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Beyond Rankings: Bayesian stochastic frontier analysis of the determinants of university efficiency*

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Abstract

University rankings predominantly focus on outputs while neglecting the efficiency with which institutions convert resources into outcomes. We contribute to addressing this limitation by analyzing the determinants of university efficiency using a Bayesian stochastic ray frontier model applied to 47 Spanish public universities over the 2016–2021 period. Unlike traditional approaches, our methodology jointly estimates efficiency and its determinants in a single stage. We adopt a multi-output framework encompassing the three university missions: teaching, research, and knowledge transfer. Using backward stepwise selection with the deviance information criterion, we identify key efficiency determinants including the average department size, number of campuses, academic staff characteristics, and multi-province location. Results reveal substantial efficiency variations across universities, with approximately half showing positive efficiency changes over the period. The Bayesian approach provides full efficiency distributions rather than point estimates, enabling robust statistical comparisons. Our findings offer valuable insights for university managers and policymakers seeking to enhance institutional performance beyond traditional output-based rankings.

Keywords: determinants, efficiency, Bayesian, education, stochastic frontier, universities

JEL classification: C61; J24; R11

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1. Introduction

University rankings assessing the performance of universities in terms of research, mainly, but also education or graduate employability have proliferated over the past two decades. Examples include the Academic Ranking of World Universities (ARWU), the Centre for Science and Technology Studies Leiden Ranking (CWTS), the Center for World University Rankings (CWUR), or the Times Higher Education World University Rankings (THE). High positions in these rankings yields positive effects for universities in terms of reputation and prestige, attraction and retention of talented students and researchers, access to funding and partnerships, and political influence. As a result, rankings have become powerful reference points, shaping institutional behavior and priorities. Both governments and universities increasingly use them not only as benchmarks for performance but also as strategic tools, actively designing policies aimed at improving their ranking positions (Hazelkorn, 2013; Shattock, 2017).

These university rankings are, with a few exceptions, based predominantly on output indicators: the greater the number of publications, Nobel laureates, or highly cited researchers, the higher the institution's position. However, from a policy evaluation perspective, focusing solely on outputs, irrespective of inputs, is a limited and partial approach. Of course, it is reasonable to expect that universities with greater resources will tend to achieve higher levels of output. For example, more than 70% of Spanish universities, on which we focus, lose position in the CWUR 2025 ranking compared to the previous year, and a plausible explanation for this decline points to the relative underfunding of Spanish institutions compared to their international counterparts. Nevertheless, the relationship between inputs and outputs is neither linear nor deterministic because it also depends on how effectively institutions convert resources into outcomes, that is, on the fundamental economic concept of *efficiency*. A large literature has also examined university efficiency with a focus on three main areas, namely: (i) the measurement of university efficiency (Johnes, 2006; García-Tórtola et al., 2025); (ii) the determinants of efficiency (Rhaiem, 2017; Wolszczak-Derlacz, 2017; Herberholz and Wigger, 2021); and (iii) the impact of university efficiency on the broader socio-economic environment (Agasisti et al., 2019, 2021; Crespo et al., 2022). In this paper, we focus on the first and second areas.

The literature on the determinants of efficiency in general, and for the case of universities in particular, has faced a significant methodological challenge, namely, how to incorporate the determinants into the analysis. This challenge becomes particularly complex when dealing with multiple outputs, which universities are considered to be because of their three missions: teaching, research, and knowledge transfer (Laredo, 2007; Sánchez-

Barrioluengo, 2014). Traditional approaches have often relied on two-stage procedures, where efficiency scores are first obtained and then regressed against potential determinants. However, this approach suffers from significant methodological limitations, including separability issues and statistical dependencies that can lead to biased results (Simar and Wilson, 2007, 2011; Daraio et al., 2019; Bădin et al., 2014).

For parametric methods such as stochastic frontier analysis (SFA), the literature has established that two-stage approaches are not methodologically sound (Battese and Coelli, 1995; Kumbhakar et al., 2020). Instead, one-stage models that jointly estimate efficiency and its determinants are required. While single-output SFA models with determinants have been developed within both frequentist and Bayesian frameworks, the extension to multiple outputs presents considerable challenges. The combination of multiple outputs with the incorporation of efficiency determinants in a single-stage framework has received limited attention, with only two known contributions from the frequentist perspective (Chiariello et al., 2022; Bigerna et al., 2025) and no known references using the Bayesian approach.

This gap in the literature is particularly significant given the growing importance of understanding what drives institutional performance beyond simple output comparisons. Analyzing what might impact on the efficiency of decision making units (DMUs), higher education institutions in our case, has received a great deal of attention over the years. However, the degree of heterogeneity among possible determinants of university efficiency is remarkable, influenced by factors including different data sources, varying classifications of university activities, and diverse socioeconomic environments (Rhaiem, 2017). While some efforts have been made to synthesize the existing literature, the lack of analytical tools that rely on statistical methods rather than depending solely on previous studies represents a significant limitation.

Against this backdrop, this paper makes an attempt to contribute to the literature from different perspectives. First, we develop and implement a Bayesian stochastic ray frontier model that jointly estimates efficiency and its determinants in a single stage for multiple-output institutions, specifically addressing the methodological gap identified above. This approach provides full efficiency distributions rather than point estimates, enabling robust statistical comparisons between institutions. Second, we employ a systematic variable selection approach using backward stepwise selection with the deviance information criterion (DIC) to identify key efficiency determinants from a comprehensive set of potential factors. This methodological innovation moves beyond *ad hoc* variable selection based on previous studies toward a more analytically rigorous approach grounded in statistical criteria. Third, we provide a comprehensive analysis of Spanish public universities over the 2016–2021 period, encompassing all three university missions through a balanced multi-output framework. Our analysis identifies several key efficiency determinants, including average department size, number of campuses, academic staff characteristics, and multi-province location, offering valuable insights for university managers and policymakers. Fourth, we extend our analysis to examine productivity dynamics through Malmquist indices, providing insights into efficiency changes, technological progress, and total factor productivity growth over the study period. This dynamic perspective reveals that approximately half of the universities show positive efficiency changes, with substantial variations in the probability of improvement across institutions and time periods. Finally, our Bayesian approach provides methodological advantages including full posterior distributions for all parameters and efficiency scores, allowing for probabilistic statements about efficiency changes and robust statistical inference. This represents a significant advancement over traditional approaches that yield only point estimates without measures of uncertainty.

The remainder of the paper is organized as follows. Section 2 provides background on the determinants of efficiency for higher education institutions and reviews the relevant methodological literature. Section 3 describes our data and the measurement of university efficiency across the three missions. Section 4 presents our methodology, including the Bayesian stochastic ray frontier model with determinants and the variable selection procedure. Section 5 discusses the results, including model selection, efficiency scores, identified determinants, and productivity dynamics. Section 6 concludes with policy implications and directions for future research.

2. Background

2.1. Determinants of efficiency: a review of methods

Understanding what factors influence the efficiency of decision making units (DMUs)—in our case, higher education institutions—has been a central concern in the efficiency literature for decades. This interest has persisted since the early foundational studies on efficiency and productivity using frontier techniques (Charnes et al., 1978; Banker et al., 1984), spanning both methodological developments and empirical applications. However, despite extensive research efforts, one might conclude that the greatest consensus in this field is actually the lack of consensus on how to properly measure and incorporate the impact of factors affecting DMUs' performance (Simar and Wilson, 2007, 2011; Banker and Natarajan, 2008; Bădin et al., 2014; Mergoni et al., 2025).

The methodological approaches proposed in the literature vary significantly depending on how efficiency itself has been measured. Researchers can choose between nonparametric methods such as data envelopment analysis (DEA) (Charnes et al., 1978; Banker et al., 1984; Farrell, 1957) or parametric approaches such as stochastic frontier analysis (SFA) (Aigner et al., 1977; Meeusen and van Den Broeck, 1977). Each methodological family presents distinct challenges when incorporating efficiency determinants, as the underlying assumptions and statistical properties differ substantially. In the specific context of higher education institutions, the methodological preference has leaned overwhelmingly toward nonparametric methods, following a broader trend observed in public sector efficiency studies—a particularly relevant consideration given our focus on Spanish public universities.

Nonparametric methods, particularly linear programming techniques such as DEA, give rise to several methodological problems arise when attempting to identify efficiency determinants. The most significant issue relates to the statistical inconsistency between efficiency scores obtained in the first stage and the econometric methods applied in the second stage to evaluate determinants. This inconsistency stems from the fact that DEA efficiency scores are statistically dependent (as they result from linear programming optimization), while traditional second-stage methods such as ordinary least squares (OLS) or Tobit regression assume statistical independence among observations. This fundamental problem was simultaneously highlighted by Simar and Wilson (2007) and Balaguer-Coll et al. (2007), who proposed different methodological solutions to address these statistical dependencies. Soon after, Banker and Natarajan (2008) offered an alternative approach that still permitted the use of OLS in the second stage under certain conditions. However, these solutions may not always be valid, as some researchers have argued that it might not always be possible to legitimately separate the two stages of analysis—that is, measuring efficiency first and then determining its drivers second. This limitation arises when the separability condition (Daraio et al., 2019) is not satisfied, meaning that the variables affecting the production process cannot be clearly distinguished from those affecting efficiency.

Given these methodological challenges, it may be more appropriate to employ conditional efficiency analysis when the two-stage separation is not feasible. In this unified approach, both efficiency measurement and the identification of its explanatory factors occur within a single analytical framework. Various methodological contributions have emerged for this one-stage analysis, including the influential work of De Witte and Kortelainen (2008) and Bădin et al. (2012). More recent developments can be found in Bădin et al. (2024) and Mergoni et al. (2025), along with comprehensive reviews such as Bădin et al. (2014). While many university efficiency studies have employed nonparametric methods such as DEA, parametric alternatives like SFA remain equally valid and, in many cases, preferable.

For parametric methods, particularly SFA, the challenges of incorporating efficiency determinants differ substantially from those encountered in nonparametric approaches. SFA allows researchers to analyze relationships between multiple inputs and a single output while accommodating different probability distributions for the inefficiency term (Kumbhakar and Lovell, 2000). The Bayesian perspective offers a particularly attractive framework for making inferences about SFA model parameters, as evidenced by its extensive application in numerous studies (Van den Broeck et al., 1994; Koop et al., 1994, 1995, 1997; Fernández et al., 2000; Tsionas, 2000; Fernández et al., 2001; Martín et al., 2009; Barros and Rossi, 2014; Galán et al., 2014; Carvalho and Marques, 2016; Assaf et al., 2017; Tsionas et al., 2019).

However, extending SFA to handle multiple outputs—a critical requirement for university efficiency analysis given the three missions of teaching, research, and knowledge transfer—presents significant technical challenges. Within the Bayesian framework, two main approaches have emerged to address this limitation. Fernández et al. (2000) proposed a method for handling multiple outputs, but this requires complete programming of the Gibbs sampling procedure, limiting its accessibility and practical implementation. A more practical alternative involves using the Bayesian approach to make inferences about a refined version of SFA: the stochastic ray frontier model, originally introduced by Löthgren (1997) and subsequently improved by Henningsen et al. (2017). This approach enables Bayesian inference either through custom Gibbs sampling programming (Tsionas et al., 2022) or more conveniently through software packages like `JAGS` (Plummer, 2003), as shown in García-Tórtola et al. (2025).

The incorporation of efficiency determinants in SFA presents its own methodological considerations. An alternative could involve obtaining efficiency scores in a first stage and then regressing these scores against potential determinants in a second stage. However, as established by Battese and Coelli (1995) and Kumbhakar et al. (2020), this two-stage approach is methodologically flawed. The first stage involves the specification and estimation of the stochastic frontier production function and the prediction of the inefficiency effects under the assumption that these inefficiency effects are identically distributed. However, the second stage involves the specification of a regression model for predicted inefficiency effects, which contradicts the assumption of identically distributed inefficiency effects for parametric frontier models. Therefore, it is more advisable to use a one-stage model that jointly estimates efficiency and its determinants within a unified statistical framework.

