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R&D productivity in Europe: towards a regional taxonomy in the European Union

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Abstract

Research, development and innovation activities have become key sources of competitive advantage, which is one of the main factors behind the wellbeing of citizens living in a given territory. Being aware of this fact, public administrations at different administrative levels have encouraged the production of innovations through public policies. If we focus in Europe, regional disparities in the amount of innovation inputs and outputs are very high.

In this paper, the authors will measure the productivity of research and development activities performed by all regions in the EU. In order to do so, authors will take into account some indicators to measure innovation inputs and outputs at the regional level. Using Data Envelopment Analysis (DEA) authors will measure regional productivity in the field of R&D and then compare this productivity outcome between regions in the EU. After explaining this first DEA model, authors will use cluster analysis to achieve a typology of regions regarding their productivity in R&D activities. With all these results, policy makers could compare the situation of their own regions and adapt policies of efficient regions to their own institutional and economic background in the field of R&D.

Key words

DEA analysis, productivity, efficiency, R&D policy, regional policy.

Resumen

Las actividades de investigación, desarrollo e innovación se han convertido en una de las fuentes principales de ventaja competitiva, clave para el bienestar de los ciudadanos de un determinado territorio. Siendo conscientes de este hecho, las diversas Administraciones Públicas han apoyado la producción de innovaciones a través de distintas políticas públicas. Si nos concentramos en Europa, las disparidades regionales entre *inputs* y *outputs* de innovación son muy elevadas.

En este artículo, los autores medirán la productividad de las actividades de I+D realizadas en todas las regiones de la Unión Europea. Para ello, los autores calcularán los *inputs* y *outputs* de innovación dentro del ámbito regional. Posteriormente, utilizarán el análisis envolvente de datos (DEA) para evaluar la productividad regional de las actividades de I+D y compararla entre las distintas regiones Unión Europea. Después de realizar este primer modelo DEA, los autores utilizarán el análisis *cluster* para conseguir una tipología de regiones teniendo en cuenta la productividad en actividades de I+D. Con todos estos resultados, los decisores políticos podrán comparar la situación de sus regiones y adaptar las políticas de las regiones más eficientes a su propia realidad económica e institucional en el campo de la I+D.

Palabras clave

Análisis DEA, productividad, eficiencia, política I+D, política regional.

It would be convenient to establish learning processes among regions to spread successful/ efficient R&D policies

1. Introduction

R&D investment has become one of the main variables to achieve competitive advantages. These competitive advantages, in the long run, will create higher levels of prosperity in a given region. This idea has been accepted by economic theory since Adam Smith, but it has been in recent times when economic theory has focused in R&D and its connection with policy makers and society in general (Dodgson & Rothwell, 1994; Porter, 1998; Porter, Furman & Stern, 2000).

Once we have highlighted the importance of R&D as a basic tool to achieve higher levels of prosperity in a given society, it would be obvious that the public administration would support R&D activities through a proper public policy. Additionally, the different schools of economic thought are in favor of this kind of behavior. The neoclassical literature accepts that the competitive market underinvests in R&D activities (Mani, 2002). Hence, the level of R&D investment that maximizes profit for firms is smaller than the level of R&D that maximizes social prosperity (Arrow, 1962; Beije, 1998).

On the other hand, the evolutionary school, linked with the concept of national/regional innovation system (NIS/RIS), proposes the public intervention to strengthen the different economic agents inside a NIS/RIS, and also to increase the interaction among these actors (Lundvall, 1992).

A consequence of the positive economic results that governments and firms link with R&D investment has been a non-stop increasing in the public and private funding devoted to R&D in almost all developed economies (Martínez & Aguado, 2009).

Although the volume of private and public expenditure in R&D activities has been growing for the last decades both at the national and regional levels, there are few studies about the efficiency of this kind of expenditure, especially at the regional level.

In this work, we are going to present a comparative study of all regions in the European Union (27 countries). In this paper, we will analyze the efficiency of R&D expenditures taking into account EU-27 regions, in order to build a common taxonomy, discovering similarities and disparities between regions.

Some attempts to measure the efficiency of RIS at the European level have been done by different authors in recent times (Navarro, Gibaja, Aguado & Bilbao-Osorio, 2009; Martínez Pellitero, 2007). In these studies, the conceptual framework of RIS has been used to select a range of variables linked with inputs and outputs of R&D activities. In all these cases, the methodology and statistical use of data has been similar: principal component analysis to highlight the main dimensions that explain regional behavior in R&D activities and then a cluster analysis to gather regions in groups with common features measured in the axes defined previously in the principal component analysis.

This kind of econometric analysis is used to group regions with similar levels of economic development, R&D inputs and R&D outputs. Moreover, it helps in finding the strong and weak points of each group of regions in comparison to the rest of groups.

However, this kind of analysis do not link directly the amount of output achieved with the amount of inputs devoted to R&D. A region (region Y) using a great quantity of R&D inputs and achieving exactly the same output as other region (region Z) that uses a smaller amount

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High efficiency regions do not coincide with regions having high R&D expenditure

of R&D inputs would appear in a higher position in the ranking of innovative regions. In reality, region Z is using its resources in a more efficient way than region Y, so region Z should be highlighted as more efficient and rank in a higher position.

Different authors have tried to measure the efficiency of RIS in certain national economies (Buesa and Heijs, 2007; Miceli, 2010). In these analyses, the number of patent applications in the national patent office or in the European Patent Office (EPO) has been used as one of the main or even unique R&D output indicator.

The number of patent applications has been a widely used indicator in the economic literature (Kamien & Schwartz, 1975; Mani, 2002), and allows quick comparisons between regions and nations. However, the use of this indicator as the only variable to measure the R&D output does not allow to take into consideration the whole result achieved by a region in this field (Álvarez, Aguado & Martínez, 2008). In some economic sectors, the propensity to patent may be very low. In other cases, firms may develop products or processes which are new to the firm, but not to the sector at the global level. In this case, a patent is not possible, although that company has achieved an R&D output. Due to the aforementioned facts, it may sensible to complement the number of patent applications with other variables in order to have a better measure of the R&D output of European regions.

The objective of this research is to measure the efficiency (productivity) of EU-27 regions in R&D activities, building a regional taxonomy according to those efficiency levels. In order to fulfill this task we will use the statistical tool Data Envelopment Analysis.

The paper is developed as follows. In section 2, the evolution of the R&D expenditure will be analyzed, in the context of the EU. In section 3, the Data Envelopment Analysis tool will be explained in detail and also its relation with measuring the efficiency (productivity) of R&D activities. In section 4, the methodology followed in this paper will be described and, in section 5, the results of the DEA analysis will be presented. The paper ends with a conclusions section.

