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How does a situation of economic crisis influence the cost efficiency of public universities? A convergence analysis in the Spanish University System (2008-2019)

Yolanda Fernández-Santos[a, b], Almudena Martínez-Campillo[a], María-Pilar Sierra-Fernández[a]

a) Departamento de Dirección y Economía de la Empresa, Universidad de León. León-SPAIN.

[b]Corresponding author.
E-mail address: yfers@unileon.es

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ABSTRACT

Managers of public universities are increasingly required to manage resources effectively and efficiently when carrying out core university functions, in order to achieve cost cuts without eliminating services or compromising quality. In this context, the two objectives of this work are: first, to evaluate cost (in)efficiency in the Spanish Public University System during the period 2008-2019, comparing the situation during and after the global economic crisis of 2008; and, second, to study the convergence of the cost efficiency of universities -throughout these periods, within the sector and towards best practices- as well as its possible dependence on the crisis situation. To achieve these objectives, on the one hand, the conditional panel data Data Envelopment Analysis model is applied and, on the other, different regression models are used to determine the convergences β, σ y λ. Our findings show an improvement in average cost efficiency between 2008 and 2019, revealing a reduction in university costs to achieve a given level of outputs. In that period, furthermore, the universities that initially managed their funds worse improved their cost efficiency more than those that initially behaved better, also reducing inequality between them at the end of the period. There was also intense convergence towards the best practice frontier. When distinguishing between sub-periods, compared to the crisis stage (2008-2013), Spanish public universities, on average, made better cost reduction decisions when providing their services during the post-crisis period (2014-2019), also producing greater institutional convergence both over time and towards the sector average and best practices.

¿Cómo influye una situación de crisis económica en la eficiencia en costes de las universidades públicas? Un análisis de convergencia en el Sistema Universitario Español (2008-2019)

RESUMEN

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Cada vez se exige más que, a la hora de desarrollar las funciones docente, investigadora y social, los gestores de las universidades públicas administren los recursos de una manera eficaz y eficiente para conseguir recortar los gastos, sin eliminar servicios ni perjudicar la calidad. En este marco, los dos objetivos del trabajo son: primero, estimar la eficiencia en costes en el Sistema Universitario Público Español (SUPE) durante el periodo 2008-2019, comparando la situación durante y tras la crisis económico-financiera global del 2008; y, segundo, estudiar la convergencia de la eficiencia en costes de las universidades -a lo largo de dichos periodos, dentro del sector y hacia las mejores prácticas-, así como su posible dependencia de la situación de crisis. Para ello se aplica, por un lado, un Análisis Envolvente de Datos (DEA) de panel de datos condicional y, por otro lado, diferentes modelos de regresión para determinar las convergencias β, σ y λ. Nuestros hallazgos muestran una mejora de la eficiencia en costes media entre 2008 y 2019, poniendo de manifiesto una reducción de los gastos de las universidades para lograr un nivel dado de outputs. Además, a lo largo de ese periodo, las instituciones que en 2008 gestionaron peor sus fondos mejoraron más su eficiencia en costes que las que inicialmente se comportaron mejor, disminuyendo también la dispersión dentro del SUPE al final del mismo. También se produjo una intensa convergencia hacia las mejores prácticas del sector. Cuando se distingue entre sub-periodos, frente a la etapa de crisis (2008-2013), las universidades públicas españolas, por término medio, tomaron mejores decisiones de reducción de costes a la hora de prestar sus servicios durante el sub-periodo postcrisis (2014-2019), produciéndose, además, un mayor acercamiento institucional tanto a lo largo del tiempo como hacia la media del sector y las mejores prácticas.

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1. Introduction

Universities are probably the institutions that provide greatest added value to their territory, in that they create knowledge through research activities, disseminate it through teaching and transfer it to society through support for the industrial sector (Agasisti et al., 2021; Agasisti & Bertoletti, 2022). Financial autonomy is a necessary requirement for them to survive in the contexts of the International Tertiary Education Area and the European Higher Education Area (EHEA) (Pérez-Esparrells, 2022). However, with the global economic crisis of 2008, many countries, including Spain, significantly reduced the allocation of public funds to university education (Clarke et al., 2018). This gave rise to greater competition for increasingly limited public funding and forced universities to step up their income from other sources, such as enrolment fees or contracts with the private sector, in order to maintain adequate funding and guarantee their educational and socio-economic contributions (Cattaneo et al., 2019).

In Spain, the percentage of Gross Domestic Product (GDP) earmarked for universities dropped by 16.2% between 2008 and 2013, thus reducing expenditure per student in proportion to GDP per capita by 15% (European University Association, 2014). A number of factors sparked growing interest in ensuring that Spanish public institutions carried out their functions with increasing efficiency: the shortage of public funds in this context of budgetary restrictions; the rising number of private universities which amounted to additional competitive pressure for the public institutions; the start-up of the European Higher Education Area and subsequent regulatory changes to adapt to it in Spain (Organic Law 6/2001 on Universities - *LOU*, and Organic Law 4/2007 amending the LOU - *LOMLOU*), which, for the first time, introduced the criterion of efficiency in university management in order to improve their performance and competitiveness in a global market (Martínez-Campillo & Fernández-Santos, 2020). In fact, over recent years, the debate on the need to evaluate and improve efficiency in the administration of the resources used by public university systems is attracting greater attention and creating concern among political and institutional leaders, academics and society in general, both nationally and internationally (Agasisti et al., 2023; Clarke et al., 2018; Crespo et al., 2022).

Efficiency in the management of university resources relates the inputs used in the productive process of Higher Education Institutions (HEIs) with their teaching, research and social performance, and can be analysed from two basic viewpoints: "*technical efficiency*", which refers to whether inputs are used to their maximum productive capacity, and "*cost efficiency*" which refers to whether, in addition, the cheapest combination of inputs is being used. Almost all research to date has aimed either to analyse the technical efficiency of public universities, both internationally (Agasisti et al., 2021; Agasisti & Dal Bianco, 2006, 2009a; Johnes, 2014; Papadimitriou & Johnes, 2018, among others) and in Spain (Berbegal-Mirabent, 2018; Fernández-Santos et al., 2013; Martínez-Campillo & Fernández-Santos, 2020; El Gibari et al., 2022, among others), or to compare this efficiency among different countries (Agasisti & Pérez-Esparrells, 2010; Wolszczak-Derlacz, 2017, among others).

However, generally speaking, just estimating technical efficiency as a criterion for evaluating and monitoring public universities is insufficient. Of special relevant is the measurement of their cost efficiency, especially in a context of austerity that requires them to be more productive in their use of public funds and when they are inevitably obliged to be answerable to society for the public service they provide (Carrington et al., 2018). So the managers of public HEIs are increasingly required to use their funds effectively and efficiently, cutting costs while neither eliminating services or compromising quality (Pérez-Esparrells, 2022). For this purpose, they have to evaluate the cost efficiency of the institutions they govern so that those that achieve the best performance, managing their funds well and minimising their costs for a given level of university production, may become more competitive globally. However, to our knowledge, there have been few studies in the international literature focusing on the cost efficiency of public universities, with just two on Spain (Crespo et al., 2022; Johnes & Salas-Velasco, 2007).

Moreover, another of the goals of the reforms introduced in Spanish university systems within the framework of the EHEA aiming to achieve greater harmonisation among them was to perfect integration in university management processes and thus to reduce inequality in terms of performance among HEIs (Guccio et al., 2016 a,b; Witte et al., 2009). Any study on the possible convergence of cost efficiency in a country's public universities could be of interest for European, national or regional policy-makers. They need to consider the stability and patterns of institutional convergence of the higher education systems for which they are responsible so that they can take decisions on any cuts needed in the case of divergence. However, to date, no empirical evidence has been found to show whether such reforms have led to a process of convergence in the cost efficiency of national university systems.

