Universidade de Aveiro Departamento de Economia, Gestão, Engenharia Industrial e Turismo
2018

Sara Reis Gomes Baptista

Avaliação da Eficiência de Inovação: Evidência para as regiões (NUT-II) da União Europeia

Evaluation of the Efficiency of Innovation: Evidence for European Union regions (NUT-II)

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Evaluation of the Efficiency of Innovation: Evidence for European Union regions (NUT-II)

Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Economia, realizada sob a orientação científica do Professor Doutor Victor Manuel Ferreira Moutinho, Professor Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro e sob coorientação científica da Professora Doutora Celeste Amorim Varum, Professora Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro.

Dedico este trabalho há minha família que, com todo o apoio incansável, me fez chegar até aqui e me fez percorrer todo este percurso com enorme sucesso.

o júri

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palavras-chave

Eficiência da Inovação, NUT-II, União Europeia, Determinantes da Eficiência, DEA, Estimador dos Erros-Padrão corrigidos em Painel, Método Generalizado dos Momentos.

resumo

Numa altura em que a Inovação é vista como um dos motores principais para o crescimento económico regional, este trabalho visa avaliar a eficiência da inovação de 104 regiões (NUT-II) da União Europeia de 2006 a 2012. Desta forma, o estudo cria um ranking das regiões mais eficientes baseado em indicadores de inovação e procura perceber quais os fatores que estão na origem desses resultados do ranking. Por outro lado, também a crise financeira global de 2008 veio abalar todas as perspetivas de crescimento sustentado para a Europa pelo que o impacto da mesma na Inovação e eficiência das regiões é tido em conta. Para isso foi utilizada a metodologia DEA, numa primeira fase para determinar os níveis de eficiência encontrados e *scoring* das regiões, e numa segunda abordagem a utilização das metodologias PCSE e GMM, para analisar os fatores que influenciam a eficiência da inovação medida pelo indicador proposto. Os resultados obtidos revelam grandes disparidades entre regiões, nomeadamente devido à crise, sendo que as regiões mais eficientes pertencem à Roménia, Bélgica e Bulgária. Os resultados apontam ainda para os recursos humanos como sendo o fator mais significativo para a evolução positiva da eficiência de Inovação.

keywords

Innovation Efficiency, NUT-II, European Union, Determinants of Effciency, DEA, Panel Corrected Standard Error estimator, System GMM.

Abstract

At a time when Innovation is seen as one of the main drivers of regional economic growth, this study aims to assess the efficiency of innovation of 104 regions (NUT-II) of the European Union from 2006 to 2012. In this way, the study creates a ranking of the most efficient regions based on innovation indicators and seeks to understand what factors are at the origin of these ranking results. On the other hand, the global financial crisis of 2008 has also shaken all prospects of sustained growth for Europe, so the impact of the crisis on Innovation and efficiency of the regions is taken into account. For this purpose, the DEA methodology was used in a first phase to determine the levels of efficiency found and scoring of the regions, and in a second approach the use of the PCSE and GMM methodologies to analyse the factors that influence the efficiency of the innovation measured by the proposed indicator. The results show large disparities between regions, namely due to the crisis, with the most efficient regions being Romania, Belgium and Bulgaria. The results also point to human resources as being the most significant factor for the positive evolution of Innovation Efficiency.

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Glossary

CRS – Constant Returns to Scale

DEA – Data Envelopment Analysis

DMU – Decision Making Units

EU – European Union

GDP – Gross Domestic Product

GMM – Generalized Method of Moments

HRST – Human Resources in Science and Technology

IE – Innovation Efficiency

IER – Innovation Efficiency Ratio

NSI – National System of Innovation

NUT - Nomenclature of Territorial Units

PCSE – Panel Corrected Standard Error

RIS – Regional Innovation Scoreboard

RSI – Regional System of Innovation

UK – United Kingdom

VRS – Variable Returns to Scale

1. Introduction, Context and Motivation

1.1. Introduction

Globalisation and regionalisation are a major challenge for European economies. Simultaneously, the key goal of these economies is to bridge the gap between regions in socio-economic terms and concerning efficiency, namely through the specialisation of European regions (Zabala-Iturriagagoitia, Voigt, Gutiérrez-Gracia, & Jiménez-Sáez, 2007).

Since the beginning of the 21st century, innovation has been considered one of the main sources of economic growth and dynamism. Globalization, phenomenon linked to technology and innovation, goes beyond national borders, with new concepts such as regional systems of innovation. Such concepts are a fundamental part of the industrial and economic development of regions (Doloreux, 2002; Patra & Krishna, 2015).

Regions create and accumulate knowledge and new ideas and this is a key source of value for advantage over other regions. Regions are networks, sharing and disseminating knowledge through other regions, including firms and institutions, (Doloreux, 2002). On the other hand, regions have different abilities to innovate and accumulate technology, hence disparities between regions emerge more visibly with the globalization process (Han, Asmild, & Kunc, 2016). Patra and Krishna (2015) argue that there should be communication between governments, universities and industry and even between firms. The Regional System of Innovation (RSI) was created for this purpose. According to Natário, Braga, Couto and Tiago (2012) the RSI is an adaptation of the National System of Innovation (NSI), but in regional terms. Nation-wide policies are thus adapted to the regional scope, where there is more proximity between the various players of innovation (firms, universities and institutions). Asheim, Smith and Oughton (2011) argue that the RSI was created because of the disparities between regions and also because innovation is regarded as a source of competitive advantage.

Furthermore, the scarcity of natural resources, or the excessive use of natural resources is one of the main challenges for modern societies. It becomes increasingly necessary to seek solutions to produce more with the same resources, or to produce the same with lower levels of resources.

In addition, innovation activities may have been affected by the most recent financial crisis, particularly in less developed regions. Subsequently to the global financial crisis of 2008, the interest in the reaction of regions to economic shocks has increased, especially concerning the identification of the factors originating different reactions among regions. According to Crescenzi, Luca and Milio (2016) and Lagravinese (2015), the regional resistance to economic shocks and the ability to recover after financial crisis are the main factors behind the heterogeneity across European regions.

1.2. Contextual setting and motivation

The truth is, based on the Eurostat report (2017), the medium and long-term effects of the crisis regarding regional GDP per capita are quite disparate. However, Eastern regions such as Poland, Romania and Slovakia have recovered faster, possibly because they were less affected. On the other hand, less industrialized and less populated regions kept their GDP unchanged. Also, competitive regions with industrial and scientific production and high-technology manufacture are those with higher growth rates in the post-crisis period (Statistical Office of the European Communities, 2017).

Regarding innovation performance and its components, the Eurostat 2017 annual study (Statistical Office of the European Communities, 2017) shows that the higher levels of R&D expenditures, number of researchers and Human Resources in Science and Technology (HRST) are found in capital city regions and neighboring regions, or clusters regions. This is the case of United Kingdom (UK), Germany and Austria regions. In contrast, the lower levels of R&D intensity are concentrated in Southern and Eastern Europe. Interestingly, between 2000 and 2007 the levels of R&D intensity (R&D expenditures regarding regional GDP) did not change significantly, but in 2008 and the following years there was a slight increase in R&D intensity, because the crisis caused GDP to fall more than R&D expenditures (Statistical Office of the European Communities, 2017).

Additionally, the more recent report of Regional Innovation Efficiency (European Commission, 2017), shows that over time there has been a divergence in terms of innovation performance. In fact, regions from countries such as Belgium, France, the UK, Greece and Poland show an increase in innovation performance, while regions from more peripheral countries, such as Portugal, Spain and Romania show a decrease over time. The same happens with the Czech Republic and Germany, declining in recent years their innovation performance.

Based on that recent evidence for the European regions performing, would it be possible to build a ranking of the regions that stand out most at the level of innovation performance and efficiency of innovation and see the differences between the pre-crisis period and during-crisis period? With all this in mind, it is essentially to understand what impact innovation has on the efficiency of European regions and what factors contribute most to increasing or decreasing their efficiency. Taking into account that the global financial crisis was one of the worst crisis after the Great Depression, it becomes important to analyse the way that the countries and respective regions were affect by this crisis and it is fundamental to understand the role of innovation as main contribution for the recovery.

Based on Figures A1 and A2 (see Annex) show that the regions with higher regional GDP in 2008 and 2015 are Southern Germany, South UK, Northern Italy, Belgium, Luxembourg, the Netherlands, Austria and Ireland. These are the most dynamic regions economically. Lower GPD regions are located in the south-eastern periphery of the European Union, including the more recent Member States. In 2008 (Figure A1 in Annex) such regions were far behind those with a consolidated position, meaning that the gap between regions is still wide. Nevertheless, they converge over time. By 2015 (Figure A2 in Annex), GDP growth was very significant in Bulgaria, Hungary, Poland and Romania, and there is a smaller gap between European Union regions.

Therefore, it is essential to understand the reasons for this evolution of regional GDP over time. In terms of Science, Technology and Innovation, it is also possible to confirm the disparities between the NUT-II regions, namely in 2008 (Figure A3 in Annex). The Eurostat report (Statistical Office of the European Communities & European Commission, 2011) showed that in 2008 regions from Germany and the UK had higher levels of R&D intensity, as well as all Nordic regions. In 2014 (Figure A4 in Annex), after the financial crisis, disparities subsist, but with a slight increase in R&D intensity levels, partly due to the Regional GDP decrease.

In addition, there are disparities between regions of the same country, for example in Belgium. A recent Eurostat report (2017) shows higher levels of R&D intensity in capital city regions. Nearby regions also show high levels. Peripheral regions suffer more over time, namely the southern and eastern European regions.

In the same way, Human Resources in Science and Technology (HRST) are considered key factors in regional economy development. Based on their evolution over time (Figure A5 and A6, see Annex) they concentrate in urban and capital regions, with more head offices and government institutions. In 2009 (Figure A5 in Annex), UK was the country with more HRST, followed by some regions in Spain. By the opposite, lower levels of HRST are located in Turkey, Romania and Portugal. By 2015 (Figure A6, in Annex), the scenario remains and UK regions keep the higher HRST levels, although with lower R&D. Romania shows the lowest levels of HRST. Again, Spain has high levels of HRST.

Finally, considering the Regional Innovation Index (RII), the most innovative regions are usually located in the most innovative countries, and according to Chart A1 (see Annex), the most innovative regions are located in Germany, Denmark, France, Finland and the UK. The less innovative regions are in Romania, Poland, Italy, Croatia and Bulgaria. Nevertheless, Poland, Italy and Bulgaria have a positive evolution over time. Germany, Belgium, France, The Netherlands, Finland and the UK have RII levels above average in the EU.

Taking into account some components of the Regional Innovation Scoreboard 2017, such as Population with high education levels (Chart A2, in Annex), R&D expenditure (Chart A3 in Annex), European Patents Office (EPO, Chart A4 in Annex) and Employment and high tech industries and knowledge-intensive services (Chart A5, in Annex), some conclusions may be vented. Firstly, Germany regions have low levels of population with high education levels, such as Romania, Italy and the Czech Republic. Spain, Belgium, Poland and the UK have the highest levels of this indicator. Regarding R&D expenditure, Germany, Finland and Sweden have the higher levels. Romania, Poland, Greece, Spain and Italy have the lowest levels of R&D expenditure. Regarding EPO patents, Germany and The Netherlands have the highest levels, and Bulgaria, the Czech Republic, Greece, Spain, Poland, Portugal and Romania the lowest. Lastly, Germany, the Czech Republic, the UK and Sweden have the higher levels of Employment medium and high tech industries and knowledge-intensive services, while once again, Greece, Spain, Poland, Portugal and Romania, except for the Vest region, have the lower levels of this component of RIS 2017.

Focusing on this previous analysis of Eurostat reports (2011; 2017) and European Commission (2017) about the evolution of regions in terms of GDP growth and innovation performance, namely in time of crisis, the motivation for this study is to understand the evolution of efficiency in EU regions based on the impact of innovation. In other words, how does innovation contribute to the growth and dynamism of regions?

Accordingly, the general goal of this study is to create an up-to-date ranking of European regions, particularly NUT-II regions, more efficient in terms of innovation. More specifically, the purpose of the present research is to verify the socio-cultural and economic dimensions that impact the most the growth and dynamism of regions. It is therefore important to understand the impact of the financial crisis not only on the efficiency of regions but also on the different components of innovation. Traditionally, the study of innovation activities and the efficiency of regions involve R&D expenditures and number of patents. The main contribution of this study is the application of a new ratio to measure the efficiency of regions, the Innovation Efficiency Ratio (IER). This ratio was not used before according to the literature review. It is the ratio between the Regional

GDP and the number of patents. IER consists of the inverse of Technological Production Intensity Index and its purpose is to measure how much regional gross value added is possible to reach given the number of patents.

In this perspective this study intends to answer the following research questions:

1. Which EU NUT-II regions are more efficient in terms of innovation and which countries do they belong to?
2. Which factors most affect the innovation efficiency of the regions?
3. What is the impact of the more recent financial crisis on innovation efficiency?

The truth is that there are not too much studies based on the levels of efficiency in terms of innovation of the NUT-II regions of European Union and in the construction of rankings that are focused on the territory and not focused on the institutions. In this sense, this study uses the Data Envelopment Analysis (DEA) methodology, created by Charnes, Cooper, and Rhodes (1978), to construct the ranking of most efficient regions, in terms of innovation, based on 104 NUT-II regions of European Union from 2006 to 2012. The DEA methodology is very popular among this type of studies because is a non-parametric methodology for measuring the technical-efficiency in the multiple-output and multiple-input cases (Wu, Zhao, & Liu, 2017; Zuo & Guan, 2017). Additionally, it is also used the super-efficiency DEA methodology to perceive which regions, which are efficient in terms of innovation, stand out more from the other regions (Han et al., 2016).

The second part of the study consists in the econometric application with the Panel Corrected Standard Error (PCSE) methodology and the Generalized Method of Moments (GMM) estimations to measure the impacts of the different socio-economic and cultural dimensions affect the levels of Innovation Efficiency.

In connection with this studies (Han et al., 2016; Kalapouti, Petridis, Malesios, & Dey, 2017; Sanso-Navarro & Vera-Cabello, 2017; Wu et al., 2017; Zuo & Guan, 2017) about innovation efficiency, the innovation policies play an important role here, because it is increasingly necessary to ensure the diffusion of knowledge between regions in order to ensure that all regions have the potential to become efficient. In fact, regional innovation policies should to support firms for innovation and to promote the share of knowledge between them and institutions, and Regional System of Innovation (RSI), and thus improve the innovation performance of regions.

The thesis is structured as follows:

- Chapter 2 consists of the literature review about the previous innovation efficiency studies, the DEA methodology and the inputs and outputs selection;

- Chapter 3 presents the Data used in the analysis and the Empirical setting, namely the DEA methodology, PCSE and GMM estimations;

- Chapter 4 have three sections: the first section is about the efficiency and super-efficiency analyses, the second is the econometric application with PCSE and GMM estimations and lastly, the discussion about the results;

- Chapter 5 is the main conclusions and the limitations of this study.

2. Literature Review

Innovation is considered one of the most important sources of economic growth in the long term. This is because it allows industry and services a chance to overcome the crisis periods, but also because it allows less excessive use of the increasingly scarce natural resources to manufacture the same products, or even more and better products (Tubadji & Nijkamp, 2016; Wang, Fan, Zhao, & Wang, 2016; Zuo & Guan, 2017). It is therefore important to define what innovation is. Innovation is a process conducted by many agents, namely enterprises, universities and research institutions, affected by various internal and external factors. Also, agents influence one another and form a network of cooperation and dissemination of knowledge. Governments play a key role because they regulate the regional innovation environment by formulating science and technology policies (Wang et al., 2016). Linked to innovation, the R&D process is considered creative work aimed at the expansion of knowledge for society, through culture, and also through the application in different products (Chen, Kou, & Fu, 2017). Innovation and R&D are increasingly concerning companies and governments because they have an impact at various levels, namely regional, educational and institutional levels (Han et al., 2016; Liu, Lu, & Ho, 2015).

In fact, given the importance of innovative activities, the National System of Innovation (NSI) was created and is based on the creation of new policies towards widespread innovation (Lundvall, Johnson, Andersen, & Dalum, 2002). The main goal of NSI is to develop incentives and efforts from countries in innovation activities with the production and accumulation of knowledge where the institutions and firms interact in a national context. However, although important for economic development, this is difficult to implement in all countries. In fact, given the characteristics of the countries, the Nordic European countries are more receptive, whereas southern countries require several adjustments to enable the application of the same system (Lundvall et al., 2002).

Similarly, the concept of Regional System of Innovation (RSI) stemmed from the concept of National System of Innovation (NSI). It is a combination of regional characteristics and settings that provide a favorable environment for innovation and in which the firms and organisations learn from each other (Doloreux, 2002; Zabala-Iturriagagoitia et al., 2007). Subsequently, the RSI is connected to the knowledge stock of firms from a given region and their intercommunication. This depends on internal and external factors to the firms, namely the network of private and public sectors. Hence, the RSI is constituted by firms, institutions, knowledge infrastructures and innovation policies that are applied in a specific territory. When firms and institutions interact, this is considered interactive learning, generating innovation, since the firms share know-how (Doloreux, 2002). Also, Natário et al.(2012) argue that the RSI tries to reduce the disparities between northern and southern regions in the EU, not only concerning innovation but also education, thus assuring the generation and dissemination of knowledge. It is therefore possible to conclude that proximity is important regarding innovation, namely space agglomeration and transaction costs. However, there are also barriers to RSI, specifically when there is no cooperation between regions and there is no trust between the different agents for innovation (Doloreux, 2002).

On the other hand, innovation is directly linked to the efficiency of the country and the region. Broekel, Rogge and Brenner (2018) defined innovation efficiency as a benchmarking measurement of the relation between innovative outputs, such as the number of patents in a region, and innovative inputs such as R&D employment, comparable with other regions.

Han et al. (2016) explain that more efficient regions are those with higher levels of productivity from the R&D process. For Schaffer, Simar and Rauland (2011) a region is considered comparatively efficient if one or more other regions equipped with a similar or worse level of inputs generates a higher level of outputs. Furthermore, Han et al. (2016) and Liu et al. (2015) created various groups of regions and countries according to their characteristics in terms of innovation and efficiency levels. They created four groups: the *Deteriorating, Lagging, Catching-up* and *Leading*. The *Deteriorating group* includes efficient regions whose productivity level is declining. The *lagging group* includes regions with low levels of efficiency and also low levels of productivity. The *Catching-up group* includes outstanding regions due to productivity increase, but with relatively low regional efficiency. Finally, the regions and countries included in the *Leading group* are those with high levels of productivity and also high levels of efficiency (Han et al., 2016).

Liu et al. (2015) organized a set of nine groups because they divided countries according to the inputs/outputs that favour or hinder the country, taking into account which inputs/ outputs stand out the most between the studied countries.

