. This endeavor had begun a few years earlier, when members of the same research team explicitly analyzed, from a broader perspective, which indicators were key for evaluating university activities (Palomares-Montero and García-Aracil, 2011). In turn, Martínez-Campillo and Fernández-Santos (2020) look at how the overall efficiency of Spanish universities evolved during the Great Recession period. Other papers have adopted a more specific focus. For instance, Berbegal-Mirabent et al. (2013), De La Torre et al. (2017), and Berbegal-Mirabent (2018) examine the issue of knowledge transfer and efficiency, whereas Berbegal-Mirabent and Ribeiro-Soriano (2015) address the links with the measurement of quality.

Other studies have conducted comparisons of Spanish universities within the context of European higher education. This category includes the contribution by Agasisti and Pérez-Esparrells (2010), among others. These initiatives face the challenging task of having to choose variables that do not always coincide across countries, and their results mainly refer to the comparisons among universities in different countries—rather than the country-specific analysis.

A related stem of research has been evaluating the impact of Spanish universities on their home regions. This is also a relatively unexplored area, in which both the number of contributions and authors are relatively low. Notable in this field is the work of Duch Brown et al. (2011), who focus on Spanish regional development. In this regard, the more general perspective provided by Palomares-Montero and García-Aracil (2011) turns out to be essential when the aims are to define what universities do. We will deal with this issue more explicitly in the following sections.

This study makes three main contributions to the literature. First, we contribute to the burgeoning and relatively scarce literature on the efficiency of Spanish universities along the lines described in the introduction. The context, despite having been analyzed in several studies, is of particular interest given the financial strain placed on Spanish universities during the austerity years. Second, up to now, the Bayesian methods considered have not been applied either to the specific context of Spain or to the more general issue of the performance of HEIs' efficiency. Finally, we adopt both a static and a dynamic approach, which is infrequent in this specific literature.

3. Measuring the activities of universities

The concept of productive efficiency refers to the linkages between inputs and outputs obtained. From the microeconomics theory, an economic unit is said to be efficient when it is on its production possibilities frontier, that is, when its use of inputs yields the best output (maximization problem), or similarly, when it obtains a given level of output with a minimal use of inputs (minimization problem). Deviations from the frontier represent its degree of inefficiency. In this context, we will refer to technical efficiency as a notion in which inputs and outputs are physical units and to cost efficiency as a notion in which inputs and outputs are monetary, so we need information not only in quantities (i.e., physical units) but also in prices (Kumbhakar and Lovell, 2000).

In the case of universities, some of their features hinder efficiency measurement (Johnes, 2006). On the one hand, universities, particularly public ones, are purposeful organizations whose main motivation is not to maximize profit but to contribute to social progress and growth by producing knowledge and disseminating it to the economy and society through multiple channels (Goddard et al., 2012). The various activities that universities undertake in the production and dissemination of knowledge are usually referred to as their "three missions" (Sánchez-Barrioluengo, 2014; Iorio et al., 2017; Degl'Innocenti et al., 2019; Horner et al., 2019). Although there is some debate as to the exact delineation, compatibility, and complementarity of the three missions (Sánchez-Barrioluengo, 2014), the usual distinction refers to teaching activities as the first mission, research activities as the second mission, and interactive activities to generate, use, and apply knowledge to address the challenges of the socioeconomic environment (in short, knowledge transfer activities) as the third mission. Because of these three missions, in the field of efficiency, HEIs are usually considered to be multi-output organizations, which is a second particularity for measuring their efficiency (Agasisti and Pérez-Esparrells, 2010; Martínez-Campillo and Fernández-Santos, 2020).

A third relevant issue to consider when measuring HEIs efficiency, from a technical efficiency perspective, is that the distinction between input and output is not always obvious. For instance, although staff (academic or not) are usually considered as an input, and publications are usually considered as an output, other variables, such as student enrollment or grants obtained, are less clear-cut (see Berbegal Mirabent and Solé Parellada, 2012, for a review on this issue). Finally, and also related to the difficulties in measuring inputs and outputs of HEIs, many of the inputs used and outputs obtained by universities in their various activities are intangible and have no prices, so they are difficult to trace and count and can be considered from both quantity and quality perspectives.

We have taken these issues on board to build our model to measure HEIs efficiency. On the output side, we consider two outputs for each of the three university missions. The teaching output is measured by the number of graduates at the bachelor (undergraduate) level and the master (postgraduate) level (Berbegal Mirabent and Solé Parellada, 2012). The output for the research mission is proxied by the number of papers published in the Web of Science journals by the academics affiliated with the university as well as by the number of research projects from national and European calls that are granted each year to researchers affiliated with the university (Berbegal Mirabent and Solé Parellada, 2012; Crespo et al., 2022). Finally, the third mission can encompass a larger variety of activities. Mainly for reasons of data availability, we use the number of patents universities apply for (either in the national office or with a Patent Cooperation Treaty (PCT) extension) and the number of academic spin-offs founded by the university's staff (Berbegal Mirabent and Solé Parellada, 2012; Crespo et al., 2022).

We, therefore, consider two outputs for each of the three missions to maintain, *a priori*, a balance among the three missions. Moreover, all the outputs considered are quantitative; qualitative outputs are not considered. Although we acknowledge the importance of the quality dimension in HEIs activity, we do not consider them for several reasons. First, data for quality indicators are much more difficult to access. For research outputs, it is quite straightforward to use readily available data on citations or share of papers in top journals, but data for quality indicators of teaching and knowledge transfer missions are much scarcer and more difficult to source. Measures such as average salary or employment rate one year after graduation, or survival rate and funds raised by university spin-offs can reflect the quality dimension of HEIs' activities, but they are not systematically available across universities and over time (Brooks, 2005). Second, since data availability prevents us from using quality measures for some missions, we chose not to use any quality indicators to keep the balance of outputs across missions. Moreover, mixing qualitative and quantitative outputs may confound the interpretation and comparison of efficiency scores. Finally, we do not use too many outputs to avoid the artificial inflation of efficiency that tends to occur when additional outputs are included.

On the input side, rather than considering the various productive resources necessary to obtain HEIs output, we assume that the overall costs to pay for their use are reflected in the universities' budgets; we, therefore, use a single input: overall expenditure on nonfinancial operations. This includes current operating expenses (such as personnel and expenses on current goods and services, financial expenses, and current transfers) and capital operations (i.e., expenditure on real investments and transfers intended to finance capital operations). Hence, we take neither a purely technical nor a purely cost approach to efficiency. The technical efficiency approach is conceptually closer to the traditional production function perspective in which labor and capital are combined to produce an output, but the problem of identifying, measuring, and classifying all inputs prevents us from using it. Our approach is not purely technical because, although outputs are measured in terms of physical units, we use monetary rather than physical units for the inputs side. Neither is it a cost-efficiency approach because we have physical units on the output side and, although we include monetary units on the inputs side, they represent overall expenditure and not prices and quantities for each input.