This research aims to cast some light on this topic, with two goals. First, it aims to evaluate the cost efficiency of the Spanish Public University System (SPUS) from 2008, when the international economic and financial crisis began and public administrations started to cut funding for higher education, until 2019, the last year of the post-crisis recovery period, before the recession caused by the coronavirus pandemic. Second, it aims to analyse any convergence in the cost efficiency of Spanish public HEIs during that period, as well as convergence towards the sector average and best practices. Moreover, in order to find out how the global crisis of 2008 affected both cost efficiency and its convergence, in both cases the overall period is divided into two sub-periods: the crisis period which started in 2008 and ended in 2013, and the post-crisis period, from the start of economic recovery in 2014 until 2019. To achieve the first of these goals, conditional panel data Data Envelopment Analysis is applied (López-Torres & Prior, 2022), which can include the time factor in the estimation of efficiency while also controlling for the role of contextual factors. For the second, various economic models are estimated considering the longitudinal structure of the data and correcting the problem of endogeneity in order to find the β, σ and λ convergence (Guccio et al., 2016 a,b).

Since there are hardly any studies on the cost efficiency of public universities and their possible convergence, our paper enriches the literature because: (1) it provides new empirical evidence on the performance of the SPUS by evaluating the cost efficiency of Spanish public universities and thus contributing broader knowledge on whether their managers have managed to reduce expenditure while carrying out core university functions; (2) it considers a more recent and longer period than the two prior studies performed in the Spanish context, thus finding trends in cost efficiency between 2008 and 2019, and during the two sub-periods of crisis and economic recovery, so that comparisons can be made between them and the possible influence of the crisis can be traced; (3) it is the first study which, to our knowledge, performs an analysis of the convergence of cost efficiency in a country's public universities while also assessing the possible impact of the global crisis of 2008 on such convergence. This analysis is relevant because, while the SPUS is characterised by great internal structural heterogeneity and a considerable geographical gap, it was performed in the context of the reforms of the Spanish university system to adapt it to the EHEA which, amongst other objectives, sought to reduce inequality among HEIs in terms of performance; and (4) it applies an innovative conditional panel data DEA model to obtain more robust and reliable results than the techniques that are traditionally used in this line of research.

The remainder of this paper is structured as follows. The second section reviews the empirical background. The third describes the methodology used, the fourth explains the design of the empirical research, the fifth presents and discusses the results and, finally, the sixth draws some conclusions.

2. Literature review

2.1. Evaluation of efficiency

There have been few prior studies on the cost efficiency of public universities either nationally or internationally. Since those that exist consider different national contexts and time frames, use different input and output variables and apply different estimation techniques, it is difficult to make comparisons between them. Table A (in the Annex) lists those that, to our knowledge, have been published to date in quality journals, with their main methodological data, input and output variables used and results found. It should be noted that most of the studies consider European universities and longitudinal data, also that most of them use total costs as the input variable and the number of students who graduate and/or enrol and research revenue (grants, projects, etc.) as output variables. They also mostly use two main methodologies - DEA and Stochastic Frontier Analysis (SFA).

Considering research performed in Europe, after a thorough review of the literature, we find that three studies use DEA methodology to calculate cost efficiency. In the case of British public universities, in a sample of 45 HEIs during the 1992/93 academic year, Athanassapoulos & Shale (1997) find that the average level of cost efficiency was 83.1%, while Thanassoulis et al. (2011), in 121 universities during the period 2000/01-2002/03, find an average level of efficiency of 86.3%. In addition, Agasisti & Salerno (2007), after analysing 52 Italian institutions during the 2002/03 academic year, find that, on average, the cost efficiency markers vary between 81% and 89%, depending on the inputs and outputs used in the various models specified.

Studies that use SFA methodology include Kempkes & Pohl (2010) who, in a sample of 72 German public universities between 1998 and 2003, found that the highest cost efficiency reached was 80% in 2003. A study on Italian universities by Agasisti & Johnes (2010) found, in a sample of 57 HEIs between the 2001/02 and 2003/04 academic years, an average cost efficiency of 81%, and Agasisti (2016), in a panel of 55 institutions during the period 2001-2011, found an average value between 33.3% and 64.6%. Finally, in Spain, Johnes & Salas-Velasco (2007), in their analysis of 26 Spanish public universities between 1998 and 2004, found cost efficiency in excess of 98%.

When both methodologies are combined, Agasisti & Dal Bianco (2009b), after examining a sample of 58 Italian universities during the 2002/03 academic year, concluded that average cost efficiency varied between 66.4% and 80.6% using DEA, and between 58.5% and 76.8% using SFA, depending on the models specified.

Finally, with a different goal and using other methodologies apart from DEA and SFA, Crespo et al. (2022) used the Malmquist index to evaluate university performance over time and whether this was affected by changes in efficiency and/or technological progress. On a sample of 47 Spanish public universities, they found that average performance rose by 6.4% between 2009 and 2016 because of an increase in cost efficiency of 0.9% and a technological improvement of 5.7%.

Outside Europe, to our knowledge, studies were performed by Taylor & Harris (2004), McMillan & Chan (2006) and Lu (2012), providing information on cost efficiency in universities and using DEA as their methodology, although the context and input and output variables used varied between them. Taylor & Harris (2004) examined 21 South African public universities between 1994 and 1997 and reported an average cost efficiency of close to 90%; McMillan & Chan (2006), in 45 Canadian public universities during the 1992/93 academic year, found average cost efficiency of 91.2%; and, finally, Lu (2012) in an evaluation of 40 universities in Taiwan in 2008 found average efficiency of 91.3%.

2.2. Analysis of convergence in efficiency

In the scientific literature, the analysis of convergence in efficiency has been applied in various economic sectors to find to what extent there is convergence or divergence in the use of resources by the various entities analysed over time. Most of these studies focus on the financial sector (Casu & Girardone, 2010; Degl'Innocenti et al., 2017; Izzeldin et al., 2021, among others).

In the education sector and, more specifically, in the non-university public sector, Aparicio et al. (2018) and López-Torres & Prior (2022), who worked respectively with 298 and 124 primary schools in Catalonia (Spain) between the 2009/10 and 2013/14 academic years, found a strong pattern of convergency towards the sector average during the period of the global crisis of 2008. While the former applies the analyses of convergence to markers of educational performance, the latter applies them to levels of technical efficiency.

Regarding public university education, there are very few studies in the international literature on convergence in efficiency, and none at all on a national level. Moreover, as far as we know, the only two studies published to date are based on the technical efficiency of universities (Guccio et al., 2016 a,b), with none at all on cost efficiency. Both these studies, based on samples of public HEIs in Italy, show convergence in the management of the Italian university system, both over time and towards the sector average and best practices, during adoption of the Bologna Process (2000-2010).

3. Methodology

3.1. Evaluation of efficiency

DEA is a non-parametric linear programming technique that evaluates the relative efficiency of a set of similar Decision-Making Units (DMUs). This allows the identification of those that represent the best practices by comparing each of them with all the possible linear combinations of the rest. The group of fully efficient DMUs forms the so-called "efficient frontier", which, in this case, captures the minimum level of costs at which it is possible to produce a given level of outputs, such that the radial distance of the rest of the entities to that frontier quantifies the inefficient behaviour (Daraio et al., 2020).

The conventional DEA model has a series of advantages over parametric approaches such as SFA (Bogetoft & Otto, 2011): (1) it does not require the establishment of a specific functional form of the production frontier; (2) it allows the inclusion of exogenous variables, as well as uncontrollable inputs; (3) it constructs an efficient frontier with best practices that serves as a benchmark for inefficient entities, facilitating benchmarking analysis; and, (4) it does not need the fulfilment of statistical hypotheses, for example, normality or heteroscedasticity. However, it also suffers from several constraints such as absence of statistical properties due to its deterministic nature, possible existence of dimensionality in the sample or difficulties in handling any longitudinal structure in the data. In addition, efficiency indices are highly conditioned by the composition of the sample, the presence of extreme values or the measurement errors of the input and output variables, generating biased estimates (Simar & Wilson, 2008). Some proposals have been put forward to overcome the main limitations of the traditional DEA model and thus obtain more robust efficiency values, including the conditional order-m model (Cazals et al., 2002), the order-α model (Aragon et al., 2005) or the panel data DEA model (Surroca et al., 2016).