Additionally, researchers must also consider the separability assumption—whether a relationship exists between the input variables used in the production function and the variables hypothesized to determine efficiency levels. In our study, we believe that factors beyond the control of universities—such as institutional or personnel characteristics—do not affect the production process (that is, the transformation of inputs into outputs) directly, but rather explain the efficiency of the educational production process.

For single-output SFA models, two main approaches exist for incorporating efficiency determinants, differing in whether distributional assumptions are imposed on the inefficiency term. The first approach assumes that efficiencies follow a known probability distribution whose parameters are linked to the determinant variables. This methodology was pioneered by Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) for cross-sectional data and extended by Battese and Coelli (1995) for panel data applications.[1] Both frequentist and Bayesian inference procedures have been developed for this approach (Koop et al., 1997; Griffin and Steel, 2007).

The second approach avoids imposing specific distributional assumptions on inefficiency. Instead, efficiency levels are directly linked to determinant variables through standard link functions such as logit or probit transformations. Within the frequentist framework, applications of this approach remain relatively scarce.[2] Bayesian implementations, in contrast, are somewhat more common, with some contributions such as Emvalomatis (2012), Skevas et al. (2018), Skevas (2020), Lachaud and Bravo-Ureta (2022), and Gargallo et al. (2025) employing logit links, and Tsionas (2006) using the probit transformation.

The combination of multiple outputs with efficiency determinants in a single-stage framework represents the most challenging methodological scenario and has received extremely limited attention in the literature. From the frequentist perspective, only Chiariello et al. (2022) and Bigerna et al. (2025) have addressed this combination. Remarkably, no studies using the Bayesian approach for this methodologically demanding but practically important case appear to exist in the literature—a gap that the present paper seeks to address.

2.2. Identifying the determinants of university efficiency

Regardless of the method considered to measure efficiency and the impact of exogenous variables, the researcher should also decide *how to define* what universities do, and *what determines* their levels of (in)efficiency. This section discusses the later issue, while the former is discussed in section 3.

The literature has identified a broad set of covariates that may account for efficiency differences across universities. However, as Rhaiem (2017, p. 605) concludes from his literature review, "the determinants of academic efficiency seem to be chosen in an *ad hoc*

[1] A comprehensive review of the various modeling options within this framework can be found in Kumbhakar et al. (2020).

[2] See, for instance, Emvalomatis et al. (2011), who employed the logit link, while Paul and Shankar (2018, 2022) used the probit specification.

manner and without necessarily being grounded in theory. Many studies among those selected in our systematic review did not refer explicitly to models or theoretical approaches when they considered the explanatory variables of academic efficiency." Therefore, there is little consensus on the appropriate set of explanatory variables, which has led to a considerable degree of heterogeneity across studies. This diversity arises from several sources. First, cross-country heterogeneity plays a central role: universities operate under country-specific regulatory frameworks and organizational structures, and the way they function is strongly influenced by the socioeconomic and institutional environments in which they are embedded (national and regional). Thus, some relevant studies that undertake international comparisons, have considered how the determinants differ depending on the country under analysis (Agasisti and Wolszczak-Derlacz, 2016; Agasisti, 2011; Agasisti and Haelermans, 2016; Agasisti and Pohl, 2012; Wolszczak-Derlacz and Parteka, 2011; Wolszczak-Derlacz, 2017; Herberholz and Wigger, 2021). Moreover, differences in the availability and quality of data further shape the set of variables that can be included in empirical analyses. Second, studies vary in how they define and classify both the activities of universities (outputs) and the resources they use (inputs). Some analyses address overall efficiency, while others adopt a more mission-oriented perspective, focusing separately on teaching, research, or knowledge transfer (see, for instance, Rhaiem and Amara, 2020; Chapple et al., 2005; Curi et al., 2012; Degl'Innocenti et al., 2019; Hou et al., 2021; Johnes and Yu, 2008; Lee, 2021; Pastor and Serrano, 2016; Siegel et al., 2003, among others). Third, the scope of the determinants also depends on the type of organization under consideration. In particular, public and private universities often differ substantially in their objectives, funding mechanisms, and governance structures, which in turn influence the determinants of their efficiency (Anderson et al., 2007).

Given the long list of potential covariates, several papers have attempted to classify them according to different categories, such as for instance, controllable vs uncontrollable factors (Narbón-Perpiñá et al., 2020), or environmental vs contextual variables (Giménez et al., 2024). Based on a review of the literature, Rhaiem (2017) classifies variables used as determinants of higher education institution (henceforth, HEI) efficiency into twelve categories.[3] He finds that variables accounting for *seniority and composition of staff*, *institutional factors*, *size effects*, *funding structure* and *scientific meritocracy* tend to have an overall positive effect on HEI efficiency. However, the conclusions for the variables in the other categories are more uncertain, because either they are found to be non-significant, or a relevant popu-

[3]Namely, (i) size effects; (ii) institutional factors; (iii) seniority and composition of staff; (iv) funding structure; (v) prestige and reputation of the institution; (vi) scientific meritocracy; (vii) gender effect; (viii) agglomeration effects; (ix) social capital; (x) quality indicator; (xi) characteristics of students; and (xii) protection of intellectual property.

lation of studies find positive and negative effects of these variables. Inspired by Rhaiem's classification, we develop our own analytical categorization of factors potentially affecting university efficiency. This classification aims to capture the multidimensional nature of efficiency determinants by grouping them into four categories.

The first category refers to university organizational factors, encompassing the structural and organizational characteristics internal to the institution. This category can cover a broad range of elements. It includes, first, size-related aspects such as the number of faculties, departments, total staff, or total students. Second, it captures the scope and balance of activities undertaken by the university, referring both to the equilibrium across its missions and to its disciplinary profile, whether generalist or specialist (Herberholz and Wigger, 2021). Third, it involves organizational attributes such as public or private status, age, number and location of campuses, human resource policies for hiring and promoting academic staff, or governance structure. Moreover, it includes the availability of specific services that can significantly affect costs and/or outputs, such as the presence of medical or engineering schools, university business parks, or technology transfer offices among others. Finally, the structure of university funding may also influence institutional efficiency. The second category concerns the features of HEI staff. The basic intuition is that staff members represent a fundamental input in the university production process. The higher their quality, the greater the potential output the institution can achieve. Beyond academic and administrative staff numbers (a size effect), this category considers characteristics related to composition (e.g., gender, age, academic-to-administrative ratio) and the scientific quality of academic personnel. In a similar vein, the third category refers to the quality of the student body. The higher the *students' academic level*, the higher their expected educational outcomes and subsequent employability will be. Student characteristics may include both compositional aspects (age, gender, nationality) and pre-entry academic performance. Finally, the fourth category relates to the external environment of universities. This encompasses, on the one hand, the economic context, including factors such as the specialization profile of the surrounding economy, regional economic dynamism, or the strength of the regional innovation system; and, on the other hand, the institutional context, both formal and informal, including the regulatory framework, existence of research evaluation bodies, social capital, and institutional quality, among others.

Hence, given the remarkable heterogeneity and diversity of variables that could potentially determine university efficiency, we argue for a more systematic and analytically rigorous approach that moves beyond the variable selection practices commonly found in the literature. Rather than relying solely on what previous studies have considered, and as we shall see below, we propose to use statistical methods for variable selection that can objectively identify the most relevant efficiency determinants from a comprehensive set of candidates. In this regard, Bayesian methods offer particular advantages for university efficiency analysis, including the ability to handle complex multi-output scenarios, provide full distributional information about efficiency scores and their determinants, and incorporate model uncertainty through formal variable selection procedures.

3. Data: measuring the efficiency of universities

Measuring the efficiency of universities—i.e., how well a university converts inputs into outputs relative to the best-performing universities (the frontier)—faces some particularities (Johnes, 2006), for several reasons. Firstly, the main motivation of (public) universities is not profit maximization but to contribute to social progress and growth by producing and disseminating knowledge. Second, the various activities that universities undertake with that aim are usually referred to as their "three missions": teaching, research and knowledge transfer to the socioeconomic environment (Laredo, 2007; Sánchez-Barrioluengo, 2014). Because of these three missions, in terms of efficiency, universities are considered as multi-output organizations (Agasisti and Pérez-Esparrells, 2010; Martínez-Campillo and Fernández-Santos, 2020). A third issue, also related to the previous one, is the definition of inputs and outputs (for each of the three missions), as well as their measurement. On the one hand, the distinction between what is an input and what is an output is not always obvious (for a review on this issue see Berbegal Mirabent and Solé Parellada (2012)). On the other hand, many of the inputs used and outputs generated by universities across their various activities are intangible and lack market prices, making them difficult to identify and quantify; moreover, they can be assessed from both quantitative and qualitative perspectives.

We have taken these issues on board to build our model to measure HEI efficiency. Thus, following García-Tórtola et al. (2025), on the output side, we consider a balanced set of two quantitative outputs [4] for each of the three university missions: *i)* teaching output is measured by the number of graduates at the bachelor (undergraduate) level and at the master (postgraduate) level (Berbegal Mirabent and Solé Parellada, 2012); *ii)* research output is measured by the number of papers published in Web of Science-indexed journals and by the number of research projects (funded through national and European calls) awarded annually to academics affiliated with the university (Berbegal Mirabent and Solé Parellada, 2012; Crespo et al., 2022); and *iii)* knowledge transfer output, although it encom-

[4] Although we acknowledge the relevance of qualitative indicators, data to proxy them are not equally available for all three missions. Moreover, mixing quantitative and qualitative indicators may confound interpretation of efficiency scores

passes a larger variety of activities, due to data availability, we use the number of patents universities apply for (either in the national office or with a PCT extension) and the number of academic spin-offs founded by the universities staff (Berbegal Mirabent and Solé Parellada, 2012; Crespo et al., 2022). On the input side, we use the overall expenditure on non-financial operations, a single input that we assume covers the overall costs universities have to pay for their physical inputs. 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). Thus, our approach to efficiency is neither purely technical nor purely cost-based, but rather a combination of both, as we use physical units on the output side and monetary units on the input side.[5]

We also adopt an output-oriented approach, under which universities maximize their outputs given their current cost structure and spending levels. Accordingly, a university is output-oriented (cost) efficient if it cannot increase its production of graduates, research, or other outputs without increasing its total costs. Hence, under this perspective the question analyzed would be if, given the current HEI budget and spending, it is producing the maximum possible outputs. In contrast, an input-oriented approach would measure how well a university minimizes its costs while maintaining its current level of outputs.

The choice between these orientations often reflects institutional priorities and constraints, whether universities face pressure to cut costs (input-oriented) or expand their impact and enrollment (output-oriented). Most of the literature on the efficiency of universities has adopted an output approach (Chapple et al., 2005; Curi et al., 2012; Anderson et al., 2007; Agasisti and Pohl, 2012; Wolszczak-Derlacz, 2017, among others). For our study based on 47 public Spanish universities, we consider an output-oriented approach to be particularly appropriate given the institutional constraints these universities face. Spanish public universities operate under rigid cost structures where the majority of their expenditures are predetermined (faculty and administrative staff are predominantly civil servants with standardized salary scales set by government regulations, limiting universities' ability to adjust personnel costs). Additionally, infrastructure investments, utility costs, and many operational expenses are subject to public procurement rules and bureaucratic processes that constrain cost flexibility. However, these same universities retain significant autonomy in implementing policies to enhance productivity and output generation. They can introduce, to some extent, research incentive schemes, establish performance-based promotion

[5] In this regard, only a few contributions have analyzed the cost efficiency of HEIs (see, for instance Agasisti and Salerno, 2007; Crespo et al., 2022); however, in contexts where public universities dominate, and given they can be subject to important budget constraints (Qian and Roland, 1998), it is particularly relevant to evaluate how efficiently they manage their resources.

criteria, create centers of excellence, develop industry partnerships, implement innovative teaching methodologies, and design programs to attract high-quality students and faculty. Since Spanish public universities have limited control over their input costs but more capacity to influence output levels through strategic policies and management practices, an output-oriented efficiency framework might better capture their operational reality, providing more actionable insights for performance improvement (Wolszczak-Derlacz, 2017; Degl'Innocenti et al., 2019).