In this study, we focus on the case of Spanish public universities for the period 2010–2019, specifically, 47 of the 50 Spanish public universities. We excluded UNED, UIMP, and UIA because of their particular characteristics: UNED provides only distance learning, and UIMP and UIA do not have permanent academic staff since they only offer postgraduate courses through outsourced academics. Data for inputs and outputs of Spanish universities were obtained from two main sources: the Spanish Ministry of Universities and the IUNE Observatory. The Spanish Ministry of Universities, through its Integrated University Information System (SIIU), provided the information on the HEIs' budgets (in euros) that we use here as inputs. To take into account the eventual effects of inflation in the period, we deflated the monetary variables using the regional-level price index published by the National Statistics Institute. The SIIU also provided data on the number of graduate students (bachelor's and master's degrees), which are our output for the teaching activities. The IUNE Observatory, sponsored by researchers from four Spanish universities, collects and homogenizes data from the Web of Science and various Spanish administrative sources (e.g., RedOtri). We obtained data from the IUNE Observatory about the output of universities in research activities (number of publications in the Web of Science and research grants in national and international calls) as well as on knowledge transfer activities (patents granted and spin-offs created). Table 2 shows the descriptive statistics for the inputs and outputs used.

4. Methods

In what follows we present the above-mentioned SRPF proposed by Löthgren (1997) and recently improved by Henningsen et al. (2017). This multiple-output generalization of the single-output stochastic frontier production model is perfectly suited to the context of HEIs, which employ multiproduct cost functions. In line with Tsionas et al. (2022), we also conduct inference within the Bayesian context for the SRPF, specifically by implementing it in `JAGS` (Plummer, 2003). The SRPF model and its implementation in the Bayesian context are presented in the first subsection, while the second subsection describes how to perform the dynamic analysis.

Table 2
Variables: definition and descriptive statistics (2010–2019)

Variable name	Definition	Mean	SD	Min.	Max.
Outputs					
$publications$	Number of publications in the Web of Science	1,345.70	1,115.68	151	6,074
$grantsNatUE$	National and international research grants	53.23	38.93	3	200
$patents$	Patents	17.21	15.17	0	86
$spinoff$	Spin-offs	2.15	3.40	0	24
$undergrads$	Bachelor's degree graduates	3,354.57	2,055.14	0	11,696
$mastergrads$	Master's graduates	1,031.44	727.10	94	4,367
Inputs					
$Budget : expenditure$	Deflated HEIs budget (in euros)	206,052,060	129,171,418	41,304,881	658,268,318

4.1. A Bayesian stochastic ray frontier panel data model

The multi-output ray production function that provides the maximum Euclidean norm of the output vector $||y_{it}|| = \left(\sum_{j=1}^{p} y_{jit}^2\right)^{1/2}$ (for $i = 1, \dots, N$ and $t = 1, \dots, T$) attainable given the technology (see Löthgren, 1997, for a more detailed description) is defined as

$$f(x, \theta_{jit}) = \max\{\lambda \geq 0 \,:\, \lambda \cdot m_{jit}(\theta_{jit}) \in P(x)\}\,, \tag{1}$$

where $m(\theta_{jit}) = \frac{y_{jit}}{||y_{it}||}$ represents the output mix vector and θ_{jit} the output polar-coordinate angles. The function $m : \left[0, \frac{\pi}{2}\right]^{p-1} \longrightarrow [0, 1]^p$ is defined in terms of the output polar-coordinate angles as

$$m_{jit}(\theta_{jit}) = \cos(\theta_{jit}) \prod_{l=0}^{j-1} \sin(\theta_{lit}), \tag{2}$$

where $\theta_{jit} \in \left[0, \frac{\pi}{2}\right]^{p-1}$, $\sin(\theta_{0it}) = \cos(\theta_{pit}) = 1$. The polar-coordinate angles θ_{jit} are obtained recursively from the inverse transformation $m_{jit}^{-1}\left(\frac{y_{jit}}{||y_{it}||}\right)$ as follows:

$$\theta_{jit}\big(y_{jit}\big) = \cos^{-1}\left(\frac{y_{jit}}{||y_{it}|| \prod_{l=0}^{j-1} \sin(\theta_{lit})}\right). \tag{3}$$

The first angle is given by $\theta_{1it} = \cos^{-1}\left(\frac{y_{1it}}{||y_{it}||}\right)$, which is used to calculate θ_{2it} which is given by $\theta_{2it} = \cos^{-1}\left(\frac{y_{2it}}{||y_{it}||\sin(\theta_{1it})}\right)$. The remaining angles θ_{jit}, $j = 3, \dots, p-1$, are obtained by following the recursive equation (3).

In line with Löthgren (1997), the panel data stochastic ray frontier model that allows us to measure technical (in)efficiency in the context of multiple outputs is given by

$$\log ||y_{it}|| = \beta_0 + z_{it}^t \boldsymbol{\beta} - u_{it} + v_{it}, \quad i = 1, \ldots, N \quad \text{and} \quad t = 1, \ldots, T, \tag{4}$$

where z_{it}^t is a vector containing the transformed inputs of HEI i in time period t (via the translogarithmic functional form) and the angles of the polar coordinates of the outputs of HEI i in time period t. The terms u_{it} and v_{it} are the usual two independent and identically distributed error terms in SFAs. Specifically, u_{it} represents a truncated normal at 0 ($u_{it} \sim \mathrm{N}_{TR}^{+}(0, \frac{1}{\lambda})$) random variable associated with the technical inefficiency of HEI i in time period t. Note that the truncated Normal is the most frequently used distribution for inefficiencies, although other options such as Exponential (Aigner et al., 1977; Meeusen and van Den Broeck, 1977) and Gamma (Stevenson, 1980; Greene, 1990) could also have been applied. Finally, an additional Gaussian error term v_{it} is specific to each HEI i in time period t ($v_{it} \sim N(0, \sigma^2)$).

Once the stochastic ray frontier model has been set up, our next step is to make inferences on its parameters. As we are using the Bayesian paradigm, we must specify the prior distributions for each parameter involved in the model. This elicitation process result is sometimes complex and tricky because we may lack both the experience and the intuition to express all our prior knowledge about the parameters in terms of probabilities. The challenge is exacerbated when no previous information is available about the parameters. In such situations, the use of noninformative priors is a valuable solution because they help declare our lack of knowledge and prevent the introduction of undue influence from subjective opinions or assumptions.

Accordingly, our choice for the priors of the parameters governing model (4) is deliberately uninformative: $\mathrm{N}(0, 10^6)$ for the regression coefficients β_0 and $\boldsymbol{\beta}$; $\sigma \sim \mathrm{Un}(0, 1000)$; and $\lambda \sim \mathrm{Ga}(1, -\log\ 0.875)$. Although this distribution is quite informative (indicating an *a priori* median inefficiency value of 0.875), Koop and Steel (2003) demonstrated that the *a posteriori* results do not strongly depend on this assumption.