In this paper, given the availability of complete panel data between 2008 and 2019 and the fact that one of the objectives is to analyse the patterns of convergence of cost efficiency scores in that period, a conditional panel data DEA model has been chosen. This model allows us to determine the time-variant and time-invariant efficiency estimates, overcoming the limitations of the inter-temporal model and, since it is a conditional approach, it is able to control any contextual factors that might influence efficiency.

In addition, according to the scarce existing literature on cost efficiency in the university sector (Agasisti & Dal Bianco, 2009b; Agasisti & Salerno, 2007; Lu, 2012; Thanassoulis et al., 2011, among others), this DEA model will be applied under variable returns-to-scale and with an input orientation, since the objective is to evaluate the ability of universities to minimize their costs when reaching a given level of outputs. Thus, any inefficiency identified will measure the excess of financial resources used to obtain the results.

3.1.1. Conditional panel data DEA model

In the field of education, the transformation function of inputs into outputs is often influenced by contextual factors that are not controllable by educational entities, which can affect their management and cause heterogeneity within the production process. The conditional model proposed by Cazals et al. (2002) allows exploration of the exogenous factors that can affect efficiency levels, without the need to fulfil the separability condition between efficiency values and these factors. This model has been used in university (Agasisti et al., 2023; Bonaccorsi et al., 2006) and non-university contexts (Harlemans & De Witte, 2012; López-Torres & Prior, 2022).

This paper applies a conditional input-oriented variable returns-to-scale panel data DEA model proposed by López-Torres & Prior (2022), which is an extension of the initial panel data DEA model developed by Surroca et al. (2016). To do this, a smoothing technique is employed for exogenous variables (z), based on the Epanechnikov kernel density function and the maximum likelihood cross-validation criterion, in order to obtain the optimal bandwidth (b) (Daraio & Simar, 2007).

The following mathematical development is based on the notation of López-Torres & Prior (2022). Assume that for S units $[s = 1, \ldots, S]$ there are N inputs $\left[x^s = x_1^s, \ldots, x_n^s, \ldots, x_N^s \in \Re_+^N\right]$ producing M outputs $\left[y^s = y_1^s, \ldots, y_m^s, \ldots, y_M^s \in \Re_+^M\right]$, where the variables corresponding to the observed unit (DMU$_0$) are $\left[x_1^o, \ldots, x_n^o, \ldots, x_N^o \in \Re_+^N\right]$ y $\left[y^o = y_1^o, \ldots, y_m^o, \ldots, y_M^o \in \Re_+^M\right]$. In addition, since the observation set has a panel data structure, a new variable τ is defined $(\tau = 1, \ldots, T)$, which represents the corresponding time period for the inputs and outputs: $\left[x_1^{s,\tau}, \ldots, x_n^{s,\tau}, \ldots, x_N^{s,\tau} \in \Re_+^N\right]$ and $\left[y^{s,\tau} = y_1^{s,\tau}, \ldots, y_m^{s,\tau}, \ldots, y_M^{s,\tau} \in \Re_+^M\right]$. Thus, the dual program to calculate conditional cost efficiency estimates with a conditional input-oriented variable returns-to-scale time-invariant panel data DEA model is as follows:

$$Min_{\lambda^{s,\tau}} h^{ti} = \alpha^{ti} \tag{1}$$

s.t.

$$\sum_{s|(z-b\le z^0\le z+b)}^{S|(z-b\le z^0\le z+b)} \sum_{\tau|(z-b\le z^0\le z+b)}^{T|(z-b\le z^0\le z+b)} \lambda^{s,\tau} x_n^{s,\tau} \le \alpha^{it} \tilde{x}_n^o; \quad \mathrm{n} = 1, \ldots, \mathrm{N};$$

$$\sum_{s|(z-b\le z^0\le z+b)}^{S|(z-b\le z^0\le z+b)} \sum_{\tau|(z-b\le z^0\le z+b)}^{T|(z-b\le z^0\le z+b)} \lambda^{s,\tau} y_m^{s,\tau} \ge \tilde{y}_m^o; \quad m = 1, \ldots, M;$$

$$\sum_{s|(z-b\le z^0\le z+b)}^{S|(z-b\le z^0\le z+b)} \sum_{\tau|(z-b\le z^0\le z+b)}^{T|(z-b\le z^0\le z+b)} \lambda^{s,\tau} = 1;$$

$$\lambda^{s,\tau} \ge 0$$

where $\tilde{y}_m^o$ is the average value of output m, for the complete time period T for the DMU$_0$ $\left(\tilde{y}_m^o = \sum_{\tau=1}^{T} y_m^{o,\tau}/T\right)$; $\tilde{x}_n^o$ is the average value, corresponding to the input n, for the complete time period T for the DMU$_0$ $\left(\tilde{x}_n^o = \sum_{\tau=1}^{T} x_n^{o,\tau}/T\right)$ and $\lambda^{s,\tau}$ is the activity vector. After implementing the program [1], we obtained for each university: a single time-invariant conditional panel data efficiency coefficient $\left(h^{ti}\right)$, which represents the complete period being evaluated, M weights of outputs $\left(u_1^{ti}, \ldots, u_m^{ti}\right)$ and N weights of inputs $\left(v_1^{ti}, \ldots, v_n^{ti}\right)$.

In addition, in order to compare the results and justify the choice of the conditional model *versus* the non-conditional model, the time-invariant cost efficiency scores are also estimated according to the non-conditional panel data DEA model applied by Pérez-López et al. (2018), who were the first to extend the panel data DEA model from Surroca et al. (2016).

Finally, to know the annual efficiency indices over the complete period, it is necessary to determine the conditional time-variant panel data efficiency estimates. To do this, according to the notation of López-Torres & Prior (2022), the conditional time-invariant efficiency coefficient of each university $\left(h^{ti}\right)$ is the weighted average of the conditional input-oriented variable returns-to-scale time-variant panel data efficiency coefficients for each institution by year $\left(h_\tau^{tv}\right)$:

$$h^{ti} = h_1^{tv} w^1 + \ldots + h_\tau^{tv} w^\tau + \ldots + h_T^{tv} w^T = \sum_{\tau=1}^{T} h_\tau^{tv} w^\tau \tag{2}$$

Cost efficiency estimates were calculated using the R program (R Development Core Team, 2023) and statistical packages such as *Benchmarking*® (Bogetof & Otto, 2022), *np*® (Hayfield & Racine, 2008) and *rcDEA*® (Mergoni, 2022).

3.2. Convergence analysis

To investigate the convergence of the cost efficiency levels of Spanish public universities over the period 2008-2019, we apply the concepts of β-convergence and σ-convergence[1] (Barro & Sala-i-Martin, 1991, 1992, 2004) to the values achieved in the conditional time-variant panel data cost efficiency (h^{tv}) analysis. In addition, λ-convergence (Guccio et al., 2016 a,b) is used to assess whether the efficiency values of these entities tend towards the efficient frontier where best practices are located.

