Journal of Engineering and Technology Management 47 (2018) 68–80

Contents lists available at ScienceDirect

Journal of Engineering and Technology Management

journal homepage: www.elsevier.com/locate/jengtecman

The influence of regulatory frameworks on research and knowledge transfer outputs: An efficiency analysis of Spanish public universities

Jasmina Berbegal-Mirabent

Department of Economy and Business Organization, Universitat Internacional de Catalunya, C. Immaculada, 22, 08017, Barcelona, Spain

ARTICLE INFO

Keywords:
Universities
Research and knowledge transfer
Data envelopment analysis
Malmquist index
Truncated regression

JEL classifications:
C67
I21
I23

ABSTRACT

In 2007, Spain reformed its regulatory framework to give priority to research and knowledge transfer activities at universities. It is in this context that we examine the efficiency of Spanish public universities and their evolution during the period 2006–2010. Results report that on average, universities have improved their efficiency. Economies of scope and scale are also discussed, observing that large universities with a concentrated academic offering are more likely to display higher efficiency scores. Surprisingly, neither the existence of specific infrastructures aimed at boosting knowledge transfer outputs (i.e., business incubators) nor regional wealth seems to influence universities' efficiency.

1. Introduction

The enhanced institutional autonomy that universities have been given has been accompanied by requirements for greater accountability and more stringent, detailed quality assurance procedures. There is an abundance of public accountancy reports on universities' performance. Traditionally, these reports depended heavily on data from governmental statistical agencies that were far from being collected on an annual, standardized and systematic basis (Salerno, 2004). Moreover, the available data tended to be aggregated, rather than reported on a per institution or per academic discipline basis. It was also country-specific and tended to largely ignore knowledge transfer activities.

This changed with the rise of the evaluative state, the improvement in information systems and the emergence of business analytics; it is now easy to access large amounts of valuable information. The body of data from the higher education system contains a very large number of indicators, metrics and complex associations. Internal use of this information could help university managers to better allocate resources and improve performance.

Institutes, research centers, public and independent organizations and companies operating in the media sector are increasingly reporting more and more information about universities' performance online. Making it easier to access such information has several implications. It enables universities to benchmark their performance and decide their strategy without resorting to complex market studies, because the information they require is now at their fingertips. It also makes it easier to improve current proxies for universities' inputs and outputs. A further benefit is that there is the potential to aggregate and analyze the raw data to help students, potential partners and governments make better decisions (Soares, 2012).

In this study we exploited this newly available information. On the basis of comprehensive data reported by various online sites, our empirical work considers the Spanish public higher education system during the period 2006–2010. In Spain, it is compulsory to

E-mail address: jberbegal@uic.es.

https://doi.org/10.1016/j.jengtecman.2018.01.003
Received 16 August 2016; Received in revised form 21 December 2017; Accepted 7 January 2018
Available online 10 January 2018
0923-4748/

assess the teaching and research credentials of candidates when hiring staff. The National Agency for Quality Assessment and Accreditation (ANECA) is the body responsible for all such evaluations. In 2007, several modifications to the framework regulating the hiring and contracting of academic staff were introduced. For the most part, the changes mirrored the shift in universities' activities, from a teaching-oriented model to a research-oriented one. This meant that the research credentials of candidates for university posts became more important relative to the other components of an academic CV (i.e. educational background, teaching experience, work experience).

The aim of this study is thus to assess how the incorporation of more stringent research requirements into the regulatory framework has influenced universities' operations and, more precisely, whether the efficiency of universities improved or worsened because of the modifications. To this end, we carried out a three-stage analysis: (i) an efficiency analysis (using data from 2006, 2008 and 2010); (ii) an investigation of changes in efficiency using the Malmquist index; and (iii) development of a truncated regression model to determine the external factors influencing efficiency.

There are several procedures for assessing university performance; we chose to use Data Envelopment Analysis (DEA), a non-parametric efficiency technique. There are several advantages to this method. DEA models are very flexible, freeing us from imposing any structure on the relationship between outputs and inputs (Archibald and Feldman, 2008) and not requiring the specification of any particular functional form for the best practice frontier (Seiford and Thrall, 1990). Yet, it does require the imposition of certain a priori hypotheses about the technology (free-disposability, convexity, constant or variable returns to scale). Notwithstanding, the specific characteristics of universities – multiple inputs and/or outputs and the absence of market prices – make DEA, rather than other parametric approaches, a more reliable technique (Barra and Zotti, 2016; Greene, 1980). The large amount of existing work in the higher education field using DEA supports its use (see Berbegal-Mirabent and Solé, 2012 for an extensive review).

This paper is innovative in two main ways. First, we focus special attention on research and knowledge transfer (RKT) outputs. These activities help universities to provide a stimulating learning environment, attract and retain qualified faculty and students, ensure that curricula cover topics at the cutting edge and contribute to the economic development of their region (Hazelkorn, 2005). Furthermore, RKT outcomes are increasingly considered in evaluation procedures and are regarded as among the best indicators of success (Shattock, 2009). We therefore argue that more attention should be devoted to how universities allocate resources in pursuit of RKT outputs. Prior studies examining universities' efficiency have mainly concentrated in teaching and research outputs (Agasisti and Pérez-Esparrells, 2010), but neglected knowledge transfer activities. Settled in the Spanish context, the article of Berbegal-Mirabent et al. (2013) was pioneering in including third stream activities in the universities' objective function. Recent developments that have followed this direction are the works of Sagarra et al., (2015) and de la Torre et al. (2016b). Both articles integrated DEA and Multidimensional Scaling (MDS), discussing the potential complementarities. A cluster analysis is later used to identify different patterns across the universities in the sample. Our paper contributes to the existing literature by modelling and testing a different objective function where RKT outputs play a critical role.

Second, a growing attention is now being paid to how the reforms introduced by European countries in their respective higher education systems have impacted the operations of universities (Agasisti and Wolszczak-Derlacz, 2015; Kyratzi et al., 2015; Sagarra et al., 2015). Our study contributes to this stream of research by analyzing the evolution of efficiency scores in light of a reform that took place in Spain that brought about important challenges for universities in that they are now called to prioritize knowledge-oriented outputs.

The remainder of this paper is organized as follows. The next section discusses basic and applied research outcomes, the indicators commonly used to proxy these activities and the incentives for researchers to carry out both types of research. After this, we outline the Spanish regulatory framework. This is followed by a description of the method and presentation of the data. Next, results are reported. This paper ends with a discussion of policy implications and concluding remarks.

2. Basic versus applied research outcomes

Research is an intrinsically competitive endeavor encompassing basic academic investigations and collaborative partnerships between universities and industry. Outputs are traditionally measured in terms of bibliometric data (Sarrico et al., 2010). Such data are freely available and facilitate the use of measures related to the number of papers published in scientific journals or citation counts. Although it has been argued that these metrics reflect both the quantity and quality of research activity (Abramo et al., 2008), they are usually criticized for being vague or incomplete and failing to capture the full range of universities' research productivity (van Raan, 2005). Some critics (e.g. Coccia, 2008) have claimed that publications other than journals – i.e. conference proceedings, books, book chapters and reports – are usually undervalued in evaluations, although they reach a wider audience and disseminate research beyond academia. It is nevertheless widely accepted that such publications are usually of lower quality than articles in peer-reviewed journals.

Variables linked to indices and bibliometric data are, however, widely used in assessment procedures and ranking systems. For instance, in the Academic Ranking of World Universities (ARWU), 20% of the total score depends on the number of papers published in journals indexed in the Science Citation Index (SCI) and the Social Science Citation Index (SSCI). Another 20% is based on the number of papers published in the journals Nature and Science, and yet another 20% is based on the number of citations per researcher, which is considered a proxy for impact. In summary, 60% of the total ARWU score is based on subjective metrics that, although they are based on agreed quality standards and are accepted by the academic community, present an incomplete picture of an institution's research performance. Similar methods are used by universities and external agencies to assess the performance of individual academics for recruitment and promotion purposes. This means that in order to remain in academia, scholars are forced to concentrate on producing the outputs regarded as most valuable in these assessment frameworks. It is essential to publish high quality articles in top journals, particularly for young academics and staff who do not have a permanent position (Lafuente and Berbegal-Mirabent, 2017).