2. Evolution of R&D expenditures in the context of the EU

As mentioned in the introduction, the relevance of the productivity of investment in R&D in the long-term growth of the economy is a topic widely accepted in economic literature (Cameron, 1998). Recent articles have been working on the relationship between investment in R&D and production showing its importance. In this section, we will make a brief overview on the status of R&D in EU-27 countries.

As seen in Table 1, Spain's position is low in terms of total investment in R&D relative to GDP, from 1.12% in 2005 to 1.38% in 2010. In the Italian case, the evolution is similar: from 1.07% to 1.21%. The development is positive but of insufficient entity to reach the leading countries, like Sweden and Finland, which by far exceed 3%. Both countries are below the average for the EU-27 and the EU-15. Countries with low rates on business investment in R&D (such us, Portugal, Italy and Spain) show a growth rate above average in this indicator. This would indicate the existence of a process of convergence in this variable, at least until 2010 (last year available for the whole EU-27), between those countries and the EU-27 average. The effect of the current economic crisis in this process of convergence might be negative (OECD, 2013).

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Table 1
R&D expenditure by performance sectors, in % of GDP, 2005-10

	Business enterprise sector		Government sector		Higher education sector	
	2005	2010	2005	2010	2005	2010
EU-27	**1.15**	**1.23**	**0.25**	**0.27**	**0.41**	**0.49**
Euro area	**1.16**	**1.27**	**0.27**	**0.30**	**0.40**	**0.48**
Belgium	1.24	1.32	0.15	0.19	0.41	0.46
Bulgaria	0.10	0.30	0.31	0.22	0.05	0.07
Czech Republic	0.86	0.97	0.27	0.30	0.22	0.28
Denmark[1]	1.68	2.08	0.16	0.06	0.60	0.90
Germany	1.74	1.90	0.35	0.41	0.41	0.51
Estonia	0.42	0.81	0.11	0.17	0.39	0.62
Ireland	0.81	1.22	0.09	0.06	0.34	0.51
Greece	0.19	-	0.12	-	0.28	-
Spain[2]	0.60	0.71	0.19	0.28	0.33	0.39
France[3]	1.31	1.38	0.37	0.37	0.40	0.48
Italy[4]	0.55	0.67	0.19	0.18	0.33	0.36
Cyprus	0.09	0.09	0.13	0.10	0.16	0.25
Latvia	0.23	0.22	0.11	0.14	0.23	0.24
Lithuania	0.15	0.23	0.19	0.14	0.41	0.42
Luxembourg[5]	1.35	1.16	0.19	0.29	0.02	0.19
Hungary	0.41	0.69	0.26	0.21	0.24	0.23
Malta	0.38	0.37	0.03	0.02	0.16	0.23
Netherlands	1.01	0.67	0.24	0.22	0.65	0.75
Austria	1.72	1.88	0.13	0.75	0.67	0.72
Poland	0.18	0.20	0.21	0.26	0.18	0.27
Portugal	0.30	0.72	0.11	0.11	0.28	0.59
Romania	0.20	0.18	0.14	0.17	0.06	0.12
Slovenia[2]	0.85	1.43	0.35	0.36	0.24	0.29
Slovakia	0.25	0.27	0.15	0.19	0.10	0.17
Finland	2.46	2.69	0.33	0.36	0.66	0.79
Sweden[6]	2.59	2.35	0.18	0.17	0.78	0.90
United Kingdom	1.06	1.08	0.18	0.17	0.44	0.48
Iceland[7]	1.43	1.64	0.65	0.62	0.61	0.77
Norway[8]	0.81	0.88	0.24	0.28	0.47	0.55
Switzerland[9]	-	-	0.02	-	0.66	-
Croatia	0.36	0.32	0.21	0.20	0.30	0.21
Turkey[7]	0.20	0.34	0.07	0.11	0.32	0.40
Japan[10, 11]	2.54	2.70	0.28	0.29	0.45	0.40
United States[11]	1.79	2.02	0.31	0.30	0.36	0.36

[1] Break in series, 2007.
[2] Break in series, business enterprise sector, 2008.
[3] Break In series, business enterprise sector, 2006.
[4] Break in series, higher education sector, 2005.
[5] Break in series, government sector. 2009.
[6] Break in series, business enterprise sector and government sector, 2005.
[7] 2009 instead of 2010.
[8] Break in series, government sector and higher education sector, 2007.
[9] 2006 instead of 2005.
[10] Break in series, higher education sector, 2008.
[11] 2008 instead of 2010.

Source: Eurostat (online data code: tsc00001), OECD.

Some regions are efficient in patent creation, others in employment in advanced sectors

3. Assessing R&D effectiveness and productivity using data envelopment analysis (DEA)

In many economic studies, performance/productivity is defined or measured as the quantity of resource (inputs) needed to obtain some quantity of product (outputs).

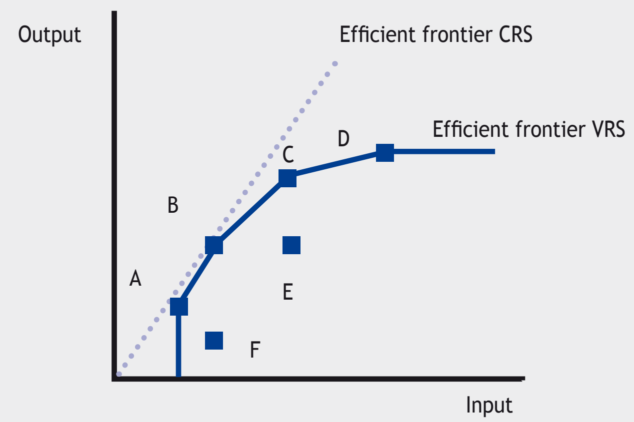
This performance analysis leads us to the study of efficiency: how to obtain the best mix of resources for obtaining those results.

In general terms, the modelling approach to measuring comparative performance could be summarized in two groups:

- Parametric methods, like the Stochastic Frontier Analysis (SFA), which uses multivariate techniques to analyze the variation in the production rate or cost rate among different organizations running the same activity (i.e. financial services, hospitals…).
- Non parametric methods, like Data Envelopment Analysis (DEA), that tries to measure the efficiency of those homogeneous entities estimating the optimum level of product as function of the type and quantity of available resources (Smith & Street, 2005).

In this paper, DEA[1] is being used as it was coined by Charnes, Cooper and Rhodes (1978) in their seminal paper on DEA, based on a previous work by Farell (1957). DEA is for measuring relative efficiency, so an organization that consumes fewer resources for getting the same quantity of product can be considered as more efficient.