First, β-convergence indicates whether the institutions that initially managed their resources worse improve their efficiency faster than those that initially performed them better, i.e., whether the HEIs that lag behind in terms of cost efficiency levels at the beginning of the period show greater growth in the indicator than those with higher initial values. Thus, it is assumed that the growth rate of efficiency in period τ depends on the initial level of efficiency. According to the notation established by the literature, the β-convergence is determined with the following specification of the regression model:

$$\Delta h^{tv}_{s,\tau} = \alpha + \beta \left(\ln h^{tv}_{s,\tau-1}\right) + \rho \Delta h^{tv}_{s,\tau-1} + \varepsilon_{s,\tau} \tag{3}$$

where $h^{tv}_{s,\tau}$ and $h^{tv}_{s,\tau-1}$ are the calculated conditional cost efficiency levels of university s in periods τ and $\tau-1$, respectively; $\Delta h^{tv}_{s,\tau} = \ln h^{tv}_{s,\tau} - ln h^{tv}_{s,\tau-1}$; α, β and ρ are the parameters to be estimated, with β being the convergence indicator and $\varepsilon_{s,\tau}$ the error term. A statistically significant negative value for the parameter β indicates that, over time, the most cost-inefficient HEIs at the beginning of the period have improved their efficiency indicators more than those that initially managed their resources better, and the higher their value in absolute terms, the greater the β-convergence.

Second, σ-convergence captures if the dispersion around the sector average decreases over the period. To this end, the following regression model is applied to study the dynamics of the dispersion of efficiency values:

$$\Delta E_{s,\tau} = \alpha + \sigma E_{s,\tau-1} + \rho \Delta E_{s,\tau-1} + \varepsilon_{i,\tau} \tag{4}$$

where $E_{s,\tau} = ln h^{tv}_{s,\tau} - \ln \overline{h}^{tv}_{\tau}$; $E_{s,\tau-1} = ln h^{tv}_{s,\tau-1} - \ln \overline{h}^{tv}_{\tau-1}$; $h^{tv}_{s,\tau}$ and $h^{tv}_{s,\tau-1}$ are the estimated conditional cost efficiency levels of university s in periods τ and $\tau-1$, respectively; $\overline{h}^{tv}_{\tau}$ and $\overline{h}^{tv}_{\tau-1}$ are the averages of the conditional efficiency levels of universities in periods τ and $\tau 1$, respectively; $\Delta E_{s,\tau} = E_{s,\tau} - E_{s,\tau-1}$; α, σ and ρ are the parameters to be determined, with σ being the convergence indicator and $\varepsilon_{s,\tau}$ the error term. A statistically significant negative σ value reveals that the cost efficiency levels are closer to the sector average at the end of the period than at the beginning. Thus, the higher this value in absolute terms, the faster the inequality reduction in the efficiency of university expenditure management.

Finally, in order to determine whether university management tends towards total cost efficiency levels, we employ a variant of the standard partial adjustment model (PAM), called λ-convergence, which allows us to assess convergence towards the best practice frontier through the adjustment mechanism:

$$\begin{aligned}\ln h^{tv}_{s,\tau} - \ln h^{tv}_{s,\tau-1} &= \gamma \left(\ln h^{tv}_{total} - \ln h^{tv}_{s,\tau-1}\right) \\ &+ \delta\ Crisis * \left(\ln h^{tv}_{total} - \ln h^{tv}_{s,\tau-1}\right) + \varepsilon_{s,\tau}\end{aligned} \tag{5}$$

where $h^{tv}_{s,\tau}$ and $h^{tv}_{s,\tau-1}$ are the estimated conditional cost efficiency levels of university s at time τ and $\tau-1$, respectively; h^{tv}_{total} is the total cost efficiency value to which each university aspires, which is 1; $\varepsilon_{s,\tau}$ is the error term; and γ represents the adjustment parameter, which measures the speed of adjustment towards the efficient frontier or the gap between the current and desired value in each period. In addition, in order to verify whether the crisis period has influenced the convergence of cost efficiency towards best practices, we consider a dummy variable "*Crisis*" in the model, which takes the value 1 in the crisis period (2008-2013) and 0 in the rest. Thus, δ will be the interaction term between *Crisis* and $\left(\ln h^{tv}_{total} - \ln h^{tv}_{s,\tau-1}\right)$, allowing us to analyse whether there was faster adjustment towards best practices over the crisis period ($0 < \gamma + \delta < 1$) than in the subsequent period of economic recovery. Reordering equation (5) and substituting $\lambda = 1-\gamma$ and $\eta = -\delta$, the following formulation is obtained:

$$\ln h^{tv}_{s,\tau} = \lambda \left(\ln h^{tv}_{s,\tau-1}\right) + \eta\ Crisis * \left(\ln h^{tv}_{s,\tau-1}\right) + \varepsilon_{s,\tau} \tag{6}$$

where $\lambda = 1-\gamma$ captures the persistence of $h^{tv}_{s,\tau-1}$ in $h^{tv}_{s,\tau}$. Thus, the higher the statistically significant value of λ, the lower the value of γ and, hence, the greater the persistence of cost inefficiency and the slower the convergence towards the efficient frontier. On the other hand, a statistically significant negative value of η corresponds to a statistically significant positive value of δ, indicating faster adjustment towards the efficient frontier during the crisis period (2008-2013).

To correct any endogeneity problems associated with the convergence estimates, the formulations [3], [4] and [6] are solved by applying the following models: a) pooled regression models with lags and the "cluster" option to control the longitudinal structure of the data and to estimate robust standard errors; and, b) dynamic panel data models based on the "difference" Generalized Method of Moments (difference GMM) estimator (Arellano & Bond, 1991), which provides more efficient and consistent estimates of the parameters than previous models[2]. These regressions were carried out using the *STATA*® v.17 program.

4. Research design

4.1. Sample

The study period stretches from 2008, when the global economic and financial crisis began and central and regional governments were obliged to cut funding for higher education, to 2019, the last year of the post-crisis recovery period before the recession caused by COVID-19 in 2020. This global period is then divided into two sub-periods: the crisis period,

[1] One of the necessary, although not sufficient, condition for σ-convergence is the presence of β-convergence, since in both cases the initially less efficient institutions have to improve their management over time more than those that are initially more efficient (Sala-i-Martin, 1996).

[2] Since we have a macro panel structure, with small n (<100) and high t (>10), it is not possible to use the system GMM estimator, since this leads to over-identification of the models to be estimated. Therefore, the difference GMM estimator is needed, as it reduces the number of instruments to be used by using the lagged differences as instrumental variables (Labra & Torrecillas, 2018).

from 2008 to 2013, and the post-crisis period, from 2014, the start of economic recovery, until 2019.

The Spanish University System was made up of 84 universities in 2019, of which 50 were public (almost 60% of the total). This study focuses on the 47 Spanish HEIs offering face-to-face teaching that existed during the study period (94% of the total of the SPUS). However, after a process to detect atypical observations (Simar, 2003), two universities were removed in all the years considered.

So, the sample analysed was made up of full panel data for 45 Spanish public universities in the 12 years of the study period (2008-2019), giving rise to a total of 540 DMUs or observations.

4.2. Variables

One of the critical points for measuring efficiency in HEIs using the DEA methodology is the selection of the input and output variables involved in the complex functions of production and costs, so the existence of data is essential. The serious limitation in this area in Spain forced us to choose these variables in line with the information that was publicly available, although, in order to make it easier to compare the results with the prior evidence, this selection followed other studies in this field.

Since we aimed to assess cost efficiency in public universities, determining how much it would be possible to reduce cost when considered as the single input while maintaining the same level of outputs, in this study, as in most of the few prior studies in this area (Agasisti & Dal Bianco, 2009b; Agasisti & Johnes, 2010; Agasisti & Salerno, 2007; Crespo et al., 2022; Thanassoulis et al., 2011), the *input variable* is measured with the *total cost of the services provided*. This variable is built as follows:

Total cost of services provided (TC): Current and capital expenditure from the HEIs budgets, excluding expenditure of a financial nature (in thousands of euros). Specifically, total costs include expenditure on staff (chapter 1), current goods and services (chapter 2), current transfers (chapter 4), capital investment (chapter 6) and capital transfers (chapter 7).