Nevertheless, if research activities are to be meaningful, they must produce economically useful knowledge with industrial relevance (Hsu et al., 2015). This assumes that the market is a driver of external collaborations between academia and industry and that this improves universities' performance and facilitates access to additional, non-public funding and resources. In other words, if the knowledge generated by universities is not spread to society – in any of its forms – it loses its value (Montesinos et al., 2008). For the dissemination of knowledge to take place, universities and businesses must identify common interests in order to build alliances that enable the exploitation of universities' scientific knowledge and make efficient use of their infrastructures and advanced services (Plewa et al., 2013). Patenting, licensing agreements and collaborative research projects are the traditional channels through which research results are transferred to industry (van der Ploeg and Veugelers, 2008), but there is another way to exploit or transfer knowledge generated in the university sector. Scientific knowledge can be the starting point for a business idea and, by extension, the birth of new a company. Spin-offs represent the entrepreneurial route to commercialization of public research (Rasmussen, 2008).

Although the benefits of knowledge transfer activities are widely documented in the literature (Geuna and Muscio, 2009), they are still undervalued relative to traditional basic research outcomes (i.e. publications). Boardman and Bozeman (2007) and Boardman and Ponomariov (2007) provided empirical evidence that academics in pre-tenure positions are reluctant to engage in knowledge transfer activities, preferring to devote their time to basic research activities. Similarly, Balsmeier and Pellens (2014) and Agarwal and Ohyama (2013) found that although the number of publications was positively associated with promotion prospects, researchers with a track record of patenting activity were more likely to drop out of academia. These findings suggest that from the researcher's perspective, the main motivation for engaging in knowledge transfer activities is because they potentially offer access to new sources of funding for research or activities one would not otherwise be able to undertake, mainly due to the lack of resources. Knowledge transfer activities may also generate new ideas that can be developed further.

3. Spanish regulatory framework

3.1. Career path

Over the past 15 years, there have been substantial changes to the procedures for recruiting and employing academics in the Spanish higher education system. In 2001, a new legal framework, the LOU, was approved to replace the Organic Law of University Reform (LRU) 11/1983. The types of contract available in the academic sector differentiate between civil servants (permanent faculty) and non-civil servants (fixed-term faculty).

The requirements for becoming a civil servant were specified by Royal Decree 774/2002. The procedure was similar to that of civil service examinations, where candidates were required to pass a series of examinations and demonstrate their teaching ability and expertise in a particular area of knowledge. The Reform of the Organic Law of Universities (RLOU) 4/2007 came into force in April 2007. This eliminated some contractual figures and replaced the examination process with an accreditation system, specifying the criteria that all candidates were required to meet before being hired by a university in a particular capacity. The accreditation system has been in effect from 2008 and should be administered by an external agency (ANECA or the competent regional quality assurance agency). The new procedure was expected to make the recruitment process more competitive and enable universities to choose the candidates that best suited their requirements.

The LOU (2001) also provided for important changes in the assessment and recruitment of non-civil servants. The aim was to consolidate the body of skilled researchers. The number of roles available expanded. In increasing order of status, these roles were: assistant, PhD assistant lecturer, collaborating lecturer and PhD lecturer. A positive external assessment was also a prerequisite for appointment to any of these roles, with the exception of assistant, for which universities were free to set their own criteria. Under the terms of Royal Decree 1052/2002, assessments were carried out by the ANECA or the competent regional authority on the basis of a CV. Some modifications to the assessment procedure were introduced by the RLOU 4/2007, most notably, the criteria for the level of research performance required to access the various academic positions were made more stringent.

The LOU (2001) also recognized a third category of academic staff, namely part-time faculty, i.e. specialists with recognized competence and a record of current professional activity outside the university who performed a reduced amount of university teaching, were paid hourly and were not required to carry out any research activities. Because they were not required to carry out research, we do not consider them in this study.

3.2. Accreditation system

There is an accreditation system for both civil servant and non-civil servant academics. The primary objective of the evaluation is to ensure that candidates for academic positions have an appropriate level of academic merit. ANECA implements two assessment programs: the Assessment Program for civil servant faculty (ACADEMIA) and the Academic Staff Evaluation Program (PEP) for non-civil servant faculty. The weight assigned to the various components of a CV (i.e. teaching experience, research experience, educational background and work experience) varies according to the teaching body, academic discipline and academic position.

At this point, it is worth mentioning that the different categories are substantially research-biased. The higher the position, the more important are the academic's research credentials. Table 1 compares the indicators and weights of the various components for all the academic positions to which the system applies (PhD assistant lecturer, PhD lecturer, senior lecturer and full professor) based on the modifications introduced by the Reform of the Organic Law of Universities 4/2007. Table 1 makes it clear that RKT experience

Table 1
Criteria and weights assigned to each indicator and academic post, according to ANECA.

Criteria	Indicator	PEP				ACADEMIA			
		PhD assistant lecturer		PhD lecturers		Senior lecturer		Full professor	
Educational background	PhD	21		6		5		-	
	Scholarships and grants								
	Academic background								
	Mobility								
	Research posts (coordination)	–		–					
Teaching experience	Teaching experience	9		30		37		32	
	Teaching training								
	Teaching innovation and teaching material								
	Mobility	-		-					
	Academic posts (coordination)								
	Academic supervision (thesis)								
Research experience	Research projects and research contracts	5–9	60	5–12	60	4–7	50	6–10	55
	Technology transfer	26–35		26–35		2–9		3–12	
	Publications (articles)					27–37		27–37	
	Books and book chapters	3–16		3–16					
	Conferences and seminars taught	9		2–5		3–5		3–5	
	Academic supervision (thesis)	-		4		–		–	
	Other research merits	4		1–2					
Work experience	Work experience outside the university	5		2		3		3	
Other merits	Other merits	5		2		2		2	
Coordination	Academic posts	–		–		5		10	
Total		100		100 (+2 extra)		100 (+2 extra)		100 (+2 extra)	
Minimum required score for a positive evaluation		55		55		65		80	

Note: For those criteria that scores vary depending on the discipline, we present the range values.

typically accounts for at least half of the total score, thus confirming that these activities are more highly valued than the other criteria.

4. Data and method

4.1. Data

Our main source of information was the Observatory of Spanish University Research Activity (IUNE) online database, which compiles information from various official sources and makes it publicly available. We also used the biannual reports of the Council of Rectors of Spanish Universities (CRUE) and the annual reports of the Spanish Network of Technology Transfer Offices (RedOTRI). Additional information about regional variables was obtained from the Spanish National Institute of Statistics (INE) website.

The original database consisted of information on 47 Spanish public universities for the academic years 2006, 2008 and 2010. Statistical analysis was carried out using STATA (version 13). Efficiency scores and Malmquist index values were calculated using software packages FEAR (Wilson, 2008) and Benchmarking, which can be implemented in the statistical software R.

4.2. Efficiency analysis: DEA

Efficiency analysis usually uses frontier methods grounded in economic production theory to deal with multiple inputs yielding multiple outputs. Farrell (1957) stated that technical efficiency could be analyzed in terms of observed deviations from an ideal frontier isoquant, thus characterizing the relationship between observed production and a potential production level in terms of the observations. This definition of efficiency relates to the use of resources, that is, how efficiently inputs are transformed into outputs in comparison with a maximally efficient unit. A production unit can be considered technically efficient if it is impossible to produce more of any output without producing less of some other output or consuming more inputs (Koopmans, 1951).

Farrell's efficiency measure was popularized by Charnes et al. (1978), who introduced a technique, DEA, for assessing the efficiency of a sample of organizations (decision making units; DMUs). DEA-based measures are non-parametric, deterministic techniques that use linear programming mathematical models to approximate the true but unknown technology. They do not impose restrictions on sample distribution, nor do they require input and output prices. The best practice frontier is determined by the performance of the most efficient DMUs, and DEA computes an inefficiency score for other DMUs that reflects their distance from this frontier.

Table 2
Descriptive statistics for the selected variables.