As usual in this context, there is no closed expression for the posterior distribution of the parameters. Numerical approximations, such as Markov chain-based Monte Carlo (MCMC) methods, are therefore needed. These methods can be programmed, as demonstrated in Fernández et al. (2000) and Tsionas et al. (2022), among others, or implemented using one of the many statistical packages available. In this article, we use MCMC through `JAGS` (Plummer, 2003), a statistical software program that provides a straightforward implementation of a wide range of complex statistical models.

4.2. Obtaining efficiencies and productivity indices

From the simulation procedure presented above, we obtain an approximate sample of the posterior distribution (from which we can make inferences via posterior means and medians, credible regions, quantiles, etc.) of each parameter defining the ray production frontier that helps us to understand the relationship between inputs and outputs and the structure of the technology.

However, one of the biggest advantages of the Bayesian approach is that we can use the posterior distribution of the parameters of the frontier model to approximate the posterior probability density function or its properties of the technical efficiency of any HEI, which is a transformation of the random variable $u_{it}|\lambda$:

$$TE_{it} = \exp(-u_{it}). \tag{5}$$

The resulting posterior distribution of these efficiencies can be utilized to rank HEIs from the most to the least efficient. More interestingly, we can study the causes of these differences by making inferences using the posterior mean, median, credible region, quantiles, etc., of the efficiencies, enabling statistical comparisons between the institutions. Indeed, as with any estimator, it is not enough to know whether the estimation of the efficiency indicates a higher or lower efficiency, but whether those changes are relevant in a statistical sense (as pointed out in Simar and Wilson, 1998, among others by their contributions). It is also worth noting that these posteriors give us a better knowledge of the behavior of the estimator in the tails and not only in the mean or median.

A similar procedure can be followed to make inferences with respect to the productivity of HEIs. As productivity indices, such as Malmquist indices, are a function of distance estimators, the methodology presented for efficiencies can be easily adapted in this case, except that now the time-dependence structure of the data must be taken into account.

In particular, from the posterior distribution of the parameters, we can obtain the posterior distribution of the following measures by incorporating similar lines of code in `JAGS`:

- Rate of change in efficiency (TEC):

$$TEC_i = \frac{TE_{it}}{TE_{is}}, \tag{6}$$

  where i denotes the HEI and t, s (where $t > s$) correspond to the time periods for calculating the change in efficiency. The interpretation of TEC_i is as follows: if TEC_i is equal to 1, it indicates no change in relative technical efficiency between periods t and s. If TEC_i is greater than 1, it indicates progress in technical efficiency, while if it is less than 1, it indicates regression in technical efficiency.
- Rate of technological change (TC):

$$TC_i = \exp\left\{\frac{1}{2}\left[\frac{\partial \ln y_{is}}{\partial s} + \frac{\partial \ln y_{it}}{\partial t}\right]\right\}. \tag{7}$$

  The interpretation of TC_i is as follows: if TC_i is equal to 1, it indicates no change in the relative technological frontier between periods t and s. If TC_i is greater than 1, it indicates progress in the technological frontier, while if it is less than 1, it indicates regression.
- The rate of change in total productivity (TPF), also known as the Malmquist index, is obtained by multiplying Equations (6) and (7)

$$TFP_i = TEC_{it} \times TC_{it}. \tag{8}$$

  The interpretation of the latter is as follows: if TFP_i is equal to 1, it indicates no net effect of changes in technical efficiency and the technological frontier. If TFP_i is greater than 1, it indicates increasing productivity, while if it is less than 1 it indicates decreasing productivity.

Again, and in line with the previous comment, with the resulting posterior distribution of these indices, we are able to perform statistical comparisons between the institutions and analyze whether the productivity growth/decline is relevant in a statistical sense.

5. Results

As posterior distributions of the parameters of the SRPF do not have a straightforward interpretation, in what follows we only focus on and present results corresponding to performance change and its decomposition. We first adopt a static approach to look at the inefficiency of universities in each of our sample years, that is, the distance of each university to the stochastic frontier in that particular year t. Second, we adopt a dynamic perspective to analyze the changes in efficiency over time. These changes are decomposed into two types of movements, namely shifts in the efficiency of universities closer to (or further from) the best practice frontier (catching up) and shifts of the best practice frontier itself over time.

5.1. Efficiency of universities

Figure 1 shows a 95% credible interval of the efficiency of each university for the years 2010, 2014, and 2019. In each of the panels, universities are ranked by the mean of their efficiency distribution. Efficiency studies generally rank universities using the efficiency scores yielded by the choice of efficiency measurement technique—usually data envelopment analysis (DEA) or SFA (see, for instance, Bonaccorsi et al., 2006; Johnes and Yu, 2008; Curi et al., 2012). The fact that we have the entire distribution of the efficiency for each university instead of a single value is actually one of the strengths of or value-adding reasons for using Bayesian estimation techniques rather than classical ones.

The visual inspection of these (in)efficiency distributions of Spanish universities reported in Fig. 1 reveals several patterns. On the one hand, the arithmetic means of universities' distributions look quite similar overall, but we observe a constant increase in inefficiency as we move down in the ranking. For example, the mean of the efficiency distribution of the bottom 10% is 12% lower than that of the top 10%, although this decrease is mostly concentrated in the last third. On the other hand, the range of the credible interval increases as we move down in the ranking. Both patterns are consistent for each of the years in our sample period (2010–2019).

In addition, we can look at shifts over time in the position of universities in a ranking based on the mean of their distribution. Table 3 shows the correlation matrix of the rankings of efficient universities over time. The values just below the main diagonal are relatively high, with some exceptions. From this perspective, although the specific ranking of each university changes from year to year, there is some persistence, that is, universities tend to occupy similar positions for several years. This would suggest that the worst performing Spanish public universities (compared to their peers) might be making efforts to meet the quality standards established by central and regional governments, especially in terms of research and teaching (Martínez-Campillo and Fernández-Santos, 2020; El Gibari et al., 2022).