Furthermore, Fagerberg and Srholec (2008) argue that there are a positive correlation between Innovation and GDP per capita. In this way, when a country aims at developing from a lagging-behind position to a catching-up position, this requires a good system of innovation. One the other hand, the same authors (Fagerberg & Srholec, 2008) also argue that the poorer countries don’t have absorptive capacity, given their story, geography and nature. This means that the countries that can develop and keep their strong innovation capacities and a good governance system will be economically successful and countries that fail will tend to lag behind.

Additionally, some authors argue that innovation is not distributed homogeneously through regions, but rather tends to agglomerate in certain areas (Enright, 2003; Feldman, 1994; Porter, 1998; Valdez Lafarga & Balderrama, 2015). The main reasons for this disparity in terms of efficiency between regions are the availability and quality of local inputs and the geographically bound knowledge spill-overs (Fritsch & Slavtchev, 2011). Sanso-Navarro and Vera-Cabello (2017) conclude that regional innovation also depends on the knowledge stock available in nearby regions, and not only on the regional resources. On the other hand, Li and Wang (2017) showed that the main problems in industry concern insufficient investment in R&D resources, lack of technological innovation capability, significant waste of resources and low conversion rate of scientific and technological achievement. Also, the levels of internal expenditure of R&D and R&D personnel input are higher in some industries than in others. For those industries with insufficient input of R&D resources, the output is also insufficient. Regional areas have different features compared to national areas because there are connections due to the interaction between the areas, such as clusters or special economic zones where knowledge is shared. This includes the spillover effect among regions that allow higher productivity and regional performance (Bosco & Brugnoli, 2010).

In this sense, Doloreux (2002), Ozkan and Kazazoglu (2016), Rodríguez-Pose and Crescenzi (2008), Zabala-Iturriagagoitia, Voigt, Gutiérrez-Gracia, and Jiménez-Sáez (2007) argue that the clusters and networks play an important role on innovation efficiency and in regional development. Additionally, Broekel et al.(2018) argue that universities and firms should connect and collaborative networking is also important. In the same way, Li and Wang (2017) conclude it is necessary to strengthen the cooperation between universities and research institutions with firms. This cooperation will allow enterprises to become more competitive and in turn generate added value for economy. Finally, Ozkan and Kazazoglu (2016) advocate that government support, namely grants programs for research institutions and projects is very important for regional development and innovation.

Apart from concepts, it is also important discuss the best model to measure innovation and efficiency. Many authors argue that one of the most popular and best model is the Data Envelopment Analysis (DEA) model (Dzemydaitė, Dzemyda, & Galinienė, 2016; Gitto, 2017; Liu et al., 2015; Zuo & Guan, 2017). The DEA model was developed by Charnes and Cooper (1984). It's a non-parametric methodology to measure the technical-efficiency in the multiple-output and multiple-input case (Zuo & Guan, 2017). Specifically the nonparametric DEA estimators are based on linear programming methods and they have been widely applied in productive efficiency analyses (Gitto, 2017).

First of all, DEA allows building a ranking of relative efficiency through a production frontier based on all Decision-making units (DMUs). This way, the analysis is applicable to several levels of aggregation, such as a firm, an organization, universities, banks or a nation (Liu et al., 2015; Valdez Lafarga & Balderrama, 2015). In this case, the DMUs are the regions under study. Furthermore, the DEA model does not take into account the input and output weight. This means that if two DMUs have the same output but different levels of mixed inputs, both DMUs may be considered efficient (Chen et al., 2017; Wang et al., 2016). On the other hand, the DEA model is based on several assumptions, namely regarding the input or output orientation and also in constant or variable returns to scale (CRS or VRS, respectively). When this model assumes constant returns to scale (CRS) this indicates that the regional innovation efficiency is uncorrelated to region size (Broekel et al., 2018).

In summary the DEA model is a powerful tool to measuring the innovation-efficiency performance at regional level and, consequently allows an orientation to public policies related with the regional efficiency (Dzemydaite & Galiniene, 2013). Nevertheless, there are other models that derive from DEA model, such as the Super-efficiency DEA model. Particularly the Super-efficiency model is also a model that allow to identify the most efficient regions, yet, it facilitates this discrimination because all the regions that in the Standard DEA have a score of 1, in the case of super-efficiency scores of these regions, these will be equal to or higher than 1. In this way, theses scores represent the degree to which the DMU can decrease the inputs while maintaining the level of outputs and still remain efficient (Han et al., 2016). Furthermore the super-efficient regions are seen as benchmarks to less efficient regions or, in other words inefficient regions. In this perspective, the super-efficiency DEA model is considered as computationally efficient and it is able to measure efficiency performance as anticipated (Bongo, Ocampo, Magallano, Manaban, & Ramos, 2018).

Regarding the inputs and outputs used by the literature on innovation, the main inputs are R&D expenditure, R&D personnel and R&D capital stock (Chen et al., 2017; Dzemydaitė et al., 2016; Guan & Zuo, 2014; Kalapouti et al., 2017). R&D expenditure is the main input to measure innovation and the ability to adapt to external innovation (Rodríguez-Pose & Crescenzi, 2008). Concerning outputs, the most used are the number of patents and the number of publications and/or articles on scientific journals (Chen et al., 2017; Zuo & Guan, 2017). However, Sanso-Navarro & Vera-Cabello (2017) argue that the number of patents is only a fraction of innovation, since patents don't include protected process or innovative organizational activity.

On the other hand, knowledge spill-overs are a good indicator for new knowledge (Sanso-Navarro & Vera-Cabello, 2017). Sometimes the GDP per capita is also used as output variable (Dzemydaitė et al., 2016; Dzemydaite & Galiniene, 2013). It is important to emphasize that the search for new variables and/or indicators to measure innovation and efficiency is a constant goal for researchers, scholars and statistical institutes. New variables may provide useful, detailed and flexible results for public policies and policy makers (Bosco & Brugnoli, 2010).

The variables that represent human resources are increasingly important in these innovation-related studies, for example the tertiary education and /or employed in science and technology or population age 25-64 by education level, because according to several authors (Dzemydaitė et al., 2016; Guan & Zuo, 2014; Kalapouti et al., 2017; Li & Wang, 2017) human resources are the most significant variables. Even in times of crisis, firms are reluctant to fire their researchers and qualified human resources (Filippetti & Archibugi, 2011). Human capital and education are thus considered determinant sources of economic growth, contributing to the efficiency of regions.

Additionally, Rodríguez-Pose and Crescenzi (2008) argue that inputs related to human resources and education level are a social filter, because they describe the socio-economic characteristics of regions, namely the ability to acumulate skills at a local level.

Table 1 show a summary of the variables and the main models used to measure the efficiency of innovation.

Table 1. Summary of variables and methods used to evaluate the efficiency of innovation

Author(s)	DMUs	Methods	Variables		Results
			Inputs	**Outputs**	
Evaluation of multi-period regional R&D efficiency: An application of dynamic DEA to China's regional R&D systems **(Chen et al., 2017)**	29 China's Provinces during a time-period of 2006 to 2010	**- Dynamic DEA:** - CRS model - Input-orientation	- R&D expenditures; - R&D personnel; - R&D capital stock (carry-over),	- SIC papers; - Domestic granted patents;	- In general terms no regions are considered efficient based on the the general operation of R&D production systems over the first five years; - In average, the developed regions are more efficient than the developing regions, which means that the favorable innovation environmental factors can improve the regional R&D efficiency, like information technology, education and training, and industry cluster; - The institutions play a very important role because they directly influences the process management of R&D activities.
Regional R&D Efficiency in Korea from Static and Dynamic Perspectives **(Han et al., 2016)**	15 Korea Regions for the period 2005-2009	**- DEA:** - Standard DEA; - Super-efficiency DEA; - CRS model; - Input orientation; **- MPI (Malmquist Productivity Index);**	- R&D expenditures including the R&D staff and Accumulated knowledge;	- Codified Knowledge; - Number of Patents;	- The results obtained allowed to create three groups of regions under study, i.e. deteriorating, lagging and improving regions; - There are also the fourth group, the leading-group but there is no region with this characteristics; - Seoul was categorized as a deteriorating region characterized as efficient but with decreasing productivity; - The case of Seoul demonstrates that abundant researchers, finance and government support do not necessarily imply high static or dynamic R&D efficiency; - There are some interregional disparity in terms of static R&D efficiency.
National characteristics: innovation systems from the process efficiency perspective **(Liu et al., 2015)**	40 countries in a time-period of 2005 to 2009	**- Multi-stage DEA:** - VRS model - **Network-based ranking method;**	**KPP:** - R&D capital stock; - Education expenditure; - The number of researchers;	- The number of social science articles and science and engineering articles; - High-tech exports;	- The authors created nine groups of regions based on their characteristics; - The groups of regions that most stood out were those of the emerging economies and those have a high levels of producing high-tech exports;

			KCP: Business expenditure on R&D; - Employment in industry and service;	- Productivity in industry and productivity in service are the products; -domestic patents and overseas patents;	- The close interaction with neighboring countries has a positive effect on a country's innovation process that is the knowledge spillover.
Regional innovation environment and innovation efficiency: the Chinese case **(Wang et al., 2016)**	**Chinese regional innovation systems** » 22 variables for the period between 2009 and 2012	**- DEA:** - VRS Model	- Full-time equivalent of R&D personnel; - Annual total R&D intramural expenditures;	- The number of invention patent applications - The number of utility model and design patent applications - Indicator of new product outputs (NPO)	- The Innovation Efficiency (IE) is affected by the Economic Infrastructure (EI), Quality and Structure of Innovators and the Regional Openness (RO) and all of them have a positive impact in the IE. - QSI is the only one with a direct impact on IE; - The results indicate that China is in a transition period from pursuing its growth rate and size to pursuing efficiency and quality. In this way, it is necessary to construct an innovation environment; - It is essential that China's government pay more attention to the improvement of university-quality evaluation; - The high-tech industry is increasingly important for innovation; - The public policies should be adapted to the levels of regions development.
Performance of national innovation systems during the global crisis: a cross-country analysis **(Ozkan & Kazazoglu, 2016)**	58 countries during the global crisis from 2007 to 2012	**- DEA:** - input oriented; - output oriented; - CRS Model; - VRS Model;	- Net FDI Inflow in billions (current US$) Human; - Expenditure on R&D in billions (current US$); - Total researchers per million habitants; - Internet users per 100 people; - Mobile subscriptions per 100 people;	- Patents per million population; - Publications per million pop.; - ISO 9001 certificates issued in absolute numbers; - High technology exports in billions (current US$);	- There are negative effects on the countries' efficiency caused by the crisis of 2008; - Turkey is one of the countries with lowest efficiency scores despite increasing its R&D investment; - The clusters and network play an important role on the Knowledge diffusion and the government support, namely the grant programs, are very important to the research groups and projects. - Particularly, it necessary to analyse the regional development and the innovation system plans to better understand the efficiency scores, namely In Turkey.

			- Electricity Consumption (kWh per capita); - GDP per unit of energy use (constant 2011 PPP $ per kg of oil equivalent);		
The Efficiency of Regional Innovation Systems in New Member States of the European Union: A Nonparametric DEA Approach **(Dzemydaitė et al., 2016)**	- 40 EU regions (NUTS 2) - 2013	**- DEA:** - input oriented	- The intramural cumulative expenditures for research and development (R&D) in pps per inhabitant; - Human resources in science and technology calculated as a number of persons with tertiary education (ISCED) and/ or employed in science and technology, as percentage of total population; - Human capital employed in high technology and knowledge-intensive sectors, the percentage of total employment;	– Number of patents per inhabitant; - Gross domestic product in purchasing power parity per inhabitant;	- There are some disparities between the regional inputs and the real output which means that even if regions spend a lot on R&D and have a lot of human resources this doesn't guarantee high levels of value added for the economy; - The efficiency of regions depends of the levels of available resources; - Skilled and creative human resources are very important to the regional innovation system.

***The innovation efficiency of German regions – a shared-input DEA approach* (Broekel et al., 2018)**	- 150 German labor market regions for the period 1999 to 2008	**- Shared input DEA model:** **-** CRS model; - Output Orientation - Malmquist Productivity; Index (MPI); - Robustness analysis;	- Total R&D employment;	- Nº of patents;	- The connection between universities and firms are very important and collaborative network is also important; - The robust shared-input Data Envelopment Analysis is an advantageous model to measure the regional efficiency, namely when is used the employment data.
***Evaluation and analysis on R&D input-output performance of the major sectors of industrial enterprises based on the DEA method* (Li & Wang, 2017)**	- 25 industries of industry in Hebei province. - 2014 compared to 2010	**- DEA:** - CRS model; - VRS model;	- R&D personnel full time equivalent; - Internal expenditure of R&D funds;	- Sales revenue of new products; - Nº patents;	- The cooperation of the universities and the research institutions with the firms is very important; - The allocation efficiency of R&D expenditure is low which means that is necessary to focus on optimizing allocation of R&D resources; - The human resources and the R&D personnel play an important role on the innovation process; - For an industry whose comprehensive efficiency is low, and its return to scale is decreasing, it is necessary to reduce the waste of R&D resources and improve the technical efficiency.
***A cross-country comparison of innovation efficiency* (Guan & Zuo, 2014)**	- 35 countries - 2007 to 2011	**- Dual network-DEA models:** - CRS and VRS assumption;	- full-time equivalent researchers; - Gross domestic expenditure on R&D; - Prior accumulated knowledge stocks;	- Number of patents granted; - Publication in scientific journals (PAPER) as the proxy for scientific outputs. - Added value of industries (AVI); - The export in high-tech industries (EHTI);	- Several countries of this study are considered inefficient; - Austria, Estonia, Finland, Iceland, Portugal, Slovenia, and South Africa are considered countries with increasing returns-to-scale which means that to acquire better performance, this countries need to increase the innovative inputs; - For countries like the Australia, Canada, France, Germany, Netherlands, United Kingdom, China, Japan, Korea, and United States it is necessary reformulate some R&D activities namely with the innovation systems; - It Is essential to invest on universities and in the human resources to increase the R&D productivity.

Evaluation of regional efficiency disparities by efficient frontier analysis **(Dzemydaite & Galiniene, 2013)**	Lithuanian NUTS3 territories - 2011	**- DEA:** - Output Orientation; - Free disposal hull (FDH); - Order-α frontier analysis;	- Region’s transport infrastructure; - Human capital;	- The per-capita gross domestic product;	- DEA model is appropriate when there are not a lot of observations as the case of Lithuania; - The most efficient regions as Vilnius, Klaipėda, Utena, and Marijampolė should focus on indirect programmes to increase the number of human resources and develop the transport infrastructure; - Alytus, Tauragė, Kaunas, Šiauliai and Panevėžys were considered inneficient regions, so it is import to adopt direct programmes of the economic development.
Efficiency of Mexico's regional innovation systems: an evaluation applying data envelopment analysis (DEA) **(Valdez Lafarga & Balderrama, 2015)**	Mexico´s regional innovation systems, as defined by its 32 states;	**-DEA:** - CRS Model; - Output-oriented; - ANOVA	- Quality graduate programmes; - Number of CONACYT scholarships; - Research centres; - Higher Education Institutes (HEI) with graduate programmes linked to science and technology; - Budget applied to R&D funds; - National System of Researchers; - Enrolment in Science and Technology graduate programmes;	- Patent applications; - Scientific publications;	- There are not a positive relationship between the amount of innovative resources and the levels of productivity efficiency; - The group of states with the lowest efficiency scores are the same with the highest levels of R&D expenditures; - The states that suffered more with the scarcity of resources are those have the poorest results of efficiency.
Measuring efficiency of innovation using combined Data Envelopment Analysis	192 NUTS-2 for 12 years (1995–2006)	**- DEA:** - CRS Model; - VRS Model;	- Human Capital; - Expenditures in Research and Development;	- PATTPS - PATGPS (patents according to application date	- The regions with highest levels of patent activity are the same with high levels of innovation efficiency and, in this way, are an influence for the neighbours regions not only in geographical but

and Structural Equation Modeling: empirical study in EU regions **(Kalapouti et al., 2017)**		- SEM (Structural Equation Model) modeling		measured per million of inhabitants) **SEM** MODELING Y: EFFICIENCY SCORES X: - Patent Applications; - Employment Level; - Development Level - Degree of Innovation Diversity	also in a technological space (inter-regional knowledge spill-overs); - The regions with higher levels of employment get more efficiently the exploitation of innovation sources; - The regional development affects the innovation efficiency i.e. the regions less developed can achieve high levels of innovation efficiency if they pursuit a centralised innovation policy, in specific technological fields and the regions more developed will get high levels of innovation efficiency if they follow a decentralised policy;
Regional Efficiency, Innovation and Productivity **(Bosco & Brugnoli, 2010)**	185 EU regions averages 1995 -2007	**- DEA:** - Output Oriented; - CRS Assumption; - OLS;	- Employment in technology and knowledge-intensive sectors; - Total intramural per capita R&D expenditure; - Total R&D personnel and researchers; - Number of students at the tertiary education; - Population and labor productivity (computed as regional gross value added divided by the regional employment)	- Nº of patent applications; - Gross value added at basic prices;	- There are a positive relationship between innovation and R&D and patents; - There are a positive relationship between labour productivity and patents, R&D expenditures and tertiary education; - The regions with best performance are both rich, large regions but small regions as well;

Source: Our Elaboration

Regarding the results of the different studies on innovation and efficiency, they are unanimous concerning the positive impact of innovation activity on innovation efficiency. Using a Dynamic DEA model Chen et al. (2017) evaluated China's provinces between 2006 and 2010 and concluded that more developed regions have more favorable environment for innovation because they enjoy better conditions, namely more information technology, high levels of education and training and industry clusters. These characteristics are not so clear in developing regions, which explains the lower levels of innovation efficiency. On the other hand, Chen et al. (2017) explain that soft innovation, concerning institutions such as universities, is more important that hard innovation (education and training, industry clusters, etc.), because soft innovation affects R&D activities and the innovation process directly.

Sometimes, institutions are a critical factor for the technological development of a region (Chen et al., 2017). Wang et al.(2016) showed that regional innovation has a positive impact on regional efficiency. Studying 288 science and technology policies in China, the authors conclude that concerning innovation output, China pursues efficiency and quality and a high growth rate. Thus, regional innovation has a significant impact on innovation efficiency. In addition, Wang et al.(2016) argue that China's policy makers should pay more attention to building innovation environments, namely through universities quality improvement and the high-tech industry sector, because industry clusters are a major force towards technological development.