Year	Statistic	Inputs			Outputs			
		Faculty*	TTO staff*	R&D expenditure**	Graduates	Publications	Research projects	Spin-offs
2006	Mean	1,113.362	14.216	54.627	3,114.107	685.426	55.319	3.196
	Std. Dev.	792.105	11.192	41.273	1,968.269	583.221	41.517	4.593
	Min.	145.000	1.000	8.852	599.000	99.000	11.000	0.000
	Max.	3,850.000	45.000	195.800	9,226.000	2,698.000	192.000	22.000
2008	Mean	1,153.979	14.975	67.331	3,190.447	823.957	51.745	2.304
	Std. Dev.	810.2755	12.875	50.681	1,907.369	704.207	39.512	3.040
	Min.	250.000	2.000	8.360	709.000	107.000	8.000	0.000
	Max.	3,995.000	66.000	205.157	8,514.000	3,211.000	187.000	12.000
2010	Mean	1,184.170	13.951	72.989	3,159.404	951.340	52.170	2.522
	Std. Dev.	803.520	11.908	51.437	1,845.218	784.475	37.125	3.298
	Min.	274.000	2.000	17.109	586.000	148.000	8.000	0.000
	Max.	3,931.000	56.000	199.740	8,585.000	3,548.000	158.000	13.000
Total	Mean	1,150.504	14.380	64.982	3,154.674	820.241	53.078	2.674
	Std. Dev.	796.785	11.933	48.295	1,894.200	699.130	39.176	3.699
	Min.	145.000	1.000	8.360	586.000	99.000	8.000	0.000
	Max.	3,995.000	66.000	205.157	9,226.000	3,548.000	192.000	22.000

Note: Sample size: 47 universities (141 observations including years 2006, 2008 and 2010).
* Faculty and TTO staff computed as full-time equivalent.
** R&D expenditure in million euros. Data for years 2006 and 2008 were inflation-corrected and reported in 2010 €.

DEA models are based on several assumptions. First, one must define the frontier production function assuming constant returns to scale (CRS) or variable returns to scale (VRS). For this study, we used VRS, which allows the researcher to estimate distances to the production frontier while controlling for the size of the benchmarks (Cooper et al., 2007). Although the assumption of CRS is attractive, the extant evidence indicates that in practice, VRS is much more common (Chambers and Pope, 1996). The second assumption deals with the choice of measurement orientation (input minimization or output maximization). Since our analysis focuses on public universities, we opted to use an output orientation on the grounds that in public universities the workforce and budget tend to be fixed, and managers are asked to maximize output from the available resources (Tone and Sahoo, 2003).

Given these considerations, the linear equation that must be solved is presented in Eq. (1). Maximization of δ^i involves the production of the highest level of outputs (y) possible given the resources available (x). The term δ^i represents the efficiency score for each unit (university). For efficient universities, i.e. those situated on the best practice frontier, $\delta^i = 1$. Values of $\delta^i > 1$ indicate the degree of inefficiency as a function of distance from the best practice frontier.

$$
\begin{aligned}
&T(x^{i'}, y^{i'}) = \max \delta^i \\
&\text{subject to } \textstyle\sum_{i=1}^{N} \lambda^i y_m^i \geq \delta^i y_m^{i'} \quad ,m = 1,\ldots, M \\
&\textstyle\sum_{i=1}^{N} \lambda^i x_j^i \leq x_j^{i'} \quad ,j = 1,\ldots, J \\
&\textstyle\sum_{i=1}^{N} \lambda^i = 1 \\
&\lambda^i \geq 0 \quad ,i = 1,\ldots, N
\end{aligned}
\tag{1}
$$

Our model assumes that universities use three inputs (x) to produce four outputs (y). Descriptive statistics are presented in Table 2.

In terms of the outputs related to each mission, the teaching mission is expressed as the number of graduates. Universities have been recognized as providers of graduates through teaching activities, that is, future professionals that capitalize their knowledge stock available at universities (van der Ploeg and Veugelers, 2008).

Concerning RKT outputs, we considered those indicators that are most valued by the ANECA to accredit professors. As shown above in Table 1, these outputs are: publications, research projects and technology transfer. Although the weights assigned to the different outputs vary according to the academic position and discipline, we can conclude that these outputs are relevant indicators as they are the main determinants of whether a candidate is evaluated positively.

The publications variable was operationalized as the number of academic papers published in the ISI Web of Knowledge. The reasoning for this was threefold. First, the ANECA guidelines state that publications in journals included in this database are more valuable than those in journals included in other databases. Second, the ISI Web of Knowledge is considered to reflect both quantity and quality (Kao and Hung, 2008). Acceptance of papers is based on a blind peer review process that follows quality standards accepted by the academic community. Third, information on the number of papers published is reliable and well documented.

We also took into account the number of research projects granted by the Spanish Ministry of Education. Because research projects are awarded on a competitive basis, this indicator captures a university's ability to conduct high quality, innovative research activities. This criterion is particularly relevant in the fields of engineering, as well as the medical and experimental sciences.

Lastly, technology transfer outputs were operationalized through the number of spin-off companies created. Spin-offs represent the entrepreneurial route to commercialization of public research (Rasmussen, 2008) and are one of the most appropriate indicators of knowledge transfer activities.

As for the selected inputs, the first input we considered was human resources. Universities are labor-intensive organizations and, as such, the labor force is a critical input. We therefore included the number of faculty staff, that is, scholars that are responsible for the teaching and carrying out of RKT activities. The efficient running of a university also depends on the technical and administrative workers who manage its day-to-day operations and support RKT activities (e.g., provide guidance on how to apply for a research project or assist researchers that start up a new business). In this analysis, we represented this input as the number of technical staff working in a university's Technology Transfer Office (TTO). Submitting a project proposal or starting a new business demand specific skills that researchers might not possess, but are tasks that can be more easily performed with the support of TTO staff. Finally, the third input we considered was expenditure on research and development (R&D) activities, that is, the amount universities allocate for conducting R&D activities. As shown in Table 2, Spanish public universities have increased their R&D expenditure, indicating the increase in importance accorded to this area of activity.

In order to correct the estimated efficiencies from the sampling bias, this study applies bootstrap techniques (2000 replications) on the efficiency scores obtained (Simar and Wilson, 1998). 95% confidence intervals of the biased corrected efficiency scores are also reported.

4.3. Changes in efficiency: malmquist index

We investigated changes in efficiency for the periods 2006–2008 and 2008–2010 using the non-parametric Malmquist index (see Färe et al., 1994, 1992 for pioneering research on the Malmquist index). This approach has been applied to a number of services, including the higher education system (e.g. Kim, 2013; Agasisti and Pohl, 2012; Groot and García-Valderrama, 2006).

The Malmquist index compares data from two different periods, t and $t+1$, to the same reference technology from period t. Consistent with the initial assumption (output-oriented), the output-based Malmquist index of change in productivity is specified by the equation formulated by Coelli et al. (1998) and reproduced in Equation (2):

$$M_0^{t+1}(y_t, x_t, y_{t+1}, x_{t+1}) = \left[\frac{D_0^t(y_{t+1}, x_{t+1})}{D_0^t(y_t, x_t)} \times \frac{D_0^{t+1}(y_{t+1}, x_{t+1})}{D_0^{t+1}(y_t, x_t)}\right]^{1/2}, \tag{2}$$

where the subscript O indicates an output orientation; M is the productivity at the most recent production point ($xt+1$, $yt+1$) (using period $t+1$ technology) expressed relative to the earlier production point (xt, yt) (using period t technology); and D is an output distance function. The Malmquist index can also be expressed in the form given as Eq. (3):

$$M_0^{t+1}(y_t, x_t, y_{t+1}, x_{t+1}) = \frac{D_0^{t+1}(y_{t+1}, x_{t+1})}{D_0^t(y_t, x_t)} \times \left[\frac{D_0^t(y_{t+1}, x_{t+1})}{D_0^{t+1}(y_{t+1}, x_{t+1})} \times \frac{D_0^t(y_t, x_t)}{D_0^{t+1}(y_t, x_t)}\right]^{1/2}, \tag{3}$$

The first part of Eq. (3) is a measure of efficiency change, i.e. the technical efficiency in period $t+1$ relative to the technical efficiency in period t ("pure" efficiency change, indicating the ability of universities to improve their own performance with respect to the performance of the others). The second part measures movement relative to the production frontier, reflecting the technical change. Values > 1 indicate an increase, values < 1 denote a decrease and a value of 1 represents no change. The Malmquist index resulting from combining the two components is equal to 1 if there are no changes in technical efficiency and frontier changes. When there is a net positive or negative change in efficiency, the index is respectively greater or lower than 1.

4.4. Regression analysis

An important strand of research into the performance of universities is based on two-stage analysis, involving evaluation of efficiency (using the DEA methodology), followed by regression analysis to explain the differences in efficiency scores. However, according to Simar and Wilson (2007), log-linear models (estimated using the ordinary least squares (OLS) method), censored regression models (i.e. Tobit models) or other models (estimated using the maximum likelihood (ML) method) are ad hoc rather than structural and are not valid. These authors argued that estimates thus produced are inconsistent because they do not take into account contextual variables as they are not based on a well-defined statistical model in which such structures would follow from the first stage in which the initial DEA estimates are obtained.