As already discussed, the literature identifies a wide and diverse range of variables that may influence university efficiency. Given that we apply a model selection approach (see Section 4), we remain agnostic regarding the specific choice of explanatory variables. Accordingly, and based on our discussion in section 2, we have sought to include as many potential determinants of HEI efficiency as identified in the literature. Nonetheless, our selection is limited by: (i) data availability; (ii) the requirement that the variables used as determinants have to be exogenous to the efficiency computation; and (iii) the need to avoid co-linearity issues due to high correlation between explicative variables.

Thus, we include two sets of explanatory variables. The first set captures institutional characteristics of the university and comprises the following: the number of faculties (*Faculties*); a dummy variable indicating the presence of a Faculty of Medicine (*Medicine*); the age of the university, calculated as the difference between the current year and the year it was founded (*Age*); the specialist or generalist profile of the university, measured by a Herfindahl-Hirschman Index (HHI) based on the distribution of students across the five main fields of study (*StudentHHI*); the average department size, defined as the ratio of total employees (academic and administrative staff) to the number of departments (*StaffDepartment*); the number of campuses (*Campuses*); and a dummy variable indicating whether these campuses are located in the same or different provinces (*Multi-province*). The second set of variables relates to characteristics of university personnel, considered a key resource in institutional performance. These include: the ratio of academic to administrative staff (*StaffRatio*); the average age of academic personnel (*StaffAge*); the proportion of academic staff holding tenured civil servant positions (*StaffCS*); the proportion of female academic staff (*Women*); and, as a proxy for research performance, the average number of *sexenios* per academic staff member[6] (*Sexenios*). All the variables used as determinants (except the dummy variables) were standardized. Conversely, we do not have variables filling the requested conditions for the categories of quality of students and features of the environment, although we have included a random effect for autonomous regions.

[6]In the Spanish system, a *sexenio* is an official recognition awarded by a national agency for having conducted sufficient research over a six-year period. Each approved evaluation grants a permanent salary bonus.

This study focuses on the 47 Spanish public universities that maintained continuous in-person teaching between 2016 and 2021.[7] Data on university inputs and outputs were obtained from two main sources: the Spanish Ministry of Universities and the IUNE Observatory. The Ministry, through its Integrated University Information System (SIIU), provided information on university budgets (in euros), which we use as input variables. Data for most of the determinants of efficiency were also obtained from the SIIU. In some cases, such as the universities' age and the multi-province location of campuses, data were manually collected from the universities' websites. To account for inflation over the period, monetary values were deflated using the regional price index published by the National Statistics Institute (INE). The SIIU also supplied data on the number of graduates from bachelor's and master's programs, which serve as output indicators for teaching activities. Research output and knowledge transfer data were sourced from the IUNE Observatory. From this database, we obtained indicators of research activity (number of Web of Science publications and research grants from national and international calls) and knowledge transfer (number of patents granted and spin-offs created). Descriptive statistics for all input and output variables are presented in Table 1.

The first universities in Spain were established several centuries ago. However, the major quantitative and qualitative transformation of the Spanish university system began in the 1970s, following two key legal and institutional reforms. First, the transition to democracy brought a decentralized political-administrative structure, which transferred responsibility for higher education to the regional governments (Autonomous Communities). These now hold authority over university governance and funding. Second, the enactment of the University Reform Law (Ley de Reforma Universitaria, LRU) in 1983 marked a decisive step toward the modernization of Spanish universities. The subsequent reforms in 2001, 2007, and 2023 further aimed to align the system with the Bologna Declaration and to promote internationalization, research excellence, and knowledge transfer.

Our analysis focuses on 47 public universities with a diverse spatial distribution.[8] Each Autonomous Community hosts at least one public university, and every province contains at least one public university campus. Nevertheless, the spatial organization of the system varies: in some regions, a single university operates multiple campuses across provinces, while in others, each province hosts an independent university. We study the period 2016–2021, a time marked by economic recovery, during which the most severe public budget cuts introduced in the wake of the Great Recession had been reversed. Thus,

[7] However, most universities switched to online teaching only during the years of the COVID-19 pandemic.

[8] We omitted the public universities Universidad Nacional de Educación a Distancia (UNED), Universidad Internacional Menéndez y Pelayo (UIMP) and Universidad Internacional de Andalucía (UNIA) due to their distinctive characteristics: they either function solely for distance learning or lack a permanent staff.

despite increases in the overall budgets of Spanish public universities during this period, investment levels remain relatively low compared to other European countries, and there are substantial disparities across regions.

Public universities must allocate their budgets across their three core missions: teaching, research, and knowledge transfer. After the slight decline in student enrollment during the final years of the Great Recession, the total number of students in the higher education system began to increase again. However, since the 2016–2017 academic year, this growth has been driven primarily by private universities (outside the scope of this study), while enrollment in public universities has fallen by approximately 1.6%. Regarding research and knowledge transfer, expectations placed on universities are now higher. The growing influence of global rankings has intensified inter-university competition, particularly in the research domain. In parallel, the transition toward a knowledge-based and innovation-driven economy, where universities are expected to play a pivotal role, has become a dominant policy discourse. This role is explicitly acknowledged in frameworks such as the triple helix model and regional innovation systems. Consequently, recent policy reforms have increasingly linked academic career progression to performance in research and knowledge transfer activities.

4. Methodology

In this section, we describe the methodology for jointly estimating efficiency and its determinants in a single stage by extending the stochastic ray frontier model (Löthgren, 1997). The first subsection presents the proposal and outlines the methodology for performing inference on it within the Bayesian framework. The second subsection provides a detailed explanation of the methodology for selecting the determinants of efficiency. The final subsection details the methodology for conducting the dynamic analysis.

4.1. A Bayesian stochastic ray frontier panel data model with determinants of efficiency

In line with recent work such as, for instance, García-Tórtola et al. (2025), and in order to analyze efficiency with multiple outputs, our proposal will be based on the stochastic ray production Frontier (SRPF), which was first proposed by Löthgren (1997) and more recently improved by Henningsen et al. (2017). Indeed, the methodology fits particularly well the HEI context, which utilizes multi-product cost functions.

As previously stated, this paper does not merely analyze efficiency, but seeks to jointly describe the efficiency and its determinants in a single stage. In the context of stochastic frontier analysis, the challenge of addressing multiple outputs while incorporating the determinants into a single stage is a complex undertaking, with limited contributions evident in the literature. This observation pertains to both the frequentist perspective and the Bayesian approach, with no known references utilizing the latter, and only the works by Chiariello et al. (2022) and Bigerna et al. (2025) in the frequentist context.

In particular, the panel data stochastic ray frontier model that allows us to measure the efficiency in the context of multiple outputs is given by

$$\log ||y_{it}|| = \beta_0 + x_{it}^t \boldsymbol{\beta} + v_{it} + \log(\mathrm{TE}_{it}), \;\; i = 1, \ldots, N \text{ and } t = 1, \ldots, T, \tag{1}$$

where, as is usual in this context, $\log ||y_{it}||$ is the logarithm of the Euclidean norm of the output vector of HEI i in time period t, that is, $||y_{it}|| = \left(\sum_{j=1}^{p} y_{jit}^2 \right)^{1/2}$; x_{it}^t is a vector containing the transformed inputs of HEI i in time period t (via the translogarithmic functional form) as well as the angles of the polar coordinates of the outputs of HEI i in time period t (θ_{jit}); TE_{it} is the efficiency of HEI i in time period t; and the term v_{it} is the usual independent and identically Gaussian distributed error term, $v_{it} \sim \mathrm{N}(0, \sigma_v^2)$. In order to reduce the magnitude of rounding errors when calculating the angles of the polar coordinates of the outputs, we follow the suggestion by Henningsen et al. (2017), that is, these angles are obtained as:

$$\theta_{jit}(y_{jit}) = \cos^{-1}\left(\frac{y_{jit}}{||y_{it}||} \right). \tag{2}$$

As can be observed in Equation (1), this model is not expressed in terms of the conventional inefficiency component, u_{it}, but rather focuses on the efficiency of each HEI i in time period t, $\mathrm{TE}_{it} = \exp(-u_{it})$. The underlying reason for this is that we use this efficiency directly to determine its potential determinants by means of:

$$\mathrm{logit}(\mathrm{TE}_{it}) = \log\left(\frac{\mathrm{TE}_{it}}{1 - \mathrm{TE}_{it}} \right) = z_{it}^t \boldsymbol{\delta} + \xi_{A(i),t}, \tag{3}$$

where z_{it}^t denotes the vector containing the exogenous variables associated with the efficiency determinants for each HEI i in time period t; the vector of parameters associated with the determinants of efficiency is represented by $\boldsymbol{\delta}$; $\xi_{A(i),t}$ represents an additional Gaussian error term that captures the possible effect associated with belonging to a specific autonomous region for each HEI i in time period t (that this, $\xi_{A(i),t} \sim \mathrm{N}(0, \sigma_A^2)$); and finally, in line with previous proposals (Emvalomatis, 2012; Skevas et al., 2018; Skevas, 2020), the logit transformation (the inverse of the logistic function) is used to project the efficiency from the unit interval (i.e., 0 to 1) to the real line (i.e., $-\infty$ to $+\infty$).

Having defined the extended stochastic frontier model of efficiency and its possible determinants via the logit link, our next step is to infer the model's parameters. We propose working within the Bayesian paradigm here, as this allows for a detailed study of parameter uncertainty during model estimation, and efficiency and determinant prediction (see, for instance, Skevas et al., 2018; Skevas, 2020; Gargallo et al., 2025).

Within this context, we must specify our prior beliefs about the parameters involved in the model, mainly the regressors of the inputs and the determinants, as well as the hyperparameters, such as the variance of the random effect associated with the region effect. Eliciting this information can be complex and challenging because we may lack the experience and intuition necessary to express all our prior knowledge about the parameters in probabilistic terms. When no prior information about the parameters is available, the usual approach is to use non-informative priors, which recognizes our lack of knowledge and prevents subjective opinions or assumptions from unduly influencing the outcome. Accordingly, our prior choices for the parameters of equations (1) and (3) are as follows: $\mathrm{N}(0, 10^3)$ for the regression coefficients β_0 and $\boldsymbol{\beta}$; $\sigma_v \sim \mathrm{Un}(0, 10^3)$; $\boldsymbol{\delta} \sim \mathrm{N}(0, 5)$; and $\sigma_A \sim \mathrm{Un}(0, 10^3)$.

The final result of the Bayesian inferential process is the posterior distribution of the parameters and hyperparameters. However, as is common in this context, there is no closed-form expression for those posterior distributions, and numerical approximations, such as Markov chain Monte Carlo (MCMC) based methods, are needed. These methods can be programmed, as demonstrated in Fernández et al. (2000) and, more recently, Tsionas et al. (2022), among others, or implemented using one of the many statistical packages available. We used the software package `JAGS` (Plummer, 2003), which offers a more user-friendly implementation of the MCMC approximation for non-experts in the Bayesian approach (García-Tórtola et al., 2025).