Focusing on European regions, Dzemydaitė et al.(2016) showed that the highest values of all indicators used in the study tend to be in capital regions, particularly in Central European Union, with higher values of human resources in science and technology. Studying 40 regions from Eastern and Central European Union applying the DEA model, these authors identified that the regions with high GDP ratio, capital regions, may reach higher levels of GDP ratio with the same resources. In this way, these regions were considered inefficient comparatively to other regions with lower levels of GDP ratio because they don't generate enough real output. One the other hand, the regions with lower levels of GDP ratio were considered efficient because, even with a reduced level of inputs the same regions can achieve better economic results. In these sense the authors conclude that the human resources and tertiary education in science and technology are fundamental indicators to create more value added for certain regions. Even though, the investment in these indicators does not guarantee that the regions will achieve higher levels of value added and higher levels of efficiency. So, it is necessary that policy makers pay more attention to this situation and think how they can improve the regional innovation policies, namely in inefficient regions that can generate higher output with the same innovation inputs (Dzemydaitė et al., 2016). Studying 192 NUTS-II European Regions during 12 years applying the DEA model in the first stage and the Structural Equation Model (SEM) in the second stage, Kalapouti et al. (2017) concluded that the regions with higher levels of innovation activity measured by the number of patents applied also have high levels of innovation efficiency. Accordingly, these regions are considered knowledge spill-overs towards their neighbours, geographically and technologically.

This means that the more these regions innovate, the greater will be their ability to create and develop knowledge spill-overs. Furthermore, the authors argue that regions with more employment in high-tech sectors also achieve better results more efficiently because they manage innovative resources better. As a result, these regions become desirable for innovative agents and partners (Kalapouti et al., 2017). Additionally, Kalapouti et al.(2017) argue that regional development impacts innovation efficiency.

Specifically, less developed regions in terms of GDP per capita are regions with high levels of innovation efficiency, which means that the regions are more powerful in managing their innovative sources, even if inputs are reduced and their level of regional development is lower. However, this does not mean that more developed regions are not efficient. They are efficient but waste more innovative inputs. The authors argue that these regions may achieve better results if they follow a more decentralised policy. The less developed regions should follow more centralised policies (Kalapouti et al., 2017).

Finally, Bosco & Brugnoli (2010) evaluated the innovation and productivity and the relationship between them in European regions and they found that the education and productivity have a positive correlation in several regions, not only in rich and large regions but also in poorer and smaller regions. This is possibly because poorer regions use innovative inputs more efficiently, through a catching-up process. Additionally, the authors found a positive correlation between patent application and the regional Gross Value Added (GVA), of almost 77% considering all observations.

However, when they consider patenting activity alone there are no regions with positive and significant effects on GVA. In more recent regions in the EU this correlation is negative and significant. In terms of labour productivity there is a positive correlation between patents, R&D expenditures, tertiary education and productivity. On the other hand, Matei and Spircu (2012) based on a nonparametric approach (DEA) evaluated the efficiency of Regional Systems of Innovation in 116 regions (NUT-II) from 13 countries in Europe and concluded that the most efficient regions concerning RSI are those with more proximity between private and public institutions, with a greater number of large companies and research institutions and holding more qualified human resources, as the Lisbon region in Portugal.

Studying United Kingdom (UK) enterprises, Frenz and Ietto-Gillies (2009) concluded that innovation performance is also affected by the internalization of the enterprises. The more internationalized, more innovative activities will be developed. However, this also depends on the characteristics of each country, particularly regarding the National System of Innovation. For Frenz and Ietto-Gillies (2009), UK is a leading country because it has a good NSI structure and a high internalization level. Nevertheless, the results obtained by these authors do not apply to other countries.

3. Data and Methodology

3.1. Data

This study collected data from 104 Nut-II regions from European countries for the period between 2006 and 2012. The considered inputs are the levels of tertiary education and/or employed in science and technology (HRST), intramural R&D expenditure (GERD) by sector of performance (all sectors) in euros per inhabitant and the employment in high-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services) as percentage of total employment. The outputs are Gross Domestic Product at current market prices in purchasing power standard (PPS) per inhabitant and number of patents per million of in inhabitants (EPO). Additionally, other variables were chosen for the second stage of the study, the Gross Value Added at basic prices focused on Industry measured in million euros, the number of total R&D personnel and researchers by sector of performance, and population aged 25-64 by tertiary level education. The source for all data was the Eurostat database[1] and the data were selected based on the several components of Regional Innovation Scoreboard.

3.2. Methodology

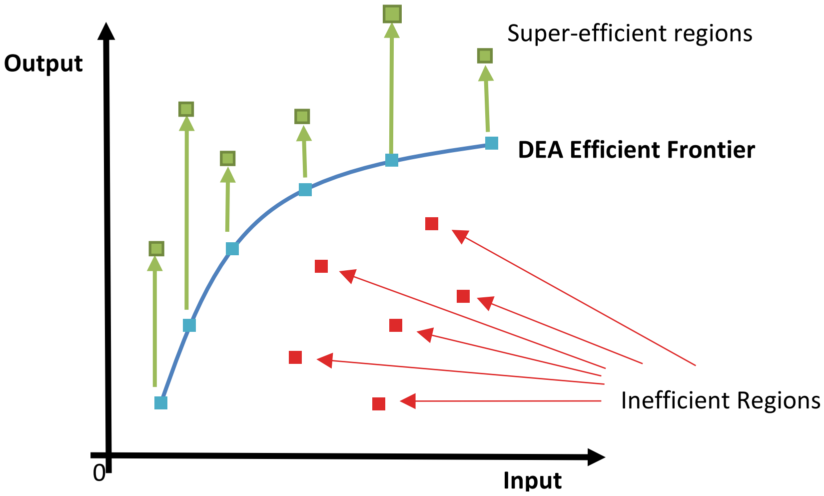
3.2.1. DEA Model

To evaluate regional innovation in European regions, the first stage will be to organize a ranking of regions standing out for the best and the worst performance. The chosen model for this analysis was the DEA model. The DEA is a non-parametric method that Charnes, Cooper and Rhodes (1978) based on mathematical linear programming methods and measures the levels of efficiency of different relative independent units, named DMUs. The DMUs are comparable units that use the same resources but in different proportions, and they are responsible to transform multiple inputs into multiple outputs.

In this case, the DMUs are the NUT-II European regions. Additionally, the DEA model does not impose an explicit functional form and consequently does not require an a priori assignment of input and output weights, which are not fixed or pre-determined (Cooper, Seiford, & Tone, 2006). The weight for each input and output is variable and derives from data. Graphically, the DEA model builds a technological production function named efficiency frontier that is composed by regions considered efficient:

[1] http://ec.europa.eu/eurostat/data/database

Chart 1. DEA Frontier



Source: Our Elaboration

The efficiency frontier represents the Production Possibility Set; the set of all possible combinations between the multiple inputs and outputs of the production sector. In other words, the efficiency frontier bounds the area where DMUs can be located.

To maximise the relative efficiency of unit j_0, or adopt the most favourable set of weights for DMUs requires the following function:

$$RE_{j_0} = max \frac{\sum_{p=1}^{s} v_p y_{pj_0}}{\sum_{q=1}^{m} w_q x_{pj_0}} \qquad (1)$$

Subject to:

$$\frac{\sum_{p=1}^{s} v_p y_{pj}}{\sum_{q=1}^{m} w_q x_{pj}} \leq 1, \qquad j = 1, \dots, n$$

$$v_p \geq \varepsilon, \qquad p = 1, 2, 3, \dots, s$$

$$w_q \geq \varepsilon, \qquad q = 1, 2, 3, \dots, m$$

This function corresponds to the maximization of the ratio of the weighted sum of the outputs relative to the weighted sum of the inputs, where the weights are established by the DEA model for each DMU. Specifically, $RE_{j_0}$is the score of relative efficiency of unit j_0 or, more precisely, of DMUj_0; x and$y$ are, respectively inputs and outputs, and v and w are weights of outputs and inputs, respectively; p is the number of outputs ($p = 1, 2, 3, \dots, s$), q is the number of inputs ($q = 1, 2, 3, \dots, m$), and n is the number of DMUs of the sample.

Subsequently, the most efficient regions are those with the best combinations of inputs and outputs and are considered benchmarks for less efficient regions. When the optimal weighting of outputs and inputs for a region yields an efficiency ratio of one, the region is efficient, but when it is less than one the region is considered inefficient. The weights are determined through the DEA model and vary from one DMU to another DMU.

3.2.1.1. CCR and BCC models

Efficiency is related to the waste reduction ability in the productive process. An organization is efficient when it reaches the maximum output level with a certain level of inputs, using the least possible production inputs to reach a certain level of outputs.

Hence, the regional efficiency may be estimated through the DEA model considering less inputs and constant outputs (input orientation), or constant inputs and higher outputs (output orientation). The choice between the two orientations depends on study goals and DMUs (Rebelo, 2017). The formulations are as follows:

Input Orientation

For the linearization of the expression (1) with input orientation it is necessary maximise the numerator and set the denominator equal to 1:

$$RE_{j0} = max \sum_{p=1}^{s} v_p y_{pj0} \qquad (2)$$

Subject to:

$$\sum_{q=1}^{m} w_q x_{pj0} = 1$$

$$\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} \leq 0$$

$$v_p \geq \varepsilon, \qquad p = 1, 2, 3, \dots, s$$

$$w_q \geq \varepsilon, \qquad q = 1, 2, 3, \dots, m$$

As a result, the estimations of the DEA model will present the necessary amount of inputs that must be reduced, taking into account the output level in order to reach 100% efficiency.

Output Orientation

For the linearization of the expression (1) with output orientation the denominator has to be minimised and the numerator has to be equal to 1:

$$RE_{j0} = min \sum_{q=1}^{m} w_q x_{pj0} \qquad (3)$$

Subject to:

$$\sum_{p=1}^{s} v_p y_{pj0} = 1$$

$$\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} \leq 0$$

$$v_p \geq \varepsilon, \qquad p = 1, 2, 3, \dots, s$$

$$w_q \geq \varepsilon, \qquad q = 1, 2, 3, \dots, m$$

With this orientation, DEA model estimations will present the output amount to increase, considering input levels to reach 100% efficiency. The ratio of the weighted sum of outputs considering the weighted sum of inputs equals 1.

In both orientations, assuming constant returns to scale, the ${RE_{j0}}^*$ is the optimal relative efficiency score for DMUj_0 and the $\varepsilon$is an infinitesimal positive number.

The production function of the efficient DMUs are also characterised by the returns to scale. They can be divided in constant returns to scale (CRS) and variable returns to scale (VRS). When a production process presents constant returns to scale it means that input variation may cause output variation in the same direction and proportion; when a production process has varying returns to scale it means that input variation may cause proportional output decrease in case of decreasing returns or increase if case of increasing returns to scale.

In this context the DEA methodology takes into account those characteristics of returns to scale and therefore two different approaches have been created in mathematical programming terms, to compute the DEA model which are the Charnes-Cooper-Rhodes (CCR) that assumes constant returns-to-scale (Charnes et al., 1978) and the Banker-Charnes-Cooper (BCC) which is a variable returns-to-scale model (Cooper et al., 2006). Both models are input-or-output oriented depending if the goal is minimize the input where the output is constant or maximize the output with the input levels constant.

DMUs, which are responsible for the transformation of multiple inputs into multiple outputs, are differently projected in the efficiency frontier (Cooper et al., 2006). In the case of DEA-CCR the DMUs are compared with all the DMU's of the sample, and evaluated taking into account the performance of others. Subsequently, this model is basically a global technical efficiency (TE) measure. On the contrary, the DEA-BCC model are a measure of pure technical efficiency (PTE) where the DMUs are compared with the DMUs of the sample and that have a same scale of operation, taking into account the process of transformation of the inputs into outputs.

This comparison between the two types of efficiency, TE and PTE, allows creating a potential productivity gain of a DMU in reaching the optimal dimension. This is known as Efficiency Scale (ES) and corresponds to the ratio between technical efficiency and pure technical efficiency:

$ES = \frac{TE}{PTE}$, and the same expression is equivalent to $TE = PTE \times ES$.

The maximum value of efficient scale is one (1), and when not achieved it means that the pure technical efficiency is always higher than the technical efficiency. This way, what puts forward that a DMU inefficiency sources may result from an inefficient operation (PTE) or from a disadvantageous dimension in productivity terms (SE), or even both (PTE and SE) (Madaleno, Moutinho, & Robaina, 2016; Rebelo, 2017).

This study employs both models. The DEA-CCR and DEA-VRS are compared with input-orientation because the goal is to minimize input levels considering a set output level. According to Han, Asmild and Kunc (2016) the regional R&D system derives from a micro-level process and easier to manage input levels for a given output level.

On the other hand it is important to point out that a use of mixed data, with different ratios/ percentiles and raw data is possible in DEA applications. Cook, Tone, and Zhu (2014) argue that it is too restrictive to impose that the two forms of data cannot coexist in a model.

3.2.1.2. Super-efficiency DEA model

Additionally, there are some other models of DEA based on the DEA-CCR and DEA-BCC models. One of these models is the Super-efficiency DEA model.

The Super-efficiency model was originally proposed by Andersen and Petersen (1993) and also allows creating a ranking with the efficient DMUs. This model was designed to increase the discriminatory power of basic DEA models in which DMUs may have an efficiency ratio of more than 1, or in other words DMUs under evaluation have an efficiency score below 1 are not included in the reference set. Also, the application of super-efficiency model does not change the efficiency frontier drawn by the original DEA model. This means that only efficient DMUs are changed and non-efficient DMUs values remain unchanged. The super-efficiency scores allow identifying input levels increase of output level decrease that DMUs may suffer without losing their efficiency status (Bongo et al., 2018; Han et al., 2016; Rebelo, 2017). From the perspective of linear programming, the CCR super-efficiency model can be expressed as:

$$SE_{j0} = max \sum_{p=1}^{s} v_p y_{pj0} \tag{4}$$

Subject to:

$$\sum_{q=1}^{m} w_q x_{pj0} = 1$$

$$\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} \leq 0, \qquad \forall\, j, \qquad j \neq 0$$

$$v_p \geq \varepsilon, \qquad p = 1, 2, 3, \dots, s$$

$$w_q \geq \varepsilon, \qquad q = 1, 2, 3, \dots, m$$

The main difference between the basic DEA model and the super-efficiency model is the second constraint where the DMU j_0 is excluded (Bongo et al., 2018).

3.2.2. Innovation Efficiency

In the second stage of this study, the same regions are considered and the same models are used. However, there are some differences related to variables that represent inputs and outputs. A new indicator was created considered the output variable. This new indicator was named Innovation Efficiency Ratio and refers to the ratio between Regional GDP and number of patents. The regional GDP is the numerator and the number of patents is the denominator. In other words, this new indicator represents the reverse of the Technological Production Intensity Index $\left(\frac{Nº\ of\ Patents}{GDP}\right)$. Broekel, Rogge and Brenner (2018) argue that it is important to create new measures of Innovation, namely more specific measures that allow enhanced scientific precision of results.

Generally, the use of this ratio will allow knowing how much is necessary to increase considering the existing number of patents per region. Based on the demographic structure the used input was population aged 25-64 with tertiary level education; in terms of R&D, the ration between R&D expenditure and regional GDP was considered, and the number of total R&D personnel and researchers by sectors of performance. Concerning the education sector, the inputs were the level of tertiary education and/or employed in science and technology (HRST), concerning In-tech Labour force were Employment in Technology and Knowledge intensive sectors. Lastly, based on Industrial structure and economic growth, the ratio between the GDP of Industry sector and the regional GDP was identified. As argued by Broekel, Rogge and Brenner (2018), separate estimations are more reasonable than global measurements because that allow understanding the impact of each sector on Innovation Efficiency. Sometimes, the same inputs are used in different sectors, namely, the Industrial Sector (Broekel et al., 2018). Lastly, the data were all collected from the Eurostat database.

3.3. Econometric model and estimation strategies

The empirical evaluation comprises the presentation of a panel data econometric model to analyse the different impact of the determinants of Innovation Efficiency (Variable Y), such as the Education: X_1 = Tertiary education and /or employed in Science and Technology; (ii) In tech Labour force: X_2 = Employment in Technology and Knowledge intensive sectors. (iii) Demographic structure: X_3 = Population age 25-64 by educational attainment level (tertiary education); (iv) Research and Development: X_4 = ratio between R&D Expenditures to GDP and (v) X_5 = Total R&D personnel; and (vi) Industrial structural economic growth: such as, X_6 = the ratio between GVA industry to total GDP.

The purpose is to identify in the chosen European regions if there is a significant relationship between the Innovation Efficiency of these related determinants. Subsequently, the following linear regression equation was applied:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \sum_{k=2006}^{2012} D_k + C_i + \varepsilon_{it} \quad (5)$$

Where $i = 1, 2, ..., N$ is the *cross-section* identifier for the sampled geographical locations with $N = 103$, $t = 1, 2, ..., T$ is the identifier of the annual observations in each European region of the sample, with $T = 7$, β_0 is the intercept of the equation, β_1, $\beta_2, \beta_3, \beta_4, \beta_5, \beta_6$
are the coefficients of each explanatory of independent variable, $\sum_{k=2006}^{2012} D_k$ are the control *dummies* for the control of annual and fixed time effects, when considering the

year 2006, C_i is the parameter for non-observed specific effects that do not vary over time in a given geographical location and ε_{it} the idiosyncratic error term.

It is assumed that the unobservable heterogeneity of geographic locations is modelled by a unidirectional error component, such as $u_{it} = C_i + \varepsilon_{it}$, where C_i can be estimated using the fixed effects or random effects model. If the estimation is conditional to specific effects, i.e. if C_i are treated as parameters to be estimated, there is a specific application of the fixed effects model. Under these conditions, it is admitted that $E(C_i\varepsilon_{it}) = E(X_{it}\varepsilon_{it}) = 0$, $E(C_i X_{it}) \neq 0$ and $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$, assuming the covariates and parameter C_i are independent of the error term. It is not assumed the independence between the covariates X_{it} and the latent effects associated with geographic location. On the other hand, it is assumed that individual effects are random with the unconditional estimation of C_i allowing the random effects model. In this case: $C_i \sim IID(0, \sigma_C^2)$, $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$, $E(C_i\varepsilon_{it}) = E(C_i X_{it}) = 0$, $E(u_{it}u_{js}) = \sigma_C^2 + \sigma_\varepsilon^2$ if $i = j$ and $t = s$, $E(u_{it}u_{js}) = \sigma_C^2$ if $i = j$ and $t \neq s$.

In the random-effects model, independence is assumed between the covariates and the latent heterogeneity of geographic location. If there is correlation between the individual effects of each geographical location and the covariates, the fixed effects model should be used because it produces consistent estimates of the coefficients, which does not occur with the method of random effects under this hypothesis (Badi H. Baltagi, 2008).

With data combining cross-section and time series, the panel data models often have a complex structure in the matrix of variance-covariance of disturbance errors, such as heteroscedasticity between geographical locations: $E(\varepsilon_{it}^2) = \sigma_i^2$, cross-section dependence (special correlation or contemporaneous correlation), $E(\varepsilon_{it}\varepsilon_{jt}) = \sigma_{ij}$, and serial correlation (arbitrary).