We based our analysis of institutional and environmental drivers of efficiency on the theoretical work by Simar and Wilson (2011) and an application of it to the higher education system (Wolszczak-Derlacz and Partera, 2011). It consists of a truncated regression model that paid special attention to the inference problem that arises from the inherent correlations amongst DEA estimates in finite samples, while obtaining coherent statistical models that led to meaningful second-stage regressions. Standard errors of coefficients were estimated by the bootstrapping technique (2000 replications).

The dependent variable was the inefficiency scores obtained through the robust (bootstrap) procedure, after correcting for bias, and the independent variables included two dummy variables controlling for the effect of having a business incubator or being affiliated to a science park. We predicted that both forms of infrastructure would be associated with better university-industry interactions and hence enhanced innovation and technological spillovers (Berbegal-Mirabent et al., 2015; Caldera and Devande, 2010). Because Spain is a country with important regional differences in economic development and territorial investment, we also

Table 3
Descriptive statistics for the selected variables.

Year	Statistics	Size (students)	Age HEI (years)	Age TTO (years)	Educational diversity	Business incubator	Science Park	R&D intensity	Regional wealth (euros)
2006	Mean	24,215.360	131.489	14.447	3.167	0.426	0.804	0.778	21,939.430
	Std. Dev	15,589.910	223.560	4.353	0.800	0.500	0.401	0.313	4,315.359
	Min.	6,501.000	8.000	4.000	1.101	0.000	0.000	0.230	15,054.000
	Max.	80,761.000	806.000	27.000	4.237	1.000	1.000	1.550	28,850.000
2008	Mean	23,414.280	133.489	16.447	3.123	0.596	0.913	0.878	23,605.060
	Std. Dev	15,041.100	223.560	4.353	0.789	0.496	0.285	0.287	4,542.275
	Min.	5,808.000	10.000	6.000	1.089	0.000	0.000	0.250	16,341.000
	Max.	76,537.000	808.000	29.000	4.255	1.000	1.000	1.550	31,010.000
2010	Mean	23,382.040	135.489	18.447	3.939	0.723	0.935	0.899	22,840.700
	Std. Dev	14,774.970	223.560	4.353	0.881	0.452	0.250	0.272	4,652.005
	Min.	5,677.000	12.000	8.000	1.280	0.000	0.000	0.190	16,828.000
	Max.	73,383.000	810.000	31.000	4.942	1.000	1.000	1.330	31,314.000
Total	Mean	23,670.560	133.489	16.447	3.410	0.582	0.884	0.852	22,795.060
	Std. Dev	15,035.580	221.963	4.622	0.901	0.495	0.321	0.294	4,524.969
	Min.	5,677.000	8.000	4.000	1.089	0.000	0.000	0.190	15,054.000
	Max.	80,761.000	810.000	31.000	4.942	1.000	1.000	1.550	31,314.000

used two exogenous variables to capture the geographic location of universities. Using the Nomenclature of Territorial Units for Statistics (NUTS)-2 division of countries, regional wealth was represented in terms of two proxies, Gross Domestic Product (GDP) per capita and R&D intensity (R&D investment over sales). In addition to the set of explanatory variables, we controlled for variance in university size (number of students) and age (both of the university and the technology transfer office). Lastly, aiming at mirroring the subject-mix of universities, a last variable was included that accounted for the academic spread. Following the work of McMillan and Chan (2006), we used a Herfindahl index (HHI) to assess the degree of diversification amongst the sampled universities in terms of degrees. The index is calculated as $HHI = \sum_{j=1}^{J} s_j^2$, where s is the proportion of degrees offered by the university in the *jth* disciplinary category. For each academic year, degrees were grouped into the following categories (j): humanities studies, social sciences, experimental sciences, medical sciences and engineering studies. To facilitate the interpretation of the results, we use the inverse value of this factor throughout our analyses.

Descriptive statistics for the variables investigated are presented in Table 3. It is worth noting that an increasing proportion of universities acquired business incubators and science parks. In 2006, only 43% of Spanish universities had a business incubator, but by 2010 almost three quarters (72.3%) did. Science parks have also become common. In 2010, 9 out of 10 universities had an affiliated science park.

5. Results

5.1. Efficiency and malmquist

First, we ran a DEA analysis for three years. In addition to the efficiency results, Table 4 also reports the biased corrected efficiency estimates calculated following the bootstrap algorithm introduced by Simar and Wilson (1998). The results obtained are consistent with earlier analyses of the Spanish higher education system, although they model a different objective function (; Agasisti and Pérez-Esparrells, 2010).

Our model suggests that overall, universities have become more efficient during the period of interest; inefficiency was 7.8% in 2006, 6.7% in 2008 and 5.7% in 2010. The number of efficient universities against which the others could be benchmarked remained quite steady (22 in 2006, and 23 in 2008 and 2010), signaling that Spanish universities are adjusting their internal activities to the new regulatory framework. Corrected DEA scores suggest that inefficiencies are, however, slightly higher (ranging between 9.9% and 11.6%). It is also worth noting that when using the estimations obtained through the bootstrapping procedure, no unit obtained a score of 1, meaning that there is no unit performing as fully efficient during all the 2000 replications that were run in the bootstrapping algorithm.

Although in absolute numbers, universities seem to be doing quite well, there are still several obstacles that hinder them from being more efficient when transforming resources into outputs. First, the allocation of resources is complicated when faculty members are expected to excel simultaneously at several activities. Time is a limited resource, and it is difficult to conduct high quality teaching in combination with research activities that generate publications, research projects and spin-off companies. Second, it is important to note that motivations vary among faculty members, and consequently, their interest in RKT activities may also vary. Time constraints mean that academics have to prioritize and direct their efforts toward the activities that are most likely to help them achieve their goals. Accordingly, young academics and professors in a weaker contractual position might have more incentive to produce research outcomes, which are a way of signaling their academic credentials and thus increasing their chances of obtaining an academic position. These incentives diminish as one's academic career becomes more secure (Lissoni et al., 2011). In the case of full

Table 4
Efficiency scores.