Figure 1
Efficient frontiers



Note
In this figure, A, B, C and D are efficient DMU under VRS. On the contrary, E and F are relative inefficient units. It can be observed that unit C achieves greater output level than E with the same input level, while unit B achieve the same level of output than E with smaller level of input. Under CRS, the only efficient DMU is B.

[1] A thorough study of this methodology can be found in Cooper, Seiford and Zhu (2004), Thanassoulis (2001) and Coelli, Rao and Battese (1998).

Some regions are efficient in all estimated models; others are not efficient at all

With such premise, this methodology starts from the definition of Decision Making Unit (DMU) as the unit of assessment or entity whose efficiency would be relatively measured. And the efficiency ratio defined as a weighted sum of outputs to a weighted sum of inputs.

How to obtain the weight factors? A linear programming is, then, used to get those numbers where the objective function is the efficiency ratio of a DMU and the constraint set is defined by the fact that the efficiency ratio of the rest of DMUs cannot be upper than 1 (or 100%).

Repeating the analysis for each DMU allow us to build up an efficiency frontier where more efficient DMUs are located (those which minimize inputs levels for given outputs levels or alternatively, maximize the output for given inputs levels). All those efficient DMUs have an efficiency score equal to 1 while the rest will get a lower value. The outcome of the process is shown in Figure 1.

DEA models could be classified regarding two criteria:

- The Pareto Definition: Two definitions are given:
  - the one labelled “output oriented”- when outputs are controllable (i.e. goods produced), so trying to produce with given amounts of inputs the highest possible amount of outputs and
  - the one labelled “input oriented” – when inputs are controllable (i.e. workers and machinery) and, therefore, produce given amounts of outputs with the lowest possible amount of inputs.

- The focus on the technical efficiency, that is
  - Constant Returns to Scale (CRS) models (Charnes et al., 1978)
  - Variable Returns to Scale (VRS) models (Banker, Charnes & Cooper, 1984).

As R&D investment is mainly focused in the obtaining of results (output maximization) and following, for example, Graves and Langowitz, 1996 who studies the behaviour of R&D expenditure, an output oriented CRS model has been selected.

Let us assume that we have n DMUs ($k = 1, 2, \ldots, n$) using r inputs to secure s outputs. Let x_{jk} ($j = 1, 2, \ldots, r$), be the input levels used by DMU k and y_{ik} the levels of output i ($i = 1, 2, \ldots, s$) secured by DMU k. And let λ_j be the weight factor assigned to each DMU.

The following linear programming model can be stated, and be solved for every DMU:

$$\max \theta + \varepsilon \left(\sum_{j=1}^{r} e_j^- + \sum_{i=1}^{s} e_i^+ \right)$$

$$\text{s.a.} \sum_{l=1}^{n} x_{jl}\lambda_l + e_j^- = x_{jk}, \qquad j=1,2,\ldots,r$$

$$\sum_{l=1}^{n} y_{il}\lambda_l - e_i^+ = \theta y_{ik}, \qquad i=1,2,\ldots,s$$

$$\lambda_l \geq 0, \qquad l=1,2,\ldots,n$$
$$e_j^- \geq 0, \qquad j=1,2,\ldots r$$
$$e_i^+ \geq 0, \qquad i=1,2,\ldots s$$

where ε is a very small positive number to avoid null weight factors.

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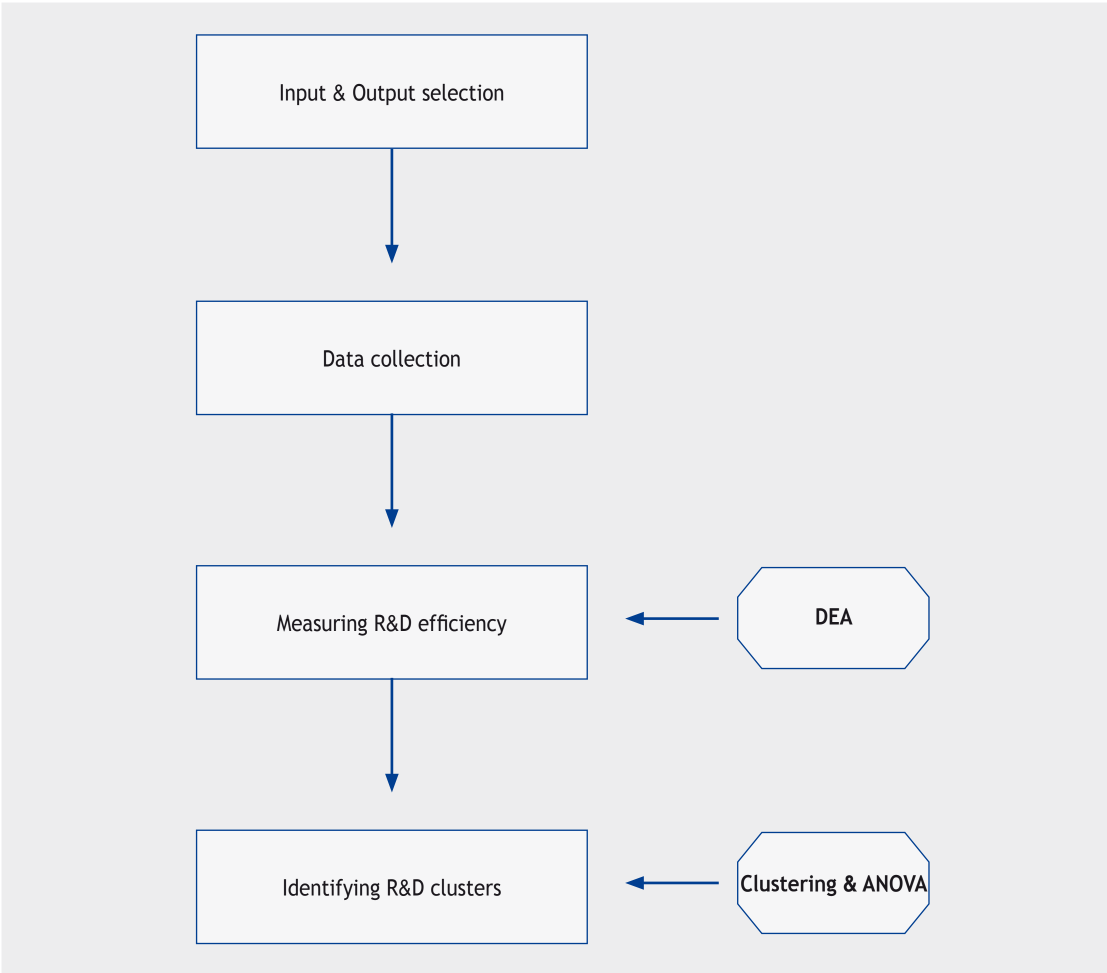
The number of low efficiency regions is extremely high

4. Methodology

The methodology used in this paper is very straightforward. It is depicted in Figure 2.