3.3.1. Panel Corrected Standard Errors (PCSE)

In the above-mentioned conventional models of fixed and random effects, the starting point considered is a one-way model, or models with a disturbance term with two components, contemplating the specific unobserved characteristics of individuals (that don’t change over time), and another component identifying the dispersion. In the case of fixed effect models, the constant term is not considered, allowing the disturbance error component to record the characteristics of each individual, considered fixed. In the random effect models, the constant is considered an average of all the cross section observations and is added to the terms of disturbance as a portion regarding the characteristics of each individual. However, two-way error component models may be considered. Disturbance terms consider the three components of the error jointly. One considers the specific non observed individual characteristics of the individuals (that don't change over time), another component associated with the non-observed effects of time, and another error component considers the remainder of the error dispersion. In the fixed effects model, for example, the first two parameters are considered fixed.

The impact of dependence between sectional units in estimation depends on different factors, such as the magnitude of the correlation between sections and the nature of the dependence. When assuming the sectional dependence is caused by the presence of common factors that are not observed (and this component affects the error term) but are not correlated with the other regressors, the estimators of fixed effects and random effects is consistent but not efficient, and the estimated errors are skewed.

On the other hand, if unobserved components that create the sectional dependence are correlated with other regressors, this causes bias and inconsistency in estimators, either estimators of fixed effects or random effects estimators. Pesaran (2006) suggests the inclusion of instrumental variables in Fixed and Random Effect to solve this issue. However, it is actually difficult to include instrumental variables correlated with the remaining covariates and not unobserved factors.

A solution suggested by Beck and Katz (1995) to correct the correlation problem between standard error of cross-sections and the heteroscedasticity between groups consists in using the Panel Corrected Standard Errors (PCSE) instead of the application of the OLS method. For Greene (2003), this type of analysis implies covariance between the observation units (cross-sectional covariance), and in the presence of non-spherical perturbation errors, the OLS method produces inefficient estimates for the coefficients, and the corresponding standard errors are skewed. However, Parks (1967) proposed an estimation method based on the generalized least squares (GLS) in order to correct these standard errors, producing asymptotically efficient coefficients and standard errors without specific trend. Parks (1967) admits the structure of covariance of error is properly specified and that the elements of the error covariance matrix are known.

However, the problem is not solved when the process generating errors is not known; hence the errors of elements of the covariance matrix must be estimated. This can be done through the PCSE method proposed by Beck and Katz (1995). In the PCSE method of estimation, a diagonal matrix is considered, where diagonal elements are the elements of a square matrix N by N covariance of the errors of the 'cross-sections', and the diagonal elements of the square matrix are the variances specific to each unit of 'cross-section'. For each cross-section unit of the variance of the error term is estimated as the mean square error of waste estimation. The cross-sectional dependence on errors may be caused by common shocks, in particular affecting the components that are not observed and are part of the error term known as a cross-section dependence;

The PCSE advantage is that it considers information available on the panel structure. Therefore, to estimate the variance of the error term, all time periods that make up the residue for each cross-section are considered. For Beck (2008), this method differs from White's procedure for correction heteroscedasticity since it deals with a one-term variance of observation as there are T observations by estimation in each cross-section unit, so that one increased time dimension itself increases the performance of the PCSE estimate.

PCSE estimates may be considered robust to correlation between cross-sections, since they estimate the covariance between units. However, the model is restrictive, assuming that diagonal elements of each cross-section variance matrix are constant and the off-diagonal elements are always zero.

The existing discussion in the literature regarding the improvement of PCSE estimates from estimates obtained by FGLS validates the comparison of the results of these two important methods, emphasising the former. Hoechle (2007) developed the nonparametric estimator of variance-covariance Driscoll and Kraay (1998), which is a robust estimator for general forms of autocorrelation, heteroscedasticity and cross-section dependence. The Driscoll and Kraay estimator does not assume a fixed number of panel units, so that the N size does not become a constraint in finite samples. The variance-covariance matrix is estimated in a consistent manner, regardless of the sample size (N), which goes for $N \to \infty$. The Monte Carlo simulations made by Hoechle (2007) indicate that the estimator properties of Driscoll and Kraay in finite samples are better than those obtained by the PCSE and cluster estimators in the presence of contemporaneous correlation, including large panels ($N = 2500$) and a few remarks in time (($T = 10$ for example). To decide between the model of fixed or random effects, the Hausman specification test is used.

This study uses data from micro panel, with a significant number of sectorial observations. The sectorial dimension N is relatively high (104 cross-sections), for a small number of time units (7 annual observations), that is a small temporal dimension T. Comparing the results from the so-called conventional models of fixed effects and random effects with those from the Panel Corrected Standard Errors method, there are particularities that justified the present methodological option. Since Panel T is small and

N is large and/or may grow indefinitely, the asymptotic properties of estimators favour setting up a high N when compared to T, as suggested by Wooldridge (2002).

To understand these issues, estimation diagnostic tests were carried out. To test the hypothesis of heteroscedasticity between the cross-sections units, the Wald test proposed by Greene (2000, p. 598) was used. This test has been employed in econometric software Stata by Baum (2001). The spatial correlation hypothesis was studied through three different tests: Friedman's test (1937), Frees' test (1995) and Pesaran's test (2004), also employed in Stata software by Hoyos and Sarafidis (2006). The Lagrange multiplier test by Breusch and Pagan (1980) is commonly used to test the dependency between the cross-section in a data panel units, but the test assumes a fixed N and T tending to infinity. The Friedman test, the Frees test and the Pesaran test, on the other hand, are valid when T<N, which is the case for the present study. The serial correlation may be tested through the Wooldridge test (2002), introduced in Stata by Drukker (2003).

3.3.2. Dynamic data models in panel – GMM

Panel data models lack a component that represents the dynamics of economic relations experienced in a society which is changing ever faster.

The estimation of dynamic linear models with panel data, including a number of p lags (lag) of the dependent variable (as explanatory) and fixed or unobserved random effects, there is a correlation between the lagged dependent variable and the error term (fixed or random effects not observed). This problem causes the OLS estimation to be skewed and not consistent.

The dynamic panel data models are characterized by (1) autocorrelation due to the presence of the lagged dependent variable among the regressors, and (2) individual effects characterized by heterogeneity between individuals. In the dynamic data modelling in micro panels, according to Matyas and Sevestre (2008, p. 251), one of the assumptions is that being reduced and fixed number of time units T, such admissibility implies that the analysis of stationarity is not necessary. Furthermore, the process of generating the initial observations is important in these models, as whether there is endogeneity or exogeneity between the covariates because these situations may occur from the moment the various covariates are considered.

In this context, the traditional estimators are inconsistent, and the estimation by the Generalized Method of Moments (GMM), proposed by Arellano and Bond (1991), is most commonly used solution to overcome this problem (B. H. Baltagi, Mátyás, & Sevestre, 2008). An alternative is to consider the processing method of the first differences (FD), and in this case, the correlation will be easily resolved. With these initial differences, instrumental variables (IV) will be built. These instrumental variables will provide a consistent but not necessarily efficient estimation method for model parameters. According to Matyas and Sevestre (2008) the method of instrumental variables (IV), proposed by Balestra and Nerlove (1966), is the preferred method for estimation, assuming there is no correlation between the individual or sectional effects and the error term, thus justifying the use of these variables as valid instruments.

If there is correlation, it is necessary to consider the alternative transformation of FD, which means the reformulation of the model through the use of first differences and then applying the method of instrumental variables (IV), i.e. the GMM method.

Alternatively to GMM, Matyas and Wild (2008) advise the use of the Maximum Likelihood Estimator (MLE) method, where it is assumed that the sectional effects and the error term is normally distributed, however, it should be noted a specific case, the case of small size samples that can apparently show a good performance in the estimation of dynamic data models in micro panel. In the estimation of dynamic models with panel data, there is a correlation between the lagged dependent variable and the error term. This problem causes the OLS estimation method to be skewed and not consistent. The solution to this problem is to use the GMM method, which refers to the use of instrumental variables to obtain the weighted weights matrix, where the transformation of variables is performed by an operator, that instead of considering the transformation of the first differences, considers the transformation in "orthogonal differences", i.e. via the respective orthogonal projection that constitutes transformation to deviations from the average future values as a means of eliminating the individual effects without compromising the orthogonality of the terms processed disturbances (Brandao Marques, 2000). The matrix of weights is a need caused by the greater number of instruments in relation to the number of parameters to be estimated.

In dynamic models of panel data, the methods used for estimation of dynamic models of panel data are the Generalized Method of Moments (GMM), the method of Two- Stage Least Squares (TSLS) (Wooldridge, 2002), the method of instrumental variables, the method of least squares (OLS) and Maximum Likelihood method (MLE). However, the same methods are considered special cases of the GMM; as suggested by Wooldridge (2002).

The use of the GMM method, compared with the TSLS method has the advantage of facilitating the definition and choice of instrumental variables, as well as using more variables than necessary. The GMM method estimation involves conducting specification tests, namely the J test, also called Hansen-Sargan test initially proposed by Sargan (1958) to test the model specification, then used by Hansen (1982) to assess the specification of a model estimated by GMM. The TSLS method and GMM are the most used in data modelling in micro panel with dynamic behaviour. In addition, Stock and Watson (2011) consider that if the errors have homoscedasticity then the choice should be TSLS, which in this case is the most efficient estimator. If errors present heteroscedasticity the choice should be the method of instrumental variables, or GMM, which in this case is the most efficient.

Focusing on the estimations of absolute and conditional convergence of Innovation Efficiency across the EU regions, it is used the dynamic panel data methodology as other authors have used, for example, Islam (1995), Caselli, Esquivel and Lefort (1996), Blundell, Bond and Windmeijer (2001) and Hoeffler (2002). Specifically, Arellano and Bover (1995) and Blundell Bond (1998) argue that the System Generalized Method of Moments (GMM) estimator is the best to overcome modelling issues such as fixed effects, potential endogeneity of regressors and dynamic panel bias.

In fact for the dynamic panel data framework, the OLS levels and Within Groups techniques are not well recognized in the literature although they are widely applied in several studies. The main reasons for this are that the estimations of OLS levels and Within Groups are inconsistent and biased because in the case of OLS levels omits unobserved time invariant country effects and the Within Groups takes account for the unobserved country specific effects with a fixed time period in dynamic panel data model (Hsiao, 2014; Nickell, 1981). For these reason, several authors, such as Arellano and Bover (1995), Blundell, et. al. (2001) and Blundell and Bond (1998, 2000) recognize the GMM System is better because the results are not biased, in comparison with the OLS levels and Within Groups practises. Moreover, Roodman (2009b) argues that the estimations of consistent and efficient parameters of a regression are obtained through the System GMM because it’s a technique that takes into account the endogeneity issue in which the independent variables are correlated with past and current realizations of the error, and/or in which heteroscedasticity and autocorrelation within individuals exist. This means that the independent variables are not strictly exogenous and the System GMM uses, as an instrument, the lagged dependent variable and/or any other endogenous variables with variables, which are thought to be uncorrelated with the fixed effects (Nickell, 1981; Roodman, 2009a) as a solution for the endogeneity issue.

This way, the GMM System is recognised as more efficient than other techniques, for example, the Difference GMM estimator (Arellano & Bond, 1991) because it considers that the first differences of instruments are uncorrelated with the fixed effects, which in turn allows the inclusion of more instruments (Roodman, 2009b), and contrary to the Difference GMM estimator, that tends to be biased with large finite sample when the series are close to being random and when the instruments are weak, the System GMM allows obtaining efficient estimates (Blundell & Bond, 2000; Hoeffler, 2002).

Essentially, and according to Blundell (2001) and Blundell and Bond (1998, 2000), the System GMM estimator is designed for panel data sets with small time dimension, and relatively large cross-sectional dimension. In this sense, Blundell et al. (2001) and Roodman (2009a) argue that this estimator is very important for empirical growth models due to the adequacy to linear equations with one dynamic dependent variable, additional control variables, and fixed effects.

On the other hand, the System GMM estimator consists of two sets of equations. The first set of equations is the original equation in levels, for which the lagged first differences of the dependent variable and the control variables are used as instruments. The second set of equations is the transformed equation in first differences, for which the lagged levels of the dependent variable and the control variables are used as instruments.

Additionally, it is important to verify the validity of the assumptions the System GMM estimator is based on. Firstly, the Arellano Bond test (1991) is employed to verify if the error term does not have serial correlation problem. The Hansen (1982) test is subsequently employed to certify the validity of the instruments that should not be correlated with the error term. Lastly, the Difference-in-Hansen test is used for additional moment restrictions. Particularly, the Arellano-Bond (1991) test identifies the first and the second order serial correlations in the first-differenced residuals and it takes into account the second-order correlation in differences to analyse the first-order serial correlation in levels, since this will determine the correlation between dependent and independent variables. AR (2) reports the p-values for the null hypothesis of no second-order serial correlation in the first-differenced residuals. The Hansen (1982) test of over-identifying restrictions allows to identify the p-values for the null hypothesis of instrument validity. Finally, the Difference-in Hansen test reports the p-values for the null hypothesis of the validity of additional moment conditions. There is a fourth condition to ensure the consistency of the System GMM estimations which is the number of instruments should be smaller than or equal to the number of groups in a regression to avoid finite sample bias caused by overfitting (Roodman, 2009a).

4. Results

This section presents the main results of this study, namely the efficiency analysis and the econometric application.

4.1. Efficiency Analysis

Firstly, this section focus on the efficiency analysis with the DEA methodology performed on the 104 DMUS for the two models. The two assumptions, CRS and VRS are considered and discussed. The results are presented by a different set of analyses, namely in global terms and, after, are presented the results of UK, Spain and Poland. The regions from these three countries were chosen because these countries have more regions. Specifically the UK has 29 regions Nut-II, Spain has 17 regions and Poland has 16 regions. Furthermore, the choice between this 3 countries are also based on the division in groups that Filippetti and Archibugi (2011) did in their article. The countries are divided in 4 groups: Frontrunners, Declining, Lagging-behind and Catching-up and each group has its characteristics. Frontrunners have a consolidated position not only in terms of investment in R&D by firms but also in terms of NSI. Declining countries, where is UK, show high levels of NSI but the investment in R&D by firms is reduced. Next, Lagging-behind group, where Spain and Portugal are, is characterized by the darker scenario because show low levels of NSI and firms don't invest in R&D activities. Last but not least, the Catching-up group, where are the more recent Member States of UE, such Poland or Romania, is characterized by high levels of investment in R&D by firms, but in terms of NSI the levels are very low. Filippetti & Archibugi (2011), analysed the countries' position before the financial crisis (2006-2008) and during the crisis (2009) and verified that the countries of declining group tend to move towards frontrunners group, the lagging-behind groups are getting close to the catching-up group and the catching-up countries tend to move close of lagging-behind countries. Based on this evidence it is important to analyse some countries of each group, namely UK, Spain and Poland.

The DEA Super-efficiency results are also considered.

All Tables presented in this section include the efficient scores from DEA methodology for each model under CRS and VRS assumption and the results are presented in Annex and Appendix.

The descriptive statistics of all variables used in this study are shown in Table 2 below.

Table 2. Definition, sources and descriptive statistics of variables used in the DEA methodology

Variable	Description	Source	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables /Outputs							
Regional GDP	Gross Domestic Product at current prices by NUT II regions (PPS per in habitant)	EUROSTAT	728	20999.86	8432.087	6100	57700
Patents	Number of patent applications per million of in habitants (EPO) by NUT-II regions (*per capita*)	EUROSTAT	728	44.4065	58.43013	0.177	409.817
Innovation Efficiency Ratio (IER)	Ratio between Regional GDP and Patents - This ratio measures the inverse of the Regional Technological Production Intensity by NUT-II regions (*per capita*)	Self Elaboration (Numerator and Denominator - EUROSTAT)	728	3358.199	7011.088	73.935	60326.09
Independent Variables / Inputs							
HRST	Human Resourses with tertiary education and/or employed in Science and Tecnology sectors by NUT-II regions (thousand)	EUROSTAT	728	365.0613	299.4402	41.6	2077.2
Employment	Employment in technology and Knowlegde intensive sectors by NUT-II regions (High-technology sectors) (% total employment)	EUROSTAT	728	3.422802	1.972424	0.6	11.7
Population	Population aged 25-64 by educational attainment level by NUTS 2 regions - Tertiary Education (%)	EUROSTAT	728	25.34739	9.177118	6.8	55.7
R&D Expenditure (GERD)	Intramural R&D expenditure (GERD) by sectors of performance (all sectors) PPS per in habitant	EUROSTAT	728	275.6772	334.9594	5.3	2767
R&D Expenditure (GERD) Ratio	Ratio between Intramural R&D expenditures (GERD) and Regional GDP (*per capita*)	Self Elaboration (Numerator and Denominator - EUROSTAT)	728	1.079279	1.019535	0.06	8.044
R&D Personnel	Total R&D personnel and researchers by sectors of performance by NUTS II regions - Full-time equivalent (FTE)	EUROSTAT	728	7363.366	8542.089	191	54721
GVA-Industry Ratio	Industrial Structural economic growth ratio (GVA Industry/GDP) (*per capita*)	Self Elaboration (Numerator and Denominator - EUROSTAT)	728	27.93723	19.16048	1.584	138.079

Source: Our Elaboration

The first model considers two outputs: The Regional GDP per inhabitant and the number of patents (EPO) under the two assumptions CRS and VRS. The second model considers just one output that is Innovation Efficiency Ratio, with some others inputs that aren't used in the model 1 as described in the previous section. The main results from Model 1 application are also in Annex.

4.1.1. CRS and VRS analysis by Model 2

The Top 20 Efficient Regions in the European Union and the Top 10 efficient regions in the UK, Spain and Poland were analysed adding a time frame from before and during the financial crisis (2006-2008 / 2009-2012), as shown in all tables below.

Table 3 shows the global Top 20 ranking. The results are a little different from Model 1 (see Table A1). Romania and Bulgaria are the countries with more regions in this Top 20, 7 and 5 regions, respectively. Furthermore, Belgium and the UK don't have any regions in this Top 20, as can be seen in the Model 1 (see Table A1).On the other hand, Yugoiztochen, region of Bulgaria, is the first in this Top 20, the second is Sud-Est (Romania), and the third is Algarve (Portugal).

In general, comparing the before and during financial crisis time frame, several regions increased their efficiency score, such as Algarve (Portugal), Nord-Vest and Vest (Romania).

Specifically in Table 4, UK are the country with more regions with a score of 100% and Cornwall and Isles of Scilly is the first on Top 10. Extremadura in Spain is also a 100% efficient region in all time period. Poland doesn't have regions 100% efficient in all time period but Podlaskie is the first in this Top 10. Furthermore, several regions decreased their score during the financial crisis, for example Northern Ireland (UK), Illes Balears (Spain) Swietokrzyskie (Poland) and Lubuskie (also Poland).