University	2006				2008				2010			
	DEA score	Bootstrapping DEA score	Lower bound	Upper bound	DEA score	Bootstrapping DEA score	Lower bound	Upper bound	DEA score	Bootstrapping DEA score	Lower bound	Upper bound
EHU	1.1694	1.2239	1.1724	1.3270	1.0606	1.0858	1.0394	1.1754	1.1451	1.0787	1.1294	1.2135
UA	1.0846	1.0976	1.0591	1.1495	1.0262	1.0569	1.0259	1.1136	1.0753	1.0428	1.0639	1.1399
UAB	1	1.0769	1.0022	1.2383	1	1.0705	1.0021	1.2151	1	1.0634	1.0022	1.2083
UAH	1.175	1.2165	1.1771	1.2939	1.1926	1.1759	1.1282	1.2322	1	1.2488	1.0019	1.1587
UAL	1.2775	1.3485	1.2804	1.4591	1	1.0690	1.0019	1.2136	1.1254	1.0458	1.1278	1.224
UAM	1	1.0787	1.0025	1.2455	1	1.0700	1.0022	1.2104	1	1.0620	1.0019	1.2001
UB	1	1.0761	1.0016	1.2392	1	1.0714	1.0017	1.2197	1	1.0626	1.0018	1.2032
UBU	1.1646	1.242	1.1670	1.3768	1.3120	1.2049	1.1086	1.3714	1	1.3704	1.0024	1.1518
UC3M	1	1.0628	1.0025	1.1601	1	1.0606	1.0020	1.1444	1	1.0541	1.0017	1.1405
UCA	1.1682	1.1668	1.1102	1.2598	1.1865	1.1636	1.1258	1.2105	1.2808	1.1267	1.1700	1.2954
UCLM	1	1.0706	1.0023	1.1687	1	1.0671	1.0022	1.1869	1.095	1.0320	1.0972	1.1694
UCM	1	1.0767	1.0020	1.2318	1	1.0715	1.0023	1.2167	1	1.060	1.0017	1.1988
UCO	1.168	1.2055	1.1694	1.2686	1.1379	1.1584	1.1291	1.1999	1.2058	1.154	1.1942	1.2592
UDC	1.0346	1.0753	1.0371	1.1493	1.0164	1.0603	1.0188	1.1175	1	1.0764	1.0018	1.1711
UDG	1.0027	1.0431	1.0047	1.1149	1.1292	1.1264	1.0841	1.1781	1.0899	1.1685	1.0918	1.1918
UDL	1	1.0746	1.0018	1.2390	1	1.0696	1.0024	1.2157	1.0523	1.0407	1.0543	1.1414
UGR	1	1.0757	1.0025	1.1994	1	1.0696	1.0020	1.2202	1	1.061	1.0019	1.1965
UHU	1	1.0509	1.0024	1.1326	1	1.0562	1.0022	1.1430	1.1987	1.0459	1.2010	1.3001
UIB	1.0968	1.1328	1.0927	1.2045	1.1135	1.1340	1.0955	1.1899	1.0725	1.1522	1.0748	1.1699
UJAEN	1.1637	1.2066	1.1664	1.2714	1.1507	1.1525	1.1120	1.2126	1.0208	1.1876	1.0230	1.1102
UJI	1.1444	1.155	1.1078	1.2237	1.0841	1.1106	1.0720	1.1717	1	1.1386	1.0018	1.1392
ULL	1.2302	1.2547	1.2226	1.3084	1.2609	1.2549	1.2071	1.3101	1.2627	1.2549	1.2266	1.2998
ULPGC	1.2051	1.134	1.0856	1.2046	1.0753	1.0920	1.0619	1.1352	1.2236	1.1099	1.2171	1.3487
UM	1.1915	1.163	1.1095	1.2292	1	1.0711	1.0020	1.2137	1.1583	0.9939	1.1091	1.2027
UMA	1.0436	1.0802	1.0440	1.1439	1.0320	1.0628	1.0328	1.1102	1	1.096	1.0022	1.2019
UMH	1.1573	1.2113	1.1601	1.3080	1.0895	1.1005	1.0551	1.1803	1.035	1.1331	1.0373	1.1367
UNAVARRA	1.027	1.0761	1.0292	1.1434	1	1.0462	1.0021	1.1113	1	1.0583	1.0024	1.1597
UNEX	1	1.0619	1.0020	1.1572	1.0547	1.0932	1.0571	1.1522	1.0524	1.0879	1.0543	1.1326
UNICAN	1	1.0758	1.0022	1.2140	1.1603	1.2139	1.1625	1.3079	1	1.2164	1.0023	1.1547
UNILEON	1	1.0788	1.0019	1.2393	1	1.0721	1.0024	1.2174	1	1.0615	1.0025	1.1958
UNIOVI	1.0564	1.0987	1.0579	1.1762	1	1.0708	1.0022	1.2100	1	1.0625	1.0015	1.2003
UNIRIOJA	1	1.0776	1.0021	1.2134	1	1.0713	1.0023	1.2104	1	1.0601	1.0022	1.2032
UNIZAR	1.103	1.1281	1.0950	1.1818	1.1327	1.1404	1.0889	1.2095	1.0562	1.1626	1.0564	1.1506
UPC	1	1.0684	1.0023	1.1873	1	1.0567	1.0024	1.1515	1.0995	1.031	1.0953	1.1951
UPCT	1	1.043	1.0020	1.1165	1	1.0473	1.0027	1.1351	1	1.0654	1.0023	1.201
UPF	1	1.0777	1.0021	1.2338	1	1.0703	1.0023	1.2178	1	1.0625	1.0022	1.2015
UPM	1.3885	1.0412	0.9413	1.1719	1.0638	1.0835	1.0321	1.1688	1	1.1274	1.0017	1.2017
UPO	1	1.0776	1.0019	1.2351	1	1.0701	1.0030	1.2081	1	1.0608	1.0022	1.1825
UPV	1.2438	1.1797	1.1175	1.2580	1.2185	1.1508	1.1133	1.2067	1.1698	1.1996	1.1035	1.2202
URJC	1	1.0765	1.0021	1.2280	1	1.0613	1.0023	1.1494	1	1.0618	1.0017	1.2014
URV	1.1125	1.1699	1.1153	1.2720	1.1915	1.1750	1.1123	1.2529	1.0109	1.2279	1.0125	1.0994
US	1	1.0699	1.0021	1.1825	1	1.0647	1.0024	1.1843	1	1.0597	1.0022	1.1988
USAL	1	1.0693	1.0027	1.1796	1	1.0703	1.0022	1.2141	1	1.0618	1.0025	1.1983
USC	1.2062	1.1698	1.1068	1.2506	1.2722	1.1627	1.0974	1.2708	1.1036	1.2937	1.0798	1.1975
UV	1	1.0742	1.0022	1.1960	1.0151	1.0565	1.0170	1.1319	1.0128	1.049	1.0147	1.1035
UVA	1.03	1.0688	1.0241	1.1709	1.1595	1.1212	1.0510	1.2207	1.0145	1.1983	1.0164	1.1321
UVIGO	1	1.0695	1.0022	1.1802	1	1.0705	1.0023	1.2124	1.095	1.0518	1.0973	1.2271
Mean	**1.0775**	**1.1160**			**1.0667**	**1.0990**			**1.0565**	**1.1089**		
Std. Dev.	**0.0980**	**0.0688**			**0.0885**	**0.0501**			**0.0792**	**0.0797**		

professors, the incentives to carry out research may be purely internal, based on personal interest.

To check the robustness of the efficiency scores, several sensitivity analyses were additionally performed. First, we took into consideration different interpretations of the variables of interest. In this sense, publications (research mission) were operationalized through the number of papers published in journals indexed in the Scopus database, and the number of patents awarded by the Spanish Office of Patents and Trade Marks (OEPM) was used as an alternative approximation for knowledge transfer outputs. Although the granting of a patent does not guarantee the future marketability of a technology, it does indicate that the university has the capacity for technological innovations. These checks revealed that our results were not very sensitive to the use of different measures. Second, we tested a variety of model specifications combining different research and knowledge transfer outcomes. Despite minor marginal changes, efficiency scores were not significantly altered. Therefore, we concluded that measurement errors did not seem to bias our results.

Since we have data for three different periods, we wanted to analyze how the performance of universities changed during the period in which we were interested. We therefore calculated the Malmquist index and its decomposition into efficiency and technical change (see Table 5).

Table 5
Malmquist index, efficiency change and technical change (periods 2006–2008, 2008–2010).

Statistics	2006–2008			2008–2010		
	Malmquist	Efficiency change	Technical change	Malmquist	Efficiency change	Technical change
Mean	0.9107	0.8908	1.0190	1.0151	1.0182	0.9889
Median	0.8869	0.8864	1.0000	1.0117	1.0000	1.0123
Std. Dev	0.1653	0.1212	0.1187	0.2070	0.1181	0.1798
Min.	0.6159	0.6485	0.8236	0.3656	0.8013	0.3656
Max.	1.3172	1.3172	1.5311	1.3590	1.4536	1.3590

Over the first two years for which data were analyzed, we observed a slight decrease in the Malmquist index. Although the technical change improved, the reduction in the efficient component determines the overall negative change in performance. Analyses of individual universities revealed that 30 of them had worse results in 2008. On the contrary, the trend over the next period (2008–2010) was much more encouraging: Despite a small decline in technical change, there was an overall improvement in the Malmquist index based on a substantial change in the efficient component. 25 universities improved their results, while 16 scored lower. Turning to the specificity of the results, when comparing the fluctuations that universities exhibit between these two periods, we observe that 4 universities have consistently improved their Malmquist index. However, 10 universities have worsened their results. It is also remarkable that for the remaining universities, 6 improved their performance during the first period (2006–2008), but then decreased it in the subsequent period. Contrarily, 18 universities operated the other way round (the index for the period 2006–2008 is below 1, but greater than 1 in 2008–2010).

The general picture that emerges from this analysis is that there was an improvement in the productivity index during the period investigated (in 2008–2010, the average Malmquist index was above 1). This improvement was not due to technical changes (the index was < 1 in both periods) but to efficiency advances. Like Agasisti et al. (2011), we define "technology" as the bundle of policies that helps to improve research efficiency. These policies include internal programs and initiatives designed to support research activities at universities. Over the years, universities have developed specialized infrastructure and services to support such activities. In this respect, universities have yet to find the best way to support research activities whilst also using their resources efficiently. Researchers are often not aware of the potential utility of the TTO and the skills of the staff working there. TTOs' expertise in advising on intellectual property issues, assisting entrepreneurs in the initial stages of business creation and in preparing project proposals should be very valuable in helping academics to transfer their research to the marketplace and deal with the bureaucratic procedures this entails (Caldera and Debande, 2010). On the other hand, expenditure on R&D activities has increased; the efforts university managers make to increase the economic resources devoted to this area of activity reflect the importance they attach to it. Nevertheless, results seem to indicate that all these investments (either in terms of infrastructures or financial resources) seem to be insufficient or not as effective as expected. There is a different explanation for the increase in the efficiency change parameter. Our findings reveal that universities' ability to transform inputs into outputs has slightly increased. All these data seem to indicate that the Spanish higher education system has improved; nevertheless, there remains a need for investigation the support mechanisms universities are implementing aimed at nurturing RKT activities. As it can be inferred from the results, it takes time to shift to a research-oriented strategy.

