AN EXHAUSTIVE APPROACHMENT TO THE INNOVATION EFFICIENCY IN SPAIN

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ABSTRACT

The objective for this article is to analyze the innovation efficiency in Spain by activity branch. To this end we will work with the 2009 data from the INE (Spanish National Institute of Statistics) innovation and R&D activities surveys. To this aim, we will use the following methodology for the efficiency analysis: the one based on output oriented DEA (Data Envelopment Analysis) with constant returns to scale and weight restrictions.
This technique will be completed in three aspects. Firstly with the introduction of more inputs and outputs without causing an increment of efficient units. Secondly, we will use the Principal Component Analysis to extract the idea to implement the weight restrictions in the DEA. Thirdly, the analysis will be completed with a robustness Analysis of the efficient activity branches to improve the DEA discrimination capacity.

MOTIVATION OF THE RESEARCH AND LITERATURE SURVEY

The structure of the Spanish economy is suffering nowadays some very significant changes marked by a double crisis at the same time. On one hand the serious international crisis, and on the other hand a national crisis product of a long term growth model based on exhausted activity branches: construction and tourism.
It has been pointed out within the new strategic goals for this decade set at the Lisbon European Council, in march 2000, that the European Union will become one of the most competitive and dynamic knowledge-based economies in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion. Achieving these goals requires an overall strategy aimed at preparing the transition to a knowledge-based economy and society by better policies for the information society and R&D, as well as by stepping up the process of structural reform for competitiveness and innovation and by completing the internal market. (Lisbon European Council, 2000).
Spain should add value to the European Union, and became more competitive and efficient, with a dynamic economy based on the knowledge, such as education, innovation, research and development.
In that point, we would need to know which is the role of the innovation in the transformation of the economic structure of Spain and which activity branches of the Spanish economy are the most efficient ones.
These key questions will be studied throughout the present paper to understand the current structure of the Spanish economy and to be able to offer information to economic politics decision makers. Structural transformations needed to the economic growth and increase of the rent per capita imply changes of certain relevance in the structure of the production, in the role of the trade and in the public sector weight. (García and Myro, 2008).
These changes leaded by the upward tendency of some activity branches and the decline of others, alter the structure of the whole economy. The research, development and innovation, all of them focused on the increase of productivity, are needed to lead these significant structure changes. Throughout the base of a balanced and sustainable Economic growth based on innovation must be designed the nowadays Spanish economy structure change.
There are two motivations in this paper. Firstly, we want to answer the previous key questions related to the Spanish economy. Secondly, we want to propose a new methodological approach to improve the Data Envelopment Analysis, looking for improving one previous research developed in this field (De Vicente *et al*, 2009), (Guede *et al*, 2011).
Although there has been carried out very interesting researches on this topic (Buesa *et al*, 2006), (Galende del Canto 2008), (Gómez and Zabala 2008), (De Vicente *et al*, 2009), (Guede *et al*, 2011), the solution proposed in this paper has not been applied in this field previously, and it’s new in the application of the most advanced DEA research methods too. (Cooper *et al.* 2004), (Doyle and Green, 1994), (Dyson *et al,* 2001),

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(Lugones *et al,* 2003), (Madlener *et al,* 2006), (Maystre *et al,* 1994), (Raftery, 1993), (Roy and Bouyssou, 1993), (Zhu and Cook, 2007).
In order to follow the most authorized data analysis methodology it has been developed the study under the Oslo Manual framework and in concordance with the the INNO-policy reports, INNO Metrics (2007) and the European regional innovation scoreboard report (2009).