Figure 2
A four-step methodology



Source: own elaboration based upon Lee and Park (2005).

- Firstly, the input-output variables have been selected following recommendations found in previous studies that analyze the RIS efficiency.
- Secondly, data from all EU-27 regions has been collected.
- Next, R&D activities' efficiency have been measured based on DEA.
- Finally, an exercise of clustering the analyzed regions has been made according to the previous findings and results.

On building the efficiency models, three inputs and three outputs have been considered. Table 2 summarizes their key characteristics.

Table 2
Input and output variables

Variable	Description	Unit of Measurement	Source	Variable as Used on DEA
INPUT BERD	Expenditure in R&D made by firms	% GDP	Eurostat	Average 2004-2007[1]
INPUT PERD	Expenditure in R&D made by Public Administrations	% GDP	Eurostat	Average 2004-2007[1]
INPUT UERD	Expenditure in R&D made by High Education Institutions	% GDP	Eurostat	Average 2004-2007[1]
OUTPUT GDPpc	GDP per capita	Thousands €/million pers.	Eurostat	Average 2008-2009[2]
OUTPUT Patents	Ordered Patents EPO per capita	Thousands patents/ million pers.	Eurostat	2008
OUTPUT Employment	Knowledge intensive services and high & mid tech manufacturing employment	%	Eurostat	2008[3]

[1] If data for the whole period is available. If it is not the case, it is the average of the available data.
[2] For Brandenburg (DE40) 2009 data.
[3] Or the latest available data.

Source: own elaboration based on Eurostat data.

For measuring R&D outputs three variables have been selected: GDP per capita, knowledge intensive services and high & mid tech manufacturing employment and the number of patents applied for in the European Patent Organization. Several examples to measure R&D outputs can be found in the recent literature. Some authors (Navarro et al., 2009) have used the number of patents, while others (Martínez Pellitero, 2002, 2007; Buesa & Heijs, 2007) have used GDP per capita and knowledge intensive services and high & mid tech manufacturing employment as output variables.

On selecting the time period covered by input and output data, a lag has been used, as R&D inputs are not turned into outputs instantaneously. Some studies (i.e. Lee & Park, 2005) state that there is a three to five years lag since R&D inputs is reverted into outputs. In this paper, inputs are being measured as the average of the values obtained in the period 2004-2007 while all output data has been gathered from 2008-2009 (or latest available data).

The whole dataset has been obtained from Eurostat. We will be using regions at the NUTS 3 level, with the exception of Belgium where the only data available is at NUTS 2 level. We have eliminated from the analysis regions with at least one of the following characteristics:

- Number of patents < 10 per million of inhabitants.
- R&D expenditure performed by Public Administration < 0.02% over GDP.
- R&D expenditure performed by businesses < 0.02% over GDP.
- R&D expenditure performed by universities < 0.02% over GDP.

These filters are necessary in order to obtain valid results, not distorted by regions without significant R&D expenditures. After applying the filters, we have ended with 190 regions as valid units for the final analysis.

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R&D investment is a key element to achieve competitive advantages/ prosperity at the regional level

5. Results

This section shows the results of measuring the efficiency of R&D investment of the 190 regions using data envelopment analysis (DEA). First, we made the analysis of efficiency using the basic model (which includes all inputs and outputs). Then we have proceeded to the execution of partial models that combine a single output with all inputs. In this way, it is possible to measure the efficiency in R&D for each selected output.

For example, the DEA model that includes all inputs and that incorporates patents as output can be understood as the model that measures the efficiency oriented to the achievement of patents. Additionally, we have estimated other additional modes apart from the basic model (which includes all inputs and outputs): the GDP-oriented efficiency, the patent-oriented model and the employment efficiency-oriented model. Table 3 shows inputs and outputs included in each of the seven DEA models that have been calculated.

Table 3
Inputs and Outputs considered in the DEA models

	Input			Output		
DEA MODEL	PERD	BERD	UERD	GDPpc	Patents	Employment
Basic Model	❍	❍	❍	❍	❍	❍
GDP-oriented efficiency	❍	❍	❍	❍		
Patent-oriented efficiency	❍	❍	❍		❍	
Employment-oriented efficiency	❍	❍	❍			❍

Source: Own elaboration.

Table 4 shows the results of the efficiency of R&D for the 190 regions using the basic DEA model, in which all inputs and outputs have been taken into account. Regions are divided in three different groups according their level of efficiency: high efficiency regions (efficiency equal or higher than 0.70), average efficiency regions (efficiency between 0.69 and 0.40), and low efficiency regions (efficiency below 0.40). Regions highlighted in cursive fonts achieve maximum efficiency. Inside each group, regions are always ordered from maximum to minimum efficiency.

Regions from different countries are able to achieve maximum efficiency in the basic model. On the other hand, the most inefficient regions (less than 40% efficiency) are also widespread at the European level. The rest are in an intermediate position between these two extremes. It is noteworthy that some of the regions 100% efficient in the basic model show a small level of R&D investment over GDP compared to others, such as capital regions (Madrid, London, Lazio, Berlin...) that have higher levels of use of inputs.

These results differ from those obtained by Buesa and Heijs (2007) using a DEA model based on patent application as the only output for R&D investment. For Buesa and Heijs, the more efficient regions tend to coincide with that showing the highest R&D expenditure per capita and in absolute terms. However, in this study, those regions are in most cases in an intermediate position (Bruxelles, Stockholm). In contrast, some regions with a reduced R&D investment, both in absolute and relative terms, are capable of reaching the highest level of efficiency (Sardegna, Illes Balears).