5.2. Regression

Table 6 displays the results of the truncated regression on the bias-corrected efficiency scores. Standard errors are computed through a bootstrap procedure in order to account for the bias arising from the serial correlation of the error terms. Data from the different years are merged, including a set of dummy variables to rule out the potential effect of time trends (year 2010 was excluded as the base year).

As far as the control variables are concerned, results indicate that large universities are better at transforming resources into outcomes; in other words, they tend to be more efficient than small universities. Even though small universities might be easier to manage and therefore easier to readjust their structures to new demands, our findings corroborate the theory of economies of scale. That is, large universities seem to benefit from the reduction of cost per unit of output and, often, might also enjoy lower variable costs. However, this result should be interpreted with caution, as the effect, although significant, is weak. The process through which universities transform inputs into outputs is still poorly understood (Daraio et al., 2015). Notwithstanding this, previous research seems to converge in signaling that teaching activities are subject to economies of scale, since it is feasible to expand the number of students attending a lecture while keeping the input (lecturing staff) constant (Laband and Lentz, 2003). As for RKT activities, results are more inconclusive. Arguments for economies of scale are typically linked to the adoption of policies for the recruitment of top researchers (Carayol and Matt, 2006) and the access to larger scientific networks (Horta and Lacy, 2011). Considering the characteristics of the Spanish public higher education landscape, we posit that in all likelihood, the main sources of economies of scale come from undergraduate education, while research contributes little. Further studies exploring this issue will undoubtedly bring new, additional insights.

As for the degree of educational diversification, results show that universities with a broad coverage of subjects tend to be more inefficient. This finding is in accordance with the works of Chapple et al. (2005) and Curi et al. (2012) who found that subject

Table 6
Parameter estimates of truncated regression models explaining HEIs inefficiency.

Variables	Coefficient	95% Confidence Interval	
		Lower bound	Upper bound
Size	−0.0720*** (0.0226)	−0.1162	−0.0278
Age HEI	0.0097 (0.0081)	−0.0061	0.0255
Age TTO	0.0861*** (0.0301)	0.0272	0.1451
Educational diversity	0.0527* (0.0311)	−0.0083	0.1136
Business incubator	0.0115 (0.0169)	−0.0216	0.0447
Science park	0.0597** (0.0244)	0.0120	0.1075
R&D intensity	−0.0398 (0.0349)	−0.1083	0.0286
Regional wealth	−0.0040 (0.0502)	−0.1024	0.0944
Year 2006	0.0491** (0.0225)	0.0050	0.0932
Year 2008	0.0050 (0.0184)	−0.0311	0.0411
Intercept	1.4650*** (0.5377)	0.4111	2.5189

Note: Bootstrapped standard errors are presented in brackets. *, **, *** indicate significance at the 10%, 5%, 1%, respectively. Confidence intervals obtained from 2000 bootstrapping iterations.

specialization is significantly related to efficiency. This result, however, should be taken with a grain of salt. In order to further explore this effect, we replaced the HHI by two new dummy variables. The first one, taking the value 1 for technical universities (four, in our sample) and 0 otherwise, and the second one, accounting for the presence of a medical school (1: yes, 0: no). Results reported that while being a technical university does not seem to play a role, to increase efficiency it is preferable to have the absence of a medical school (p-value: 0.003). This result, similar to that obtained in Foltz et al. (2012) and Curi et al. (2012) – who showed that a university-related hospital plays an important role in dampening efficiency – seems to corroborate that if specialization is too strong, new capabilities might be more difficult to be developed and research in emerging or at the interface of different fields will remain underexplored due to a lack of expertise (Moed et al., 2011). Future research efforts are therefore needed in order to better understand the effect of heterogeneity – associated to different disciplinary fields – on efficiency.

We failed to detect any significant effect due to the age of the university. However, contrary to our initial intuition, the analysis revealed that the seniority of the TTO has a negative effect. Similar to Siegel et al. (2008), we argue that the rationale behind this result might lie in the strategic vision of the TTOs. While older TTOs might decide to concentrate on maximizing the profit derived from the commercialization of research outputs, universities with a newer TTO might tend to maximize the number of research outputs commercialized, as a way to generate market awareness. As for the regional variables, neither the regional GDP per capita nor the regional R&D intensity seems to shape efficiency.

Another remarkable finding is that business incubators are not key determinants of HEIs' efficiency, while science parks exert a negative effect. Both incubators and science parks emerged in the 1990s and spread throughout the Spanish university system in response to various policies designed to promote knowledge transfer activities. Universities developed these infrastructures very rapidly; however, it seems that they have failed to develop strategies to use them efficiently.

6. Discussion and conclusions

In recent years, the Spanish higher education system has undergone important modifications and RKT outcomes have increasingly been viewed as critical determinants of an academic institution's success. The movement from a teaching-oriented model toward a research-oriented model has led to significant changes in the way universities allocate internal resources and capacity.

Using data from three different periods – before, during and after the reform – we analyzed how the efficiency of Spanish public universities has changed over time. We found that the number of efficient units and the mean average efficiency score remained quite stable during the period investigated. Furthermore, for the last period under study (2008–2010), we also observed that although productivity declined in terms of technical change, there were substantial improvements in terms of "pure" efficiency. In the final stage of our analysis, we scrutinized the explanatory effect that certain external factors – the size and age of the university, the age of the TTO, the educational diversity, the existence of specific infrastructures (business incubators and science parks), the regional wealth and the R&D intensity of the region – have on universities' efficiency.

This study has several policy implications. First, although universities are expected to simultaneously excel at teaching, research and knowledge transfer activities, the current Spanish incentive system does not seem to support this, being highly biased toward research outputs, and publications in particular. There should be reconsideration of the weights assigned to the various activities in evaluation procedures (both at the university and the researcher level). Moreover, there are calls from both public and private organizations across the world for a narrowing of the gap between academy and industry and an emphasis on research outputs with clear practical uses (Bansal et al., 2012; Bawden, 2015). Some countries have begun to promote closer links between knowledge institutions and trade and industry, with areas like Silicon Valley (California) and Route 128 (Boston) at the forefront of these developments. However, in Europe, and Spain in particular, there is still a long way to go. Recently, in June 2015 a new reform was introduced (Royal Decree 415/2015), modifying the evaluation criteria and standards for civil servants. The new standards are expected to allow a more balanced assessment of the merits of the applicant, particularly, in terms of technology transfer activities. In the next few years, when data will be available, it will be valuable to analyze its impact on RKT outcomes.

Second, academics are asked to teach, perform RKT activities and participate in service work. This forces them to prioritize the activities that will produce them the greatest benefit, which is usually stability security (Lafuente and Berbegal-Mirabent, 2017). This has two important policy implications. The first has to do with the typical academic career trajectory. We suggest that there is scope to introduce different career paths corresponding to the differentiation between teaching- and research-oriented academic profiles. Spain could follow the example of countries such as the UK or USA, where such models have been successful. The second issue concerns the workload of contemporary academics. Some of the administrative tasks currently performed by academics could be effectively executed by administrative staff, but budget restrictions have made it difficult for universities to expand their workforce. This leads us to question whether the current structure of the higher education system is appropriate. Specifically, there is a need to reconsider the current administrative/academic staff ratio, which constitutes a structural defect of the Spanish public university system (De la Torre et al., 2016a).

Third, the Spanish higher education system is decentralized, with regional governments in charge of the education policy but operating in coordination with the central government. Yet despite this decentralization, there is only one type of HEI (i.e., universities), and all universities are embedded in the same legal framework (de la Torre et al., 2016b). As such, the higher education system is rather homogenous across the entire Spanish landscape. Nevertheless, universities are autonomous organizational structures with individual activity mixes and characteristics that generate heterogeneity. The observed differences in the efficiency scores reveal that universities use various strategies to address their objective function – focus and intensity in which they develop each of the three missions – . Future studies should deepen our understanding of the effect that economies of scale and scope have on efficiency scores.