Table 3. Top 20 of Efficient Regions (Model 2 - CRS) - All Regions

Model 2 – CRS								
All regions - Top 20								
		Before			During			
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Bulgaria	Yugoiztochen	**100.0%**	**100.0%**	**100.0%**	62.4%	**100.0%**	70.5%	**100.0%**
Romania	Sud-Est	32.6%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	75.4%
Portugal	Algarve	**100.0%**	54.0%	39.9%	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Romania	Sud - Muntenia	**100.0%**	**100.0%**	50.9%	73.0%	74.5%	62.4%	26.9%
Romania	Sud-Vest Oltenia	**100.0%**	33.6%	41.6%	26.1%	28.3%	79.6%	**100.0%**
Romania	Nord-Vest	44.4%	54.9%	20.0%	**100.0%**	20.2%	12.9%	26.5%
Romania	Vest	**100.0%**	17.6%	9.6%	81.0%	23.5%	10.0%	19.6%
Romania	Centru	65.2%	29.8%	61.6%	12.9%	18.3%	29.1%	26.3%
Spain	Extremadura	22.9%	43.1%	16.8%	78.3%	16.0%	33.0%	31.0%
Bulgaria	Severoiztochen	21.9%	21.7%	26.4%	64.4%	58.7%	15.5%	26.2%
Romania	Nord-Est	18.0%	88.4%	17.0%	26.9%	18.4%	30.1%	21.2%
Poland	Podlaskie	68.5%	11.0%	23.4%	20.7%	18.2%	35.6%	40.9%
Bulgaria	Severozapaden	34.3%	30.5%	24.0%	40.8%	33.0%	29.7%	18.4%
Bulgaria	Severen tsentralen	19.1%	**100.0%**	10.0%	34.4%	27.0%	8.9%	7.9%
Poland	Warminsko-Mazurskie	28.5%	32.7%	16.6%	76.9%	12.6%	20.1%	13.4%
Portugal	Alentejo	19.1%	49.2%	9.3%	62.4%	15.6%	5.0%	9.2%
Poland	Opolskie	11.9%	16.2%	5.0%	25.5%	4.9%	**100.0%**	4.4%
Poland	Swietokrzyskie	81.3%	20.1%	12.2%	8.9%	13.9%	8.9%	12.5%
Bulgaria	Yuzhen tsentralen	14.6%	56.6%	8.6%	15.0%	6.3%	28.8%	7.5%
Slovakia	Stredné Slovensko	9.1%	24.7%	21.0%	23.5%	10.9%	11.9%	20.6%
Annual Average – 104 regions		**12.9%**	**12.8%**	**7.6%**	**12.7%**	**9.0%**	**10.2%**	**9.2%**

Source: Our Elaboration

Table 4. Top 10 of Efficient Regions (Model 2 - CRS) - UK, Spain and Poland

Model 2 - CRS							
UK, Spain and Poland - Top 10							
		Before			During		
UK	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Cumbria	**100.0%**	**100.0%**	61.2%	**100.0%**	70.4%	**100.0%**	87.8%
Devon	**100.0%**	**100.0%**	73.7%	98.1%	59.2%	**100.0%**	88.3%
East Yorkshire and Northern Lincolnshire	86.7%	55.8%	74.8%	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Northern Ireland (UK)	**100.0%**	**100.0%**	**100.0%**	67.4%	97.4%	95.2%	37.2%
West Midlands	84.9%	90.3%	73.8%	**100.0%**	86.4%	80.2%	44.8%
South Yorkshire	83.1%	85.3%	49.7%	97.1%	69.1%	96.2%	67.3%
West Yorkshire	72.1%	72.7%	57.3%	87.9%	82.0%	**100.0%**	67.2%
Greater Manchester	77.8%	72.0%	73.7%	69.6%	96.7%	83.3%	56.4%
West Wales and The Valleys	**100.0%**	94.0%	85.6%	62.0%	75.7%	53.1%	40.5%
Annual Average – 29 regions	**60.7%**	**58.0%**	**51.2%**	**55.9%**	**56.1%**	**61.8%**	**47.6%**
Spain							
Extremadura	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Canarias (ES)	**100.0%**	55.2%	44.2%	47.1%	**100.0%**	80.3%	48.0%
Illes Balears	**100.0%**	58.1%	60.5%	33.7%	68.2%	**100.0%**	48.6%
La Rioja	44.8%	12.5%	51.3%	12.2%	47.9%	72.4%	38.2%
Castilla-la Mancha	49.5%	24.5%	31.5%	14.9%	36.0%	52.4%	24.3%
Andalucía	33.5%	23.5%	23.3%	7.1%	25.8%	31.8%	13.2%
Región de Murcia	32.1%	17.1%	30.0%	8.3%	21.0%	23.8%	7.3%
Cantabria	24.3%	27.1%	15.8%	5.0%	23.4%	20.0%	12.7%
Castilla y León	20.4%	9.1%	13.2%	6.6%	26.4%	27.3%	10.7%
Galicia	23.5%	15.7%	15.9%	6.8%	20.1%	16.6%	13.5%
Annual Average – 17 regions	**35.3%**	**22.0%**	**24.8%**	**15.3%**	**31.5%**	**33.9%**	**20.9%**
Poland							
Podlaskie	**100.0%**	60.1%	**100.0%**	42.0%	**100.0%**	52.0%	**100.0%**
Warminsko-Mazurskie	53.0%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	23.4%	60.3%
Swietokrzyskie	**100.0%**	**100.0%**	77.2%	15.3%	**100.0%**	13.0%	83.6%
Opolskie	20.2%	93.8%	35.2%	41.9%	76.1%	**100.0%**	26.8%
Lubuskie	23.2%	80.1%	99.9%	17.8%	44.1%	5.7%	16.0%
Zachodniopomorskie	21.6%	62.1%	38.7%	21.2%	92.3%	10.2%	16.6%
Kujawsko-Pomorskie	42.7%	34.3%	33.6%	33.1%	72.8%	15.2%	23.6%
Slaskie	18.2%	56.1%	30.6%	9.8%	81.8%	9.0%	20.2%
Wielkopolskie	24.8%	29.9%	28.8%	15.4%	49.7%	25.1%	19.7%
Pomorskie	58.7%	17.6%	27.6%	19.2%	41.8%	9.6%	16.7%
Annual Average – 16 regions	**35.1%**	**47.4%**	**42.9%**	**23.6%**	**57.6%**	**19.4%**	**29.6%**

Source: Our Elaboration

Table 5. Top 20 of Efficient Regions (Model 2 - VRS) - All Regions

Model 2 - VRS								
All regions - Top 20								
		Before			During			
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Belgium	Prov. Luxembourg (BE)	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Severozapaden	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Severen tsentralen	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Yugoiztochen	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Czech Republic	Severozápad	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Portugal	Algarve	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Romania	Sud-Est	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Romania	Sud - Muntenia	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
UK	Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Poland	Lubuskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	93.6%	95.8%	99.6%
Bulgaria	Severoiztochen	96.9%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	91.6%	**100.0%**
Romania	Vest	**100.0%**	84.2%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Portugal	Alentejo	**100.0%**	96.3%	85.8%	**100.0%**	**100.0%**	97.7%	**100.0%**
Romania	Sud-Vest Oltenia	**100.0%**	**100.0%**	86.8%	91.6%	97.9%	95.8%	**100.0%**
Poland	Opolskie	96.9%	97.7%	90.5%	91.0%	97.2%	**100.0%**	88.2%
Romania	Centru	98.4%	99.4%	**100.0%**	85.6%	94.1%	89.5%	92.4%
Poland	Podlaskie	82.0%	78.3%	**100.0%**	**100.0%**	97.1%	**100.0%**	**100.0%**
Poland	Swietokrzyskie	**100.0%**	**100.0%**	**100.0%**	99.1%	72.6%	84.4%	**100.0%**
Romania	Nord-Est	93.7%	**100.0%**	84.4%	85.8%	84.0%	89.3%	95.1%
Portugal	Centro (PT)	**100.0%**	99.5%	89.7%	98.1%	86.8%	80.8%	76.6%
Annual Average – 104 regions		**61.4%**	**58.7%**	**62.0%**	**64.5%**	**61.0%**	**62.3%**	**64.4%**

Source: Our Elaboration

Considering VRS, Romania, Bulgaria and Poland are the three countries with more regions in the Top 20 ranking of Model 2. With Model 1 (Table A3), the 100% efficient regions were less, but the Province of Luxembourg (Belgium) is also one of the most efficient. Portugal has more regions in this ranking, namely Algarve, Alentejo and Centro. The UK is represented by Cornwall and the Isles of Scilly, considered 100% efficient.

Also, it is possible to verify that in this ranking regions increased or kept their scores during the period of financial crisis, for example, Alentejo (Portugal) and Sud-Vest Oltenia (Romania).However, the efficiency score for Lubuskie (Poland) decreased after 2009.

Table 6. Top 10 of Efficient Regions (Model 2 -VRS) -UK, Spain and Poland

Model 2 - VRS							
UK, Spain and Poland - Top 10							
	Before			During			
UK	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Cumbria	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Lincolnshire	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
East Yorkshire and Northern Lincolnshire	**100.0%**	**100.0%**	99.0%	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Essex	99.8%	95.6%	99.0%	**100.0%**	**100.0%**	**100.0%**	**100.0%**
West Midlands	95.8%	98.7%	96.5%	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Tees Valley and Durham	93.2%	97.6%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
South Yorkshire	97.8%	**100.0%**	89.8%	**100.0%**	**100.0%**	**100.0%**	95.4%
Northern Ireland (UK)	**100.0%**	**100.0%**	**100.0%**	91.2%	**100.0%**	**100.0%**	86.0%
West Yorkshire	88.2%	91.9%	91.1%	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Annual Average – 29 regions	**86.7%**	**87.8%**	**86.1%**	**87.8%**	**89.5%**	**87.9%**	**86.5%**
Spain							
La Rioja	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Extremadura	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Illes Balears	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Canarias (ES)	**100.0%**	**100.0%**	**100.0%**	96.0%	**100.0%**	**100.0%**	**100.0%**
Región de Murcia	**100.0%**	**100.0%**	**100.0%**	92.0%	**100.0%**	**100.0%**	90.1%
Castilla-la Mancha	**100.0%**	96.8%	98.3%	93.3%	94.8%	94.3%	95.5%
Andalucía	93.1%	91.2%	88.0%	87.7%	88.7%	92.6%	89.4%
Cantabria	87.2%	91.5%	85.9%	86.4%	83.9%	83.1%	83.8%
Comunidad Foral de Navarra	90.6%	91.1%	79.6%	79.0%	76.6%	83.2%	73.6%
Comunidad Valenciana	81.5%	86.4%	82.5%	83.4%	80.4%	80.3%	78.7%
Annual Average – 17 regions	**84.3%**	**84.3%**	**81.9%**	**81.4%**	**81.9%**	**82.5%**	**80.7%**
Poland							
Swietokrzyskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Podlaskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Lubuskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Opolskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Warminsko-Mazurskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	96.6%	**100.0%**
Kujawsko-Pomorskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	96.4%
Podkarpackie	97.3%	87.1%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	91.0%
Wielkopolskie	78.2%	85.4%	97.5%	**100.0%**	**100.0%**	**100.0%**	94.2%
Zachodniopomorskie	86.5%	86.3%	95.1%	97.4%	**100.0%**	92.6%	88.4%
Pomorskie	83.9%	74.0%	98.6%	93.0%	86.2%	90.3%	89.6%
Annual Average – 17 regions	**86.0%**	**85.1%**	**92.4%**	**90.7%**	**90.8%**	**90.8%**	**88.0%**

Source: Our Elaboration

More specifically, in the Top 10, Poland and UK are the countries with more regions 100% efficient. Even so, UK have regions with a higher score and some regions have become 100% efficient from 2008 to 2009, for instance, East Yorkshire and Northern Lincolnshire, Essex and West Midlands had 99.0%, 99.0% and 96.5%, in 2008 respectively and in 2009 had 100% of efficiency. In Spain, Canarias (ES) and Región de Murcia decreased their score from 2008 to 2009 but recovered in the following years.

4.1.2. CRS and VRS Super-efficiency analysis by Model 2

This sub-section analyses Super-efficiency through the DEA methodology based on both assumptions, CRS and VRS. This allows identifying the regions with the best efficiency performance. Again, the results are from model 2 and show a division between the pre and during financial crisis period. The results from model 1 are shown in Annex.

Table 7 shows the ranking with no region optimized across the analysed time period. Yugoiztochen (Bulgaria), Sud-Est (Romania) and Algarve (Portugal) are the regions reaching the best score. Romania and Bulgaria are the countries with more regions in this Top 20. On the other hand, there is no uniformity concerning the behavior of super-efficiency levels during the financial crisis period. Some regions went up while others went down the ranking in this period.

In Table 8 , where are represented the Top 10 of each country, Cornwall and Isles of Scilly (UK), Extremadura (Spain) and Opolskie (Poland) are the three regions with best performance. Both the UK and Spain have only a region with higher performance during the all the time period (2006-2012).

Table 7. Top 20 – Super-efficiency Analysis (Model 2 - CRS) - All Regions

Model 2 – Super-efficiency CRS								
All region - Top 20								
			Before			During		
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Bulgaria	Yugoiztochen	**177.6%**	**183.8%**	**277.2%**	62.4%	**132.0%**	70.5%	**401.4%**
Romania	Sud-Est	32.6%	**106.5%**	**203.4%**	**109.9%**	**340.6%**	**315.7%**	75.4%
Portugal	Algarve	**183.3%**	54.0%	39.9%	**109.6%**	**114.2%**	**124.2%**	**102.3%**
Romania	Sud - Muntenia	**150.8%**	**166.3%**	50.9%	73.0%	74.5%	62.4%	26.9%
Romania	Sud-Vest Oltenia	**134.0%**	33.6%	41.6%	26.1%	28.3%	79.6%	**119.0%**
Romania	Nord-Vest	44.4%	54.9%	20.0%	**190.1%**	20.2%	12.9%	26.5%
Poland	Opolskie	11.9%	16.2%	5.0%	25.5%	4.9%	**271.2%**	4.4%
Bulgaria	Severen tsentralen	19.1%	**188.6%**	10.0%	34.4%	27.0%	8.9%	7.9%
Romania	Vest	**104.0%**	17.6%	9.6%	81.0%	23.5%	10.0%	19.6%
Romania	Centru	65.2%	29.8%	61.6%	12.9%	18.3%	29.1%	26.3%
Spain	Extremadura	22.9%	43.1%	16.8%	78.3%	16.0%	33.0%	31.0%
Bulgaria	Severoiztochen	21.9%	21.7%	26.4%	64.4%	58.7%	15.5%	26.2%
Romania	Nord-Est	18.0%	88.4%	17.0%	26.9%	18.4%	30.1%	21.2%
Poland	Podlaskie	68.5%	11.0%	23.4%	20.7%	18.2%	35.6%	40.9%
Bulgaria	Severozapaden	34.3%	30.5%	24.0%	40.8%	33.0%	29.7%	18.4%
Poland	Warminsko-Mazurskie	28.5%	32.7%	16.6%	76.9%	12.6%	20.1%	13.4%
Portugal	Alentejo	19.1%	49.2%	9.3%	62.4%	15.6%	5.0%	9.2%
Poland	Swietokrzyskie	81.3%	20.1%	12.2%	8.9%	13.9%	8.9%	12.5%
Bulgaria	Yuzhen tsentralen	14.6%	56.6%	8.6%	15.0%	6.3%	28.8%	7.5%
Slovakia	Stredné Slovensko	9.1%	24.7%	21.0%	23.5%	10.9%	11.9%	20.6%
Annual Average – 104 regions		**15.3%**	**15.1%**	**10.3%**	**13.8%**	**11.8%**	**14.1%**	**12.3%**

Source: Our Elaboration

Table 8. Top 10 – Super-efficiency Analysis (Model 2 - CRS) - UK, Spain and Poland

Model 2 – Super-efficiency CRS							
UK, Spain and Poland - Top 10							
		Before			During		
UK	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Cornwall and Isles of Scilly	**521.2%**	**479.4%**	**721.9%**	**308.5%**	**558.7%**	**236.0%**	**239.0%**
East Yorkshire and Northern Lincolnshire	86.7%	55.8%	74.8%	**128.5%**	**120.9%**	**118.4%**	**222.7%**
Devon	**111.8%**	**127.0%**	73.7%	98.1%	59.2%	**212.4%**	88.3%
Cumbria	**115.5%**	**107.3%**	61.2%	**129.9%**	70.4%	**118.8%**	87.8%
Northern Ireland (UK)	**100.6%**	**100.6%**	**126.1%**	67.4%	97.4%	95.2%	37.2%
West Midlands	84.9%	90.3%	73.8%	**147.3%**	86.4%	80.2%	44.8%
West Yorkshire	72.1%	72.7%	57.3%	87.9%	82.0%	**143.3%**	67.2%
South Yorkshire	83.1%	85.3%	49.7%	97.1%	69.1%	96.2%	67.3%
Greater Manchester	77.8%	72.0%	73.7%	69.6%	96.7%	83.3%	56.4%
West Wales and The Valleys	**100.5%**	94.0%	85.6%	62.0%	75.7%	53.1%	40.5%
Annual Average – 29 regions	**76.2%**	**72.3%**	**73.5%**	**66.8%**	**72.6%**	**73.1%**	**56.6%**
Spain							
Extremadura	**238.5%**	**410.3%**	**432.4%**	**679.5%**	**141.4%**	**273.5%**	**553.2%**
Canarias (ES)	**101.7%**	55.2%	44.2%	47.1%	**214.5%**	80.3%	48.0%
Illes Balears	**111.1%**	58.1%	60.5%	33.7%	68.2%	**105.3%**	48.6%
La Rioja	44.8%	12.5%	51.3%	12.2%	47.9%	72.4%	38.2%
Castilla-la Mancha	49.5%	24.5%	31.5%	14.9%	36.0%	52.4%	24.3%
Andalucía	33.5%	23.5%	23.3%	7.1%	25.8%	31.8%	13.2%
Región de Murcia	32.1%	17.1%	30.0%	8.3%	21.0%	23.8%	7.3%
Cantabria	24.3%	27.1%	15.8%	5.0%	23.4%	20.0%	12.7%
Castilla y León	20.4%	9.1%	13.2%	6.6%	26.4%	27.3%	10.7%
Galicia	23.5%	15.7%	15.9%	6.8%	20.1%	16.6%	13.5%
Annual Average – 17 regions	**44.2%**	**40.3%**	**44.4%**	**49.4%**	**40.7%**	**44.4%**	**47.5%**
Poland							
Opolskie	20.2%	93.8%	35.2%	41.9%	76.1%	**1113.6%**	26.8%
Podlaskie	**223.9%**	60.1%	**291.9%**	42.0%	**132.1%**	52.0%	**530.2%**
Warminsko-Mazurskie	53.0%	**223.4%**	**108.6%**	**465.2%**	**106.2%**	23.4%	60.3%
Swietokrzyskie	**197.0%**	**127.1%**	77.2%	15.3%	**124.3%**	13.0%	83.6%
Lubuskie	23.2%	80.1%	99.9%	17.8%	44.1%	5.7%	16.0%
Zachodniopomorskie	21.6%	62.1%	38.7%	21.2%	92.3%	10.2%	16.6%
Kujawsko-Pomorskie	42.7%	34.3%	33.6%	33.1%	72.8%	15.2%	23.6%
Slaskie	18.2%	56.1%	30.6%	9.8%	81.8%	9.0%	20.2%
Wielkopolskie	24.8%	29.9%	28.8%	15.4%	49.7%	25.1%	19.7%
Pomorskie	58.7%	17.6%	27.6%	19.2%	41.8%	9.6%	16.7%
Annual Average – 16 regions	**48.9%**	**56.8%**	**55.4%**	**46.4%**	**61.5%**	**82.8%**	**56.5%**