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Table 4
Results of the basic DEA model for the EU-27 regions

High efficiency regions			
Niederösterreich	Warminsko-Mazurskie	Småland med öarna	Bratislavský kraj
Severen tsentralen	East Yorkshire an…	Weser-Ems	Saarland
Severoiztochen	Shropshire and St…	Západné Slovensko	North Eastern Sco…
Yuzhen tsentralen	Inner London	Nordjylland	Salzburg
Schwaben	Dorset and Somerset	Haute-Normandie	Nyugat-Dunántúl
Brandenburg-Nor…	Luxembourg	Vest	Outer London
Lüneburg	Dél-Dunántúl	Brandenburg-Süd…	Podkarpackie
Detmold	Észak-Magyarország	Veneto	Moravskoslezsko
Midtjylland	Calabria	Münster	Unterfranken
Anatoliki Makedon…	Provincia A. Trento	Kassel	Kriti
Sardegna	Oberfranken	Région wallonne	Oberösterreich
Illes Balears	Koblenz	Kypros	
Average efficiency regions			
Umbria	Mellersta Norrland	Alentejo	Attiki
Schleswig-Holstein	Norte	Centro (PT)	Stockholm
Východné Slovensko	Sjælland	South Western Sco…	Hannover
Nord-Pas-de-Calais	Nord-Vest	Surrey, East and…	Mazowieckie
South Yorkshire	Leipzig (NUTS 2006)	Rheinhessen-Pfalz	Lódzkie
Lombardia	Friuli-Venezia Gi…	Tübingen	Oberbayern
Mittelfranken	Provincia Autonom…	Dytiki Ellada	Cantabria
Közép-Dunántúl	Arnsberg	Wielkopolskie	Lancashire
Alsace	Slaskie	Pomorskie	Karlsruhe
Vzhodna Slovenija	Düsseldorf	Highlands and Isl…	Northern Ireland…
Gießen	Southern and Eastern	Severovýchod	Basse-Normandie
Région de Bruxell…	Castilla-la Mancha	Leicestershire, R…	Basilicata
Freiburg	Tirol	Devon	Darmstadt
Trier	Toscana	Köln	Kärnten
Picardie	Emilia-Romagna	Bucuresti-Ilfov	Piemonte
Stuttgart	País Vasco	Sydsverige	
West Midlands	Poitou-Charentes	Border, Midland a…	
Low efficiency regions			
Mecklenburg-Vorpo…	La Rioja	Berlin	Andalucía
West Wales and Th…	Liguria	Hamburg	Zahodna Slovenija
Kentriki Makedonia	Principado de Asturias	Bretagne	Campania
Aragón	Thüringen	Abruzzo	Comunidad de Madrid
Bourgogne	Lorraine	Aquitaine	Auvergne
Kent	Latvija	Praha	Derbyshire and No…
Castilla y León	Sachsen-Anhalt	Centre (FR)	Länsi-Suomi
Lubelskie	Merseyside	Lietuva	Jihovýchod
Lazio	Berkshire, Buckin…	Galicia	Wien
Canarias (ES)	Östra Mellansverige	Cataluña	Övre Norrland
Puglia	Comunidad F. Navarra	Észak-Alföld	Hampshire and Isl…
Pays de la Loire	Comunidad Valenciana	Provence-Alpes-Cô…	Gloucestershire…
Norra Mellansverige	Közép-Magyarország	Hovedstaden	North Yorkshire
Bedfordshire and…	Eesti	Lisboa	Languedoc-Roussillon
Rhône-Alpes	Dél-Alföld	Chemnitz	Pohjois-Suomi
Extremadura	Región de Murcia	Bremen	Dresden
Sicilia	Eastern Scotland	Västsverige	Midi-Pyrénées
East Wales	Etelä-Suomi	Malopolskie	East Anglia
Jihozápad	Île de France	Steiermark	Braunschweig

Source: Own elaboration.

Economic theory supports the idea of having an active innovation policy to enhance R&D activities

After the estimation of the basic model, the patent-oriented efficiency model and the employment oriented efficiency model have been calculated. As it is shown is Table 5, there is a strong correlation between the three models considered in this analysis. The basic model is highly correlated with the employment-oriented efficiency model (0.787) and the GDP -oriented efficiency model (0.847). The basic model shows a moderate correlation with the patent-oriented model (0.540). On the other hand, there is a high correlation between employment and GDP oriented efficiency models (0.722), whereas there is a low level of correlation between the patent-oriented efficiency model and the employment and GDP-oriented efficiency models. In short, we can conclude that there is a strong correlation between the basic, GDP and employment models, while all those models differ clearly from the patent-oriented efficiency model. From this analysis it is possible to conclude that similar results to the ones presented in Table 4 are to be expected in the 3 highly correlated models (basic, GDP and employment), while different ones are to be expected considering the patent-oriented efficiency model.

Table 5
Correlation coefficients between DEA models

Correlation	Coefficients
Basic-Employment	0.787
Basic-GDP	0.847
Basic-Patent	0.540
Employment-GDP	0.722
Employment-Patent	0.103
GDP-Patent	0.286

Source: Own elaboration.

Considering the output variables used to estimate all DEA models (GDP, patents and employment in knowledge intensive services and in high & mid high tech manufacturing), we have conducted a cluster analysis of the 190 regions included in the models. The results of this analysis are shown in Figure 3. The aim of this analysis is to identify groups of regions sharing similar patterns in terms of efficiency, but different in contrast with the other groups. Results from Table 5 suggests that with only two DEA models it is possible to consider almost all the information calculated in all DEA models, due to the high correlation between three of them (basic, GDP and employment). According to the fact, we have selected the employment-oriented efficiency model (highly correlated with basic and GDP models) and the patent-oriented efficiency model (no highly correlated with the other models). Moreover, the correlation between these two selected models is the smallest one (see Table 5). Following this procedure, we have identified groups of regions which share similar features in all DEA models, using only two of them.

As shown in Figure 3, we can distinguish seven groups of regions:

- **Cluster 1:** In this group, we discover regions with the smallest level of efficiency in both models. In this group, we find regions from peripheral European countries, mainly from Southern and Eastern Europe (29 regions) (see Table 6).

Table 6
Cluster 1: lagging behind regions in both employment and patent efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
ES61	Andalucía	0,135	0,055	*
FR61	Aquitaine	0,178	0,000	*
EL30	Attiki	0,203	0,090	*
ITF3	Campania	0,167	0,088	*
ES70	Canarias (ES)	0,178	0,000	*
ES41	Castilla y León	0,205	0,055	*
ES42	Castilla-La Mancha	0,229	0,086	*
FR24	Centre (FR)	0,232	0,000	*
PT16	Centro (PT)	0,138	0,064	*
ES30	Comunidad de Madrid	0,161	0,000	*
EL23	Dytiki Ellada	0,168	0,025	*
EE00	Eesti	0,230	0,124	*
HU32	Észak-Alföld	0,257	0,034	*
ES43	Extremadura	0,231	0,029	*
ES11	Galicia	0,094	0,064	*
DE60	Hamburg	0,126	0,000	*
CZ06	Jihovýchod	0,188	0,080	*
EL12	Kentriki Makedonia	0,180	0,108	*
HU10	Közép-Magyarország	0,231	0,119	*
ES23	La Rioja	0,149	0,052	*
UKD4	Lancashire	0,273	0,090	*
LV00	Latvija	0,247	0,087	*
LT00	Lietuva	0,200	0,054	*
PT17	Lisboa	0,156	0,045	*
PL21	Malopolskie	0,199	0,081	*
PT11	Norte	0,190	0,092	*
SE33	Övre Norrland	0,133	0,000	*
CZ01	Praha	0,155	0,070	*
ES62	Región de Murcia	0,095	0,064	**29**

- **Cluster 2:** In this group, we still find regions with very low levels of efficiency in both models, showing a slightly more efficient behavior regarding patents. Anyway, the cluster average is below general average in the two models. In this case, we have regions belonging mainly to France, the UK and Spain (50 regions) (see Table 7).