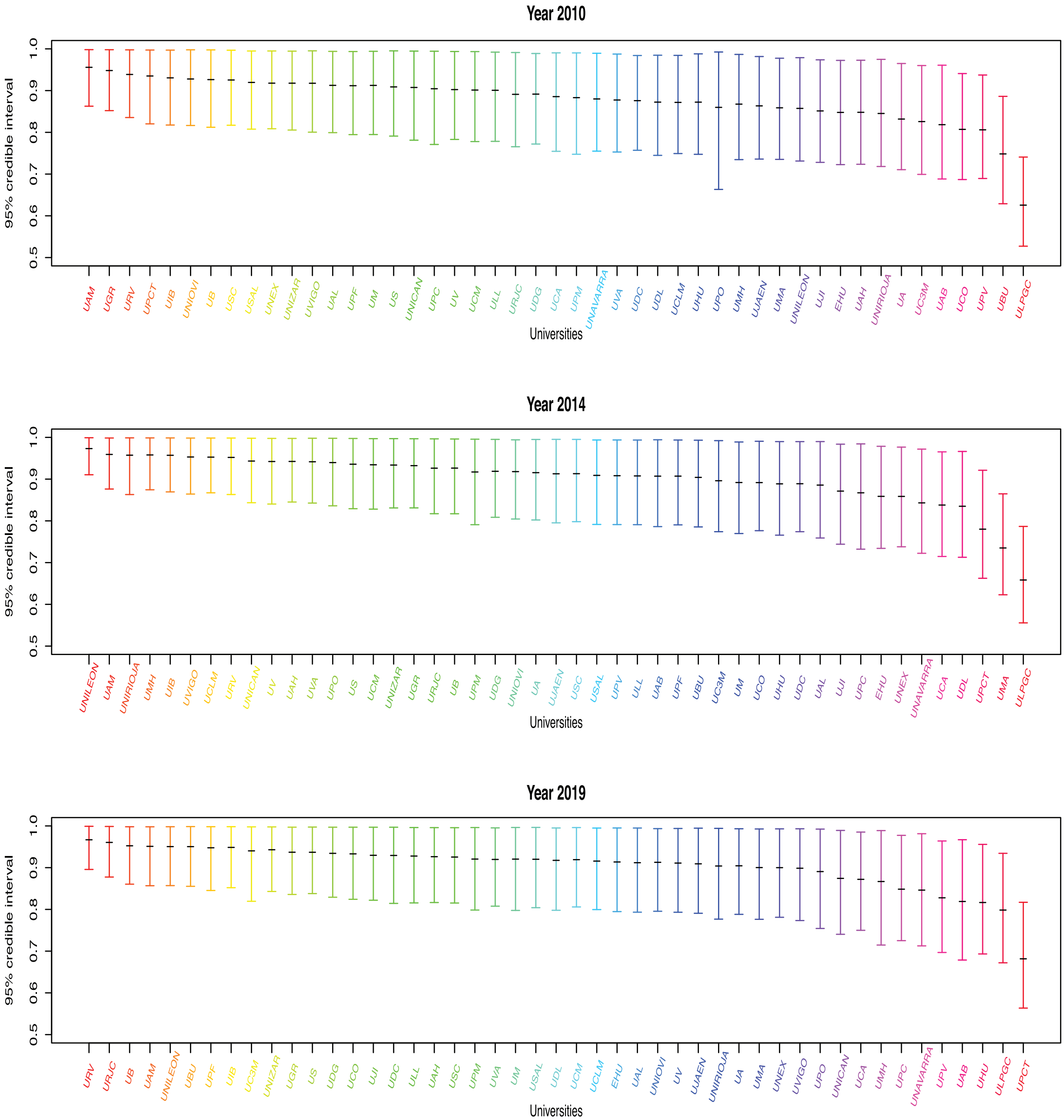

Fig. 1. Technical efficiency for Spanish universities, 95% credible interval, years 2010, 2014, and 2019.

The posterior densities reported in Fig. 2 provide a more illustrative view of what we learn by using Bayesian methods. The different subfigures display the densities of the posterior distribution of the efficiencies of selected universities in selected regions. Specifically, for each year (2010, 2014, and 2019), the lines in each subfigure correspond to the universities of the Valencian region (top

Table 3
Correlation matrix of the rankings of efficient universities over time

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
2010	1.00	0.60	0.27	0.42	0.22	0.21	0.26	0.44	0.18	0.27
2011	0.60	1.00	0.30	0.52	0.49	0.42	0.44	0.50	0.29	0.38
2012	0.27	0.30	1.00	0.47	0.47	0.42	0.55	0.42	0.19	0.39
2013	0.42	0.52	0.47	1.00	0.68	0.44	0.48	0.33	0.17	0.35
2014	0.22	0.49	0.47	0.68	1.00	0.59	0.53	0.48	0.30	0.36
2015	0.21	0.42	0.42	0.44	0.59	1.00	0.50	0.66	0.30	0.51
2016	0.26	0.44	0.55	0.48	0.53	0.50	1.00	0.55	0.46	0.45
2017	0.44	0.50	0.42	0.33	0.48	0.66	0.55	1.00	0.43	0.43
2018	0.18	0.29	0.19	0.17	0.30	0.30	0.46	0.43	1.00	0.71
2019	0.27	0.38	0.39	0.35	0.36	0.51	0.45	0.43	0.71	1.00

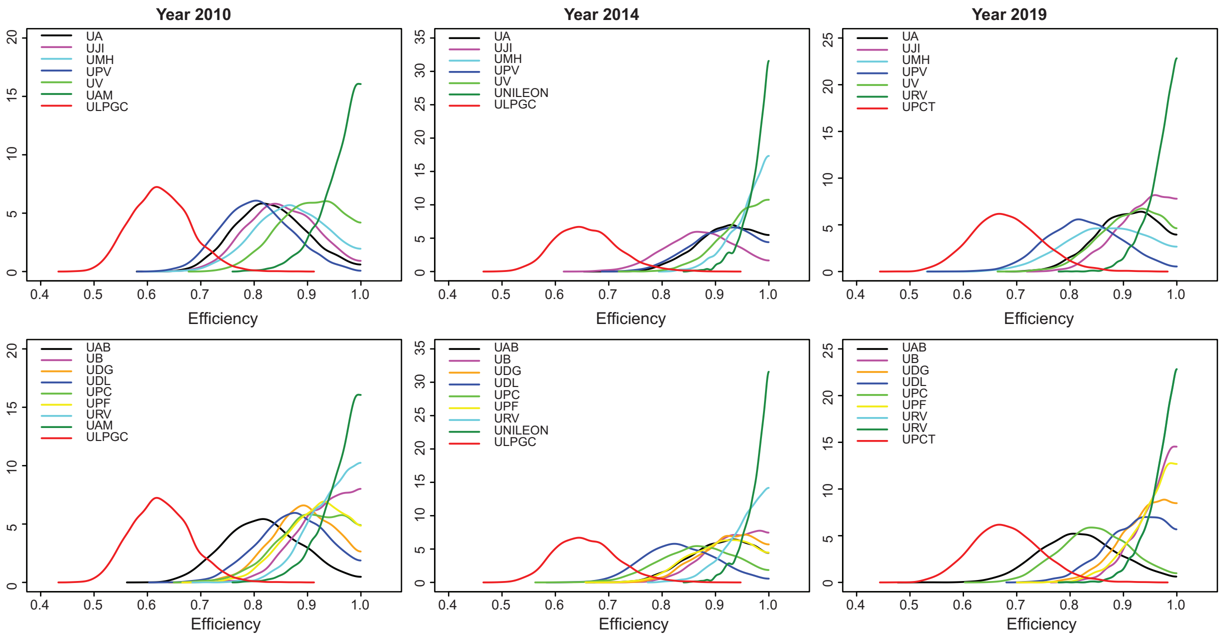

Fig. 2. Density of the posterior distributions of some universities of interest in three different years: universities from the Valencian region in the first row and from Catalonia in the second one.

panel) and Catalonia (lower panel). In all subfigures, we display the densities corresponding to the best and worst performers during those years.