4.2. A backward stepwise selection of determinants of efficiency

Most of the studies to date have analyzed the efficiency determinants by checking the statistical significance (or relevance, in the context of the Bayesian paradigm) of each regressor. This objective can be accomplished by estimating the parameters of the one-stage model previously outlined. While this approach may result in a satisfactory explanation of the importance of a determinant in the presence of all other determinants, superior methodologies exist to execute a systematic model selection.

In this study, we propose a more systematic approach to variable selection that involves the use of backward stepwise selection, a well-known and widely used approach to model selection in regression analysis. The procedure begins with a full model that includes all the variables (efficiency determinants, in this case) and proceeds by iteratively eliminating one variable at a time from the model (based on a criterion). The algorithm ends when the stopping criterion is met.

Similar to the well-known Akaike's Information Criterion (AIC; Akaike, 1974), the deviance information criterion (DIC; Spiegelhalter et al., 2002) evaluates model fit and complexity by penalizing poor fit and model complexity within the Bayesian context. Thus, it prefers models with lower values. The DIC was initially defined as follows:

$$\mathrm{DIC} = \overline{D(\boldsymbol{\theta})} + p_D = 2\overline{D(\boldsymbol{\theta})} - D(\overline{\boldsymbol{\theta}}), \tag{4}$$

where $\overline{D(\boldsymbol{\theta})}$ is the posterior mean deviance, $\boldsymbol{\theta}$ is the vector of the parameters of interest, and p_D is the effective number of parameters, which can be approximated as the difference between the posterior mean deviance and the deviance calculated using some point estimate, i.e., $\overline{D(\boldsymbol{\theta})} - D(\overline{\boldsymbol{\theta}})$.

A second version, which is more numerically stable when using MCMC via `JAGS`, was proposed by Plummer (2003) and is defined as follows:

$$\mathrm{DIC}_{\mathrm{JAGS}} = \overline{D(\boldsymbol{\theta})} + p_D = \overline{D(\boldsymbol{\theta})} + 0.5 \cdot \mathrm{Var}(D(\boldsymbol{\theta})), \tag{5}$$

where the effective number of parameters is defined in this version as half the posterior variance of the deviance. This formulation prevents instability issues arising from a skewed or multimodal posterior distribution, particularly in complex or hierarchical models.

In summary, in order to identify efficiency determinants from a comprehensive set of potential factors, our backward stepwise algorithm iteratively eliminates one variable at a time from the model, that is, the one with higher DIC. The algorithm terminates once the predetermined stopping criterion is met. In our case, this occurs when the DIC is higher for all the remaining variables than in the previous step. In cases where the DIC values are similar (less than one unit), the simpler model (the model with fewer variables) will be selected in accordance with Occam's razor.

4.3. Explaining the determinants, and obtaining efficiencies and productivity indices

The methodology presented in the previous subsections results in a random sample of the posterior distribution of each parameter of the final selected model that includes the most important determinants explaining the efficiencies. It is possible to study the type of relationship (positive or negative) between the determinants and the efficiency by describing the posterior distribution of the parameters of the regressors (δ), as shown in Equation

(3), through the use of the posterior mean, the posterior median, and the corresponding credible regions of those posterior distributions.

Moreover, the MCMC process allows us to estimate the posterior predictive distribution (or its characteristics) of the efficiency of each HEI. This capability facilitates statistical comparisons between HEIs, enables the ranking of HEIs from most to least efficient, and allows the investigation of efficiency differences. In other words, the use of Bayesian posterior distributions offers more insights than simply determining if the estimated efficiency indicates higher or lower efficiency: it provides statistical relevance.

In addition, we can also make inferences about the productivity of HEIs. In particular, given that productivity indices are a function of efficiencies, we can approximate the posterior distribution of the indices of change in efficiency, technological change, and total productivity (which, combined together can conform a Malmquist-type productivity index; see Caves et al., 1982) by performing the same transformations to the approximate posterior distributions of the efficiencies. We only have to take into account the time-dependent structure of the data.

Specifically, the index of change in efficiency (TEC) is defined as

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

where i denotes the HEI and t, s (where $t > s$) correspond to the time periods for calculating the change in efficiency. Then, the posterior distribution of TEC can be approximated by means of the quotient of the different values of the sample of the posterior distributions of the efficiency in both the numerator and denominator in Equation (6). This can be easily done by incorporating some lines in the `JAGS` code. Recall that the interpretation of TEC_i is as follows: if TEC_i is greater than 1, it indicates progress in efficiency, while if it is less than 1, it indicates regression in efficiency. If TEC_i is equal to 1, it indicates no change in relative efficiency between periods t and s.

In a similar way, we can obtain the posterior distribution of the index of technological change (TC). This index is defined as follows:

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

The interpretation of TC_i is: if TC_i is greater than 1, it indicates progress in the technological frontier, while if it is less than 1, it indicates regression. If TC_i is equal to 1, it indicates no change in the relative technological frontier between periods t and s.

Finally, we can also obtain an approximation of the posterior distribution of the index of change in total productivity (TPF). This index is defined from Equations (6) and (7) as:

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

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

5. Results

In the following section, we present the results of our empirical analysis. First, we discuss the model selection process. Second, we take a static approach to examine the efficiency of universities in each of our sample years, that is, the distance of each university to the stochastic frontier in that particular year t. Next, we examine the main determinants of the efficiency of universities. Finally, we use a dynamic approach to analyze changes in efficiency over time. We decompose these changes into two types of movements: shifts in the efficiency of universities closer to (or further from) the best practice frontier, and shifts in the frontier itself over time.

5.1. Selecting the model

Table 2 shows some of the best models that have been compared, as well as their corresponding values of the DIC criterion. To identify the most appropriate model, we first compared two initial models. The first model (M_1) included all the determinants of efficiency of universities and the random effect associated with the autonomous region of each university, while the second model (M_0) included all the determinants but excluded the random effect. Model M_1, which included all the determinants and the random effect, had the lowest DIC, indicating a better fit. Including the random effect by autonomous region allows the model to capture unobserved heterogeneity between regions, reflecting differences in regional government policies, funding systems, regulation, and macroeconomic conditions. As noted by Martínez-Campillo and Fernández-Santos (2020), this may help to explain differences in the efficiency of public universities. In addition, previous studies have also shown that there is a regional effect in the higher education sector, suggesting that university efficiency varies according to the region in which HEIs are located within a specific country (Agasisti and Pohl, 2012; Agasisti and Wolszczak-Derlacz, 2016; Wolszczak-Derlacz, 2017).

Then, we used a stepwise backward algorithm to select the determinants of university efficiency. At each step, we removed one determinant at a time and compared the resulting models using the DIC criterion. In the first step, the model with the lowest DIC was M_2, which excluded the determinant associated with the number of faculties. In the second step, none of the models had a lower DIC than M_2. However, since the DIC values of the models M_2 and M_{24} were very similar, we opted for M_{24} due to its simplicity. This model excluded the determinant corresponding to the faculty of medicine, which was not statistically relevant in the previous models (M_1 and M_2).

The same process continued with three more steps (from the third to the fifth). Of all the models obtained during these three steps (from M_{25} to M_{51}), model M_{46} exhibited the lowest DIC (-677.52). In the sixth step, none of the models had a DIC model lower than M_{46}. Therefore, we conclude that model M_{46} is the most appropriate for analyzing the efficiency of HEIs and its possible determinants. Furthermore, all determinants included in this model are relevant in the statistical sense, as indicated by the "**Yes**" label in Table 2. More details of each step, including the determinants removed from these models and the corresponding DIC value, are provided in Table 2.

5.2. Efficiency of universities

Figure 1 shows the 95% credible interval for the efficiency of each university in 2016, 2019 and 2021. In each of the panels, universities are ranked by the mean of their efficiency distribution. Efficiency studies generally rank universities based on efficiency scores obtained from the selected measurement technique, typically DEA or SFA (see, for instance Bonaccorsi et al., 2006; Johnes and Yu, 2008; Curi et al., 2012). One advantage of using Bayesian estimation techniques rather than classical ones is that they provide the full efficiency distribution for each university, rather than just a single value.

The visual examination of the efficiency distributions of Spanish universities, as shown in Figure 1, reveals several different patterns. On the one hand, the arithmetic means of the efficiency distributions are relatively similar for most institutions, though there is a gradual decline in efficiency as we move down the ranking. In particular, the mean efficiency of the lowest-ranked university is approximately 37.5% lower than that of the highest-ranked university. On the other hand, the range of the credibility interval remains relatively constant throughout the ranking, with only minor changes. These patterns are consistent across all years in our sample period (2016–2021).

The posterior densities shown in Figure 2 provide a clearer picture of the information obtained using Bayesian methods. The sub-figures illustrate the densities of the posterior distribution of the efficiencies of selected universities in specific autonomous regions in the year 2016. More precisely, the lines in each sub-figure in the upper panel correspond to the universities of the Andalusia, Canary Islands and Castilla and León regions, respectively. In the middle panel, the lines in each sub-figure correspond to the universities of the Catalonia, Galicia and Madrid regions, respectively. Finally, in the lower panel, the lines in each sub-figure correspond to the universities of the Murcia, Valencian and the remaining regions, respectively.

For example, in the Valencian region, most of the probability mass for the Polytechnic University of Valencia (*Universitat Politècnica de València*, UPV, yellow line) is below the probability mass of the other universities in the region. In particular, the overlap with the best university in the Valencian region, which is the University of Valencia (*Universitat de València*, UV, purple line), is essentially nonexistent, indicating that the posterior probability that one university outperforms the other is essentially one. In contrast, there is a remarkable amount of overlap among universities within the same autonomous region. This suggests that they may have faced similar budget cuts that could have affected their efficiency.

5.3. Determinants of the efficiency of universities

Table 3 presents the main statistics of the posterior distribution for the determinants of efficiency of Spanish public universities. All determinants show statistical relevance at the 95% credibility level because their respective credible intervals do not include zero.

In the model selected through the DIC criterion, half of the retained determinants of universities efficiency refer to organizational features of the university. First, we find that the ratio of total employees to the number of departments (*StaffDepartment*), i.e., the average department size, has a positive impact on universities efficiency. Departments are the basic units upon which Spanish universities are organized, meaning that teaching is assigned to departments, and departments are responsible for recruiting new personnel. The positive sign of the coefficient indicates the existence of a certain scale effect, which is in line with the conclusions of Leitner et al. (2007), who show that the size of departments influences its overall performance, although that relationship might not be simply linear. Second, we find a positive effect of the number of campuses (*Campuses*) on the efficiency score of the university, which might be related to the benefits of decentralization for efficiency (Balaguer-Coll et al., 2010a,b). However, the effect is negative if those campuses are located far away from each other, i.e., in different Spanish provinces ($Multi - -province$). The negative effect of multi-province universities is probably explained by (small) scale and duplication effects. It might reflect the political choice of having campuses in all provinces. This political choice can be articulated either by having smaller universities in a single province, or having a bigger university scattered over several provinces. Although both solutions are plausible and observable (e.g., Catalonia vs. Castilla-La Mancha), it seems that the second one is less efficient.