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Table 7
Cluster 2: lagging behind regions in employment

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
ITG1	Sicilia	0,242	0,099	*
ITF1	Abruzzo	0,191	0,148	*
ES24	Aragón	0,175	0,216	*
FR72	Auvergne	0,217	0,145	*
FR25	Basse-Normandie	0,187	0,275	*
UKJ1	Berkshire, Buckin…	0,196	0,240	*
DE30	Berlin	0,066	0,285	*
FR26	Bourgogne	0,188	0,202	*
DE91	Braunschweig	0,037	0,102	*
DE50	Bremen	0,102	0,213	*
FR52	Bretagne	0,152	0,251	*
ES13	Cantabria	0,100	0,186	*
ES51	Cataluña	0,152	0,162	*
DED4	Chemnitz	0,139	0,194	*
ES22	Comunidad Foral de Navarra	0,056	0,213	*
ES52	Comunidad Valenciana	0,127	0,135	*
HU33	Dél-Alföld	0,212	0,154	*
UKF1	Derbyshire and…	0,159	0,172	*
UKK4	Devon	0,221	0,324	*
DED2	Dresden	0,057	0,150	*
UKH1	East Anglia	0,064	0,120	*
UKL2	East Wales	0,185	0,174	*
UKM2	Eastern Scotland	0,115	0,258	*
FI1B	Etelä-Suomi	0,146	0,264	*
UKK1	Gloucestershire…	0,103	0,173	*
UKJ3	Hampshire and Isl…	0,153	0,141	*
DK01	Hovedstaden	0,165	0,243	*
FR10	Île de France	0,144	0,273	*
FR81	Languedoc-Roussillon	0,060	0,156	*
FI1C	Länsi-Suomi	0,131	0,201	*
ITC3	Liguria	0,202	0,262	*
FR41	Lorraine	0,145	0,273	*
DE80	Mecklenburg-Vorpo…	0,206	0,302	*
UKD7	Merseyside (NUTS…	0,149	0,228	*
FR62	Midi-Pyrénées	0,075	0,103	*
SE31	Norra Mellansverige	0,239	0,288	*
UKE2	North Yorkshire	0,113	0,156	*
SE12	Östra Mellansverige	0,098	0,313	*
FR51	Pays de la Loire	0,247	0,250	*
FI1D	Pohjois-Suomi	0,133	0,130	*

An efficiency analysis of R&D investment is needed to assess the success of that investment

Table 7 (continued)
Cluster 2: lagging behind regions in employment

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
FR53	Poitou-Charentes	0,270	0,311	*
ES12	Principado de Asturias	0,134	0,144	*
FR82	Provence-Alpes-Cô…	0,129	0,219	*
ITF4	Puglia	0,221	0,213	*
DEE0	Sachsen-Anhalt	0,152	0,252	*
AT22	Steiermark	0,093	0,233	*
DEG0	Thüringen	0,119	0,295	*
SE23	Västsverige	0,179	0,202	*
AT13	Wien	0,112	0,179	*
SI02	Zahodna Slovenija	0,113	0,183	**50**

- **Cluster 3:** In this cluster, we find regions with the most efficient result regarding patents and almost an average result regarding employment. Then, these regions are especially productive in using their inputs in order to generate patents. In this small group of successful regions, we have German, Austrian, British, Danish and Italian regions (13 regions) (see Table 8).

Table 8
Cluster 3: leading regions in patent efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
DE4A	Brandenburg-Nor…	0,448	0,809	x
DE4B	Brandenburg-Süd…	0,207	0,855	x
UKI1	Inner London	0,392	0,893	x
LU00	Luxembourg	0,455	1,000	x
DEA3	Münster	0,231	0,837	x
DK05	Nordjylland	0,303	0,907	x
UKM5	North Eastern Sco…	0,167	0,772	x
ITH1	Provincia Autonom…	0,417	1,000	x
DEC0	Saarland	0,256	0,736	x
AT32	Salzburg	0,262	0,761	x
DE26	Unterfranken	0,213	0,728	x
ITH3	Veneto (NUTS 2006)	0,404	0,740	x
DE94	Weser-Ems	0,247	0,961	**13**

- **Cluster 4:** Very high efficiency regions in both generation and employment creation. These regions are the European leaders in terms of efficiency, achieving the best result in comparison with the rest of the groups. The geographical origin of these regions is similar to the one in cluster 3 (9 regions) (see Table 9).

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Data Envelopment Analysis (DEA) is a statistical tool used to measure efficiency (minimizing inputs/ maximizing outputs)

Table 9

Cluster 4: leading regions in both employment and patent efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
DEA4	Detmold	0,652	0,819	•
UKK2	Dorset and Somerset	1,000	0,653	•
DEB1	Koblenz	0,753	0,828	•
DE93	Lüneburg	0,845	0,730	•
DK04	Midtjylland	0,675	0,986	•
AT12	Niederösterreich	0,878	0,869	•
DE24	Oberfranken	0,601	0,823	•
ITG2	Sardegna	0,797	0,571	•
DE27	Schwaben	0,734	1,000	9

- **Cluster 5:** Regions with a high efficiency regarding employment and a low efficiency regarding patent generation. These regions are more efficient than average regarding employment. Most of them are Eastern European regions, with a small number of Spanish, French and British regions (38 regions) (see Table 10).