For instance, for the University of Las Palmas de Gran Canaria in 2010 (ULPGC, solid red line), most of the probability mass is below the posterior probability mass corresponding to the rest. In particular, the amount of overlapping with the best university (Universidad Autónoma de Madrid, UAM, solid olive green line) is negligible, indicating that the posterior probability that one university outperforms the other is nearly one. In contrast, there is a remarkable amount of overlapping among the remaining universities, suggesting that location in the same region (either the Valencian region in the upper panel or Catalonia in the lower panel) might imply that some of them faced comparable budget cuts, which in turn could have impacted their efficiency.

5.2. Dynamic perspective on efficiency

The dynamic perspective can be achieved by examining estimated efficiencies at different points in time. However, it is a partial perspective, as inefficiencies are obtained by estimating an annual efficiency frontier. We extend this static approach and explicitly adopt a dynamic perspective by decomposing the overall changes in university performance into two *à la Malmquist* effects. Therefore, the first component corresponds to the change in efficiency (i.e., it would represent how close or far a university is moving to or from the frontier made up of "best practice" universities), while the second measures the shifts in the best practice frontier between two points in time (years).

The dynamic perspective looks at shifts from t to $t+1$. Although it could be estimated annually, we consider it more informative to split the sample period and examine two key subperiods separately—i.e., by looking at shifts between 2010 and 2014 for the first subperiod and between 2015 and 2019 for the second period (Crespo et al., 2022). This choice is justified by the evolution of the Spanish economy and its impact on many areas of public finances in this period. Specifically, the international economic and financial turmoil that began in 2007/08 led to a debt crisis in Spain, which prompted central and regional governments to implement severe budget cuts (Fetzer, 2019). Public universities were affected by these cuts in that they had fewer resources with which to carry out their missions (Cruz-Castro and Sanz-Menéndez, 2016; Cruz-Castro et al., 2018). In 2015, the Spanish economy entered a new period of growth, and since then, public debt tensions have eased, with a corresponding reduction in budgetary constraints for universities. These circumstances justify the choice of 2015 as the year to determine our two subperiods.

Table 4 reports the change in the efficiency component for each university for each of the two subperiods and the entire period. Values greater than, equal to, or less than one, in the entire period or subperiod considered, imply that the efficiency of the university evaluated is improving, stagnating, or deteriorating, respectively. The Bayesian techniques we use for the stochastic frontier estimations provide the full posterior distribution of efficiency for each university. Specifically, the numbers in parentheses, obtained from these posterior distributions, indicate the probability of efficiency change greater than one—i.e., positive efficiency change. These numbers are more informative than they appear, as they were calculated from the posterior distributions and, graphically, should be interpreted as the probability that the densities deviate from unity.

Table 4 reports positive efficiency change for the majority of universities for either the overall period or each of the subperiods—i.e., in most instances, the value is greater than one. However, although around two thirds of the 47 Spanish public universities are approaching the best practice frontier, there are remarkable disparities in terms of the *probability* of achieving positive efficiency change. For instance, during the first subperiod, the University of Burgos had a very high probability of experiencing positive efficiency change (0.9627), which is even higher (0.9907) when examining the entire period 2010–2019 is considered. In contrast, for the overall period, the Polytechnic University of Cartagena had a very low probability (0.0037) of experiencing positive efficiency change but in the second subperiod, 2010–2019, its estimated value for efficiency change is 0.7310.

Table 4
Change in efficiency and *a posteriori* probability, Spanish public universities

University	2010–2014	2015–2019	2010–2019
A Coruña	1.0198 (0.5600)	1.0581 (0.7260)	1.0661 (0.7493)
Alcalá	1.1178 (0.8827)	1.0258 (0.6097)	1.0986 (0.8383)
Alicante	1.1075 (0.8410)	0.9601 (0.2873)	1.0939 (0.8023)
Almería	0.9739 (0.3757)	1.0593 (0.7170)	1.0028 (0.4950)
Autònoma de Barcelona	1.1167 (0.8383)	0.9247 (0.2133)	1.0075 (0.5060)
Autónoma de Madrid	1.0051 (0.5157)	1.0283 (0.6380)	0.9966 (0.4650)
Barcelona	1.0032 (0.4850)	1.0575 (0.7630)	1.0314 (0.6567)
Burgos	1.2172 (0.9627)	1.1209 (0.9043)	1.2804 (0.9907)
Cádiz	0.9506 (0.2893)	1.1431 (0.8817)	0.9893 (0.4387)
Cantabria	1.0436 (0.6917)	1.0151 (0.5353)	0.9673 (0.3457)
Carlos III de Madrid	1.0921 (0.7913)	1.0431 (0.6947)	1.1461 (0.9147)
Castilla-La Mancha	1.0983 (0.8690)	1.1539 (0.9187)	1.0556 (0.7120)
Complutense de Madrid	1.0410 (0.6647)	0.9957 (0.4710)	1.0241 (0.5907)
Córdoba	1.1119 (0.8417)	1.1185 (0.8737)	1.1636 (0.9373)
Extremadura	0.9386 (0.2260)	1.2635 (0.9827)	0.9837 (0.4060)
Girona	1.0349 (0.6343)	1.0179 (0.5907)	1.0525 (0.7157)
Granada	0.9851 (0.3937)	1.0204 (0.5983)	0.9902 (0.4317)
Huelva	1.0242 (0.5807)	1.0533 (0.6570)	0.9410 (0.2767)
Illes Balears (Les)	1.0314 (0.6660)	1.0115 (0.5573)	1.0222 (0.6173)
Jaén	1.0631 (0.7283)	1.0526 (0.7003)	1.0591 (0.7097)
Jaume I de Castelló	1.0294 (0.5857)	1.0561 (0.7193)	1.0983 (0.8310)
La Laguna	1.0119 (0.5360)	1.0272 (0.6183)	1.0343 (0.6373)
La Rioja	1.1399 (0.9293)	1.1175 (0.8027)	1.0762 (0.7470)
Las Palmas de Gran Canaria	1.0584 (0.6753)	1.1710 (0.9183)	1.2847 (0.9867)
León	1.1419 (0.9543)	0.9904 (0.4213)	1.1152 (0.8853)
Lleida	0.9623 (0.3357)	1.1461 (0.9020)	1.0576 (0.7013)
Málaga	0.8603 (0.0800)	1.0627 (0.7120)	1.0539 (0.6893)
Miguel Hernández de Elche	1.1108 (0.8790)	0.9360 (0.2463)	1.0047 (0.5040)
Murcia	0.9808 (0.3887)	1.0753 (0.7703)	1.0125 (0.5517)
Oviedo	0.9923 (0.4557)	1.0572 (0.7217)	0.9866 (0.4130)
Pablo de Olavide	1.1065 (0.7690)	1.1412 (0.8773)	1.0485 (0.5927)
País Vasco	1.0189 (0.5513)	1.1430 (0.9017)	1.0840 (0.7940)
Politécnica de Cartagena	0.8364 (0.0353)	0.9830 (0.4253)	0.7310 (0.0037)
Politècnica de Catalunya	0.9630 (0.3380)	0.9912 (0.4407)	0.9425 (0.2653)
Politécnica de Madrid	1.0440 (0.6607)	0.9768 (0.3617)	1.0483 (0.6733)
Politècnica de València	1.1336 (0.8903)	0.9157 (0.1777)	1.0331 (0.5977)
Pompeu Fabra	0.9984 (0.4707)	1.0762 (0.8163)	1.0433 (0.7113)
Pública de Navarra	0.9627 (0.3347)	1.0193 (0.5403)	0.9663 (0.3570)
Rey Juan Carlos	1.0446 (0.6790)	1.0785 (0.8313)	1.0830 (0.8503)
Rovira i Virgili	1.0166 (0.5953)	1.0248 (0.6577)	1.0324 (0.6987)
Salamanca	0.9915 (0.4373)	0.9991 (0.4750)	1.0039 (0.5143)
Santiago de Compostela	0.9896 (0.4280)	1.0348 (0.6380)	1.0030 (0.4930)
Sevilla	1.0337 (0.6413)	1.0071 (0.5193)	1.0350 (0.6457)
València (Estudi General)	1.0485 (0.7023)	0.9947 (0.4580)	1.0137 (0.5513)
Valladolid	1.0788 (0.7963)	1.0239 (0.5837)	1.0536 (0.6960)
Vigo	1.0421 (0.7203)	1.0275 (0.5947)	0.9825 (0.4110)
Zaragoza	1.0208 (0.5933)	1.0620 (0.7630)	1.0308 (0.6427)