Source: Our Elaboration

Table 9. Top 20 – Super-efficiency Analysis (Model 2 - VRS) - All Sample

Model 2 – Super-efficiency VRS								
All region - Top 20								
		Before			During			
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Romania	Sud-Est	**121.2%**	**138.1%**	**big**	**138.7%**	**big**	**318.3%**	**183.0%**
Romania	Sud - Muntenia	**big**	**big**	**110.5%**	**115.6%**	**103.1%**	**105.2%**	**114.3%**
Bulgaria	Yugoiztochen	**199.3%**	**193.6%**	**278.7%**	**115.8%**	**134.2%**	**118.5%**	**big**
Poland	Opolskie	96.9%	97.7%	90.5%	91.0%	97.2%	**big**	88.2%
Romania	Nord-Vest	95.1%	81.9%	90.2%	**big**	82.8%	86.7%	90.6%
Portugal	Algarve	**378.9%**	**286.9%**	**270.5%**	**268.0%**	**277.8%**	**292.4%**	**271.5%**
Belgium	Prov. Luxembourg (BE)	**133.8%**	**154.7%**	**170.1%**	**184.3%**	**193.5%**	**199.5%**	**200.6%**
UK	Cornwall and Isles of Scilly	**186.0%**	**171.6%**	**143.0%**	**133.1%**	**127.0%**	**126.6%**	**104.8%**
Czech Republic	Severozápad	**122.7%**	**128.5%**	**146.9%**	**131.2%**	**120.5%**	**125.0%**	**113.5%**
Bulgaria	Severen tsentralen	**117.7%**	**196.8%**	**125.2%**	**115.2%**	**102.4%**	**102.7%**	**127.3%**
Romania	Vest	**108.1%**	84.2%	**123.4%**	**160.8%**	**118.5%**	**117.3%**	**136.4%**
Bulgaria	Severozapaden	**102.0%**	**103.6%**	**115.1%**	**118.8%**	**119.4%**	**126.4%**	**109.6%**
Poland	Lubuskie	**110.6%**	**115.7%**	**112.3%**	**133.1%**	93.6%	95.8%	99.6%
Poland	Swietokrzyskie	**150.0%**	**112.7%**	**111.6%**	99.1%	72.6%	84.4%	**121.4%**
Romania	Sud-Vest Oltenia	**136.3%**	**106.6%**	86.8%	91.6%	97.9%	95.8%	**124.6%**
Portugal	Alentejo	**119.1%**	96.3%	85.8%	**119.6%**	**102.6%**	97.7%	**111.8%**
Poland	Podlaskie	82.0%	78.3%	**113.4%**	**111.5%**	97.1%	**111.9%**	**122.7%**
Bulgaria	Severoiztochen	96.9%	**104.2%**	**104.6%**	**104.7%**	**107.1%**	91.6%	**103.4%**
Romania	Centru	98.4%	99.4%	**108.5%**	85.6%	94.1%	89.5%	92.4%
Romania	Nord-Est	93.7%	**111.8%**	84.4%	85.8%	84.0%	89.3%	95.1%
Annual Average – 104 regions		**67.8%**	**64.4%**	**67.9%**	**69.7%**	**64.6%**	**68.2%**	**69.4%**

Source: Our Elaboration

In this Top 20, VRS model 2, almost all regions have a score greater than 100%. The indication of *big* means the region remains efficient with arbitrary increased inputs. However, none of them has a score of *big* during both time periods. The values of super-efficiency are lower than for model 1. On the other hand, this Top 20 doesn't include the same regions than the Top 20 of model 1 (see Table A7 in Annex).

Table 10. Top 10 – Super-efficiency Analysis (VRS) - UK, Spain and Poland

Model 2 – Super-efficiency VRS							
UK, Spain and Poland - Top 10							
	Before			During			
UK	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Cornwall and Isles of Scilly	**881.4%**	**606.1%**	**big**	**339.8%**	**big**	**260.5%**	**285.2%**
Devon	**big**	**big**	83.7%	**152.2%**	85.0%	**big**	96.3%
East Yorkshire and Northern Lincolnshire	**104.1%**	**106.6%**	99.0%	**big**	**131.2%**	**120.8%**	**big**
Cumbria	**128.2%**	**118.8%**	**103.4%**	**138.7%**	**104.9%**	**148.6%**	**128.9%**
Lincolnshire	**107.4%**	**111.6%**	**109.3%**	**133.8%**	**122.4%**	**137.8%**	**137.8%**
West Midlands	95.8%	98.7%	96.5%	**156.1%**	**110.1%**	**106.4%**	**111.1%**
Tees Valley and Durham	93.2%	97.6%	**118.2%**	**104.9%**	**116.9%**	**126.8%**	**112.8%**
West Yorkshire	88.2%	91.9%	91.1%	**115.2%**	**100.1%**	**145.9%**	**110.8%**
Northern Ireland (UK)	**101.6%**	**101.3%**	**133.6%**	91.2%	**101.9%**	**101.5%**	86.0%
Essex	99.8%	95.6%	99.0%	**102.6%**	**103.0%**	**104.2%**	**100.5%**
Annual Average – 29 regions	**115.9%**	**107.2%**	**87.9%**	**103.2%**	**92.8%**	**100.3%**	**96.3%**
Spain							
Extremadura	**big**	**big**	**big**	**big**	**146.7%**	**big**	**big**
Canarias (ES)	**102.7%**	**104.4%**	**102.9%**	96.0%	**big**	**129.9%**	**101.6%**
La Rioja	**201.4%**	**194.0%**	**206.1%**	**183.3%**	**192.8%**	**209.5%**	**201.6%**
Illes Balears	**227.2%**	**203.8%**	**201.7%**	**187.1%**	**174.3%**	**186.5%**	**186.9%**
Región de Murcia	**106.7%**	**154.6%**	**119.8%**	92.0%	**115.3%**	**104.1%**	90.1%
Castilla-la Mancha	**102.5%**	96.8%	98.3%	93.3%	94.8%	94.3%	95.5%
Andalucía	93.1%	91.2%	88.0%	87.7%	88.7%	92.6%	89.4%
Cantabria	87.2%	91.5%	85.9%	86.4%	83.9%	83.1%	83.8%
Comunidad Foral de Navarra	90.6%	91.1%	79.6%	79.0%	76.6%	83.2%	73.6%
Comunidad Valenciana	81.5%	86.4%	82.5%	83.4%	80.4%	80.3%	78.7%
Annual Average – 17 regions	**98.4%**	**99.3%**	**95.2%**	**90.9%**	**95.1%**	**95.8%**	**91.3%**
Poland							
Podlaskie	**big**	**123.4%**	**big**	**100.0%**	**139.3%**	**159.8%**	**big**
Swietokrzyskie	**232.9%**	**132.2%**	**125.9%**	**100.0%**	**big**	**101.8%**	**178.4%**
Opolskie	**121.9%**	**123.0%**	**103.3%**	**100.0%**	**130.3%**	**big**	**113.4%**
Warminsko-Mazurskie	**101.5%**	**big**	**119.5%**	**100.0%**	**107.2%**	96.6%	**112.2%**
Lubuskie	**111.0%**	**121.9%**	**167.9%**	**100.0%**	**161.7%**	**173.3%**	**140.6%**
Kujawsko-Pomorskie	**119.0%**	**117.6%**	100.0%	**100.0%**	**110.3%**	**101.2%**	96.4%
Podkarpackie	97.3%	87.1%	**103.3%**	**100.0%**	**101.9%**	**101.8%**	91.0%
Wielkopolskie	78.2%	85.4%	97.5%	**100.0%**	**105.0%**	**102.4%**	94.2%
Zachodniopomorskie	86.5%	86.3%	95.1%	97.4%	**100.1%**	92.6%	88.4%
Pomorskie	83.9%	74.0%	98.6%	93.0%	86.2%	90.3%	89.6%
Annual Average – 16 regions	**97.4%**	**92.0%**	**99.8%**	**90.7%**	**100.6%**	**99.5%**	**96.9%**

Source: Our Elaboration

Lastly, it is possible to verify UK is the country with higher scores of super-efficiency and Cornwall and Isles of Scilly and Devon are the most efficient. However, Extremadura (Spain) and Podlaskie (Poland) have score of *big* during some years, which means that this regions remain efficient under arbitrary large increased inputs.

4.2. Econometric Analysis with PCSE methodology

This subsection presents econometric results, starting with the application of some diagnosis tests and PCSE tests. The main goal of the econometric analysis is to analyse the differentials impact of determinants of Innovation Efficiency.

Firstly, Table 11 presents the correlation matrix and the Variance Inflation Factor (VIF). It should be noted that in order to avoid any problems of estimation, the variables were firstly centred. The highest values of correlation are between Ln gvaindustry, Ln personnel and Ln hrst. Relatively to the VIF, the Ln hrst and Ln personnel show the highest values.

Table 11. Correlation matrix and Variance Inflation Factor VIF

	Ln IE	Ln hrst	Ln empl	Ln pop	Ln gerd	Ln personnel	Ln gvaindustry
Ln IE	1						
Ln hrst	0.2639	1					
Ln empl	-0.0744	0.1464	1				
Ln pop	0.005	0.2441	0.2396	1			
Ln gerd	-0.7235	-0.0637	-0.0489	-0.1981	1		
Ln personnel	-0.1695	**0.7165**	0.04	-0.0477	0.5591	1	
Ln gvaindustry	-0.0192	**0.7714**	0.0342	-0.1184	0.1927	**0.6978**	1
VIF	-	**11.69**	1.07	1.7	4.84	**9.9**	3.86
1/VIF	-	0.08553	0.930597	0.589496	0.206505	0.101024	0.259029
Mean VIF	5.51						

Source: Our Elaboration

The following Tables 12 and 13 present diagnostic tests and PCSE methodology, respectively.

Table 12. Specification and diagnosis tests – All Regions

Model 2 - All Sample » 104 regions			
	Pooled	**Random Effects**	**Fixed Effects**
Modified Wald Test (χ²)			20804.39***
Pesaran's Test		16.766***	9.306***
Frees' Test		2.118	1.374
Friedman's Test			24.944
Wooldridge Test F(N(0,1))	0.031		

Notes: The Modified Wald Test has a χ² distribution and tests the null hypothesis of group wise heteroskedasticity using stata; Pesaran tests the null hypothesis of cross section independence. Pesaran's test is a parametric test procedure and follows a standard normal distribution; Frees' test uses Frees' Q-distribution and also tests cross sectional independence. The Wooldridge test is normally distributed N(0,1) and tests the null hypothesis of no serial correlation.
***, ** and * denotes 1%, 5% and 10% significance level, respectively.

Source: Our Elaboration

Table 12 shows it is possible with the Pesaran's Test to reject the null hypothesis of cross-sectional independence for Random and Fixed Effects. However, according to the Wooldridge Test for autocorrelation in panel data isn't possible to reject the null hypothesis of no first order autocorrelation, at 1% level. A modified Wald statistics for group wise heteroscedasticity was also used to analyse the existence of heteroscedasticity. This way, the results suggest the presence of contemporaneous correlation across all the regions and through both fixed and random effects model, at 1% significance level, leading to the rejection of the null hypothesis of cross-sectional independence.

Table 13 shows the estimation results of five models using the PCSE methodology. The first model used was the Linear Regression (Model I) that is a PCSE model specification of correlation over regions and no autocorrelation. Subsequently, an independent correlation structure was used, consisting of AR1 hetonly – heteroskedastic over regions and common first order autoregressive correlation error and the AR1 model, corresponding to the Models IV and II, respectively. The Panel Specific first order autoregressive correlation structure (psAR1) for correlation over regions and autocorrelation by sector, was also used (Model III). Lastly, the Linear Regression hetonly – heteroskedastic over regions and no autocorrelation (Model V) was also included.

This way it is possible to verify that all models (Model I through V) estimated coefficients β_1 significantly positive and $\beta_2, \beta_3, \beta_4$ and β_6 significantly negative. The coefficient β_5 is only significantly positive to the models I and V.

Table 13. Results of PCSE methodology – All Regions

Dependent Variable: Ln	PCSE – Model 2				
Independent Variables	**(I) Linear**	**(II) AR1**	**(III) PSAR1**	**(IV) AR1 Hetonly**	**(V) Linear Hetonly**
Ln hrst	0.54	0.88	0.88	0.88	0.54
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Ln empl	-0.50	-0.41	-0.32	-0.41	-0.50
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Ln pop	-1.74	-1.86	-1.78	-1.86	-1.74
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Ln gerd	-0.86	-0.57	-0.65	-0.57	-0.86
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Ln personnel	0.41	0.07	0.06	0.07	0.41
	[0.000]***	[0.672]	[0.529]	[0.591]	[0.000]***
Ln gvaindustry	-0.70	-0.72	-0.71	-0.72	-0.70
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Constant	8.54	9.91	9.60	9.91	8.54
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Observations	728	728	728	728	728
R^2 /Pseudo- R^2	0.73	0.83	0.98	0.83	0.73
Wald Test (χ^2)	3519.08	784.53	987.27	784.53	1634.27
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Notes: The Wald test has $\chi 2$ distribution and tests the null hypothesis of non significance of all coefficients of explanatory variables; panel corrected standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; Corr (AR1) - first-order autoregressive error, Corr (psAR1) – correlation over regions and autocorrelation region; Corr (AR1) hetonly – heteroskedastic over regions and common first order autoregressive error AR(1); Corr (linear) – correlation over regions and no autocorrelation; Corr (linear) hetonly - heteroskedastic over regions and common correlation over regions and no autocorrelation.

Source: Our Elaboration

Consequently, these results show a positive relationship between Innovation Efficiency and Tertiary education and/or employed in Science and Technology (HRST), and a negative relationship between this dependent variable, IE, and Employment in Technology, Population with tertiary education, R&D expenditures and GVA - industry. Although the relationship between IER and R&D Personnel is not significant for most models, it is positive. Furthermore, the most significant relationships are for HRST, Population with tertiary education and GVA - industry.

Table 14. Results from usual panel data estimators – All Regions

Dependent Variable: Ln IE	Model 2 - All Sample » 104 regions			
	Random Effects	**Fixed Effects**	**Random Effects**	**Fixed Effects**
Independent Variables	**CSE**	**CSE**	**RSE**	**RSE**
Ln hrst	0.93	0.77	0.93	0.77
	[0.000]***	[0.009]***	[0.000]***	[0.015]**
Ln empl	-0.09	0.07	-0.09	0.07
	[0.071]*	[0.187]	[0.127]	[0.137]
Ln pop	-1.49	-0.85	-1.49	-0.85
	[0.000]***	[0.003]***	[0.000]***	[0.009]***
Ln gerd	-0.42	-0.14	-0.42	-0.14
	[0.000]***	[0.141]	[0.001]***	[0.406]
Ln personnel	-0.14	0.06	-0.14	0.06
	[0.170]	[0.632]	[0.298]	[0.714]
Ln gvaindustry	-0.51	-0.18	-0.51	-0.18
	[0.000]***	[0.413]	[0.000]***	[0.368]
Constant	9.26	5.33	9.26	5.33
	[0.000]***	[0.001]***	[0.000]***	[0.011]**
Observations	728	728	728	728
F test		2.81		1.7
		[0.0105]**		[0.1286]
Wald Test (χ^2)	272.36		158.38	
	[0.000]***		[0.000]***	

Note: The F-test is normally distributed N(0.1) and tests the null hypothesis of non-significance as a whole of the estimated parameters; The Wald test has Qui-Quadratic distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; Standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; CSE stands for Conventional Standard Errors; RSE for Robust Standard Errors; the regressions were performed in Stata 12.

Source: Our Elaboration

To verify the correct use of PCSE methodology and its adequacy, Table 14 shows the results of usual panel data estimators of random effects and fixed effects for comparison. These tests with usual panel data will allow verifying the robustness of the results obtained through the PCSE estimator, which will be robust if the estimations obtained through other methods are different. Furthermore, these tests also allow verifying if there are inconsistencies in coefficient estimations and bias in standard errors estimation.

The conventional standard errors (CSE) and robust standard errors (RSE) were applied to obtain robust heteroscedastic estimates.

As shown, the F-test results don't reject the null hypothesis of non-significance as a whole of the estimated parameters. However the Wald test allows rejecting the null of non-significance of coefficients of explanatory variables as a whole. Comparing the coefficient estimates of the several explanatory variables from Table 13 and Table 14 it is clear that results are more significant through PCSE. As a consequence, the results of usual panel data estimators confirm Greene's theory (2003) that the OLS method produces inefficient estimates for coefficients.

The following Tables present the results from UK, Spain and Poland for diagnosis tests and PCSE.

Table 15. Specification and diagnosis tests - UK

Model 2 - UK » 29 regions			
	Pooled	**Random Effects**	**Fixed Effects**
Modified Wald Test (χ^2)			3459.67***
Pesaran's Test		5.628***	4.648***
Frees' Test		0.238	0.032
Friedman's Test			22.877
Wooldridge Test F(N(0,1))	1.414		

Notes: The Modified Wald Test has a χ^2 distribution and tests the null hypothesis of group wise heteroskedasticity using stata; Pesaran tests the null hypothesis of cross section independence. Pesaran's test is a parametric test procedure and follows a standard normal distribution; Frees' test uses Frees' Q-distribution and also tests cross sectional independence. The Wooldridge test is normally distributed N(0,1) and tests the null hypothesis of no serial correlation.
***, ** and * denotes 1%, 5% and 10% significance level, respectively.
Source: Our Elaboration

Table 15 shows that through the Pesaran's Test it is possible to reject the null hypothesis of cross-sectional independence for Random and Fixed Effects, as previously shown for the global sample. By the opposite, Frees' Test does not allow rejecting the null hypothesis, so this test indicates the presence of contemporaneous correlation. Also, the Wooldridge Test for autocorrelation in panel data indicates the non-rejection of the null hypothesis of no first order autocorrelation, at 1% level. Lastly, a modified Wald statistics for group wise heteroscedasticity indicates rejection of null hypothesis.