The *output variables* reflect the results of the two basic activities carried out by universities, that is, teaching and research: *students graduating*, *PhDs defended*, quality *publications* and *competitive research projects*. No output for the social transfer of knowledge was included for two reasons: first, because, although the number of spin-offs is the most appropriate variable for representing the result of this activity because several agents from the university participate (Berbegal-Mirabent, 2018), the lack of data in several years of the study period significantly reduced the sample, greatly limiting the study; and, second, because, although the number of patents has been considered in some studies as an output of this activity, apart from the fact that here too data were not available for the whole period, this only captures the knowledge available in the university, without guaranteeing future commercialisation of the invention (Powers & McDougall, 2005). As in prior studies on efficiency in university costs, the teaching and research outputs for each HEI were measured as follows:

- **Graduate students (GRAD):** Total number of graduate students from official study courses, considering all university levels (undergraduate and Master's) for each academic year (Agasisti, 2016; Athanassapoulos & Shale, 1997; Crespo et al., 2022).

- **PhD defended (PhD):** Number of PhDs defended in the framework of a Doctorate programme for each year (Johnes & Salas-Velasco, 2007).

- **Publications (*PUB*):** Number of quality articles published, indexed in the multidisciplinary data bases of the *Web of Science* published by *Clarivate Analytics,* for each year (Crespo et al., 2022; Taylor & Harris, 2004).

- **Competitive research projects (*PROY*):** Number of research projects obtained in competitive calls within the Spanish National Plan for R&D+I and European Union framework programmes for each year (Agasisti & Dal Bianco, 2009b; Crespo et al., 2022).

Finally, since a conditional approach is used to estimate cost efficiency, in addition to the above-described university inputs and outputs, we consider a *contextual variable* that cannot be monitored by HEIs and has potential for affecting their production and cost functions and, therefore, their levels of efficiency, namely: *regional GDP per capita* (RGDPpc) (Agasisti & Johnes, 2010; Kempkes & Pohl, 2010).

- **Regional GPDpc (*RGDPpc*):** This is measured by regional GDP per capita (in euros) and reflects the degree of economic development in the Spanish region in which each university is located. Since powers in higher education in Spain have been devolved to the Autonomous Communities, which hold extensive control over the funding and management of their universities, their cost efficiency may be determined by decisions adopted by regional governments in line with the level of regional GDP. Moreover, this variable may also represent the socioeconomic level of families, which is closely related to efficiency in the management of the educational sector.

The variables were quantified on the basis of the official information supplied on the websites of the Ministry of Universities (www.universidades.gob.es), the *Web of Science* (www.webofknowledge.com), the IUNE Observatory of University Research Activity in Spain- (www.iune.es), the two-yearly reports published by the CRUE Conference of Spanish University Rectors (www.crue.org) and the Spanish National Statistics Institute (www.ine.es). In order to perform the statistical analyses, any values expressed in monetary units are deflated - at constant prices for 2008 - using the Spanish GDP deflator provided by the World Bank (www.worldbank.org), in order to avoid any inflation-related distortion in the results.

Table 1. Descriptive statistics for selected variables

	Mean	Std.Dev.	Min.	Max.
Input				
TC	178,742.00	105,052.90	38,296.00	485,695.00
Outputs				
GRAD	4,046.00	2,247.81	644.00	11,843.00
PhD	193.50	165.09	16.00	1,046.00
PUB	1,135.10	890.99	108.00	5,418.00
PROY	49.42	33.15	2.00	161.00
Contextual variable				
RGDPpc	22,888.00	5,076.85	15,399.00	36,332.00
n = 540 observations				

Note: TC: Total cost, in thousands of euros (not deflated); GRAD: Total number of graduates; PhD: Number of PhD defended; PUB: Number of quality scientific articles; PROY: Number of competitive research projects; RGDPpc: Regional GDP per capita, in euros (not deflated).

Table 1 summarises the main descriptive statistics for the input and output variables, as well as the contextual factor, for the 540 DMUs or observations on the study sample.

5. Results and discussion

5.1. Evaluation of efficiency

Firstly, we take the estimations of time-invariant cost efficiency after applying the conditional and non-conditional panel data DEA models, under variable returns-to-scale and input-oriented (Table 2). We then present the time-variant conditional panel data cost efficiency indices for each study year (Table 3).

Table 2. Time-invariant panel data cost efficiency

	Mean	Std.Dev.	Min.	Max.
Conditional model	0.9303	0.0913	0.6683	1
Unconditional model	0.6851	0.1179	0.4515	0.9241
n = 45 Spanish public universities				

Table 2 shows that, on average, the time-invariant conditional cost efficiency during the overall period from 2008 to 2019 reached 93.03%, indicating that, to produce a given level of outputs, Spanish public universities should have reduced their expenditure on average by 6.97% in order to be completely efficient. This result, showing low cost inefficiency in the SPUS between 2008 and 2019, is in line with the finding of Johnes & Salas-Velasco (2007) for the period 1998-2004 (average value in excess of 98%). Although the results of the two studies are not directly comparable because of different time frames, input/output specifications and methodological approaches, they show high efficiency in cost management by Spanish public universities.

In addition, estimation of the non-conditional model indicates average time-invariant efficiency of 68.51%. This result, which is in line with those obtained previously by López-Torres & Prior (2022), confirms that including contextual factors in the analysis tempers the results and perfects the efficiency indices by restricting the scope of the comparison to the group of DMUs that have similar conditions to those of the unit of analysis. Therefore, our findings, which confirm that consideration of the exogenous variable (regional GDP per capita) improves estimations of cost efficiency, justify our choice of the conditional model.

Table 3 shows the average, minimum and maximum values as well as the standard deviation of the estimations, under variable returns-to-scale and input-oriented, of time-variant conditional panel data cost efficiency. Our findings show that average annual efficiency improved by 26% over the total period analysed. This suggests that, in 2019, Spanish public universities provided the established level of services with a cost reduction of 26% in comparison with 2008. Crespo et al. (2022) found that, on average, the performance of the SPUS increased by 6.4% between 2009 and 2016, to which a contribution was made by an improvement in cost efficiency of just 0.9%. Therefore, in line with the goals of the EHEA, in the face of increasing demands for both quality production by universities using the lowest possible amount of financial resources as well as greater answerability to society, it can be stated that, between 2008 and 2019, Spanish universities became more productive in their use of public funds.

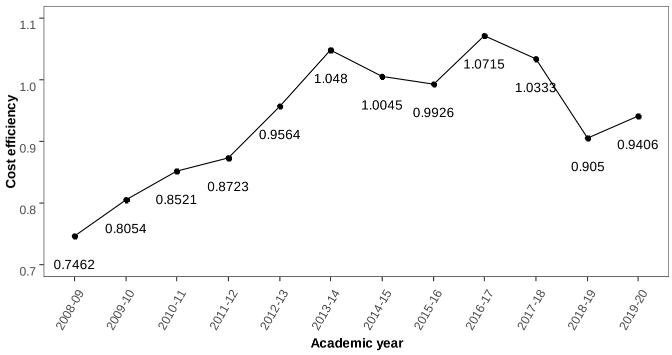
When a distinction is made between the crisis and post-crisis sub-periods, annual evolution in efficiency was considerably better during the former (improvement of 40.4% between 2008 and 2013) than during the latter (reduction of 6.4% between 2014 and 2019). This was in spite of increased instability during the first period, with large budget cuts leading to great competition among universities for increasingly limited public funding while they also had to adopt reforms to adapt the Spanish university system to the EHEA. It was therefore during the crisis situation that the institutional leaders were able to increasingly minimise costs to reach the set level of activity. As shown in Figure 1, while during the crisis the trend is upward and continuous, in the post-crisis period, it tended to level off and to move slightly downward.