Fourth, although the vast majority of Spanish universities have developed specialist infrastructure and services to support RKT activities (i.e. technology transfer offices, science parks, business incubators), there is still room for improvement. As the efficiency analysis revealed, the exploitation of such infrastructures seem to be far from its true potential.

Although we believe this study provides useful insights into the efficiency of universities, we identified some limitations. It should be noted that although DEA is a robust technique and several models have been tested, the sensitivity of the results is closely tied to the model specification. In addition, like any other analytical technique, DEA models cannot capture the potential effects of non-controllable factors on the performance of the production units under analysis. As for the second stage regression, although the semi-parametric approach applied corrects for the autocorrelation problem, it relies on the separability condition between the input-output space and the space of the external factors. Future works should consider the use of more general non-parametric efficient frontiers models, such as conditional frontiers models (Bădin and Daraio, 2011) that do not rely on such a strong hypothesis. The other limitations relate to the specificity of the context. We analyzed institutions in the Spanish public higher education system and the period of analysis – chosen in order to examine the impact of reforms to the system – coincided with a major economic downturn, which might complicate the interpretation of the results. Lastly, futures studies might consider the use of more recent data, when available, and contrast the findings presented in this study.

Acknowledgements

The author is grateful to Esteban Lafuente (Universitat Politècnica de Catalunya), Tommaso Agasisti (Politecnico di Milano), Eva de la Torre (Universidad Autónoma de Mardid), Laura López-Torres (Universidad de Alcalá de Henares) and the two anonymous reviewers for their ideas and insightful comments that helped improve the paper.

References

Abramo, G., D'Angelo, C.A., Pugini, F., 2008. The measurement of Italian universities' research productivity by a non parametric-bibliometric methodology. Scientometrics 76 (2), 225–244. http://dx.doi.org/10.1007/s11192-007-1942-2.

Agarwal, R., Ohyama, A., 2013. Industry or academia, basic or applied? Career choices and earnings trajectories of scientists. Manag. Sci. 59 (4), 950–970. http://dx.doi.org/10.1287/mnsc.1120.1582.

Agasisti, T., Pérez-Esparrells, C., 2010. Comparing efficiency in a cross-country perspective: the case of Italian and Spanish state universities. High. Educ. 59 (1), 85–103. http://dx.doi.org/10.1007/s10734-009-9235-8.

Agasisti, T., Pohl, C., 2012. Comparing German and Italian public universities: convergence or divergence in the higher education landscape? Manag. Decis. Econ. 33 (2), 71–85. http://dx.doi.org/10.1002/mde.1561.

Agasisti, T., Wolszczak-Derlacz, J., 2015. Exploring efficiency differentials between Italian and Polish universities, 2001–11. Sci. Publ. Policy 43 (1), 128–142. http://dx.doi.org/10.1093/scipol/scv026.

Agasisti, T., Dal Bianco, A., Landoni, P., Sala, A., Salerno, S., 2011. Evaluating the efficiency of research in academic departments: an empirical analysis in an Italian Region. High. Educ. Quart. 65 (3), 267–289. http://dx.doi.org/10.1111/j.1468-2273.2011.00489.x.

Archibald, R.B., Feldman, D.H., 2008. Graduation rates and accountability: regressions versus production frontiers. Res. High. Educ. 49 (1), 80–100. http://dx.doi.org/10.1007/s11162-007-9063-6.

Bădin, L., Daraio, C., 2011. Explaining efficiency in nonparametric frontier models: recent developments in statistical inference. In: Van Keilegom, I., Wilson, P.W. (Eds.), Exploring Research Frontiers in Contemporary Statistics and Econometrics. Physica-Verlag, Heidelberg, pp. 151–175. http://dx.doi.org/10.1007/978-3-7908-2349-3.

Balsmeier, B., Pellens, M., 2014. Who makes, who breaks: which scientists stay in academe? Econ. Lett. 122 (2), 229–232. http://dx.doi.org/10.1016/j.econlet.2013.11.033.

Bansal, P., Bertels, S., Ewart, T., MacConnachie, P., O'Brien, J., 2012. Bridging the research–practice gap. Acad. Manag. Perspect. 26 (1), 73–92. http://dx.doi.org/10.5465/amp.2011.0140.

Barra, C., Zotti, R., 2016. Measuring efficiency in higher education: an empirical study using a bootstrapped data envelopment analysis. Int. Adv. Econ. Res. 22 (1), 11–33. http://dx.doi.org/10.1007/s11294-015-9558-4.

Bawden, D., 2015. Research and practice revisited. J. Doc. 71 (3). http://dx.doi.org/10.1108/JD-03-2015-0033.

Berbegal-Mirabent, J., Solé, F., 2012. What are we measuring when evaluating universities' efficiency? Reg. Sect. Econ. Stud. 12 (3), 31–46.

Berbegal-Mirabent, J., Lafuente, E., Solé, F., 2013. The pursuit of knowledge transfer activities: an efficiency analysis of Spanish universities. J. Bus. Res. 66 (10), 2051–2059. http://dx.doi.org/10.1016/j.jbusres.2013.02.031.

Berbegal-Mirabent, J., Ribeiro-Soriano, D.E., García, J.L.S., 2015. Can a magic recipe foster university spin-off creation? J. Bus. Res. 68 (11), 2272–2278. http://dx.doi.org/10.1016/j.jbusres.2015.06.010.

Boardman, P.C., Bozeman, B., 2007. Role strain in university research centers. J. High. Educ. 78 (4), 430–463. http://dx.doi.org/10.1353/jhe.2007.0020.

Boardman, P.C., Ponomariov, B.L., 2007. Reward systems and NSF university research centers: the impact of tenure on university scientists' valuation of applied and commercially relevant research. J. High. Educ. 78 (1), 51–70. http://dx.doi.org/10.1353/jhe.2007.0000.

Caldera, A., Debande, O., 2010. Performance of Spanish universities in technology transfer: an empirical analysis. Res. Policy 39 (9), 1160–1173. http://dx.doi.org/10.1016/j.respol.2010.05.016.

Carayol, N., Matt, M., 2006. Individual and collective determinants of academic scientists' productivity. Inform. Econ. Policy 18 (1), 55–72. http://dx.doi.org/10.1016/j.infoecopol.2005.09.002.

Chambers, R.G., Pope, R.D., 1996. Aggregate productivity measures. Am. J. Agric. Econ. 78, 1360–1365.

Chapple, W., Lockett, A., Siegel, D., Wright, M., 2005. Assessing the relative performance of U. K. university technology transfer offices: Parametric and non-parametric evidence. Res. Policy 34 (3), 369–384.

Charnes, A., Rhodes, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444. http://dx.doi.org/10.1016/0377-2217(78)90138-8.

Coccia, M., 2008. Measuring scientific performance of public research units for strategic change. J. Infom. 2 (3), 183–194.

Coelli, T., Prasada Rao, D.S., Battese, G.E., 1998. An Introduction to Efficiency and Productivity Analysis. Kluwer, Boston.

Cooper, W., Seiford, L.M., Tone, K., 2007. Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software, 2nd. Springer, Breiningsville, USA.

Curi, C., Daraio, C., Llerena, P., 2012. University technology transfer: How (in) efficient are French universities? Cambridge J. Econ. 36 (3), 629–654.

Daraio, C., Bonaccorsi, A., Simar, L., 2015. Efficiency and economies of scale and specialization in European universities: a directional distance approach. J. Inform. 9 (3), 430–448. http://dx.doi.org/10.1016/j.joi.2015.03.002.

De la Torre, R., Lusa, A., Mateo, M., 2016a. A MILP model for the long term academic staff size and composition planning in public universities. Omega 63, 1–11. http://dx.doi.org/10.1016/j.omega.2015.09.008.

de la Torre, E.M., Sagarra, M., Agasisti, T., 2016b. Assessing organizations' efficiency adopting complementary perspectives: an empirical analysis through data envelopment analysis and multidimensional scaling, with an application to higher education. In: Hwang, S.-N., Lee, H.-S., Zhu, J. (Eds.), Handbook of Operations Analytics Using Data Envelopment Analysis. Springer, US, pp. 145–166. http://dx.doi.org/10.1007/978-1-4899-7705-2.

Färe, R., Grosskopf, S., Lindgren, B., Roos, P., 1992. Productivity changes in swedish pharmacies 1980–1989: a non-parametric malmquist approach. J. Product. Anal. 3 (1/2), 85–101. http://dx.doi.org/10.1007/978-94-017-1923-0_6.