The remaining factors in table 3 retained as affecting university efficiency refer to the staff characteristics. First, a higher proportion of female academic staff (*Women*) has a positive impact on university efficiency. Hence, universities with a greater share of women academics tend to be more efficient. This result is consistent with the findings of Wolszczak-Derlacz and Parteka (2011) for a sample of European public universities, and also aligns with other studies that have documented the positive impact of teams gender diversity on creativity and innovation (Díaz-García et al., 2013; Griffin et al., 2021). Conversely, higher average age of academic personnel (*StaffAge*) has a negative impact on university efficiency, suggesting that universities with a higher proportion of senior academic staff are less efficient. Although this might seem counterintuitive if we expect older staff members to have accumulated experience and built larger academic networks that enhance their capacity to be more efficient in teaching, research and knowledge transfer activities, there are at least two possible explanations for this negative sign. On the one hand, the incentive scheme in the Spanish university system may be less effective for older academics in the later stages of their careers (Faria and McAdam, 2014). On the other hand, although results are not always convergent, several papers have argued that age impacts negatively on innovation activities because older people work with more outdated technological knowledge and are characterized by reduced cognitive flexibility (Schubert and Andersson, 2015; Skirbekk, 2004). Third, a higher proportion of tenured academic staff holding civil servant positions (*StaffCS*) has a positive impact on university efficiency. This finding aligns with studies showing that HEIs with a greater proportion of professors are more efficient (Agasisti et al., 2016; Agasisti and Wolszczak-Derlacz, 2016; Salas-Velasco, 2020). Moreover, in the Spanish university system, this makes sense because applicants' scientific productivity and teaching experience must be positively evaluated by a national agency (ANECA). Therefore, a higher share of professors in the staff reflects the higher quality of the human resources employed by universities to produce their outputs. Likewise, the *sexenios* coefficient is also positive, meaning that the more *sexenios* a university's academic staff accumulates, the higher its efficiency. The basic logic here is similar to the result for *staffCS*. *Sexenios* are granted by ANECA to academic staff for their research performance in the previous six years. Thus, the accumulation of *sexenios* by the university staff signals the quality, at least to conduct research activities, of its staff, and the higher the quality of its staff, the higher its capacity to produce efficiently.

5.4. A dynamic perspective on the efficiency of universities

Table 4 reports the change in the efficiency component for each university for each of the consecutive years and for the entire period. Values less than, equal to, or greater than one in the entire period or the consecutive year considered, imply that the efficiency of the university evaluated is deteriorating, stagnating or improving, respectively. The posterior distribution of efficiency for each university is provided by the Bayesian techniques we use for the stochastic frontier estimations. In particular, the numbers in parentheses, obtained from these posterior distributions, indicate the probability of efficiency change greater than one—that is, positive efficiency change. These numbers are more informative than they appear, as they were calculated from the posterior distributions. Moreover, they should be interpreted graphically as the probability of the densities deviating from unity.

Table 4 shows a positive efficiency change for half of the universities for either the overall period or each consecutive year—that is, the value is greater than one. However, although around half 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 example, during the period 2018–2019, the University of A Coruña had a high probability (0.7610) of experiencing a positive efficiency change. This probability was even higher (1.0000) when considering the overall period 2016–2021. In contrast, for the entire period, the University of La Laguna had no probability (0.0000) of experiencing a positive efficiency change, but its estimated value for the efficiency change is 0.9453. Thus, although half of the universities do show a positive efficiency change, on average, the probability of improvement is not that high: 0.456 for the full period, 0.443 for the 2016–2017 period, 0.486 for the 2017-2018 period, 0.484 for the 2018–2019 period, 0.465 for the 2019-2020 period, and 0.471 for the 2020–2021 period.

Table 5 provides the results for the second component of performance change, known as the technological change, and indicates how much the frontier shifts. As in the analysis of efficiency change, values lower than, equal to or greater than 1 indicate technical regress, technical stagnation, or technical progress, respectively. The numbers in parentheses also report the probability of technical progress occurring—that is, of values greater than one. However, the patterns observed here differ from those associated with changes in efficiency, as there is a clear temporal pattern that holds for all universities. In the period 2016–2017, only three universities experienced technical progress, and the average probability of this occurring was only 0.18. In contrast, in the 2020–2021 period, all but seven universities experienced technical progress, and the average probability of doing so was around 0.78.

Table 6 reports the results for the changes in university performance based on the decomposition of the change in efficiency and the technological change. Similarly to the change in efficiency, half of the universities show improved performance over the full period, with an average probability of employment of around 0.28. Indeed, only ten universities increased productivity between 2016 and 2017, and the average probability for this increase is only 0.24. In contrast, in the period 2020–2021, all except nine of the universities increased productivity, and the average probability of doing so is around 0.71. Thus, this temporal pattern is much closer to what we observed for technological change than for efficiency change. Finally, in order to facilitate both readability and understanding of the results, Table 7 provides a summary of our findings, considering all the sub-periods analyzed.

6. Conclusions

Universities stand at the center of contemporary knowledge economies, serving as engines of human capital formation, scientific discovery, and technological innovation that drive economic growth and social progress. Understanding what makes them differ in their performance has become increasingly critical as, in a context of increased national and international competitions of students, faculty, research funding and reputation among academic institutions, also fueled by the proliferation of university rankings, governments worldwide struggle with competing demands: expanding access to higher education, maintaining quality standards, fostering research excellence, and enhancing knowledge transfer to society—all while facing persistent budgetary constraints. Hence, in order to improve universities performance, it is critical to achieve better understanding about how efficiently universities utilize taxpayers resources, and to identify the efficiency determinants—i.e., why some universities consistently outperform others despite comparable resources and even facing the same institutional and regulatory framework—. These findings have relevant implications for university governance, public funding mechanisms, and the design and implementation of higher education policies.

Our study deals with these issues by developing and implementing a Bayesian stochastic ray frontier model that jointly estimates efficiency and its determinants in a single stage. This Bayesian approach provides a full efficiency distribution rather than point estimates and enables robust statistical comparisons. Applied to 47 Spanish public universities over the 2016–2021 period, our study makes an attempt to go beyond traditional two-stage approaches by addressing separability issues and statistical dependencies. Furthermore, we move beyond previous *ad hoc* variable selection procedure, by considering a rigorous, backward stepwise selection one with the deviance information criterion to identify key efficiency determinants.

In this regard, the literature on universities efficiency reveals remarkable heterogeneity across national contexts in both, the variables used to measure efficiency itself (input and output definition) and the variables examined as explanatory factors of performance differences. This is partly reflecting data availability constraints, but also the diverse institutional, regulatory and even disciplinary frameworks under which universities operate. While studies in some countries have access to detailed information on student characteristics, regional economic indicators, or governance structures, others are limited to basic institutional metrics, and few have access to management practices, creating an incomplete and fragmented understanding of what drives university performance globally. This heterogeneity in variable selection makes it particularly difficult to discern whether observed differences in efficiency determinants across countries reflect genuine contextual variations or merely differences in data availability and methodological choices. Therefore, studies that attempt to be more comprehensive in their consideration of potential determinants—systematically examining a broader array of organizational, personnel, environmental, and institutional factors—could be valuable for advancing our understanding of university efficiency. Therefore, although with a national focus centered in Spain, our analysis adopts an inclusive approach by initially considering an extensive set of potential determinants identified across the international literature, limited only by data availability and econometric constraints, before employing rigorous statistical methods to identify those most relevant in our specific context. This comprehensive starting point not only reduces the risk of omitted variable bias but also enables more meaningful comparisons with international studies and helps distinguish between universal efficiency drivers and context-specific factors.

Our analysis has yielded several findings with implications for both educational and research policies. According to our results, substantial efficiency differences persist among Spanish public universities, suggesting that there is still room for improvement in performance. These dynamics have been identified by using Malmquist indices, which provide us with insights into efficiency change, technological progress and total factor productivity over the period. Regarding the selection of efficiency determinants, our backward stepwise selection method identified as key efficiency determinants organizational factors such as average department size, number of campuses, and multi-province location, as well as staff characteristics like gender diversity, average age, and research quality indicators such as civil servant status and *sexenios*. Our dynamic analysis also revealed significant temporal patterns, with technological progress and total factor productivity growth accelerating during the later years of our sample (2020–2021).

These findings have some implications for research policy. The substantial efficiency heterogeneity we document suggests that performance-based funding mechanisms should account for efficiency alongside absolute output levels. Funding formulas that reward efficiency improvements could incentivize better resource management, acknowledging that not all output differences reflect underlying productivity. Furthermore, our findings on organizational structure, particularly the negative efficiency impact of multi-province organization, suggest that political considerations sometimes override efficiency objectives. While geographic accessibility is an important goal to achieve regional cohesion, policymakers should be aware of the efficiency costs of this geographic dispersion, and consider alternative solutions to align geographic accessibility and higher cost efficiency such as, for instance, intensive scholarships based on residency criteria. Regarding personnel, the positive relationship between research quality indicators (*sexenios*, civil servant proportion) and overall efficiency suggests that policies promoting research excellence generate positive spillovers to institutional performance. This supports integrated policy approaches that acknowledge universities' multiple missions, where evaluation frameworks like Spain's *sexenio* system may enhance not only research output but also overall institutional efficiency. Similarly, the finding that a higher proportion of female academic staff positively influences efficiency provides empirical support for policies promoting women's advancement. It shows that gender diversity contributes to institutional effectiveness, offering a powerful dual rationale (combining normative equity arguments with instrumental efficiency gains) that may be particularly persuasive in policy debates. Finally, the temporal patterns in technological change highlight the importance of system-level coordination. The accelerating frontier progress suggests that successful innovations spread across institutions over time, implying that policies which facilitate inter-university learning and the dissemination of best practices could accelerate this diffusion process, enhancing system-wide efficiency gains.

However, this study has also faced some limitations that open directions for future research. First, while our systematic variable selection is a methodological advance, data availability constrains the set of potential determinants. In single country studies, as this one, this might be causing omitted variables bias, but for international comparisons, where there is a clear gap in the literature, the limited availability of homogeneous data is clearly a barrier. Second, and still related with the previous point, the used output measures are essentially quantitative, but it would be also important to consider the quality of the produced outputs: universities might be efficient because they produce a lot of output or because they produce less output but of very good quality. Thus, different efficiency profiles may co-exist. In that context, once again, although qualitative indicators for research activities are available (e.g. citations), for the teaching and knowledge transfer missions the data are much more scarce. Third, our output-oriented approach reflects Spanish universities' limited ability to adjust costs and may not generalize to systems with greater budgetary flexibility. Fourth, a more detailed analysis of how regional policies and funding systems affect university efficiency could inform policy design at both national and regional levels. Finally, extending the analysis beyond 2021 would enable an examination of whether the COVID-19-related acceleration in technological progress represents a permanent shift or a temporary response.