Table 3. Conditional time-variant panel data cost efficiency

Period	Mean	Std.Dev.	Min.	Max.
2008	0.7462	0.1547	0.4461	1.0963*
2009	0.8054	0.1376	0.5001	1.0777*
2010	0.8521	0.1311	0.5585	1.1862*
2011	0.8723	0.1527	0.5640	1.4459*
2012	0.9564	0.1827	0.5974	1.7152*
2013	1.0480*	0.1662	0.6266	1.6795*
2014	1.0045*	0.1612	0.6116	1.4891*
2015	0.9926	0.1351	0.7241	1.3649*
2016	1.0715*	0.3288	0.6729	2.5612*
2017	1.0333*	0.2862	0.6656	2.2424*
2018	0.9050	0.1673	0.3743	1.2091*
2019	0.9406	0.1777	0.4437	1.3235*
n = 540 DMUs				

* *Note.* Input-oriented efficiency estimates based on linear program optimization are bounded between 0 and 1. The annual averages of some years and the maximum values exceed unity because extreme values can occur when the optimal weights are taken and applied to other years to determine the time-variant efficiency estimates.

Figure 1. Annual evolution of the conditional time-variant panel data cost efficiency (2008-2019)



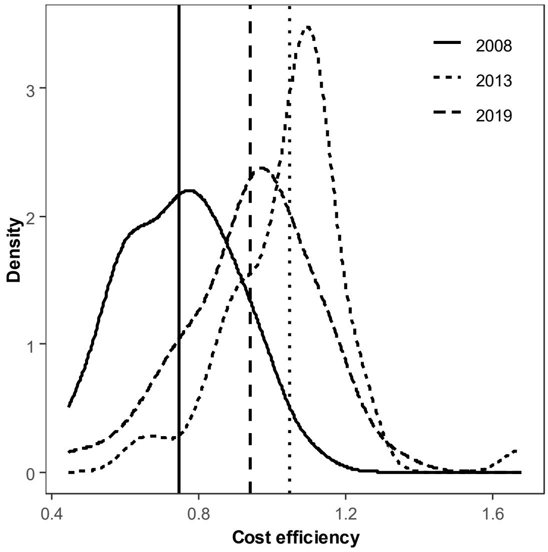
Both Table 3 and Figure 1 also indicate that, although the SPUS achieved a high level of cost efficiency in both sub-periods, the average value of the marker in the post-crisis stage was 11 percentage points higher than during the crisis (99.12% in 2014-2019 as opposed to 88.01% in 2008-2013[3]). This indicates that, on average, the managers of Spanish public universities took better cost-cutting decisions during the economic recovery, a time of less uncertainty with a slight, sustained increase over time in public funds at the disposal of the HEIs.

Figure 2 shows the Kernel density functions of cost efficiency for the three key years of the study (2008, 2013 and 2019), which limit the crisis and post-crisis periods. In 2013, the levels of efficiency in the management of university funds saw a marked rise over those of 2008, as shown in the shift of the curve and of its mean (the vertical dotted line) towards

[3]The average values corresponding to the crisis and post-crisis periods were calculated from a simple mean of the average índices for time-variant conditional panel data cost efficiency during the six years of each sub-period.

the right, becoming closer to the optimal values of best practices. However, in 2019 there was a slight decrease in the efficiency values below those of 2013. This is seen in the fall of the curve and of its mean, although it is still in a much better position than at the start of the crisis in 2008.

Figure 2. Kernel density functions (2008, 2013 and 2019)



5.2. *Analysis of efficiency convergence*

In order to analyse the possible patterns of β, σ and λ convergence of the levels of time-variant conditional panel data cost efficiency during the period 2008-2019, and in the sub-periods of crisis and economic recovery, and to check the robustness of our findings, we apply both a pooled data regression model using lags and the "cluster" option and a dynamic panel data model based on the difference GMM estimator. The results of both methodologies are aligned with the sign and statistical significance of the markers of convergence. However, as in the studies by Guccio et al. (2016 a,b) on the technical efficiency of Italian HEIs from 2000 to 2010, the absolute values of these markers are higher in the GMM estimations, which are more robust and efficient.

5.2.1. β-convergence

Table 4 shows the estimates of β-convergence, according to equation [3], for the overall period (2008-2019) and for the crisis (2008-2013) and post-crisis (2014-2019) sub-periods. These allow us to find whether the correct decisions were taken to adjust the expenditure of Spanish public universities to the level of service provided, thus promoting convergence among them in cost efficiency throughout each period.

After applying the two methodologies, we find statistically negative values of the β coefficient, at the 1% level during the period 2008-2019. This suggests that the Spanish public HEIs that were least cost-efficient in 2008 improved their efficiency during the twelve years analysed more than those that had initially managed their resources better. This confirms the existence of β-convergence in the cost efficiency of the SPUS between 2008 and 2019, pointing to the effort made by the universities that were most behind at the start of the period to better manage their costs when providing a given service level, thus coming close to those that were initially most efficient.

Moreover, there is also β-convergence that is statistically significant at 1% during both the crisis period (2008-2013) and the economic recovery period (2014-2019), although both estimations show that the convergence between universities regarding their cost efficiency levels was greater during the latter.

5.2.2. σ-convergence

After checking β-convergence, the next step is to find if there is also σ-convergence. This is formulated by equation [4], which indicates the speed at which universities converged in cost efficiency towards the average of the SPUS in each period studied. Table 5 shows the results.

Statistically significant negative values at the 1% level in the σ-coefficients both over the overall time period and during the crisis and post-crisis stages confirm that the cost efficiency of Spanish HEIs converged towards the sector average in each period analysed, thus reducing dispersion within the SPUS.

According to the difference GMM model, which presents more efficient and consistent results than the lagged pooled data model and with the "cluster" option, the absolute values of the σ-coefficient show that the speed of reduction in inequality in the cost efficiency of the different institutions was very similar over the three periods considered, and slightly higher during the post-crisis period. In addition, the high values of σ show a fairly high speed of convergence towards the sector average in all three cases.

Table 4. β-convergence of cost efficiency

	2008-2019		2008-2013		2014-2019	
	Pooled cluster	Difference GMM	Pooled cluster	Difference GMM	Pooled cluster	Difference GMM
Constant (α)	-0.015	-0.079***	0.043***	-0.073	-0.025*	-0.059*
	(0.009)	(0.028)	(0.008)	(0.050)	(0.013)	(0.034)
$lnh^{tv}_{s,\tau-1}(\beta)$	-0.424***	-1.405***	-0.208***	-0.943***	-0.564***	-1.565***
	(0.064)	(0.122)	(0.039)	(0.240)	(0.188)	(0.188)
$\Delta h^{tv}_{s,\tau-1}(\rho)$	0.033	0.188**	-0.132	-0.129	0.168	0.304***
	(0.084)	(0.084)	(0.109)	(0.132)	(0.179)	(0.117)
Goodness of fit:						
R^2	0.2172		0.1222		0.2163	
F-test	44.19***		15.17***		16.81***	
Wald chi^2		173.5***		40.70***		70.18***
Sargan test (p-value)		0.2002		0.1639		0.1867
AR(2) (p-value)		0.3661		0.1104		0.4230
Observations	450	405	180	135	180	135

*Notes:** Dependent variable $\Delta h^{tv}_{s,\tau}$: Cost efficiency growth in τ. $\ln h^{tv}_{s,\tau-1}$: Cost efficiency level in $\tau-1$; $\Delta h^{tv}_{s,\tau-1}$: Cost efficiency growth in $\tau-1$. The β coefficient measures the speed of efficiency convergence over the period.
Standard errors in brackets. *** p< 0.01; ** p< 0.05; * p< 0.1