Therefore, although most universities do show a positive efficiency change, on average, the probability of improvement is not that high: 0.62 for the full period, 0.60 for the first subperiod, and 0.64 for the 2015–2019 subperiod. However, Table 4 reveals numerous combinations: although half of the universities shift closer to the best practice frontier in the first and second subperiods, few cases show a steady increase in their inefficiency. The remaining cases are more or less equally distributed in the mixed scenarios of moving closer to or further from the frontier at different moments in time.

Table 5 shows the results for the second component of performance change, namely technological change, indicating how much the frontier shifts. In this case, as in the analysis of efficiency change, values greater than, equal to, or lower than 1 indicate technical progress, stagnation, or technical regress, respectively. The numbers in parentheses also report the probability of technical progress occurring—i.e., of values greater than one. In this case, however, the patterns differ from those observed for efficiency change, as there is a clear temporal pattern that holds for all universities. In the first subperiod, coinciding with the budget cuts and the reduction in the amount of inputs available in the Spanish public university system, all HEIs in our sample experienced technical progress from 2010 to 2014. In contrast, in the second subperiod, when the budgetary constraints started to loosen, values were lower than 1 for *all* universities, indicative of negative technological change (i.e., technical regress) during this second period.

This pattern is clearly seen in Table 5, where all universities show the same behavior across the two subperiods: above 1 in the first subperiod and below 1 in the second. A closer inspection of results for the overall period reveals more mixed outcomes. For roughly half of the universities, the technical regress found in the second subperiod does not offset the technical progress of the first subperiod; their value for the entire period is consequently greater than one. The overall result (full period) for the rest of the universities is a negative technical change effect.

Several explanations may underlie these patterns. On the one hand, in the years of budget cuts, the inputs decreased but (some of) the outputs did not (Martínez-Campillo and Fernández-Santos, 2020). When the unemployment rate is high, the opportunity cost of starting and continuing university studies falls, so the number of students enrolling and finishing their studies does not decrease. Similarly, publishing scientific papers is an increasingly important aspect of academic careers, reflected as in the number of papers and journals. The incentives and opportunities for academics to publish therefore evolve quite independently of the universities' funds. On the other hand, budget cuts may result in a reduction of physical units used (e.g., fewer staff) or in a reduction in the payments to physical units used (e.g., lower salaries). In the first case, universities can only maintain their level of output by increasing the efficiency of their physical units, mostly their academic or nonacademic staff. In the second case, the productive capacity is not constrained, so universities might continue to produce the same level of output because they are reducing inputs by simply paying less for them. In addition, there might be a lag in the impact budget cuts have on the university activities, so the effects of cuts made in the first subperiod are felt in the second one.

Finally, Table 6 shows the results for the changes in the performance of universities based on the decomposition of efficiency change and technological change. In this context, the picture is also somewhat mixed. In the overall period, as was the case for the efficiency change, two thirds of the universities show improved performance and the average probability of employment is in the vicinity of 0.65. However, the shifts in productivity have a marked temporal pattern (Table 6). In fact, all universities but three increased productivity between 2010 and 2014, and the average probability for this increase is around 0.82. In contrast, in the subperiod 2015–2019, only one third

Table 5
Change in technology and *a posteriori* probability, Spanish public universities