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth technical progress, and efficiency change in industrialized countries. Am. Econ. Rev. 84 (1), 66–83.

Farrell, M.J., 1957. The measurement of productive efficiency. J. R. Stat. Soc. (A general) 120 (3), 253–281.

Foltz, J.D., Barham, B.L., Chavas, J.P., Kim, K., 2012. Efficiency and technological change at US research universities. J. Product. Anal. 37 (2), 171–186. http://dx.doi.org/10.1007/s11123-011-0249-8.

Geuna, A., Muscio, A., 2009. The governance of university knowledge transfer: a critical review of the literature. Minerva 47, 93–114. http://dx.doi.org/10.1007/s11024-009-9118-2.

Greene, W.H., 1980. On the estimation of a flexible frontier production model. J. Econ. 13 (1), 101–115. http://dx.doi.org/10.1016/0304-4076(80)90045-7.

Groot, T., García-Valderrama, T., 2006. Research quality and efficiency. An analysis of assessments and management issues in Dutch economics and business research programs. Res. Policy 35 (9), 1362–1376. http://dx.doi.org/10.1016/j.respol.2006.07.002.

Hazelkorn, E., 2005. University Research Management: Developing Research in New Institutions. OECD, Paris.

Horta, H., Lacy, T.A., 2011. How does size matter for science? Exploring the effects of research unit size on academics' scientific productivity and information exchange behaviors. Sci. Publ. Policy 38 (6), 449–460. http://dx.doi.org/10.3152/030234211X12960315267813.

Hsu, D.W., Shen, Y.C., Yuan, B.J., Chou, C.J., 2015. Toward successful commercialization of university technology: performance drivers of university technology transfer in Taiwan. Technol. Forecast. Soc. Change 92, 25–39. http://dx.doi.org/10.1016/j.techfore.2014.11.002.

Kao, C., Hung, H.T., 2008. Efficiency analysis of university departments: an empirical study. Omega 36 (4), 653–664. http://dx.doi.org/10.1016/j.omega.2006.02.003.

Kim, Y., 2013. The ivory tower approach to entrepreneurial linkage: productivity changes in university technology transfer. J. Technol. Transf. 38, 180–197. http://dx.doi.org/10.1007/s10961-011-9217-8.

Koopmans, T.C., 1951. An analysis of production as an efficient combination of activities. In: In: Koopmans, T.C. (Ed.), Activity Analysis of Production and Allocation. Cowles Commission for Research in Economics, Monograph 13 Wiley, New York.

Kyratzi, P., Tsamadias, C., Giokas, D., 2015. Measuring the efficiency and productivity change of Greek universities over the time period 2005–2009. Int. J. Educ. Econ. Dev. 6 (2), 111–129. http://dx.doi.org/10.1504/IJEED.2015.070620.

Laband, D.N., Lentz, B.F., 2003. New estimates of economies of scale and scope in higher education. South. Econ. J. 70 (1), 172–183. http://www.jstor.org/stable/1061638.

Lafuente, E., Berbegal-Mirabent, J., 2017. Contract employment policy and research productivity of knowledge workers: an analysis of Spanish universities. Int. J. Hum. Resour. Manag. http://dx.doi.org/10.1080/09585192.2017.1323226.

Lissoni, F., Mairesse, J., Montobbio, F., Pezzoni, M., 2011. Scientific productivity and academic promotion: a study on French and Italian physicists. Indus. Corp. Change 20 (1), 253–294. http://dx.doi.org/10.1093/icc/dtq073.

McMillan, M.L., Chan, W.C., 2006. University efficiency: a comparison and consolidation of results from stochastic and non-stochastic methods. Educ. Econ. 14 (1), 1–30. http://dx.doi.org/10.1080/09645290500481857.

Moed, H.F., de Moya-Anegon, F., Lopez-Illescas, C., Visser, M., 2011. Is concentration of university research associated with better research performance? J. Inform. 5 (4), 649–658. http://dx.doi.org/10.1016/j.joi.2011.06.003.

Montesinos, P., Carot, J.M., Martinez, J.M., Mora, F., 2008. Third mission ranking for world class universities: beyond teaching and research. High. Educ. Europe 33 (2-3), 259–271. http://dx.doi.org/10.1080/03797720802254072.

Plewa, C., Korff, N., Johnson, C., Macpherson, G., Baaken, T., Rampersad, G.C., 2013. The evolution of university-industry linkage. A frameworks. J. Eng. Technol.

Manag. 30, 21–44. http://dx.doi.org/10.1016/j.jengtecman.2012.11.005.
Rasmussen, E., 2008. Spin-off Venture Creation in a University Context. An Entrepreneurial Process View. Bodø Graduate School of Business, Bodø.
Sagarra, M., Mar-Molinero, C., Rodríguez-Regordosa, H., 2015. Evaluating the success of educational policy in Mexican Higher Education. High. Educ. 69 (3), 449–469. http://dx.doi.org/10.1007/s10734-014-9785-2.
Salerno, C., 2004. What We Know About the Efficiency of Higher Education Institutions: The Best Evidence. University of Twente (The Netherlands): The Center for Higher Education Policy Studies.
Sarrico, C.S., Rosa, M.J., Teixeira, P.N., Cardoso, M.F., 2010. Assessing quality and evaluating performance in higher education: worlds apart or complementary views? Minerva 48 (1), 35–54. http://dx.doi.org/10.1007/s11024-010-9142-2.
Seiford, L.M., Thrall, R.N., 1990. Recent developments in DEA: The mathematical programming approach to frontier analysis. J. Econ. 46, 7–38. http://dx.doi.org/10.1016/0304-4076(90)90045-U.
Shattock, M., 2009. Entrepreneurialism in Universities and the Knowledge Economy. Society for Research into Higher Education and Open University Press, London, UK.
Siegel, D., Wright, M., Chapple, W., Lockett, A., 2008. Assessing the relative performance of university technology transfer in the US and UK: a stochastic distance function approach. Econ. Innov. New Technol. 17 (7–8), 717–729. http://dx.doi.org/10.1080/10438590701785769.
Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manag. Sci. 44 (1), 49–61. http://dx.doi.org/10.1287/mnsc.44.1.49.
Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. J. Econ. 136, 31–64. http://dx.doi.org/10.1016/j.jeconom.2005.07.009.
Simar, L., Wilson, P.W., 2011. Two stage DEA: caveat emptor. J. Product. Anal. 36 (2), 205–218. http://dx.doi.org/10.1007/s11123-011-0230-6.
Soares, L., 2012. The Rise of Big Data in Higher Education [online]. [cited 18 August 2015]. Available from Internet: http://www.educause.edu/library/resources/rise-big-data-higher-education.
Tone, K., Sahoo, B., 2003. Scale, indivisibilities and production function in data envelopment analysis. Int. J. Prod. Econ. 84 (2), 165–192. http://dx.doi.org/10.1016/S0925-5273(02)00412-7.
Wilson, P.W., 2008. FEAR: A software package for frontier efficiency analysis with R. Socioecon. Plann. Sci. 42 (4), 247–254. http://dx.doi.org/10.1016/j.seps.2007.02.001.
Wolszczak-Derlacz, J., Partera, A., 2011. Efficiency of European public higher education institutions: a two-stage multi-country approach. Scientometrics 89 (3), 887–917. http://dx.doi.org/10.1007/s11192-011-0484-9.
van Raan, A.F.J., 2005. Fatal attraction: conceptual and methodological problems in the ranking of universities by bibliometric methods. Scientometrics 62 (1), 133–143. http://dx.doi.org/10.1007/s11192-005-0008-6.
van der Ploeg, F., Veugelers, R., 2008. Towards evidence-based reform of European universities. CESifo Econ. Stud. 5 (2), 99–120. http://dx.doi.org/10.1093/cesifo/ifn015.

Jasmina Berbegal-Mirabent PhD in Management and M.S. in Industrial Engineering and in Engineering Management, all from Universitat Politècnica de Catalunya (UPC), Spain. Since 2013 she is working as an associate professor at the Universitat Internacional de Catalunya. Previously, she worked at the Department of Management at UPC. She has also been a Fulbright Visiting Scholar at the Haas School of Business (University of California Berkeley, USA) and a Visiting Research Associate at the Institute of Education (University College London, UK). She is the associate editor of the Journal of Innovation & Knowledge. She is also in the editorial board of Management Decision, Journal of Business Research, and Intangible Capital. Her research interests are in the areas of strategic planning and management of higher education institutions, academic entrepreneurship and knowledge and technology transfer.