Table 5. **σ-convergence of cost efficiency**

	2008-2019		2008-2013		2014-2019	
	Pooled cluster	Difference GMM	Pooled cluster	Difference GMM	Pooled cluster	Difference GMM
Constant (α)	-0.008	-0.016	-0.003	-0.016	-0.015	-0.049
	(0.007)	(0.024)	(0.009)	(0.031)	(0.013)	(0.034)
$E_{s,\tau-1}(\sigma)$	-0.413***	-1.546***	-0.276***	-1.548***	-0.534***	-1.579***
	(0.078)	(0.130)	(0.046)	(0.230)	(0.167)	(0.168)
$\Delta E_{s,\tau-1}(\rho)$	0.015	0.221***	-0.110	0.215**	0.148	0.295***
	(0.095)	(0.072)	(0.120)	(0.105)	(0.159)	(0.101)
Goodness of fit:						
R^2	0.1949		0.1740		0.2072	
F-test	35.24**		18.32***		16.63***	
Wald chi^2		176.63***		59.45***		88.27***
Sargan test (p-value)		0.5806		0.3582		0.1640
AR(2) (p-value)		0.2129		0.6155		0.4483
Observations	450	405	180	135	180	135

Notes: Dependent variable $\Delta E_{s,\tau}$: Growth of cost efficiency dispersion around the mean in τ. $E_{s,\tau-1}$: Dispersion of cost efficiency around the mean in $\tau-1$; $\Delta E_{s,\tau-1}$: Growth of cost efficiency dispersion around the mean in $\tau-1$. The coefficient σ measures the speed of efficiency convergence towards the sector average over the period.
Standard errors in parentheses. *** p< 0.01; ** p< 0.05; * p< 0.1

5.2.3. λ-convergence

Finally, λ-convergence was estimated using equation [6] to find whether the cost efficiency of Spanish public universities had converged towards the best practices in the sector or the efficient frontier. This is the point at which the group of HEIs that achieve the minimum level of costs at which it is possible to produce a given level of university outputs is located. The results are given in Table 6.

Table 6. **λ-convergence of cost efficiency (2008-2019)**

	Pooled cluster	Difference GMM
Constant (α)	-0.010	-0.002
	(0.007)	(0.010)
$lnh^{tv}_{s,\tau-1}(\lambda)$	0.535***	0.353**
	(0.067)	(0.161)
$Crisis\left(lnh^{tv}_{s,\tau-1}\right)(\eta)$	0.132*	0.334**
	(0.073)	(0.154)
Goodness of fit:		
R^2	0.4174	
F-test	242.09***	
Wald chi^2		60.44***
Sargan test (p-value)		0.3644
AR(2) (p-value)		0.2255
Observations	495	450

Notes: Dependent variable $\ln h^{tv}_{s,\tau}$: Cost efficiency level in τ. $\ln h^{tv}_{s,\tau-1}$: Cost efficiency level in $\tau-1$; Crisis $\left(\ln h^{tv}_{i,\tau-1}\right)$: interaction term between the dichotomous variable Crisis, which takes the value 1 in the crisis period (2008-2013) and 0 in the rest, and $\ln h^{tv}_{s,\tau-1}$. The coefficient λ measures the speed of efficiency convergence towards best practices over the period. The coefficient η measures the speed of efficiency convergence towards best practice in the crisis period *versus* the economic recovery period.
Standard errors in parentheses. *** p< 0.01; ** p< 0.05; * p< 0.1

After applying these methodologies, it can be observed that the λ coefficients are positive and statistically significant. This indicates that during the period 2008-2019 there was an institutional move towards the efficient frontier, that is, the universities in the SPUS tended to adjust their results towards total cost efficiency.

More specifically, the GMM estimates show, on the one hand, a positive value in the λ coefficient of 35.3%, which is statistically significant at the 5% level. This is equivalent to a γ level of 64.7%, and points to intense convergence in cost efficiency in the SPUS towards the best practices in the sector between 2008 and 2019. This shows that, during this period, the structural gap in this respect among Spanish public universities was reduced considerably.

On the other hand, a positive, statistically significant value in the η coefficient is equivalent to a negative and significant δ value of -33-4%. This suggests a slower speed of adjustment towards the efficient frontier during the crisis period (2008-2013) than during the subsequent recovery (2014-2019). More specifically, management of the institutions during the post-crisis stages contributed to a greater extent - 33.4% more - to the convergence in the SPUS towards totally efficient performance than management during the crisis.

Having analysed β, σ and λ convergence of efficiency, it can be deduced that the creation of the EHEA entailed a process of harmonisation within the SPUS in terms of cost efficiency between 2008 and 2019, which was able to drive convergence among universities in the skill at reducing costs while providing a given level of outputs over this twelve-year period. So, the HEIs that in 2008 managed their funds worse improved their cost efficiency more than those that initially performed better, while also reducing divergence from the sector average and, therefore, inequality among universities at the end of the period. There was also an intense convergence towards the efficient frontier. If a distinction is made between the crisis and recovery periods, although both saw convergence in cost efficiency in Spanish public universities, the latter period saw the most intense adjustment over time and the greatest institutional convergence towards the sector average and towards best practices in the SPUS.

6. Conclusions

The general purpose of this study was to assess out how a situation of economic crisis affects the cost efficiency of public universities and to find any convergence among them. Two goals were established: (1) to evaluate the marker of university performance in the SPUS during the period 2008-2019, comparing the situation during the global economic crisis (2008-2013) and after it (2014-2019); and (2) to analyse the patterns of convergence in efficiency, both over time and within the sector and towards best practices, and their possible dependence on the crisis. Three main conclusions were drawn.

First, since the degree of cost efficiency and trends in it are important criteria for assessing and monitoring public higher education systems, with any inefficiency identified being the result of excessive funds used for a given level of university production, it can be concluded that, in line with the objectives of the EHEA, on average, Spanish public universities increased their cost efficiency throughout the period 2008-2019. They were able to cut their expenditure without compromising the services rendered, thus achieving a favourable impact on funding adequacy and competitiveness. However, this substantial improvement took place during the crisis period (2008-2013) which, unlike the period of economic recovery (2014-2019), was characterised by great uncertainty and decreasing public expenditure in higher education and the reforms that were being adopted to align the Spanish university system with the EHEA. In spite of this trend in the marker, its average value was higher in the post-crisis stage. So, although the SPUS was very cost-efficient in both sub-periods, universities were more careful in the way they used funding after the crisis. This seems to indicate that, at a time of great pressure to reduce costs during a period of instability and austerity, Spanish HEIs increasingly adjusted the cost of providing a given level of services, substantially improving their efficiency. Even though the trend subsequent turned downwards, this dynamic remained during the stage of economic recovery when universities faced less pressure to save but continued to be careful when spending their funds, adopting better cost-cutting practices than during the crisis.

Second, in the framework of the EHEA, it can be concluded that there was also a fast convergence in the cost efficiency of the SPUS between 2008 and 2019, both over time and towards the sector average. Inequality among the HEIs decreased and there was a move towards best practices, as represented by the universities that managed to be completely cost-efficient. This indicates that, over this period of twelve years, the structural gap among Spanish HEIs regarding cost management was considerably weakened, which helped to reduce internal structural heterogeneity and to generate greater equality for carrying out university functions. Therefore, the convergence in cost efficiency within the SPUS between 2008 and 2019 was a persistent, long-term process which not even the economic crisis could hold back, to the extent that it grew during the subsequent recovery. In fact, it was during this latter stage that the gap between HEIs efficiency levels decreased most over time, within the sector and towards best practices. This suggests that the crisis had a positive impact on the subsequent patterns of convergence with the SPUS.

Third, since one of the main guidelines of the EHEA and, consequently, of the legislative reforms approved in Spain to adapt to it, was to achieve greater competitiveness among public universities in a global market by both improving their efficiency in the use of resources and closing the efficiency gap between them, our results show that these two goals were achieved by the SPUS between 2008 and 2019. This could have been the result of the requirements to improve processes for adapting the Spanish university system to the EHEA and of European harmonisation in the field of university administration as well as consolidation during the post-crisis period of the dynamic of responsible management by universities that was built up during the previous period based on cost control in view of decreasing public funding.