University	2010–2014	2015–2019	2010–2019
A Coruña	1.0802 (1.0000)	0.9509 (0.0000)	1.0126 (0.9997)
Alcalá	1.0805 (1.0000)	0.9523 (0.0000)	1.0119 (0.9927)
Alicante	1.0780 (1.0000)	0.9537 (0.0000)	1.0139 (0.9997)
Almería	1.0912 (1.0000)	0.9622 (0.0000)	1.0220 (1.0000)
Autònoma de Barcelona	1.0408 (0.9993)	0.9170 (0.0000)	0.9780 (0.0237)
Autónoma de Madrid	1.0456 (1.0000)	0.9270 (0.0000)	0.9832 (0.0140)
Barcelona	1.0533 (1.0000)	0.9308 (0.0000)	0.9926 (0.1853)
Burgos	1.0936 (1.0000)	0.9561 (0.0000)	1.0202 (0.9913)
Cádiz	1.0864 (1.0000)	0.9553 (0.0000)	1.0194 (1.0000)
Cantabria	1.0613 (1.0000)	0.9313 (0.0000)	0.9965 (0.3563)
Carlos III de Madrid	1.0778 (1.0000)	0.9648 (0.0030)	1.0221 (0.9890)
Castilla-La Mancha	1.0809 (1.0000)	0.9496 (0.0000)	1.0108 (0.9827)
Complutense de Madrid	1.0684 (1.0000)	0.9449 (0.0000)	1.0043 (0.7023)
Córdoba	1.0703 (1.0000)	0.9491 (0.0000)	1.0073 (0.9637)
Extremadura	1.0873 (1.0000)	0.9573 (0.0000)	1.0235 (1.0000)
Girona	1.0780 (1.0000)	0.9537 (0.0000)	1.0186 (0.9903)
Granada	1.0695 (1.0000)	0.9484 (0.0000)	1.0088 (0.8893)
Huelva	1.0940 (1.0000)	0.9647 (0.0000)	1.0305 (1.0000)
Illes Balears (Les)	1.0776 (1.0000)	0.9468 (0.0000)	1.0097 (0.9107)
Jaén	1.0829 (1.0000)	0.9643 (0.0000)	1.0236 (1.0000)
Jaume I de Castelló	1.0843 (1.0000)	0.9592 (0.0000)	1.0168 (0.9990)
La Laguna	1.0691 (1.0000)	0.9467 (0.0000)	1.0025 (0.6833)
La Rioja	1.0792 (1.0000)	0.9430 (0.0000)	1.0191 (0.9867)
Las Palmas de Gran Canaria	1.0824 (1.0000)	0.9589 (0.0000)	1.0177 (0.9997)
León	1.0940 (1.0000)	0.9597 (0.0000)	1.0192 (0.9997)
Lleida	1.0834 (1.0000)	0.9545 (0.0000)	1.0168 (0.9793)
Málaga	1.0745 (1.0000)	0.9528 (0.0000)	1.0159 (0.9960)
Miguel Hernández de Elche	1.0807 (1.0000)	0.9616 (0.0003)	1.0138 (0.9140)
Murcia	1.0836 (1.0000)	0.9560 (0.0000)	1.0163 (0.9987)
Oviedo	1.0665 (1.0000)	0.9435 (0.0000)	1.0025 (0.6940)
Pablo de Olavide	1.1104 (1.0000)	0.9726 (0.0020)	1.0471 (0.9947)
País Vasco	1.0664 (1.0000)	0.9410 (0.0000)	1.0010 (0.5500)
Politécnica de Cartagena	1.0777 (1.0000)	0.9348 (0.0000)	1.0105 (0.8497)
Politècnica de Catalunya	1.0359 (0.9787)	0.9384 (0.0000)	0.9900 (0.1877)
Politécnica de Madrid	1.0450 (0.9983)	0.9386 (0.0000)	0.9957 (0.3560)
Politècnica de València	1.0628 (1.0000)	0.9363 (0.0000)	0.9966 (0.3267)
Pompeu Fabra	1.0727 (1.0000)	0.9400 (0.0000)	1.0073 (0.7663)
Pública de Navarra	1.0861 (1.0000)	0.9587 (0.0000)	1.0226 (0.9987)
Rey Juan Carlos	1.0995 (1.0000)	0.9747 (0.0030)	1.0337 (1.0000)
Rovira i Virgili	1.0640 (1.0000)	0.9376 (0.0000)	1.0056 (0.8017)
Salamanca	1.0830 (1.0000)	0.9569 (0.0000)	1.0161 (0.9983)
Santiago de Compostela	1.0584 (1.0000)	0.9331 (0.0000)	0.9947 (0.2093)
Sevilla	1.0674 (1.0000)	0.9453 (0.0000)	1.0037 (0.6813)
València (Estudi General)	1.0676 (1.0000)	0.9420 (0.0000)	1.0016 (0.5793)
Valladolid	1.0814 (1.0000)	0.9529 (0.0000)	1.0114 (0.9770)
Vigo	1.0767 (1.0000)	0.9459 (0.0000)	1.0078 (0.9233)
Zaragoza	1.0642 (1.0000)	0.9427 (0.0000)	1.0023 (0.6627)

Table 6
Change in productivity and *a posteriori* probability, Spanish public universities

University	2010–2014	2015–2019	2010–2019
A Coruña	1.1016 (0.8287)	1.0061 (0.5087)	1.0795 (0.7920)
Alcalá	1.2076 (0.9840)	0.9768 (0.3543)	1.1116 (0.8697)
Alicante	1.1938 (0.9587)	0.9156 (0.1040)	1.1091 (0.8347)
Almería	1.0627 (0.7357)	1.0193 (0.5600)	1.0249 (0.6030)
Autònoma de Barcelona	1.1621 (0.9117)	0.8479 (0.0577)	0.9852 (0.4280)
Autónoma de Madrid	1.0509 (0.8400)	0.9532 (0.2217)	0.9797 (0.3307)
Barcelona	1.0566 (0.7493)	0.9843 (0.3850)	1.0237 (0.6157)
Burgos	1.3309 (0.9950)	1.0717 (0.7663)	1.3061 (0.9947)
Cádiz	1.0326 (0.6063)	1.0919 (0.7897)	1.0084 (0.5150)
Cantabria	1.1076 (0.9060)	0.9453 (0.2740)	0.9638 (0.3280)
Carlos III de Madrid	1.1770 (0.9383)	1.0063 (0.5037)	1.1714 (0.9480)
Castilla-La Mancha	1.1870 (0.9833)	1.0957 (0.8137)	1.0669 (0.7577)
Complutense de Madrid	1.1121 (0.8973)	0.9408 (0.1923)	1.0285 (0.6077)
Córdoba	1.1900 (0.9510)	1.0616 (0.7303)	1.1721 (0.9490)
Extremadura	1.0204 (0.5733)	1.2094 (0.9623)	1.0068 (0.5137)
Girona	1.1157 (0.8917)	0.9707 (0.3137)	1.0721 (0.7903)
Granada	1.0536 (0.7923)	0.9677 (0.3097)	0.9989 (0.4950)
Huelva	1.1204 (0.8657)	1.0160 (0.5400)	0.9696 (0.3657)
Illes Balears (Les)	1.1114 (0.9543)	0.9577 (0.2150)	1.0321 (0.6823)
Jaén	1.1510 (0.9230)	1.0150 (0.5440)	1.0840 (0.7873)
Jaume I de Castelló	1.1161 (0.8360)	1.0130 (0.5343)	1.1168 (0.8640)
La Laguna	1.0817 (0.7987)	0.9724 (0.3507)	1.0369 (0.6503)
La Rioja	1.2299 (0.9900)	1.0536 (0.6400)	1.0967 (0.8017)
Las Palmas de Gran Canaria	1.1455 (0.8890)	1.1227 (0.8467)	1.3073 (0.9927)
León	1.2492 (0.9983)	0.9504 (0.1453)	1.1366 (0.9270)
Lleida	1.0425 (0.6233)	1.0939 (0.8100)	1.0753 (0.7643)
Málaga	0.9244 (0.2190)	1.0125 (0.5370)	1.0706 (0.7433)
Miguel Hernández de Elche	1.2003 (0.9857)	0.8999 (0.1327)	1.0183 (0.5537)
Murcia	1.0628 (0.7543)	1.0279 (0.6077)	1.0289 (0.6270)
Oviedo	1.0582 (0.7570)	0.9975 (0.4727)	0.9890 (0.4240)
Pablo de Olavide	1.2283 (0.9753)	1.1097 (0.8173)	1.0973 (0.7393)
País Vasco	1.0865 (0.7577)	1.0755 (0.7597)	1.0850 (0.7953)
Politécnica de Cartagena	0.9013 (0.1300)	0.9188 (0.2267)	0.7387 (0.0050)
Politècnica de Catalunya	0.9974 (0.4817)	0.9302 (0.2343)	0.9329 (0.2283)
Politécnica de Madrid	1.0910 (0.8133)	0.9168 (0.1137)	1.0437 (0.6550)
Politècnica de València	1.2048 (0.9640)	0.8573 (0.0613)	1.0295 (0.5857)
Pompeu Fabra	1.0710 (0.7890)	1.0115 (0.5267)	1.0508 (0.7483)
Pública de Navarra	1.0455 (0.6363)	0.9770 (0.3937)	0.9879 (0.4347)
Rey Juan Carlos	1.1483 (0.9457)	1.0512 (0.7187)	1.1193 (0.9400)
Rovira i Virgili	1.0817 (0.8980)	0.9608 (0.2093)	1.0381 (0.7433)
Salamanca	1.0738 (0.8033)	0.9560 (0.2573)	1.0200 (0.5997)
Santiago de Compostela	1.0473 (0.7053)	0.9655 (0.3213)	0.9976 (0.4610)
Sevilla	1.1033 (0.8903)	0.9519 (0.2217)	1.0387 (0.6623)
València (Estudi General)	1.1192 (0.9247)	0.9369 (0.2033)	1.0152 (0.5587)
Valladolid	1.1665 (0.9587)	0.9758 (0.3640)	1.0656 (0.7423)
Vigo	1.1219 (0.9533)	0.9718 (0.3647)	0.9901 (0.4460)
Zaragoza	1.0864 (0.8497)	1.0011 (0.4870)	1.0332 (0.6523)