Table 10

Cluster 5: low performance regions in patent and average in employment efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
ITF5	Basilicata	0,251	0,161	☐
UKH2	Bedfordshire and...	0,337	0,133	☐
IE01	Border, Midland a...	0,374	0,226	☐
SK01	Bratislavský kraj	0,515	0,255	☐
RO32	Bucuresti-Ilfov	0,322	0,034	☐
UKE1	East Yorkshire an...	0,678	0,298	☐
UKM6	Highlands and Isl...	0,300	0,214	☐
ES53	Illes Balears	0,538	0,000	☐
CZ03	Jihozápad	0,319	0,089	☐
AT21	Kärnten	0,336	0,144	☐
UKJ4	Kent	0,380	0,128	☐
HU21	Közép-Dunántúl	0,604	0,073	☐
ITI4	Lazio (NUTS 2006)	0,271	0,173	☐
UKF2	Leicestershire, R...	0,295	0,000	☐
PL11	Lódzkie	0,351	0,000	☐
PL31	Lubelskie	0,265	0,194	☐
PL12	Mazowieckie	0,333	0,055	☐
CZ08	Moravskoslezsko	0,645	0,032	☐

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Investments in R&D made by public administrations, firms and universities are input indicators

Table 10 (continued)

Cluster 5: low performance regions in patent and average in employment efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
FR30	Nord-Pas-de-Calais	0,432	0,000	☐
RO11	Nord-Vest	0,410	0,023	☐
UKN0	Northern Ireland…	0,277	0,151	☐
ES21	País Vasco	0,298	0,146	☐
FR22	Picardie	0,366	0,000	☐
ITC1	Piemonte	0,313	0,272	☐
PL32	Podkarpackie	0,569	0,045	☐
PL63	Pomorskie	0,435	0,049	☐
BG33	Severoiztochen	0,575	0,033	☐
CZ05	Severovýchod	0,448	0,057	☐
DK02	Sjælland	0,429	0,001	☐
PL22	Slaskie	0,421	0,074	☐
SE21	Småland med öarna	0,527	0,001	☐
UKM3	South Western Sco…	0,306	0,170	☐
IE02	Southern and Eastern	0,381	0,203	☐
SK04	Východné Slovensko	0,576	0,117	☐
SI01	Vzhodna Slovenija	0,542	0,171	☐
UKG3	West Midlands	0,403	0,164	☐
UKL1	West Wales and Th…	0,308	0,000	☐
PL41	Wielkopolskie	0,311	0,094	**38**

- **Cluster 6:** Regions which are more efficient than average in patent generation and a bit less efficient than average in employment-oriented efficiency. We find mainly German regions in this group (37 regions) (see Table 11).

Table 11

Cluster 6: follower regions in both employment and patent efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
FR42	Alsace	0,181	0,595	Δ
DEA5	Arnsberg	0,212	0,511	Δ
DE71	Darmstadt	0,248	0,372	Δ
DEA1	Düsseldorf	0,263	0,511	Δ
ITH5	Emilia-Romagna	0,184	0,487	Δ

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Table 11 (continued)

Cluster 6: follower regions in both employment and patent efficiency

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
DE13	Freiburg	0,199	0,590	Δ
ITH4	Friuli-Venezia Gi...	0,174	0,535	Δ
DE72	Gießen	0,276	0,527	Δ
DE92	Hannover	0,157	0,418	Δ
FR23	Haute-Normandie	0,325	0,586	Δ
DE12	Karlsruhe	0,113	0,420	Δ
DE73	Kassel	0,473	0,530	Δ
DEA2	Köln	0,082	0,442	Δ
EL43	Kriti	0,254	0,516	Δ
CY00	Kypros	0,371	0,330	Δ
DED5	Leipzig	0,251	0,445	Δ
ITC4	Lombardia	0,424	0,453	Δ
SE32	Mellersta Norrland	0,332	0,428	Δ
DE25	Mittelfranken	0,248	0,628	Δ
DE21	Oberbayern	0,169	0,415	Δ
AT31	Oberösterreich	0,321	0,515	Δ
ITH2	Provincia Autonom...	0,247	0,427	Δ
BE10	Région de Bruxell...	0,278	0,387	Δ
BE3X	Région wallonne	0,611	0,509	Δ
DEB3	Rheinhessen-Pfalz	0,120	0,474	Δ
FR71	Rhône-Alpes	0,143	0,351	Δ
DEF0	Schleswig-Holstein	0,166	0,642	Δ
UKE3	South Yorkshire	0,382	0,410	Δ
SE11	Stockholm	0,191	0,408	Δ
DE11	Stuttgart	0,232	0,580	Δ
UKJ2	Surrey, East and...	0,341	0,333	Δ
SE22	Sydsverige	0,228	0,417	Δ
AT33	Tirol	0,122	0,467	Δ
ITI1	Toscana	0,179	0,469	Δ
DEB2	Trier	0,280	0,480	Δ
DE14	Tübingen	0,126	0,466	Δ
ITI2	Umbria	0,360	0,564	**37**

- **Cluster 7:** In this cluster, regions with the highest level of efficiency in employment are grouped. However, their efficiency regarding patents is lower than the average. We find regions belonging mainly to Eastern Europe (14 regions) (see Table 12).

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Table 12
Cluster 7: leading regions in employment efficiency with a low performance in patents

DMU	Region (DMU)	Employment-oriented efficiency	Patent-oriented efficiency	#DMU
PT18	Alentejo	1,000	0,040	▽
EL11	Anatoliki Makedon...	0,839	0,236	▽
ITF6	Calabria	0,862	0,332	▽
HU23	Dél-Dunántúl	1,000	0,192	▽
HU31	Észak-Magyarország	1,000	0,131	▽
MT00	Malta	1,000	0,036	▽
HU22	Nyugat-Dunántúl	0,779	0,097	▽
UKI2	Outer London	0,745	0,187	▽
BG32	Severen tsentralen	1,000	0,045	▽
UKG2	Shropshire and St...	1,000	0,344	▽
RO42	Vest	0,861	0,077	▽
PL62	Warminsko-Mazurskie	1,000	0,075	▽
BG42	Yuzhen tsentralen	1,000	0,060	▽
SK02	Západné Slovensko	0,902	0,021	**14**

In Table 13, we can compare average results for each of the seven clusters with the general average for the 190 regions. Each cluster presents averages in the two variables under study that are different with statistical significance (see Table 13):

Table 13
Average values for all clusters

Cluster	Employment	Patent	Symbol
Cluster 1	0.190	0.060	*
Cluster 2	0.150	0.210	*
Cluster 3	0.310	0.850	x
Cluster 4	0.770	0.810	•
Cluster 5	0.410	0.100	□
Cluster 6	0.250	0.480	Δ
Cluster 7	0.930	0.130	▽
Total average	**0.320**	**0.280**	