Table 16. Results of PCSE methodology - UK

Dependent Variable: Ln IE	PCSE – UK » 29 regions				
Independent Variables	**(I) Linear**	**(II) AR1**	**(III) PSAR1**	**(IV) AR1 Hetonly**	**(V) Linear Hetonly**
Ln hrst	0.08	-0.22	-0.07	-0.22	0.08
	[0.458]	[0.327]	[0.633]	[0.222]	[0.578]
Ln empl	-0.04	-0.08	-0.06	-0.08	-0.04
	[0.584]	[0.331]	[0.454]	[0.232]	[0.531]
Ln pop	-0.23	0.60	0.63	0.60	-0.23
	[0.461]	[0.184]	[0.060]*	[0.048]**	[0.376]
Ln gerd	-0.28	-0.32	-0.28	-0.32	-0.28
	[0.000]***	[0.001]***	[0.001]***	[0.002]***	[0.003]***
Ln personnel	-0.18	-0.11	-0.15	-0.11	-0.18
	[0.091]*	[0.382]	[0.529]	[0.409]	[0.126]
Ln gvaindustry	0.17	0.39	0.33	0.39	0.17
	[0.000]***	[0.038]**	[0.004]***	[0.021]**	[0.140]
Constant	7.34	5.03	4.55	5.03	7.34
	[0.046]**	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Observations	203	203	203	203	203
R^2 /Pseudo- R^2	0.41	0.90	0.98	0.90	0.41
Wald Test (χ^2)	866.73	96.21	145.60	60.18	158.65
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Notes: The Wald test has χ2 distribution and tests the null hypothesis of non significance of all coefficients of explanatory variables; panel corrected standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; Corr (AR1) - first-order autoregressive error, Corr (psAR1) – correlation over regions and autocorrelation region; Corr (AR1) hetonly – heteroskedastic over regions and common first order autoregressive error AR(1); Corr (linear) – correlation over regions and no autocorrelation; Corr (linear) hetonly - heteroskedastic over regions and common correlation over regions and no autocorrelation.

Source: Our Elaboration

As for the whole sample, the same five models (Models I to V) of the PCSE methodology were used for the UK. It is possible to verify that for all models (I to V) only β_4 representing Ln of Expenditures on R&D, is significant, with a negative relationship with the IE ratio. β_2 and β_5 are non-significant and negative for almost all models, although, β_5 is significant at 10% level to model I. The coefficient of Ln of GVA industry (β_6) shows a significant and positive relationship with IE, except for Model V (Linear regression – hetonly) which is not significant. β_3 is not significant for Linear Regression Models (I and V) and AR1 Model (II) and is significant and positive to the models III and IV at a 5% and 10% level of significance, respectively. GVA industry is one of the most significant, with higher coefficient.

Table 17. Results from usual panel data estimators - UK

Dependent Variable: Ln IE	Model 2 - UK » 29 regions			
	Random Effects	**Fixed Effects**	**Random Effects**	**Fixed Effects**
Independent Variables	CSE	CSE	RSE	RSE
Ln hrst	-0.16	0.06	-0.16	0.06
	[0.417]	[0.869]	[0.429]	[0.860]
Ln empl	-0.05	-0.06	-0.05	-0.06
	[0.342]	[0.330]	[0.265]	[0.178]
Ln pop	1.17	1.10	1.17	1.10
	[0.000]***	[0.029]**	[0.000]***	[0.021]**
Ln gerd	-0.21	-0.17	-0.21	-0.17
	[0.014]**	[0.069]*	[0.016]**	[0.123]
Ln personnel	-0.23	-0.08	-0.23	-0.08
	[0.023]**	[0.512]	[0.100]	[0.654]
Ln gvaindustry	0.50	0.66	0.50	0.66
	[0.001]***	[0.001]***	[0.001]***	[0.003]***
Constant	3.42	0.55	3.42	0.55
	[0.000]***	[0.701]	[0.000]***	[0.698]
Observations	203	203	203	203
F test		8.31		7.45
		[0.0000]***		[0.0001]***
Wald Test (χ^2)	58.06		102.51	
	[0.000]***		[0.000]***	

Notes: The F-test is normally distributed N(0.1) and tests the null hypothesis of non-significance as a whole of the estimated parameters; The Wald test has Qui-Quadratic distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; Standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; CSE stands for Conventional Standard Errors; RSE for Robust Standard Errors; the regressions were performed in Stata 12.

Source: Our Elaboration

Once again the adequacy of PCSE methodology was verified, now for the UK, and the results of usual panel data estimators of random and fixed effects with CSE and RSE are presented on Table 17. It is shown that the F-test and Wald test results lead to the rejection of the null hypothesis of non-significance as a whole of the estimated parameters and the rejection of the null hypothesis of non-significance of coefficients of explanatory variables as a whole, respectively.

Furthermore, comparing these results with the results presented in the previous Table 16, it is possible to verify that the coefficients of the usual panel data estimators are lower than the PCSE methodology coefficients. However, here β_3 and β_6 are some of the most significant coefficients.

Nevertheless, the results indicate that the PCSE's are more significant.

Table 18. Specification and diagnosis tests - Spain

Model 2 - Spain » 17 regions			
	Pooled	**Random Effects**	**Fixed Effects**
Modified Wald Test (χ^2)			636.04***
Pesaran's Test		0.517	0.163
Frees' Test		-0.498	-0.376
Friedman's Test			6.05
Wooldridge Test F(N(0,1))	6.614**		

Notes: The Modified Wald Test has a χ^2 distribution and tests the null hypothesis of group wise heteroskedasticity using stata; Pesaran tests the null hypothesis of cross section independence. Pesaran's test is a parametric test procedure and follows a standard normal distribution; Frees' test uses Frees' Q-distribution and also tests cross sectional independence. The Wooldridge test is normally distributed N(0,1) and tests the null hypothesis of no serial correlation.
***, ** and * denotes 1%, 5% and 10% significance level, respectively.
Source: Our Elaboration

Table 18 shows the results of specification and diagnosis tests and it is possible to verify that Pesaran's Test, contrary to previous results, lead to non-rejection of null hypothesis of cross-sectional Independence for random and fixed effects. On the other hand, the Frees' Test shows the existence of contemporaneous correlation. Furthermore, the Wooldridge Test for autocorrelation in panel data indicates the rejection of the null hypothesis of no first order autocorrelation, at 1% level and the modified Wald statistics for group wise heteroscedasticity indicates the rejection of null hypothesis.

As shown in Table 19 , for Spain were also used the same PCSE methodology with the Linear Regression Model, AR1, PSAR1, AR1 – hetonly and Linear Regression – hetonly, Model I to V, respectively. In fact, it's possible to verify that for the first time the coefficients of all models (Model I to V) are significant. $\beta_1$and β_4 are the only positive coefficients and the remaining coefficients (β_2, β_3, β_5 and β_6) are negative. This means that for Spain, Tertiary education and/or employed in Science and Technology (HRST) and R&D expenditures have a positive relationship with the IE ratio and Employment in Technology, Population with tertiary education, R&D Personnel and GVA – industry have a negative relationship with the IE ratio. Furthermore, HRST, Population with tertiary education and R&D personnel are the most significant variables.

Table 19. Results of PCSE methodology - Spain

Dependent Variable: Ln IE	PCSE – Spain » 17 regions				
Independent Variables	**(I) Linear**	**(II) AR1**	**(III) PSAR1**	**(IV) AR1 Hetonly**	**(V) Linear Hetonly**
Ln hrst	2.56	2.09	2.06	2.09	2.56
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Ln empl	-0.51	-0.45	-0.46	-0.45	-0.51
	[0.001]***	[0.025]**	[0.005]***	[0.038]**	[0.002]***
Ln pop	-2.20	-1.86	-1.98	-1.86	-2.20
	[0.000]***	[0.002]***	[0.001]***	[0.004]***	[0.000]***
Ln gerd	1.25	0.80	0.91	0.80	1.25
	[0.000]***	[0.088]*	[0.030]**	[0.057]*	[0.000]***
Ln personnel	-1.88	-1.51	-1.40	-1.51	-1.88
	[0.000]***	[0.001]***	[0.000]***	[0.000]***	[0.000]***
Ln gvaindustry	-0.79	-0.66	-0.81	-0.66	-0.79
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Constant	19.10	17.02	17.09	17.02	19.10
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Observations	119	119	119	119	119
R^2 /Pseudo- R^2	0.77	0.91	0.98	0.91	0.77
Wald Test (χ^2)	1379.26	195.82	385.79	166.77	460.7
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Notes: The Wald test has χ2 distribution and tests the null hypothesis of non significance of all coefficients of explanatory variables; panel corrected standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; Corr (AR1) - first-order autoregressive error, Corr (psAR1) – correlation over regions and autocorrelation region; Corr (AR1) hetonly – heteroskedastic over regions and common first order autoregressive error AR(1); Corr (linear) – correlation over regions and no autocorrelation; Corr (linear) hetonly - heteroskedastic over regions and common correlation over regions and no autocorrelation.

Source: Our Elaboration

Table 20. Results from usual panel data estimators - Spain

Dependent Variable: Ln IE	Model 2 - Spain » 17 regions			
	Random Effects	**Fixed Effects**	**Random Effects**	**Fixed Effects**
Independent Variables	**CSE**	**CSE**	**RSE**	**RSE**
Ln hrst	1.02	-1.74	1.02	-1.74
	[0.025]**	[0.298]	[0.232]	[0.338]
Ln empl	-0.35	-0.15	-0.35	-0.15
	[0.048]**	[0.440]	[0.090]*	[0.505]
Ln pop	-0.66	1.37	-0.66	1.37
	[0.170]	[0.345]	[0.345]	[0.402]
Ln gerd	-0.43	-1.17	-0.43	-1.17
	[0.248]	[0.008]***	[0.570]	[0.074]*
Ln personnel	-0.57	0.48	-0.57	0.48
	[0.121]	[0.295]	[0.385]	[0.380]
Ln gvaindustry	-0.45	0.69	-0.45	0.69
	[0.136]	[0.310]	[0.244]	[0.333]
Constant	10.21	6.45	10.21	6.45
	[0.000]***	[0.215]	[0.007]***	[0.260]
Observations	119	119	119	119
F test		1.89		1.27
		[0.0895]*		[0.3260]
Wald Test (χ^2)	50.58		34.73	
	[0.000]***		[0.000]***	

Notes: The F-test is normally distributed N(0.1) and tests the null hypothesis of non-significance as a whole of the estimated parameters; The Wald test has Qui-Quadratic distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; Standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; CSE stands for Conventional Standard Errors; RSE for Robust Standard Errors; the regressions were performed in Stata 12.

Source: Our Elaboration

Table 20, concerning Spain, shows the results from the application of usual panel data estimators to verify the correct use of PCSE estimators. Specifically, the F-test leads to rejecting the null hypothesis for CSE but to reject the null hypothesis of non-significance as a whole of the estimated parameters for RSE. Wald Test results lead to the rejection of the null hypothesis of non-significance of coefficients of explanatory variables as a whole.

In fact, through these estimators of random effects and fixed effects with CSE and RSE methodology, it’s possible to confirm that the coefficients are not significant when compared to the previous PCSE results. The results of usual panel data estimators for Spain show that the OLS method produces inefficient estimates for the coefficients (Greene, 2003).

Finally, the results of Poland, which consists of 16 NUT-II regions, are presented in Tables 21, 22 and 23.

Table 21. Specification and diagnosis Tests - Poland

Model 2 - Poland » 16 regions			
	Pooled	**Random Effects**	**Fixed Effects**
Modified Wald Test (χ^2)			432.82***
Pesaran's Test		1.034	1.162
Frees' Test		0.425	0.416
Friedman's Test			8.196
Wooldridge Test F (N (0,1))	0.573		

Notes: The Modified Wald Test has a χ^2 distribution and tests the null hypothesis of group wise heteroskedasticity using stata; Pesaran tests the null hypothesis of cross section independence. Pesaran's test is a parametric test procedure and follows a standard normal distribution; Frees' test uses Frees' Q-distribution and also tests cross sectional independence. The Wooldridge test is normally distributed N(0,1) and tests the null hypothesis of no serial correlation.
***, ** and * denotes 1%, 5% and 10% significance level, respectively.

Source: Our Elaboration

Table 21 shows that only the modified Wald Test leads to rejection of null hypothesis of group wise heteroscedasticity. The results of Pesaran's Test and Frees' Test indicate the non-rejection of null hypothesis of cross sectional independence and the Wooldridge Test results don't allow rejecting the null hypothesis of no serial correlation.

Table 22. Results of PCSE methodology - Poland

Dependent Variable: Ln IE	PCSE - Poland » 16 regions				
Independent Variables	**(I) Linear**	**(II) AR1**	**(III) PSAR1**	**(IV) AR1 Hetonly**	**(V) Linear Hetonly**
Ln hrst	0.31	0.54	-0.07	0.54	0.31
	[0.462]	[0.347]	[0.874]	[0.371]	[0.526]
Ln empl	-0.25	-0.26	-0.08	-0.26	-0.25
	[0.138]	[0.212]	[0.592]	[0.184]	[0.135]
Ln pop	-1.50	-1.99	-0.77	-1.99	-1.50
	[0.010]**	[0.007]***	[0.194]	[0.013]**	[0.028]**
Ln gerd	0.05	0.29	-0.05	0.29	0.05
	[0.743]	[0.178]	[0.752]	[0.196]	[0.811]
Ln personnel	0.01	-0.16	0.17	-0.16	0.01
	[0.942]	[0.479]	[0.272]	[0.522]	[0.957]
Ln gvaindustry	-0.65	-0.78	-0.68	-0.78	-0.65
	[0.000]***	[0.027]**	[0.032]**	[0.033]**	[0.028]**
Constant	12.93	15.11	11.63	15.11	12.93
	[0.014]**	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Observations	112	112	112	112	112
R^2 /Pseudo- R^2	0.20	0.69	0.98	0.69	0.20
Wald Test (χ^2)	216.25	81.28	140.47	28.53	30.99
	[0.000]***	[0.000]***	[0.000]***	[0.0001]***	[0.000]***

Notes: The Wald test has χ2 distribution and tests the null hypothesis of non significance of all coefficients of explanatory variables; panel corrected standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; Corr (AR1) - first-order autoregressive error, Corr (psAR1) – correlation over regions and autocorrelation region; Corr (AR1) hetonly – heteroskedastic over regions and common first order autoregressive error AR(1); Corr (linear) – correlation over regions and no autocorrelation; Corr (linear) hetonly - heteroskedastic over regions and common correlation over regions and no autocorrelation.

Source: Our Elaboration

Based on PCSE methodology results for Poland, presented in Table 22, it is possible to conclude that these coefficients are not very significant except for β_3 and β_6. Both coefficients are the most significant and indicate a negative relationship between them and the dependent variable. This means the Population with Tertiary Education and GVA – industry have a negative relationship with IE ratio. β_6 is the only significant coefficient in all models (Model I to V). β_2 also presents a negative relationship with Ln IER but not significant. Although β_1 and β_4 are not significant, the results indicate a positive relationship with the dependent variable, except for the Model of PSAR1 (III).

Table 23. Results from usual panel data estimators - Poland

Dependent Variable: Ln IE	Model 2 - Poland » 16 regions			
	Random Effects	**Fixed Effects**	**Random Effects**	**Fixed Effects**
Independent Variables	CSE	CSE	RSE	RSE
Ln hrst	0.61	-0.62	0.61	-0.62
	[0.349]	[0.666]	[0.143]	[0.677]
Ln empl	-0.04	-0.03	-0.04	-0.03
	[0.793]	[0.858]	[0.747]	[0.783]
Ln pop	-2.39	-1.54	-2.39	-1.54
	[0.001]***	[0.214]	[0.000]***	[0.204]
Ln gerd	0.32	0.40	0.32	0.40
	[0.146]	[0.109]	[0.367]	[0.359]
Ln personnel	-0.19	-0.38	-0.19	-0.38
	[0.531]	[0.322]	[0.558]	[0.353]
Ln gvaindustry	-0.90	-1.41	-0.90	-1.41
	[0.082]*	[0.121]	[0.011]**	[0.012]**
Constant	16.35	24.33	16.35	24.33
	[0.000]***	[0.001]***	[0.000]***	[0.012]
Observations	112	112	112	112
F test		3.84		12.35
		[0.0019]***		[0.0000]***
Wald Test (χ^2)	24.01		45.28	
	[0.0005]***		[0.0000]***	

Notes: The F-test is normally distributed N(0.1) and tests the null hypothesis of non-significance as a whole of the estimated parameters; The Wald test has Qui-Quadratic distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; Standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; CSE stands for Conventional Standard Errors; RSE for Robust Standard Errors; the regressions were performed in Stata 12.

Source: Our Elaboration

Lastly, Table 23 shows the results of usual panel data estimators. The use of these estimators intends to confirm the adequacy of PCSE methodology. It is possible to determine that the F-Test results lead to the rejection of null hypothesis of non-significance as a whole of the estimated parameters. Also, the Wald test results indicate the rejection of null hypothesis of non-significance of coefficients of explanatory variables as a whole.

Furthermore, it is also shown that almost all usual panel data estimators are not significant. β_3 is significant only in random effects and β_6 is significant for all estimations except for the fixed effects with conventional standard errors (CSE). Even so, both coefficients are the most significant.

4.3. Econometric Analysis with GMM estimators

The table 24, below, present the DIF-GMM and SYS-GMM parameter estimates of Equation 5 regarding the 104 NUT-II regions of EU. (I) represents the Dynamic panel-data estimation, one-step difference GMM, (II) Dynamic panel-data estimation, one-step system GMM, (III) Dynamic panel-data estimation, two-step difference GMM and (IV) Dynamic panel-data estimation, two-step system GMM.

Table 24. Estimations Results of GMM Method » 104 regions

Dependent Variable: Ln IE	Results of GMM Estimations - All sample » 104 regions			
Independent Variables	**One-step**		**Two-step**	
	(I)	**(II)**	**(III)**	**(IV)**
Ln IE (-1)	-0.33	0.75	-0.09	0.15
	[0.000]***	[0.000]***	[0.482]	[0.353]
Ln hrst	1.38	-0.70	1.12	-0.29
	[0.004]***	[0.231]	[0.039]**	[0.642]
Ln empl	-0.03	-0.16	-0.12	-0.09
	[0.610]	[0.207]	[0.188]	[0.434]
Ln pop	-1.22	-0.22	-0.56	-0.95
	[0.017]**	[0.032]**	[0.337]	[0.003]***
Ln gerd	-0.09	-0.30	-0.11	-1.08
	[0.678]	[0.006]***	[0.709]	[0.000]***
Ln personnel	-0.05	-0.17	0.001	0.22
	[0.787]	[0.421]	[0.996]	[0.457]
Ln personnel (-1)	0.60	0.33	0.40	0.18
	[0.002]***	[0.075]*	[0.178]	[0.446]
Ln gvaindustry	0.12	-0.14	0.31	-0.55
	[0.675]	[0.031]**	[0.428]	[0.002]***
Ln gvaindustry (-1)	-0.66	-	-0.28	-
	[0.019]**	-	[0.464]	-
Instruments	32	37	31	35
Groups	104	104	104	104
Hansen	39.07	49.68	35.53	39.62
AR1	-3.15	-3.79	-2.34	-2.61
AR2	-1.00	1.63	0.38	1.09

Source: Our Elaboration

The results show that the SYS-GMM estimations are more statistically significant and the coefficients of the lagged dependent variable are higher in SYS-GMM than in DIF-GMM. However, the One-step models, generically, present better estimations that are statistically significant, as can be seen in the case of the lagged dependent variable the population variable (Ln pop) and the lagged independent variable Ln personnel. One the other hand, the HRST variable, for the DIF-GMM show the highest coefficients that are statistically significant and positive. This is means that the human resources have a positive relationship with the Innovation Efficiency. Furthermore, the lagged independent variable, Ln Personnel is statistically significant and negative in Dynamic panel-data estimation, one-step. Although the variables Ln employment and Ln population show a negative relationship with the dependent variable, their coefficients are not statistically significant.