of the universities showed an improvement in productivity, and the average probability of doing so was only 0.44. Thus, this temporal pattern is much closer to what we observed for technological change than for efficiency change.

Few studies have evaluated the decomposition of performance change into a catching-up effect and a frontier shift effect. One example is García-Aracil (2013) and, although her findings differ from ours (as they find that efficiency improvements overshadowed technical progress), they cannot be directly compared since they focus on a different period (1994–2008), use a different definition of inputs and outputs (they do not analyze cost efficiency) and, most importantly, applies a very different efficiency estimation technique. Thus, our analysis contributes to achieve a more comprehensive view of the tendencies in the Spanish university system, providing very useful information at the individual university level.

6. Conclusions

Over the past two decades, the study of the efficiency of HEIs has witnessed significant advances, driven by a confluence of methodological innovations, technological integration, and an increased emphasis on accountability in the education sector. Scholars have increasingly used a variety of methodologies to assess the multiple dimensions of efficiency in higher education. Research has faced the challenge of modeling the missions and structures of HEIs, but these advances have contributed to a richer understanding of the complexities involved in assessing and improving the efficiency of universities in both developed and developing countries.

The evaluation of university efficiency has been generally approached using frontier techniques, particularly DEA and some of its variants—such as the nonconvex free disposal hull, and the robust order-*m*. Parametric methods such as SFA, despite some key advantages (such as being capable of distinguishing between inefficiency and random error or greater flexibility in specifying the functional form of the production frontier), have generally been less used to assess the efficiency of universities—despite their popularity in fields such as banking.

In our study, we used a type of stochastic frontier method that, despite its additional advantages, has not previously been considered to evaluate HEIs efficiency. Specifically, we work with the SRPF, a multiple-output stochastic frontier production model that swiftly suits the context of HEIs as they employ multiproduct cost functions. By conducting inference within the Bayesian paradigm, we are able to provide uncertainty quantification for the parameters governing the model but, more importantly, for the decomposition of performance change of HEIs.

Specifically, with our proposed methods, we decompose the change in performance into efficiency change (catching up) and technical change (shifts in the frontier), which is also less frequently examined in this literature. The setting for this study—Spain—also offers a relevant context to examine, as Spanish public universities' finances went through a stringent period since the 2007/08 crisis started, which only began to ease slowly a few years later. This implies that our results cannot be directly compared with those of studies in the literature from previous periods, given the intricacies of the years under analysis.

However, we should stress our finding of a generalized technical progress for the worst years (2010–2014). Given the good results of Spanish universities in terms of efficiency in these turbulent years, policymakers might be tempted to further cut university funding. This is probably a bad decision since these scores can be interpreted in several ways. One interpretation refers to the universities' resilience capacity: the system was able to resist the shock for a while, but a persistent budgetary cut may be fatal. Second, these efficient scores do not take into consideration the qualitative dimension and the global competition. Although a professor with more students in the classroom may lead to an increase in the efficiency score, it may be negative for the quality of the student-learning process. Similarly, the number of publications is increasing globally, so although Spanish universities are publishing more (even with fewer resources), they may be doing so more slowly than universities in other countries, which will increase the distance between them and leading HEIs.

Results, however, are neither generalized for all components of performance (catching up and frontier shift) nor across universities. Indeed, one of the main contributions of this study, relative to the previous literature, is that we provide more insightful information at the individual level since our estimation techniques yield a *distribution* of performance change, efficiency change, and technical change for each university. Therefore, comparisons across universities can be carried out with much more precision, as we know exactly how *probable* it is that a given HEI performance, efficiency, or technical change will be positive throughout the period or subperiods under examination.

Although we consider these findings relevant, they should be regarded as a starting point for further investigations of the efficiency of universities under the Bayesian paradigm. Future research could, for instance, evaluate the determinants of efficiency (variable selection) or the regional impact of universities' performance (economic growth model), as both issues have been examined successfully considering relevant Bayesian methodologies—such as Bayesian model selection and model averaging. Considering a complete Bayesian paradigm to examine these issues can provide a different perspective, which helps to broaden our understanding of the performance of HEIs. In this regard, the previous literature on the efficiency of Spanish HEIs has less frequently explored the regional autonomy component and how they can interact. This interaction is particularly important in this context, as most provinces have at least one university, and Spanish regions have devolved powers for education—including higher education. Therefore, for regional governments, precise information regarding the efficiency of each university in their territories, and exactly how they compare with other universities in the region—or perhaps neighboring universities—is crucial, as it could guide budget preparation and may be useful in resource reallocation. As our study shows, these comparisons can be made not only across universities but also over time.

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