METHODOLOGY

This paper intends to analyze the relationship between efficiency and innovation activity in Spanish activity branches. The methodology includes three levels of analysis.
We will apply a Data Envelopment Analysis (DEA), a non-parametric technique, to a set of several inputs and outputs associated to economic and financial data.
The practical application of Data Envelopment Analysis presents a range of procedural issues to be examined and resolved including those relating to the homogeneity of the units under assessment, the input/output set selected, the measurement of those selected variables and the weights attributed to them (Dyson *et al,* 2001).
Each of these issues can present difficulties in practice. In this work we will try to highlight some of the pitfalls related with this case, and to improve the DEA's discrimination capability.
There are two main pitfalls detected in this analysis. In first place, if there are many inputs and outputs the number of efficient DMUs increases. To obtain a more realistic result, we will apply Principal Components Analysis (PCA) over the set of inputs and, separately, over the set of outputs. This was made to reduce the number of inputs and outputs, increasing the discrimination power of the DEA.
We will use the following methodology for the efficiency analysis: the one based on output oriented DEA (Data Envelopment Analysis) with variable returns to scale.
The other main pitfall detected is related to the application of a DEA without priori information about weights, because it allows DMUs with unrealistic behaviour could be efficient.
DEA allows each decision making unit (DMU, branches in our study) to specify its own weights so as to obtain a maximum efficiency score for itself. Without the possibility of introducing weight restrictions, complete weight flexibility is allowed. This may result in identifying a Decision Making Unit with an unrealistic weighting behaviour to be efficient.
Problems arising from the total flexibility of weights in DEA model are often dealt incorporating weight restrictions. Nevertheless, weight restrictions must be meaningful and justified. Consequently, this poses a new problem to the analyst who should be able to explain why particular weights restrictions were used, especially when there is no full cooperation with the stakeholders or there is a lack of information. Moreover, weight restrictions can pose as well technical and computational problems in some cases. For example, it is necessary to look for a compromise unique weight bounds suitable for all the units.
Due to these problems, we propose to take a different approach. We will introduce weight restrictions over the set of factors obtained from the PCA. The first factor from the set of inputs explains more variance than the second, the second explains more variance than the third, and the third factor explains more than the fourth factor. In that way, weight restrictions for the inputs are the next:

$$p_1 \geq p_2 \geq p_3 \geq p_4 \qquad (1)$$

with p_1 as the first factor's weight (1).
The same idea is applied to the set of factors obtained from PCA for the outputs.
With the application of Data Envelopment Analysis, we can obtain two groups of units. The non efficient ones will be classified and we could build a ranking, but the efficient ones will be in the same group without possibility of discrimination. In this point, we would like to know which units are robust efficient DMUs.
For this aim, we are going to use Multicriteria Decision Aid to increase the discriminating power of DEA for the efficient branches.
The multicriteria Decision Aid method chosen will be Electre Tri. Electre Tri is a non compensatory, outranking relations based method and deals with the issue relating to classifying each alternative into a predefined category. Reference alternatives are used to segment criteria into categories: each category is limited below and above by two reference alternatives and each reference alternative thus serves as a border for the two categories, one upper and the other one lower.
Electre Tri is therefore a method of assigning action (regions) to pre-defined categories (hypothetical reference regions). The assigning of an action (region) "a" results from the comparing of "a" to the profiles (action – regions- reference) that define the limits of categories. Electre Tri will be applied to the crossefficiency matrix of the DEA-efficient DMUs/branches.
Efficient branches will be classified into two groups: those branches that are efficient or reach good enough efficiency values over the different set of weights for DMUs, and those ones that are efficient with their optimal weights but that reach bad efficiency values with the rest of weights for the others DMUs. We could also name these classes as the robust efficient branches and the non robust efficient branches.
To this end we will work with the 2009 data from the Spanish National Institute of Statistics innovation and R&D activities surveys.
This identification of the most innovative efficiency Spanish economy activity branches will be carried out in three levels:

First level
Firstly, we will obtain the principal components of the inputs and, separately, of the outputs.
Second level
Secondly, it will be identified the efficient and the non efficient activity branches obtained by a DEA applied over the new variables precedent from the principal components analysis. We will use an output oriented DEA, with variable returns to scale and with weight restrictions extracted from the PCA Analysis.
Third level
In third place, we will apply an Electre Tri over the DEA efficient activity branches, in order to be able of distinguee robust efficient and non-robust efficient activity branches. This Electre Tri creates two groups, fourteen robust efficient activity branches and ten non-robust efficient activity branches.