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Table 1: Definition of variables and descriptive statistics (2016–2021)

Variable name	Definition	Mean	Median	Sd	Min	Max
Outputs						
Undergrads	Bachelor's degree graduates	3,193	2,622	1,956.44	451	9,356
Mastergrads	Master's graduates	1,290.50	1,080	850.13	131	4,367
Publications	Number of publications in Web of Science	1,670.20	1,024	1,400.84	245	7,997
GrantsNatUE	National and international research grants	53.16	39	38.41	7	189
Patents	Patents	7.31	5	7.37	0	45
Spinoff	Spin-offs	1.67	1	2.98	0	24
Inputs						
Budget : expenditure	Deflated HEIs budget (in euros)	206,253,561	167,231,128	123,869,997	44,825,907	595,065,598
Determinants						
Faculties	Number of faculties	14.49	13	7.46	4	40
Medicine	The existence of a Faculty of Medicine, dummy	0.57	1	0.50	0	1
Age	Age of the university	138.40	40	215.42	18	803
StudentHHI	HHI of students across the five main fields	3,747	3,332	1,504.96	2,409	9,462
StaffDepartment	The ratio of total employees to the number of departments	59.98	52.65	22.73	23.09	152.49
Campuses	Number of campuses	3.45	3	1.84	1	9
Multi − province	The existence of campus located in different provinces, dummy	0.28	0	0.45	0	1
StaffRatio	The ratio of academic to administrative staff	1.46	1.44	0.26	0.69	2.52
StaffAge	The average age of academic personnel	49.71	49.71	1.76	44.90	54.19
StaffCS	The proportion of civil servant of academic staff	0.59	0.59	0.09	0.36	0.76
Women	The proportion of women academic staff	0.41	0.42	0.05	0.21	0.50
Sexenios	The average number of sexenios per academic staff	2.37	2.35	0.43	1.24	3.57

Table 2: DIC values of some of the compared models

	Models													
Determinants	M_0	M_1	M_2	M_{24}	M_{29}	M_{36}	$\boldsymbol{M_{46}}$	M_{52}	M_{53}	M_{54}	M_{55}	M_{56}	M_{57}	M_{58}
Faculties	No	No	×	×	×	×	**×**	×	×	×	×	×	×	×
Medicine	Yes	No	No	×	×	×	**×**	×	×	×	×	×	×	×
StaffRatio	No	No	No	No	×	×	**×**	×	×	×	×	×	×	×
Age	No	No	No	No	No	×	**×**	×	×	×	×	×	×	×
StudentsHHI	No	No	Yes	Yes	No	Yes	**×**	×	×	×	×	×	×	×
StaffDepartment	Yes	Yes	Yes	Yes	Yes	Yes	**Yes**	×	Yes	Yes	Yes	No	Yes	Yes
Campuses	Yes	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	×	Yes	Yes	Yes	Yes	Yes
StaffAge	Yes	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	Yes	×	Yes	Yes	Yes	Yes
StaffCS	No	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	No	No	×	No	Yes	No
Women	Yes	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	Yes	Yes	Yes	×	Yes	Yes
Sexenios	Yes	No	Yes	Yes	Yes	Yes	**Yes**	Yes	Yes	No	Yes	Yes	×	Yes
Multi − province	Yes	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	Yes	Yes	Yes	No	Yes	×
Autonomousregion	×	Yes	Yes	Yes	Yes	Yes	**Yes**	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DIC	−578.05	−672.73	−674.96	−673.79	−675.03	−676.36	**−677.52**	−652.17	−634.01	−634.41	−664.17	−552.37	−660.50	−654.45

Table 3: A descriptive summary of the posterior distributions of the parameters associated with the determinants of university efficiency

	Mean	Sd	Median	95% Credible Interval
$StaffDepartment$ (δ_1)	0.0536	0.0133	0.0538	$(0.0273, 0.0792)$
Campuses (δ_2)	0.0946	0.0170	0.0947	$(0.0612, 0.1274)$
$StaffAge$ (δ_3)	−0.1313	0.0224	−0.1314	$(-0.1773, -0.0869)$
$StaffCS$ (δ_4)	0.0742	0.0222	0.0744	$(0.0324, 0.1156)$
Women (δ_5)	0.2137	0.0188	0.2134	$(0.1773, 0.2499)$
Sexenios (δ_6)	0.0721	0.0201	0.0723	$(0.0325, 0.1111)$
Multi-province No (δ_{MP_1})	0.0661	0.0160	0.0660	$(0.0356, 0.0976)$
Multi-province Yes (δ_{MP_2})	−0.0661	0.0160	−0.0660	$(-0.0976, -0.0356)$

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

University	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2016–2021
A Coruña	1.0239 (1.0000)	1.0241 (1.0000)	1.0028 (0.7610)	1.0035 (1.0000)	1.0049 (1.0000)	1.0604 (1.0000)
Alcalá	1.0155 (1.0000)	1.0021 (0.9497)	0.9967 (0.0287)	0.9908 (0.0000)	0.9910 (0.0000)	0.9960 (0.0053)
Alicante	1.0161 (1.0000)	1.0031 (0.9467)	0.9921 (0.0000)	0.9908 (0.0003)	0.9906 (0.0000)	0.9925 (0.0790)
Almería	1.0085 (1.0000)	1.0097 (1.0000)	1.0153 (1.0000)	1.0253 (1.0000)	0.9895 (0.0000)	1.0489 (1.0000)
Autònoma de Barcelona	0.9974 (0.0697)	0.9975 (0.0093)	1.0083 (1.0000)	0.9998 (0.4180)	1.0141 (1.0000)	1.0170 (0.9993)
Autónoma de Madrid	0.9907 (0.0000)	0.9885 (0.0000)	1.0126 (1.0000)	1.0123 (1.0000)	0.9998 (0.4110)	1.0036 (0.7787)
Barcelona	0.9807 (0.0000)	1.0090 (1.0000)	0.9996 (0.4310)	0.9968 (0.1113)	1.0042 (0.9477)	0.9901 (0.1710)
Burgos	0.9971 (0.0573)	1.0018 (0.8417)	1.0068 (0.9293)	1.0036 (0.8257)	0.9931 (0.0000)	1.0024 (0.5930)
Cádiz	0.9930 (0.0000)	0.9864 (0.0000)	0.9911 (0.0000)	0.9997 (0.4057)	1.0118 (1.0000)	0.9820 (0.0000)
Cantabria	0.9961 (0.0023)	0.9976 (0.1427)	1.0075 (0.9900)	0.9962 (0.0470)	1.0078 (1.0000)	1.0051 (0.7403)
Carlos III de Madrid	1.0008 (0.6697)	0.9891 (0.0023)	0.9880 (0.0000)	0.9876 (0.0000)	0.9950 (0.0873)	0.9610 (0.0000)
Castilla-La Mancha	0.9978 (0.1160)	0.9907 (0.0000)	1.0192 (1.0000)	1.0118 (0.9970)	0.9954 (0.1960)	1.0147 (0.8833)
Complutense de Madrid	0.9897 (0.0000)	1.0187 (1.0000)	1.0273 (1.0000)	1.0007 (0.7407)	1.0095 (1.0000)	1.0464 (1.0000)
Córdoba	1.0172 (1.0000)	1.0366 (1.0000)	0.9988 (0.2767)	1.0087 (0.9997)	0.9844 (0.0010)	1.0458 (1.0000)
Extremadura	1.0003 (0.5507)	1.0065 (1.0000)	0.9924 (0.0063)	0.9942 (0.0483)	1.0165 (1.0000)	1.0097 (0.9667)
Girona	0.9828 (0.0000)	0.9883 (0.0000)	0.9919 (0.0107)	0.9882 (0.0000)	0.9931 (0.0193)	0.9456 (0.0000)
Granada	1.0062 (1.0000)	1.0077 (0.9997)	1.0136 (1.0000)	0.9955 (0.0000)	1.0028 (1.0000)	1.0261 (1.0000)
Huelva	1.0005 (0.5940)	1.0034 (0.9280)	1.0181 (1.0000)	1.0122 (0.9987)	0.9901 (0.0000)	1.0243 (1.0000)
Illes Balears (Les)	0.9918 (0.0000)	1.0010 (0.8360)	1.0112 (1.0000)	1.0043 (0.9983)	0.9944 (0.0000)	1.0026 (0.9537)
Jaén	1.0055 (0.9990)	0.9963 (0.0003)	1.0170 (1.0000)	1.0005 (0.5910)	1.0030 (0.8180)	1.0225 (1.0000)
Jaume I de Castelló	0.9967 (0.0583)	1.0151 (1.0000)	1.0066 (0.9637)	1.0025 (0.7870)	1.0012 (0.6530)	1.0224 (0.9840)
La Laguna	0.9869 (0.0000)	0.9922 (0.0000)	0.9917 (0.0040)	0.9842 (0.0000)	0.9890 (0.0003)	0.9453 (0.0000)
La Rioja	1.0419 (1.0000)	1.0350 (1.0000)	1.0059 (0.9960)	0.9953 (0.0267)	1.0092 (0.9990)	1.0896 (1.0000)
Las Palmas de Gran Canaria	0.9852 (0.0000)	0.9797 (0.0000)	1.0033 (0.8293)	0.9889 (0.0003)	0.9887 (0.0017)	0.9468 (0.0000)
León	0.9965 (0.0000)	1.0038 (0.9330)	1.0077 (1.0000)	1.0126 (1.0000)	0.9953 (0.0303)	1.0160 (0.9957)
Lleida	1.0055 (0.9903)	0.9860 (0.0000)	0.9683 (0.0000)	1.0365 (1.0000)	1.0355 (1.0000)	1.0304 (0.9993)
Málaga	0.9889 (0.0060)	1.0161 (1.0000)	1.0060 (0.9790)	1.0113 (1.0000)	1.0007 (0.8487)	1.0230 (0.9993)
Miguel Hernández de Elche	1.0120 (1.0000)	1.0060 (0.9493)	1.0055 (0.9903)	1.0048 (1.0000)	0.9952 (0.0173)	1.0236 (0.9907)
Murcia	0.9980 (0.0960)	0.9909 (0.0000)	0.9856 (0.0000)	0.9889 (0.0000)	0.9839 (0.0000)	0.9482 (0.0000)
Oviedo	0.9918 (0.0000)	1.0045 (0.9593)	1.0001 (0.5570)	0.9982 (0.0113)	0.9999 (0.3647)	0.9945 (0.0590)
País Vasco	1.0085 (1.0000)	0.9999 (0.4613)	0.9950 (0.0047)	1.0095 (1.0000)	1.0186 (1.0000)	1.0317 (0.9993)
Politécnica de Cartagena	1.0122 (0.9947)	0.9741 (0.0003)	0.9774 (0.0000)	1.0062 (0.7560)	1.0118 (1.0000)	0.9813 (0.2093)
Politècnica de Catalunya	1.0098 (1.0000)	1.0038 (0.9640)	1.0043 (0.9600)	0.9872 (0.0000)	0.9960 (0.0733)	1.0009 (0.5243)
Politécnica de Madrid	0.9901 (0.0000)	0.9873 (0.0010)	0.9885 (0.0073)	0.9920 (0.0067)	1.0017 (0.7910)	0.9604 (0.0040)
Politècnica de València	0.9975 (0.1780)	1.0087 (0.9920)	0.9842 (0.0000)	0.9924 (0.0187)	0.9877 (0.0000)	0.9706 (0.0047)
Pompeu Fabra	0.9826 (0.0000)	0.9837 (0.0000)	0.9870 (0.0000)	1.0071 (1.0000)	0.9854 (0.0000)	0.9467 (0.0000)
Pública de Navarra	1.0092 (1.0000)	1.0281 (1.0000)	1.0178 (0.9887)	0.9987 (0.1593)	1.0299 (1.0000)	1.0864 (1.0000)
Rey Juan Carlos	1.0081 (0.9853)	1.0025 (0.7977)	0.9868 (0.0000)	0.9965 (0.0000)	0.9950 (0.0270)	0.9888 (0.0153)
Rovira i Virgili	0.9939 (0.0000)	0.9976 (0.0593)	1.0059 (1.0000)	0.9907 (0.0000)	0.9948 (0.0000)	0.9831 (0.0040)
Salamanca	0.9993 (0.3157)	0.9927 (0.0000)	0.9981 (0.1110)	1.0034 (0.9683)	1.0027 (0.8383)	0.9962 (0.2987)
Santiago de Compostela	1.0095 (1.0000)	0.9889 (0.0000)	0.9797 (0.0000)	0.9784 (0.0000)	0.9763 (0.0000)	0.9342 (0.0000)
Sevilla	0.9909 (0.0000)	0.9963 (0.0983)	0.9994 (0.4197)	0.9937 (0.0000)	0.9914 (0.0000)	0.9720 (0.0003)
València (Estudi General)	1.0069 (1.0000)	0.9971 (0.0317)	0.9974 (0.0203)	0.9993 (0.2203)	1.0073 (1.0000)	1.0080 (1.0000)
Valladolid	0.9914 (0.0000)	0.9793 (0.0000)	0.9951 (0.0047)	1.0058 (1.0000)	1.0037 (0.9943)	0.9752 (0.0000)
Vigo	0.9944 (0.0000)	0.9923 (0.0000)	0.9920 (0.0000)	0.9837 (0.0000)	1.0069 (0.9987)	0.9696 (0.0000)
Zaragoza	0.9995 (0.3207)	1.0006 (0.9497)	0.9960 (0.0333)	1.0032 (0.9260)	1.0218 (1.0000)	1.0210 (0.9997)