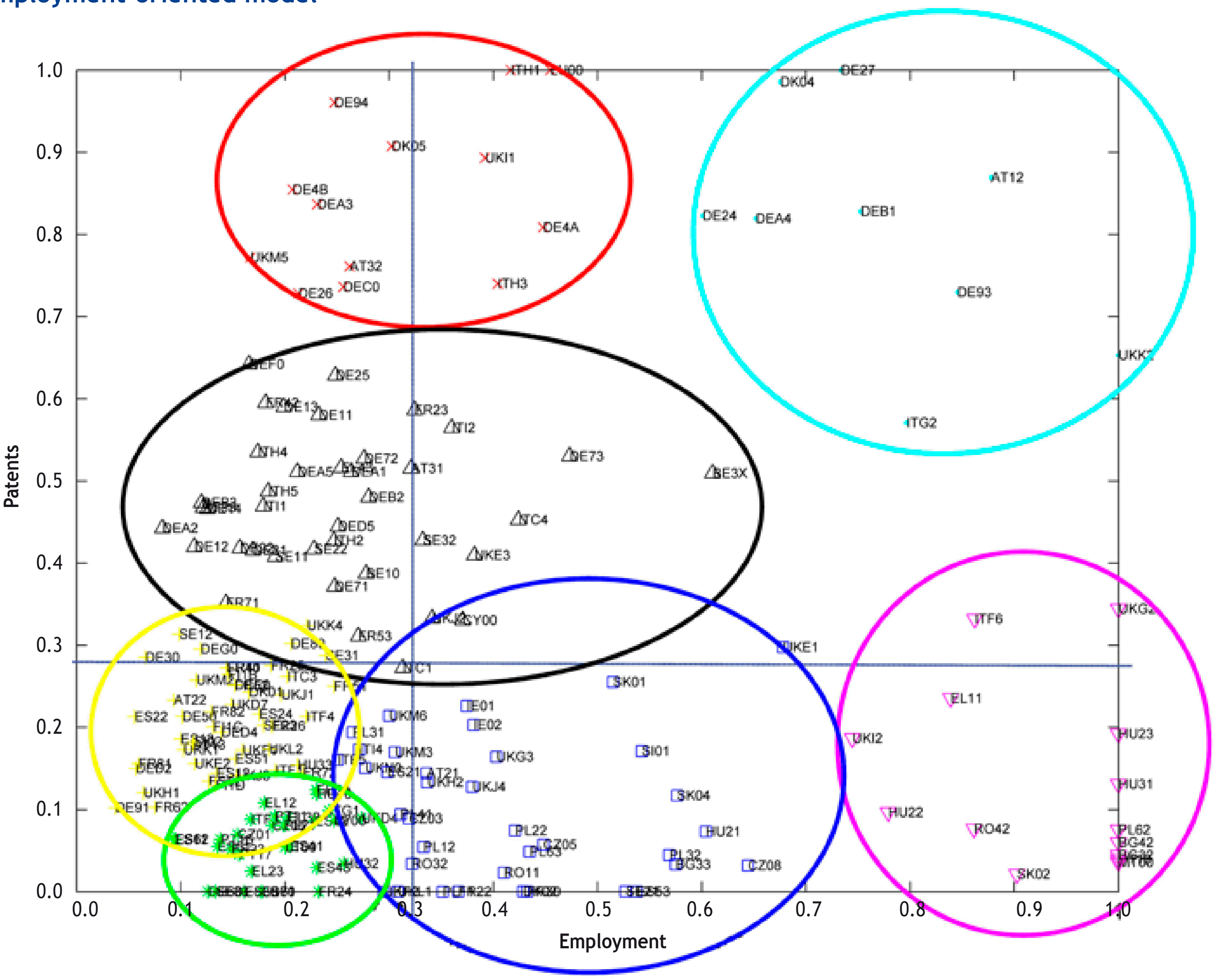
Source: Own elaboration.

In Figure 3 we can observe the concentration of the leading regions in efficiency in both models (cluster 4), regions with a high level of efficiency regarding to employment in knowledge and technology intensive sectors (cluster 7), regions with a high level of efficiency in patent generation (cluster 3), intermediate regions (clusters 5 and 6) and regions with a low efficiency level (clusters 2 and 3). The largest group of regions is one with the lowest level of efficiency regarding employment (group 2: 50 regions). The leading group of regions (4) gathers 9 regions, in contrast with the 79 regions of the low efficiency clusters (1 and 2).

We can conclude from this analysis that there is a strong polarization among leading regions and low efficiency regions. The number of low efficiency regions is extremely high in comparison with the number of leading regions in efficiency. This shows the necessity of improving the use of R&D inputs at the regional level in Europe and the convenience of establishing learning processes between regions so that low efficiency regions could adapt policies and know-how from the leading ones.

Figure 3

Cluster analysis of the EU-27 regions using results in the patent-oriented model and the employment-oriented model



Source: Own elaboration.

GDP per capita, patents and employment in advanced sectors are output indicators

6. Conclusions

The aim of this study has been to measure the efficiency of R&D activities performed at the regional level in the EU-27 using the data envelopment analysis (DEA). In addition to the basic model (that model includes three inputs and three outputs), we have built three models in order to measure the efficiency of each output. After analyzing the four DEA models, we have grouped all regions in seven different categories, according to the efficiency levels achieved in the DEA models.

The results of this study could be used to assess regional R&D policy in the EU-27 at the regional level. The final objective of DEA is to give each region a tool to ameliorate the efficiency of regional expenditures in R&D and also to offer a context to compare the results of each region with the results of other regions located in the same economic and cultural environment. With this tool, non-efficient regions could calculate the increase in output needed to become 100% efficient. Regional policy makers could benefit from this tool and take into account the efficiency level of their region in order to design policies to improve it. Policy makers in low efficiency regions should consider this low level of efficiency in their territories and analyze its causes. These causes may differ from region to region. North Eastern Scotland and Veneto, for example, obtain satisfactory results in general terms, but they show a clear weakness in terms of efficiency in employment. If these regions improve their situation in that field, they could achieve higher levels of efficiency. On the other hand, regions such as Koblenz or Niederösterreich show very high efficiency levels in all models. Low efficiency regions (especially the ones located in clusters 1 and 2) could try to adapt to their regional features and possibilities R&D policies implemented in those high efficiency regions.

The limitations of this study are twofold. On one hand, the DEA models we have estimated have been built using constant returns to scale, following the vast majority of authors presenting this kind of analysis. On the other hand, the number of input and output indicators used in this work is very limited. A wider range of the indicators taken into consideration in this study could be beneficial in order to strengthen the final outcome.

A qualitative analysis of the regional innovation systems (RIS) of regions taken into consideration in this study could clarify the reasons why some regions are more efficient than others. Using the concept of regional innovation system, it could be possible to conclude whether the lack of interaction between RIS agents, the lack of investment and/or the lack of an institutional framework at the regional level are lowering the efficiency of regional R&D activities.

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