IDENTIFICATION OF THE MOST INNOVATIVE EFFICIENCY SPANISH ECONOMY ACTIVITY BRANCHES IN THREE LEVELS

First of all it must be introduced the activity branches in which of research is focused on. How to separate or distinguish the different activity branches from the whole economy it is itself an interesting topic of research. We follow the international main stream activity branches division, leaded by the OECD Oslo Manual from 1995, improved in 2005. This reference gives the main international standard guidelines, followed as well by the INE (Spanish national institute of statistic).

Data source and specification

The basic data of our research is from the survey of technological innovation in the companies in 2009 organized per activity branches, published by the INE. This survey offers main indicators of technological innovation in 2009.

The selection of input and output variables

In our study of innovation efficiency, we use the indicators mention above as reference, with the combination of the availability of data, we finally choose twelve input variables and twelve output variables.
The input variables are:
• Total of innovative companies.
• Expenses in innovation: total in thousands of Euros.
• Expenses in innovation: R&D (internal and external) (%).
• Expenses in innovation: other innovative activities (%).
• Percentage of companies with innovative activities in 2009 over the total number of
companies.
• Percentage of companies with innovative activities with internal R&D.
• Percentage of companies with innovative activities with external acquisition of R&D.
• Percentage of companies with innovative activities with acquisition of machinery, tools and software.
• Percentage of companies with innovative activities with acquisition of external knowledge.
• Percentage of companies with formative innovative activities.
• Percentage of companies with innovative activities with introduction of innovation in the market.
• Percentage of companies with innovative activities in design and other applications to
production and/or distribution.
On the other hand, the output variables are:
• Intensity of innovation of the total companies.
• Intensity of innovation of the companies with innovation activities.
• Intensity of innovation of the companies with R&D activities.
• Percentage of companies with innovation in product (improvement of goods or services).
• Percentage of companies with innovation in the processes.
• Percentage of companies with innovation in product and processes.
• Percentage of companies that have introduced products that were a novelty only for the company.
• Percentage of companies that have introduced products that were a novelty for the market.
• Percentage of the company figure of business in 2009 consequence of the goods and/or services that were a novelty only for the company.
• Percentage of the company figure of business in 2009 consequence of the goods and/or services that were a novelty for the market.
• Percentage of the company figure of business in 2009 consequence of the goods and/or services that were a novelty only for the company in companies with innovations in course or not successful.
• Percentage of the company figure of business in 2009 consequence of the goods and/or services that were a novelty for the market in companies with innovations in course or not successful.

FIRST LEVEL
Principal Component Analysis

Firstly, we will obtain the principal components of the inputs and, separately, of the outputs, using the Principal Component Analysis.
Referring to the inputs, It has been identified four main factors over the inputs, which have a global variance explanation power of 82,685%. The explained variance of each component in 2009 could be observed in the following table**.**

Table 1: Inputs' explained total variance

INPUTS		
Component	**Variance percentage**	**Accumulated %**
1	**33,308**	**33,308**
2	**20,562**	**53,87**
3	**16,945**	**70,815**
4	**11,87**	**82,685**

Extraction method: Principal Component Analysis.

Once applied the matrix of rotated component weights, using the rotated method of Varimax normalization with Kaiser, it has been obtained four main factors that explains the most of the variance and oppose some variables to another.

Referring to the outputs, it has been identified as well four main factors over the outputs, which have bigger global variance explanation power. All the four factors explain the 93,181% of the variance. The explained variance of each component in 2009 could be observed in the following table**.**

Explained total variance: outputs

OUTPUTS		
Component	**Variance percentage**	**Accumulated %**
1	**36,543**	**36,543**
2	**28,15**	**64,693**
3	**17,328**	**82,021**
4	**11,16**	**93,181**

Extraction method: Principal Component Analysis.

As it has been previously done in the inputs case, here it has been as well applied the matrix of rotated component weights, using the rotated method of Varimax normalization with Kaiser, and it has been obtained four main factors that explains the most of the variance and oppose some variables to another.

SECOND LEVEL
Data Envelopment Analysis

Secondly it has been identified the efficient activity branches obtained by an output oriented DEA over the principal components of the inputs and of the outputs. By using this technique it is possible to identify which activity branches are efficient and which are not efficient.