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

University	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2016–2021
A Coruña	0.9833 (0.0297)	0.9695 (0.0030)	0.9849 (0.0363)	1.0106 (0.9463)	1.0190 (0.9820)	1.0073 (0.9227)
Alcalá	0.9909 (0.1500)	0.9903 (0.0863)	0.9876 (0.0280)	0.9945 (0.2080)	0.9974 (0.3903)	0.9911 (0.0473)
Alicante	0.9769 (0.0107)	0.9884 (0.0470)	1.0018 (0.6267)	1.0052 (0.7840)	1.0089 (0.8203)	0.9937 (0.1863)
Almería	0.9990 (0.4433)	0.9952 (0.2310)	0.9918 (0.1137)	1.0026 (0.6467)	1.0148 (0.9543)	1.0076 (0.9077)
Autònoma de Barcelona	0.9789 (0.0413)	0.9795 (0.0243)	0.9817 (0.0307)	0.9883 (0.1050)	0.9875 (0.1283)	0.9803 (0.0197)
Autónoma de Madrid	0.9796 (0.0197)	0.9856 (0.0323)	0.9910 (0.0897)	0.9926 (0.1440)	0.9931 (0.2223)	0.9853 (0.0163)
Barcelona	0.9813 (0.0443)	0.9858 (0.0473)	0.9927 (0.1533)	0.9966 (0.3137)	0.9979 (0.4093)	0.9895 (0.0830)
Burgos	0.9712 (0.0140)	0.9654 (0.0067)	0.9563 (0.0067)	0.9866 (0.1507)	1.0153 (0.9173)	0.9899 (0.1407)
Cádiz	0.9827 (0.0307)	0.9943 (0.2280)	0.9966 (0.3093)	1.0051 (0.7940)	1.0126 (0.9270)	0.9923 (0.1207)
Cantabria	0.9852 (0.0957)	0.9869 (0.1033)	0.9997 (0.4927)	1.0124 (0.8983)	1.0002 (0.5097)	0.9860 (0.0393)
Carlos III de Madrid	0.9958 (0.3413)	1.0029 (0.6313)	1.0157 (0.8973)	1.0266 (0.9753)	1.0282 (0.9843)	1.0100 (0.8547)
Castilla-La Mancha	0.9962 (0.3247)	0.9972 (0.3033)	0.9985 (0.3787)	1.0086 (0.9290)	1.0144 (0.9547)	1.0032 (0.7420)
Complutense de Madrid	0.9937 (0.2737)	0.9992 (0.4577)	1.0020 (0.6087)	1.0060 (0.7837)	1.0098 (0.8370)	1.0002 (0.5133)
Córdoba	0.9865 (0.0467)	0.9855 (0.0057)	0.9925 (0.0387)	1.0072 (0.9177)	1.0027 (0.6260)	0.9890 (0.0123)
Extremadura	0.9747 (0.0087)	0.9712 (0.0037)	0.9911 (0.0810)	1.0069 (0.8540)	1.0050 (0.6967)	0.9928 (0.1257)
Girona	0.9991 (0.4647)	1.0086 (0.8763)	1.0126 (0.9783)	1.0162 (0.9900)	1.0218 (0.9897)	1.0086 (0.9210)
Granada	0.9940 (0.2627)	0.9995 (0.4680)	1.0065 (0.8293)	1.0141 (0.9580)	1.0153 (0.9370)	1.0022 (0.6363)
Huelva	0.9865 (0.0720)	0.9960 (0.2847)	0.9961 (0.3043)	1.0077 (0.8327)	1.0142 (0.9260)	0.9928 (0.1763)
Illes Balears (Les)	0.9918 (0.1750)	0.9999 (0.4840)	1.0034 (0.7237)	1.0107 (0.9470)	1.0133 (0.9407)	0.9978 (0.3387)
Jaén	0.9809 (0.0340)	0.9920 (0.1430)	1.0028 (0.6793)	1.0067 (0.8080)	1.0101 (0.8397)	0.9949 (0.2700)
Jaume I de Castelló	0.9981 (0.4213)	1.0041 (0.7407)	1.0096 (0.9650)	1.0127 (0.9850)	1.0214 (0.9933)	1.0122 (0.9900)
La Laguna	0.9908 (0.1507)	0.9842 (0.0090)	0.9853 (0.0103)	0.9957 (0.2803)	0.9981 (0.4153)	0.9942 (0.1517)
La Rioja	0.9540 (0.0027)	0.9651 (0.0077)	0.9869 (0.0967)	1.0113 (0.8890)	1.0100 (0.8117)	0.9742 (0.0173)
Las Palmas de Gran Canaria	0.9999 (0.5013)	0.9981 (0.3887)	0.9989 (0.4333)	1.0080 (0.8463)	1.0139 (0.9117)	1.0065 (0.8263)
León	0.9902 (0.1467)	0.9921 (0.1340)	0.9952 (0.2257)	1.0002 (0.5137)	1.0056 (0.7233)	0.9986 (0.4117)
Lleida	0.9999 (0.4913)	1.0095 (0.8933)	1.0147 (0.9873)	1.0152 (0.9880)	1.0130 (0.9243)	1.0028 (0.6877)
Málaga	0.9882 (0.0790)	1.0021 (0.6150)	1.0044 (0.7497)	1.0115 (0.9420)	1.0160 (0.9453)	0.9947 (0.2103)
Miguel Hernández de Elche	0.9852 (0.1617)	0.9941 (0.3420)	0.9964 (0.4080)	0.9984 (0.4453)	1.0017 (0.5500)	0.9908 (0.2037)
Murcia	0.9919 (0.1617)	1.0010 (0.5620)	1.0040 (0.7850)	1.0071 (0.8533)	1.0147 (0.9493)	1.0024 (0.6950)
Oviedo	0.9835 (0.0237)	0.9917 (0.0687)	1.0025 (0.7210)	1.0036 (0.7617)	1.0053 (0.7497)	0.9958 (0.1573)
Pablo de Olavide	1.0033 (0.6003)	1.0090 (0.8357)	1.0142 (0.8867)	1.0220 (0.9683)	1.0194 (0.9547)	1.0058 (0.7113)
País Vasco	0.9885 (0.1517)	0.9918 (0.1640)	0.9970 (0.3443)	1.0029 (0.6600)	1.0066 (0.7490)	0.9974 (0.3900)
Politécnica de Cartagena	0.9568 (0.0100)	0.9674 (0.0217)	0.9867 (0.0860)	1.0028 (0.5973)	0.9977 (0.4343)	0.9709 (0.0133)
Politècnica de Catalunya	0.9823 (0.0277)	0.9873 (0.0517)	0.9854 (0.0467)	1.0081 (0.8250)	1.0192 (0.9780)	0.9912 (0.0553)
Politécnica de Madrid	0.9796 (0.0870)	0.9842 (0.0447)	0.9849 (0.0687)	0.9975 (0.3987)	1.0002 (0.5030)	0.9829 (0.0667)
Politècnica de València	0.9761 (0.0080)	0.9927 (0.1930)	0.9960 (0.3203)	0.9935 (0.2460)	0.9978 (0.4220)	0.9835 (0.0133)
Pompeu Fabra	1.0043 (0.6327)	1.0116 (0.8570)	1.0148 (0.9390)	1.0215 (0.9870)	1.0221 (0.9860)	1.0079 (0.8603)
Pública de Navarra	1.0024 (0.5813)	1.0003 (0.5143)	1.0115 (0.9647)	1.0196 (0.9953)	1.0254 (0.9930)	1.0194 (0.9970)
Rey Juan Carlos	0.9947 (0.3150)	1.0079 (0.7487)	1.0070 (0.7650)	1.0108 (0.8863)	1.0153 (0.9167)	0.9982 (0.4020)
Rovira i Virgili	0.9811 (0.0380)	0.9887 (0.0810)	0.9922 (0.1080)	1.0013 (0.5847)	1.0079 (0.8257)	0.9911 (0.0867)
Salamanca	0.9979 (0.4083)	1.0015 (0.5927)	1.0059 (0.8817)	1.0116 (0.9720)	1.0179 (0.9807)	1.0086 (0.9437)
Santiago de Compostela	0.9936 (0.2260)	0.9997 (0.4783)	1.0075 (0.8743)	1.0180 (0.9827)	1.0144 (0.9453)	0.9977 (0.3477)
Sevilla	0.9863 (0.0740)	0.9958 (0.3093)	0.9976 (0.3760)	1.0042 (0.7167)	1.0124 (0.8933)	0.9961 (0.3000)
València (Estudi General)	0.9898 (0.1290)	0.9922 (0.1243)	0.9939 (0.1453)	1.0005 (0.5377)	1.0030 (0.6433)	0.9939 (0.1343)
Valladolid	0.9889 (0.1033)	0.9848 (0.0220)	0.9866 (0.0430)	1.0020 (0.6077)	1.0061 (0.7233)	0.9946 (0.2063)
Vigo	0.9790 (0.0077)	0.9863 (0.0173)	0.9856 (0.0250)	0.9994 (0.4620)	1.0084 (0.8593)	0.9871 (0.0100)
Zaragoza	0.9939 (0.2403)	0.9990 (0.4143)	1.0039 (0.7900)	1.0099 (0.9570)	1.0104 (0.9030)	0.9993 (0.4380)