Considering possible implications at institutional level for dealing with future crises and the need for resilience that became clear during the recent COVID-19 crisis, our study shows resilience in the SPUS in terms of cost efficiency both during and after the global crisis of 2008. Since the response to future crises may once again be to restrict public funding for the university systems of European countries, if public HEIs wish to be resilient and to maintain or increase their financial autonomy and competitiveness, they will need to complement practices aiming to achieve excellence with cost containment achieved by acting in the field of university governance to facilitate stability and reduce inequality among them in terms of performance. Such institutions must reduce the gap in cost management both over time and towards the sector average and best practices, taking measures when any divergence is detected. These implications are particularly relevant for university systems in southern European countries, which share lower development and more drastic budget cuts after crises and are, therefore, weaker than those in other countries. In the framework of the EHEA, a common model for "quality" public universities for the whole of the European Union can only be viable if sufficient funds are provided to consolidate sustainable excellence while ensuring that such funds are used efficiently. This is especially important in a context of crisis and austerity when universities are required to be more productive in their allocation of any public funding and to be answerable to society for the way they use it.

Our study also has limitations that make it advisable to interpret its results with caution. They can also serve as a starting-point for future research. One is that it is difficult to generalise the findings because the sample is restricted by the type of university, the geographical area and the period analysed. Moreover, the analysis could have been richer if the pre-crisis period had also been considered to study the trend in cost efficiency before, during and after the crisis, as well as the process of convergence in it during this longer period. However, the lack of homogeneous data on the input and output variables made this impossible. Finally, all measures used for university outputs are quantitative. None of them combine quality with quantity of production in the SPUS.

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Conflict of interests

The authors declare that they have no conflicts of interest.

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ANNEX

Table A. Empirical evidence on cost efficiency in universities

EUROPEAN COUNTRIES			
AUTHOR/S	SAMPLE AND PERIOD	METHODOLOGY, INPUTS AND OUTPUTS	RESULTS
Athanassapoulos & Shale (1997)	45 British public universities (1992/93)	*Data Envelopment Analysis (DEA)* - Inputs: General academic expenditure; research income - Outputs: no. of successful leavers; no. of higher degrees awarded; weighting of research rating.	Average cost efficiency in scientific and general universities is 95.4% and 88.3% respectively. Total universities achieve an average cost efficiency of 83.1%.
Agasisti & Salerno (2007)	52 Italian public universities (2002/03)	*Data Envelopment Analysis (DEA)* 2 DEA models (depending on the outputs used) - Inputs: total cost. - Outputs Model 1: External funds for research per researcher; no. of students in Medicine and on PhD courses; no. of students enrolled weighted by drop-out rate. - Outputs Model 2: Students enrolled in scientific (non-medicine) and non-scientific courses weighted by drop-out rate and first-year students with entry mark of 9/10; students enrolled in Medicine; students on PhD courses; external funds for research staff weighted by grants from the Ministry.	Average cost efficiency in universities with and without Medicine qualifications show fairly similar levels, between 81% and 89%.
Johnes & Salas-Velasco (2007)	26 Spanish public universities (1998, 2000, 2002 and 2004)	*Stochastic Frontier Analysis (SFA)* - Dependent variable: total cost - Outputs: students on science courses; students on non-science courses; postgraduates (PhDs); research income.	Average cost efficiency of 98.9%.
Agasisti & Dal Bianco (2009b)	58 Italian public universities (2002/03)	*Stochastic Frontier Analysis (SFA)* *Data Envelopment Analysis (DEA)* 5 DEA models (depending on the inputs and outputs used) - Dependent variable/Inputs: total cost (staff and other costs); cost of academic staff; cost of non-academic staff; cost of all personnel; other non-personnel costs. - Outputs: students enrolled on scientific courses (not including Medicine); students enrolled on other non-Science courses; total no. of students enrolled; no. of competitive research projects; students enrolled on PhD courses; students enrolled on science courses (not including Medicine) weighted by drop-out rates; students enrolled on other non-Science courses weighted by drop-out rates; no. of competitive research projects weighted by a measure of quality.	Cost efficiency levels vary depending on the model applied, between 66.4% and 80.6% when DEA is applied, and between 58.5% and 76.8% when SFA is used.
Agasisti & Johnes (2010)	57 Italian public universities (2001/02 to 2003/04)	*Stochastic Frontier Analysis (SFA)* - Dependent variable: total cost (minus the cost of capital and depreciation). - Outputs: students on science degrees; students on other degrees (Humanities, Social Sciences and Art); total no. of students on PhD courses; revenue from subsidies for research and external consultancy; dichotomous variables (if the university offers studies in Medicine or not).	Average cost efficiency is 81%.
Kempkes & Pohl (2010)	72 German public universities (1998 to 2003)	*Stochastic Frontier Analysis (SFA)* - Dependent variable: total cost (minus external funds per student). - Outputs: no. of graduates per student; research grant revenue per student.	The highest value for cost efficiency achieved was 80% in 2003 in both east and west German universities.
Thanassoulis et al. (2011)	121 British public universities (2000/01to 2002/03)	*Data Envelopment Analysis (DEA)* - Inputs: total cost. - Outputs: Full-time equivalent (FTE) students in Medicine and Dentistry; FTE students on science courses; FTE students on other non-Science courses; FTE post-graduate students; revenue from subsidies and funds related to research quality; revenue for other services rendered.	The average level of cost efficiency reached over the 3 years of the study applying DEA was 86.3%.
Agasisti (2016)	55 Italian public universities (2001 to 2011)	*Stochastic Frontier Analysis (SFA)* (different models depending on the outputs used) - Dependent variable: current cost. - Outputs: total no. of graduates; no. of regular students; total no. of students enrolled; regular no. of graduates; research activity, technical or consultancy revenue from public or private entities.	The cost efficiency levels achieved depending on the model applied varied between 33.3% and 64.6%. Moreover, there was a reduction in cost inefficiency in Italian public universities between 10% and 15.33% during the period 2001-2011, depending on the model applied.
Crespo et al. (2022)	47 Spanish public universities (2009 to 2016)	*Malmquist index* - Inputs: total cost - Outputs: no. of graduates and post-graduates qualified; no. of quality publications (Web of Science); no. of competitive research projects; no. of patents; no. of spin-offs.	Average university performance increased by 6.4% during the period because of increased cost efficiency of 0.9% and technological improvement of 5.7%.

Table A. Empirical evidence on cost efficiency in universities (Cont.)

OTHER COUNTRIES			
AUTHOR/S	SAMPLE AND PERIOD	METHODOLOGY, INPUTS AND OUTPUTS	RESULTS
Taylor & Harris (2004)	21 South-African public universities (1994 to 1997)	*Data Envelopment Analysis (DEA)* - Inputs: capital employed and total expenditure - Outputs: Degree credits obtained by students completing a qualification; no. of quality publications (approved by SAPSE).	Average cost efficiency levels of about 90%.
McMillan & Chan (2006)	45 Canadian public universities (1992/93)	*Data Envelopment Analysis (DEA)* 2 DEA models depending on the number of outputs used - Inputs: total cost - Outputs: students enrolled on science courses; students enrolled on other courses; students enrolled on Masters courses; students on PhD courses; sponsored research expenditure	The average level of cost efficiency was 91.2%.
Lu (2012)	40 public universities in Taiwan (2008)	*Data Envelopment Analysis (DEA). Additive model* - Inputs: teaching cost: other operating costs; overheads and administration costs. - Outputs: full-time teaching staff; administrative staff; IT software and hardware.	Average cost efficiency in Taiwan universities was 91.3%.

Source: Drawn up by the authors.