DEA with weight restrictions
On a next step, we will introduce weight restrictions over the set of factors obtained from the PCA. The first factor from the set of inputs explains more variance than the second, the second explains more variance than the third, and the third factor explains more than the fourth factor. In that way, weight restrictions for the inputs are the next:

$$p_1 \geq p_2 \geq p_3 \geq p_4 \quad (1)$$

with p_1 as the first factor's weight (1).
The same idea is applied to the set of factors obtained from PCA for the outputs.
The weights restrictions applied in this case are detailed in the next table.

Weights

	Minimun	**Maximun**
input 1	**0**	**100**
input 2	**0**	**61,73**
input 3	**0**	**50,87**
input 4	**0**	**35,64**
output 1	**0**	**100**
output 2	**0**	**77,03**
output 3	**0**	**47,42**
output 4	**0**	**30,54**

Carrying out an output oriented DEA with variable returns to scale with these restrictions; we obtained twenty three efficient activity branches. By specifying the weights' value, the DEA eliminates possible efficient DMUs with unrealistic data. The next tables show the results of this DEA.

Efficient Activity Branches
Transport and storage
Textile
Cardboard and paper
Feeding, drinks and tobacco
Edition, impression and reproduction
Recycled
Mail and telecommunications
Other manufactures
Naval
Making and furrier
Leather and footwear
Non strong metals
Coke, petroleum and nuclear fuel
Automobiles
Office, calculation and computer machines
Other computer activities
Strong metals
Electric machines

Aerospace
Computer programs
Other material of transport
Electronic components
R&D services

Twenty three efficient activity branches

Non Efficient Activity Branches	Efficiency
Agriculture	98,51
Optic instruments and watch-make	97,33
Rubber and plastic	96,22
Machinery and mechanical machines	94,77
Radio, TV and Communication devices	94,25
Chemistry (except pharmacy)	93,44
Construction	92,82
Non Metallica minerals	92,34
Wood and cork (except furniture)	91,80
Furniture	90,83
Pharmacy	87,73
Financial services	84,58
Metallica manufactures	76,77
Trade and hostelry	76,50
Extractive	75,33
Public, social and collective se	75,00
Services to companies	74,36
Electricity, gas and water	68,23

Eighteen non efficient activity branches

THIRD LEVEL

Electre Tri

Once the previous analysis has been carried out, the final and most significance add value of this research has been completed by improving the capacity of discrimination of the DEA method by carrying out Electre Tri over the cross-efficiency matrix of the efficient activity branches when weight restrictions are considered.

We will consider the next parameters, trying to build two classes:

Indifference threshold	5
Preference threshold	10
Veto threshold	40
Profile	75

Working with these values, we obtained two classes, the first class with fourteen robust efficient activity branches, and the second class with nine activity branches.

Results are the following:

First class group: robust efficient activity branches
• Cardboard and paper
• Edition, impression and reproduction
• Making and furrier
• Leather and footwear
• Non strong metals
• Coke, petroleum and nuclear fuel
• Automobiles
• Office, calculation and computer machines
• Strong metals
• Electric machines
• Aerospace
• Computer programs
• Another material of transport
• Electronic components

Second class group: non robust efficient activity branches
• Transport and storage
• Textile
• Feeding, drinks and tobacco
• Recycled
• Mail and telecommunications
• Another manufactures
• Naval
• Other computer activities
• R&D Services

We may consider that if we work with a profile of 50% the program is not able to make a good discrimination. Nevertheless, if we improve this profile till 75% we obtain two groups, even without thresholds and veto. It suggests that we could try, for example, to build three different groups.

CONCLUSIONS

As it has been explained the three main conclusions obtained in this paper are:

1. Methodologically it is possible to introduce weight restrictions in DEA by considering the importance of the main factors obtained with Principal Component Analysis. It is possible to obtain a more realistic classification using DEA with weight restrictions.

2. Economic investment is not directly related with eficiency in innovation. It is the way of managing resourses what really supposes a wider efficiency level.

3. To be able to classify the activity branches in three groups: non efficient activity branches, non robust efficient activity branches and robust efficient activity branches, by using both DEA and Multicriteria Decision Aid methods.

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