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

University	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2016–2021
A Coruña	1.0068 (0.7363)	0.9929 (0.2750)	0.9877 (0.0860)	1.0141 (0.9853)	1.0240 (0.9953)	1.0682 (1.0000)
Alcalá	1.0063 (0.7440)	0.9924 (0.1493)	0.9843 (0.0057)	0.9854 (0.0097)	0.9885 (0.1023)	0.9871 (0.0140)
Alicante	0.9927 (0.2263)	0.9915 (0.1003)	0.9939 (0.1040)	0.9959 (0.2650)	0.9994 (0.4697)	0.9863 (0.0393)
Almería	1.0075 (0.7990)	1.0049 (0.7443)	1.0069 (0.7760)	1.0279 (1.0000)	1.0042 (0.6853)	1.0569 (1.0000)
Autònoma de Barcelona	0.9763 (0.0250)	0.9770 (0.0137)	0.9899 (0.1503)	0.9881 (0.0993)	1.0014 (0.5467)	0.9970 (0.3963)
Autónoma de Madrid	0.9705 (0.0020)	0.9743 (0.0013)	1.0035 (0.6857)	1.0048 (0.7430)	0.9928 (0.2177)	0.9889 (0.0900)
Barcelona	0.9623 (0.0007)	0.9946 (0.2717)	0.9924 (0.1543)	0.9934 (0.1930)	1.0021 (0.5867)	0.9797 (0.0397)
Burgos	0.9684 (0.0097)	0.9671 (0.0087)	0.9628 (0.0210)	0.9901 (0.2483)	1.0083 (0.7723)	0.9923 (0.2870)
Cádiz	0.9758 (0.0083)	0.9807 (0.0093)	0.9878 (0.0523)	1.0049 (0.7807)	1.0245 (0.9963)	0.9744 (0.0000)
Cantabria	0.9813 (0.0520)	0.9845 (0.0640)	1.0071 (0.7750)	1.0086 (0.8067)	1.0080 (0.7657)	0.9911 (0.1777)
Carlos III de Madrid	0.9965 (0.3717)	0.9919 (0.1837)	1.0035 (0.6120)	1.0139 (0.8480)	1.0230 (0.9547)	0.9706 (0.0043)
Castilla-La Mancha	0.9940 (0.2597)	0.9879 (0.0200)	1.0177 (0.9877)	1.0205 (0.9970)	1.0097 (0.8383)	1.0180 (0.8937)
Complutense de Madrid	0.9835 (0.0523)	1.0179 (0.9790)	1.0294 (0.9997)	1.0067 (0.8113)	1.0194 (0.9747)	1.0466 (1.0000)
Córdoba	1.0034 (0.6570)	1.0216 (0.9927)	0.9912 (0.0407)	1.0160 (0.9983)	0.9871 (0.0787)	1.0343 (1.0000)
Extremadura	0.9750 (0.0120)	0.9775 (0.0217)	0.9836 (0.0030)	1.0010 (0.5587)	1.0216 (0.9797)	1.0024 (0.6123)
Girona	0.9819 (0.0277)	0.9968 (0.3323)	1.0044 (0.7197)	1.0042 (0.7087)	1.0148 (0.9303)	0.9537 (0.0000)
Granada	1.0002 (0.4987)	1.0072 (0.8403)	1.0202 (0.9977)	1.0095 (0.8887)	1.0182 (0.9690)	1.0284 (0.9997)
Huelva	0.9870 (0.0930)	0.9995 (0.4573)	1.0141 (0.9637)	1.0201 (0.9777)	1.0041 (0.6700)	1.0170 (0.9707)
Illes Balears (Les)	0.9836 (0.0313)	1.0009 (0.5430)	1.0147 (0.9933)	1.0151 (0.9880)	1.0077 (0.8140)	1.0004 (0.5280)
Jaén	0.9863 (0.0953)	0.9884 (0.0733)	1.0199 (0.9980)	1.0072 (0.7993)	1.0131 (0.8840)	1.0172 (0.9567)
Jaume I de Castelló	0.9949 (0.2910)	1.0193 (0.9990)	1.0163 (0.9923)	1.0153 (0.9850)	1.0227 (0.9957)	1.0348 (0.9973)
La Laguna	0.9779 (0.0057)	0.9766 (0.0003)	0.9771 (0.0003)	0.9799 (0.0033)	0.9871 (0.0947)	0.9398 (0.0000)
La Rioja	0.9940 (0.3380)	0.9989 (0.4700)	0.9927 (0.2353)	1.0065 (0.7483)	1.0193 (0.9493)	1.0615 (1.0000)
Las Palmas de Gran Canaria	0.9851 (0.0567)	0.9779 (0.0027)	1.0022 (0.6100)	0.9969 (0.3487)	1.0024 (0.5793)	0.9530 (0.0000)
León	0.9868 (0.0873)	0.9959 (0.2793)	1.0029 (0.6733)	1.0128 (0.9490)	1.0008 (0.5293)	1.0145 (0.9590)
Lleida	1.0054 (0.7020)	0.9954 (0.2853)	0.9825 (0.0137)	1.0523 (1.0000)	1.0490 (1.0000)	1.0333 (0.9970)
Málaga	0.9772 (0.0030)	1.0182 (0.9947)	1.0104 (0.9460)	1.0230 (0.9973)	1.0167 (0.9507)	1.0176 (0.9847)
Miguel Hernández de Elche	0.9970 (0.4163)	1.0000 (0.4933)	1.0019 (0.5403)	1.0031 (0.5803)	0.9969 (0.4010)	1.0142 (0.8203)
Murcia	0.9900 (0.1043)	0.9919 (0.0787)	0.9895 (0.0227)	0.9959 (0.2713)	0.9983 (0.4253)	0.9505 (0.0000)
Oviedo	0.9754 (0.0010)	0.9962 (0.2790)	1.0026 (0.7257)	1.0018 (0.6353)	1.0052 (0.7427)	0.9904 (0.0547)
Pablo de Olavide	1.0040 (0.6290)	0.9904 (0.1490)	1.0136 (0.8693)	1.0262 (0.9800)	1.0062 (0.6967)	0.9787 (0.0913)
País Vasco	0.9969 (0.3983)	0.9916 (0.1557)	0.9920 (0.1063)	1.0124 (0.9500)	1.0253 (0.9943)	1.0290 (0.9957)
Politécnica de Cartagena	0.9685 (0.0407)	0.9423 (0.0000)	0.9645 (0.0000)	1.0090 (0.7520)	1.0095 (0.7070)	0.9527 (0.0250)
Politècnica de Catalunya	0.9920 (0.2100)	0.9910 (0.1470)	0.9896 (0.1230)	0.9952 (0.2963)	1.0151 (0.9357)	0.9921 (0.2367)
Politécnica de Madrid	0.9699 (0.0200)	0.9718 (0.0017)	0.9736 (0.0090)	0.9895 (0.1570)	1.0020 (0.5560)	0.9439 (0.0003)
Politècnica de València	0.9736 (0.0037)	1.0014 (0.5613)	0.9803 (0.0153)	0.9859 (0.1000)	0.9855 (0.0980)	0.9546 (0.0007)
Pompeu Fabra	0.9868 (0.1407)	0.9951 (0.3280)	1.0016 (0.5617)	1.0288 (0.9973)	1.0071 (0.7503)	0.9542 (0.0000)
Pública de Navarra	1.0117 (0.8633)	1.0285 (0.9913)	1.0295 (0.9970)	1.0182 (0.9900)	1.0560 (1.0000)	1.1074 (1.0000)
Rey Juan Carlos	1.0027 (0.5840)	1.0105 (0.8147)	0.9937 (0.2617)	1.0072 (0.7940)	1.0102 (0.8233)	0.9870 (0.0553)
Rovira i Virgili	0.9752 (0.0087)	0.9864 (0.0440)	0.9981 (0.3830)	0.9919 (0.0980)	1.0027 (0.6187)	0.9743 (0.0020)
Salamanca	0.9972 (0.3717)	0.9941 (0.1507)	1.0040 (0.7993)	1.0151 (0.9913)	1.0207 (0.9877)	1.0047 (0.7353)
Santiago de Compostela	1.0030 (0.6200)	0.9887 (0.0420)	0.9870 (0.0383)	0.9960 (0.3163)	0.9903 (0.1470)	0.9321 (0.0000)
Sevilla	0.9773 (0.0067)	0.9922 (0.1777)	0.9970 (0.3587)	0.9979 (0.3900)	1.0037 (0.6527)	0.9682 (0.0017)
València (Estudi General)	0.9966 (0.3593)	0.9894 (0.0550)	0.9912 (0.0667)	0.9998 (0.4913)	1.0104 (0.8717)	1.0018 (0.6220)
Valladolid	0.9804 (0.0123)	0.9644 (0.0000)	0.9818 (0.0113)	1.0078 (0.8377)	1.0097 (0.8413)	0.9700 (0.0000)
Vigo	0.9735 (0.0013)	0.9788 (0.0010)	0.9778 (0.0020)	0.9831 (0.0070)	1.0154 (0.9643)	0.9571 (0.0000)
Zaragoza	0.9934 (0.2220)	0.9995 (0.4580)	0.9999 (0.4917)	1.0131 (0.9817)	1.0324 (1.0000)	1.0204 (0.9957)

Table 7: Summary of results for changes in efficiency, technology and productivity

	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2016–2021
Changes in efficiency						
Growth	20	23	22	21	22	25
Decline	27	24	25	26	25	22
Stagnation	0	0	0	0	0	0
Changes in technology						
Growth	3	11	19	37	40	15
Decline	44	36	28	10	7	32
Stagnation	0	0	0	0	0	0
Changes in productivity						
Growth	10	10	21	31	38	21
Decline	37	36	26	16	9	26
Stagnation	0	1	0	0	0	0

Figure 1: Efficiency for Spanish universities, 95% credible interval, years 2016, 2019, 2021

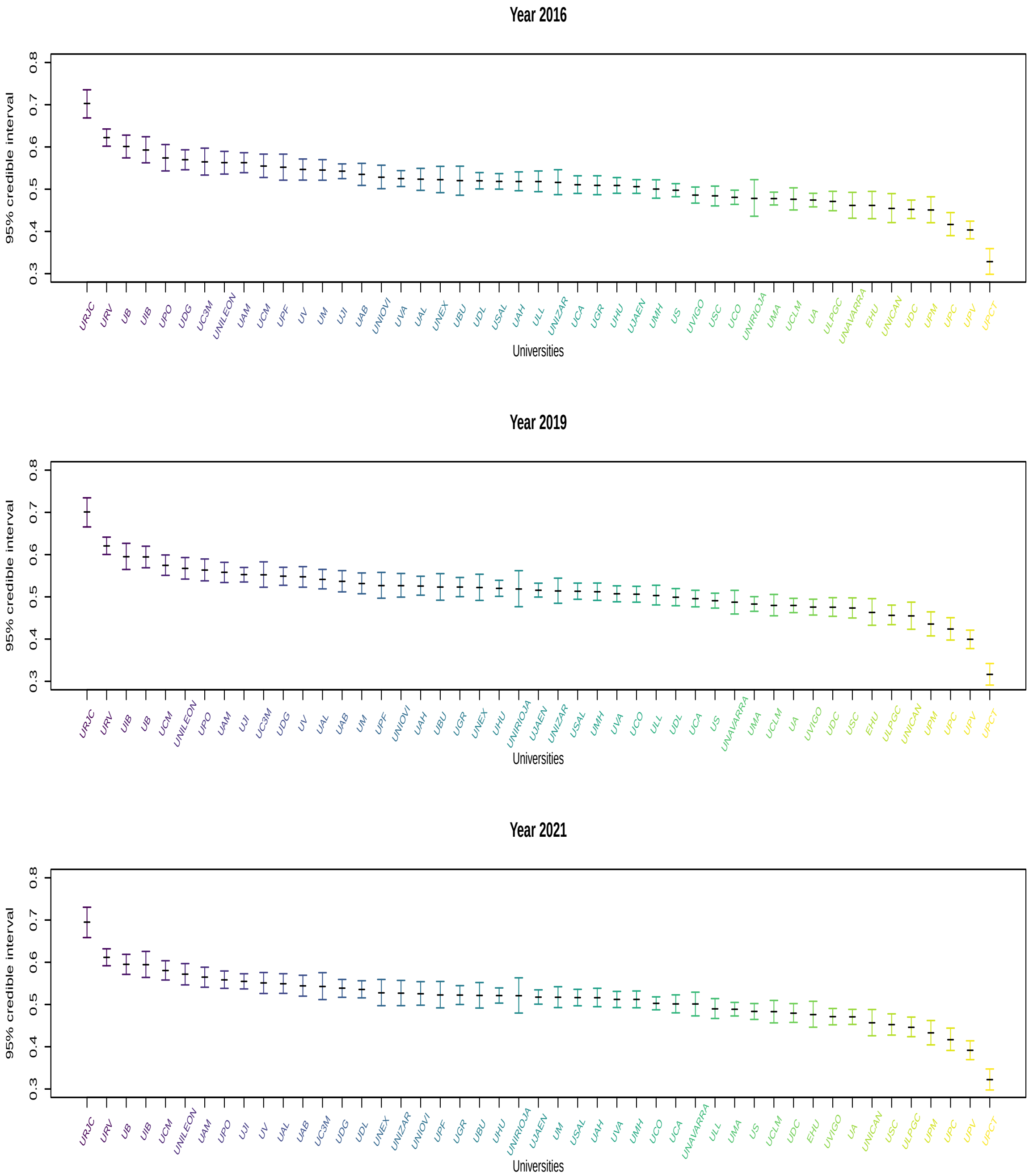

Figure 2: Density of the posterior distributions of universities in 2016.