The following tables show the results of GMM estimation for UK, Spain and Poland. (I) represents the Dynamic panel-data estimation, one-step difference GMM, (II) Dynamic panel-data estimation, one-step system GMM, (III) Dynamic panel-data estimation, two-step difference GMM and (IV) Dynamic panel-data estimation, two-step system GMM.

Table 25 shows the results of GMM parameters for UK. It is possible to verify that the SYS-GMM estimations are more statistically significant and the lagged dependent variable also present the highest coefficients in SYS-GMM. However, the coefficients of lagged dependent variable are only significant in the DIF-GMM estimations. Furthermore, the independent variables Ln Pop, Ln personnel and Ln gvaindustry present a positive relationship with the lagged dependent variable, Ln IE, in all estimations and the variable that represents the R&D expenditures (Ln gerd) is the only one that shows a negative relationship with the Ln IE, for all models. Even so, the highest coefficients are those of the independent variable Ln gvaindustry. In the case of Ln personnel and Ln gvaindustry, when the lagged variables are joined, the values of the coefficients become significant, which shows the importance of the lags of these variables.

Table 25. Estimations Results of GMM Method » UK - 29 regions

Dependent Variable: Ln IE	Results of GMM Estimations - UK » 29 regions			
Independent Variables	**One-step**		**Two-step**	
	(I)	**(II)**	**(III)**	**(IV)**
Ln IE (-1)	-0.24	0.83	-0.43	0.25
	[0.016]**	[0.000]***	[0.109]	[0.327]
Ln hrst	-0.56	0.49	0.15	1.44
	[0.518]	[0.573]	[0.843]	[0.069]*
Ln empl	-0.03	0.07	-0.06	0.08
	[0.589]	[0.350]	[0.361]	[0.541]
Ln pop	1.23	0.18	0.62	-0.47
	[0.055]*	[0.778]	[0.237]	[0.585]
Ln gerd	-0.20	-0.12	-0.15	-0.22
	[0.095]*	[0.140]	[0.384]	[0.094]*
Ln personnel	0.04	0.15	0.10	0.03
	[0.763]	[0.245]	[0.471]	[0.869]
Ln personnel (-1)	-	-0.26	-	-
	-	[0.075]*	-	-
Ln gvaindustry	1.03	1.05	1.01	0.70
	[0.018]**	[0.013]**	[0.046]**	[0.072]*
Ln gvaindustry (-1)	-	-0.89	-	-
	-	[0.033]**	-	-
Instruments	28	40	26	38
Groups	29	29	29	29
Hansen	22.31	18.65	17.27	11.05
AR1	-3.96	-3.45	-0.75	-2.00
AR2	0.28	1.56	-0.34	0.81

Source: Our Elaboration

Table 26. Estimations Results of GMM Method » Spain - 17 regions

Dependent Variable: Ln IE	Results of GMM Estimations - Spain » 17 regions			
Independent Variables	**One-step**		**Two-step**	
	(I)	**(II)**	**(III)**	**(IV)**
Ln IE (-1)	-0.32	0.67	-0.34	0.55
	[0.000]***	[0.000]***	[0.014]**	[0.401]
Ln hrst	-4.30	0.79	-9.37	1.13
	[0.254]	[0.123]	[0.537]	[0.538]
Ln empl	-0.51	-0.17	-0.24	0.45
	[0.044]**	[0.370]	[0.078]*	[0.766]
Ln pop	1.70	0.45	0.11	4.58
	[0.630]	[0.162]	[0.994]	[0.471]
Ln gerd	-0.96	-0.002	-0.002	-0.44
	[0.286]	[0.995]	[0.998]	[0.449]
Ln personnel	-1.44	-0.51	-5.69	-0.56
	[0.095]*	[0.198]	[0.056]*	[0.605]
Ln personnel (-1)	2.14	-	-	-
	[0.023]**	-	-	-
Ln gvaindustry	1.00	-0.28	3.10	-0.69
	[0.381]	[0.041]**	[0.289]	[0.405]
Instruments	33	34	26	32
Groups	17	17	17	17
Hansen	0.00	8.57	1.51	7.95
AR1	-2.07	-2.24	0.02	-1.30
AR2	-1.41	-0.19	0.48	-0.80

Source: Our Elaboration

Table 26 presents the results concerning Spain. It shows the lagged dependent variable is statistically significant for One-Step GMM, and is also significant for DIF-GMM Two-Step, at 5% level. Even so, overall the results are not too much significant not only for DIF-GMM but also SYS-GMM. Additionally, the independent variable Ln pop have the highest and positive coefficients. Ln gvaindustry also present high coefficients in DIF-GMM but are not significant and Ln personnel and Ln gerd show a negative relationship with the dependent variable. One the other hand, when the lagged independent variable Ln personnel is included their coefficients become statistically significant.

Table 27. Estimations Results of GMM Method » Poland - 16 regions

Dependent Variable: Ln IE	Results of GMM Estimations - Poland » 16 regions			
Independent Variables	**One-step**		**Two-step**	
	(I)	**(II)**	**(III)**	**(IV)**
Ln IE (-1)	-0.38	0.42	-0.30	0.13
	[0.001]***	[0.004]***	[0.610]	[0.780]
Ln hrst	-0.73	-1.63	2.97	-1.92
	[0.615]	[0.115]	[0.766]	[0.444]
Ln empl	-0.21	-0.42	0.001	-0.16
	[0.299]	[0.033]**	[1.000]	[0.634]
Ln pop	2.07	1.75	-0.23	6.31
	[0.221]	[0.266]	[0.987]	[0.360]
Ln gerd	0.71	0.948	0.49	0.03
	[0.160]	[0.041]	[0.672]	[0.965]
Ln gerd (-1)	-	-1.04	-	-
	-	[0.009]***	-	-
Ln personnel	-0.77	-1.34	-0.79	-0.13
	[0.100]	[0.000]***	[0.493]	[0.855]
Ln personnel (-1)	-	1.48	-	-
	-	[0.000]***	-	-
Ln gvaindustry	-4.20	-4.26	0.28	2.29
	[0.048]*	[0.009]***	[0.964]	[0.403]
Ln gvaindustry (-1)	-	4.43	-	-
	-	[0.014]**	-	-
Instruments	28	40	26	32
Groups	16	16	16	16
Hansen	7.75	0.00	6.08	4.25
AR1	-2.58	-2.46	-0.99	-1.48
AR2	-0.60	0.19	0.55	1.19

Source: Our Elaboration

Table 27 shows the results regarding Poland and confirms that the SYS-GMM One-Step show the more coefficients statistically significant due essentially to the inclusion of lagged independent variables, namely for the R&D expenditures (Ln gerd), R&D personnel (Ln personnel) and the GVA Industry (Ln gvaindustry). As previously, the coefficients of lagged independent variable are statistically significant only in One-Step GMM. Furthermore, the R&D expenditures show a positive relationship with the dependent variable, the logarithm of Innovation Efficiency (LN IE), and, on contrary, the R&D personnel show a negative relationship with Ln IE, such as Ln HRST and Ln Empl, except for model III. However these coefficients are not statistically significant.

4.4. Discussion

The application of the DEA methodology in this study shows that Belgium with eleven NUT-II and Romania with eight regions are among the countries with the highest number of regions in the Top 20 ranking. One the other hand, also UK, the country with more regions in this sample have always some regions that stand out, for example, Cornwall and Isles of Scilly, Cumbria and Lincolnshire. Already in Spain, the second country with more NUT-II regions, the regions that stand out are Comunidad Foral de Navarra, Extremadura, La Rioja e Illes Balears. Finally, Poland, with sixteen NUT-II regions gains prominence through the Lubuskie, Opolskie and Podlaskie regions. All these regions present, at least in one model used, very high efficiency values in comparison with other regions under study.

Furthermore, the estimated parameters of the empirical models employed show the differentials impact of determinants of Innovation Efficiency and the results suggest that education and/or employed in Science and Technology (HRST) and the GVA – Industry are the most significant variables. Hence, it would be useful to evaluate their evolution during the analysed period, namely, making the division between the period before the financial crisis and during crisis.

As a matter of fact, there are some studies (Filippetti & Archibugi, 2011; Kalapouti et al., 2017; Rodríguez-Pose & Crescenzi, 2008) that confirm the human resources are an essential part of the innovation process, namely when the country is in crisis. When the country is in crisis the levels of GVA and GDP decrease, but the most innovative firms tend not to reduce their innovation intensity. The most efficient regions remain the same during the crisis period, as shown.

In the charts below relating Innovation Efficiency and HRST and GVA-Industry.

Chart 2. Region Position pre-crisis period - HRST

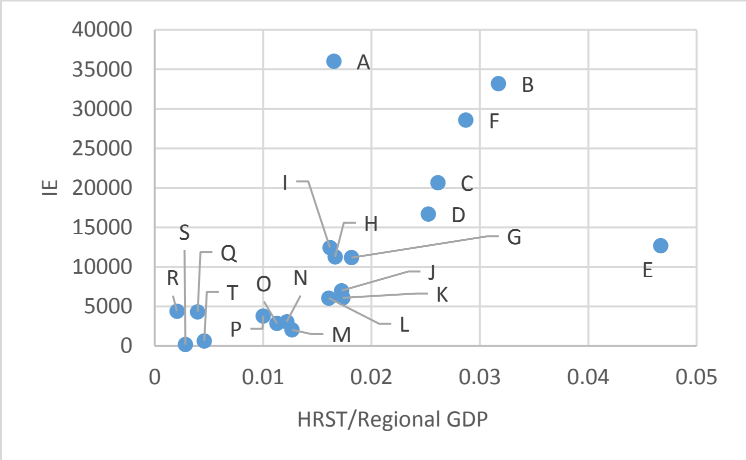
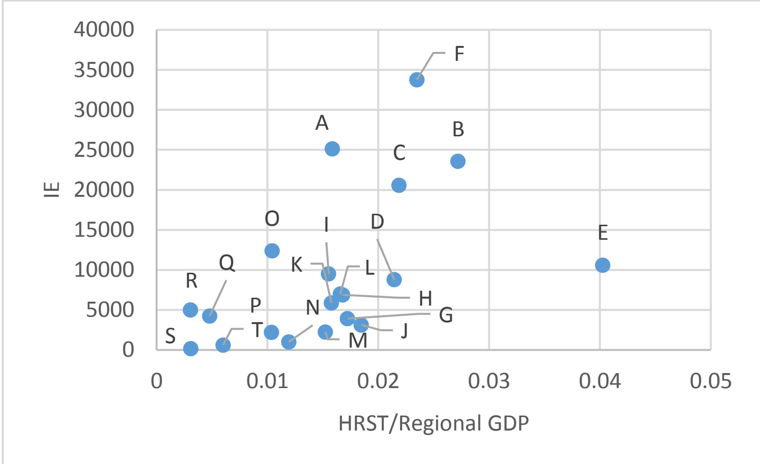


Chart 3. Region Position during-crisis period - HRST



Note: A – Yugoiztochen; B – Sud-Muntenia; C – Sud-Vest Oltenia; D – Centru; E – Nord-Est; F – Sud-Est; G – Severen Tsentralen; H – Podlaskie; I - Vest; J – Swietokezyskie; K – Severozapaden; L – Severoiztochen; M – Centro (PT); N – Lubuskie; O – Opolskie; P – Severozápad; Q – Alentejo; R – Algarve; S – Prov. Luxembourg (BE); T – Cornwall and Isles of Scilly.

Source: Our Elaboration

Charts 2 and 3 show the position of Top 20 NUT-II regions based on model 2 VRS ranking, considering the period before and during the financial crisis (2006-2008 and 2009-2012). Upper regions remain the same before and during crisis, with higher values of Innovation Efficiency. Bottom regions have lower IE, left side regions have lower levels of human resources in science and technology (HRST) and right side regions have higher levels of HRST. Considering possible to verify that regions are more concentrated in the left and bottom side, they have low levels of HRST and IE. The most efficient regions considered by the Top 20 ranking, such as the Province of Luxembourg (Belgium), Severozapaden (Bulgaria) and Severn Tsentralen (Bulgaria) are in the left and bottom side.

Yugoiztochen (Bulgaria) is the region with the highest IE ratio, but in terms of HRST ratio, the levels are low. By the contrary, Nord-Est (Romania) shows low levels of IE ratio and the highest levels of HRST. The position of each region changes downwards to the bottom from the pre-crisis period to the during-crisis period. The levels of HRST almost don´t change from one period to another. This means that the levels of HRST tend to increase while regional GDP decrease in this period. In terms of IE ratio, the levels fall slightly but recover in the during and post-crisis period namely for Yugoiztochen (Bulgaria), Sud-Muntenia (Romania) and Opolskie (Poland). The Sud-Est shows a positive evolution in IE ratio across periods. The regions from Romania show a positive evolution on HRST, but when considering the different Eurostat reports (2017) and RIS (2017), Romania regions such as Sud-Muntenia and Nord-Est always show the worst results in terms of HRST and are considered modest innovators.

Chart 4. Region Position pre-crisis period - GVA Industry

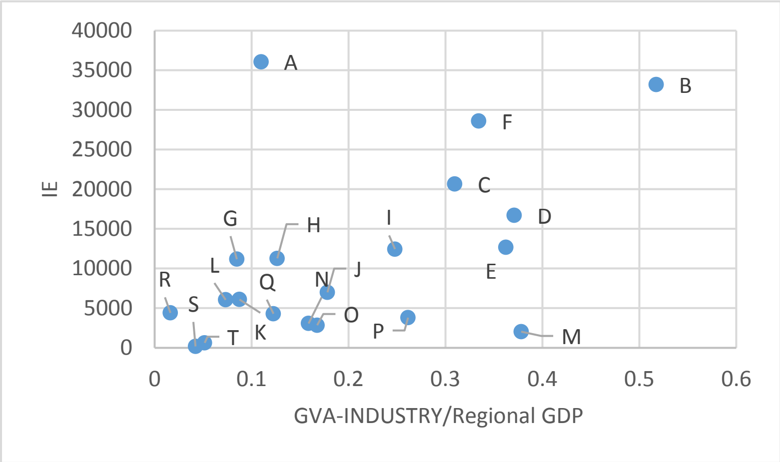
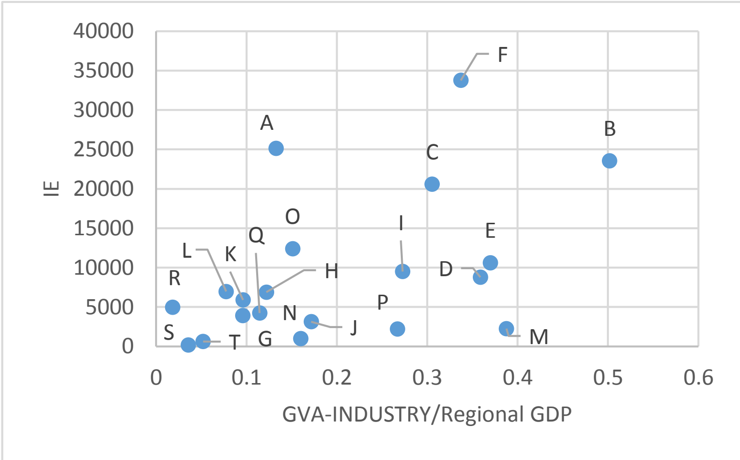


Chart 5. Region Position during-crisis period - GVA Industry



Note: A – Yugoiztochen; B – Sud-Muntenia; C – Sud-Vest Oltenia; D – Centru; E – Nord-Est; F – Sud-Est; G – Severen Tsentralen; H – Podlaskie; I - Vest; J – Swietokezyskie; K – Severozapaden; L – Severoiztochen; M – Centro (PT); N – Lubuskie; O – Opolskie; P – Severozápad; Q – Alentejo; R – Algarve; S – Prov. Luxembourg (BE); T – Cornwall and Isles of Scilly.

Source: Our Elaboration

Charts 4 and 5 show the position of the Top 20 NUT-II regions in model 2, VRS, considering GVA Industry and Innovation Efficiency. These charts represent the pre-crisis period (Chart 4) and the during-crisis period (Chart 5). As before, the upper side regions present higher IER values and bottom regions lower values. Left side regions have lower levels of GVA Industry ratio and right side regions show higher. The Sud-Muntenia region (Romania) has the highest ratios of GVA Industry, but is not the best region concerning Innovation Efficiency. The most efficient regions are concentrated on the left side of the chart and from 2006-2008 to 2009-2012 their position shifts downwards, translating the decrease of IE ratios from the pre-crisis period to the during-crisis period. The GVA-Industry ratio has no especial change because both variables GVA-Industry and Regional GDP decrease from one period to another.

These regions were considered inefficient comparatively to other regions with lower GDP ratios because they didn't generate enough real output. On the other hand, regions with lower GDP ratios were considered efficient because even with a reduced input level they reached better economic results. This indicates that human resources and tertiary education in science and technology are fundamental indicators to create more value added for regions. Investment in these indicators may not guarantee per se that the regions will reach higher levels of value added and higher levels of efficiency. However, policy makers should pay more attention to these indicators and ponder how to improve regional innovation policies, namely regarding inefficient regions that may increase the generates output with the same innovation inputs (Dzemydaitė et al., 2016). Also, Kalapouti et al. (2017), showed that high levels of innovative activity through patents production allow high levels of innovative efficiency.

Next, are presented the Charts that correspond to the UK, Spain and Poland regions.

Chart 6. Region Position pre-crisis - HRST (UK)

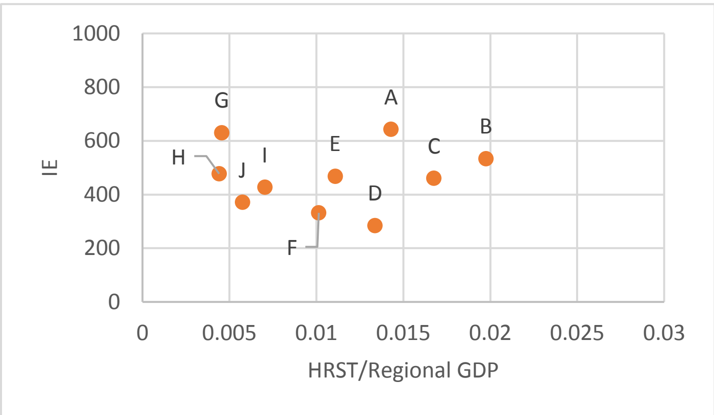
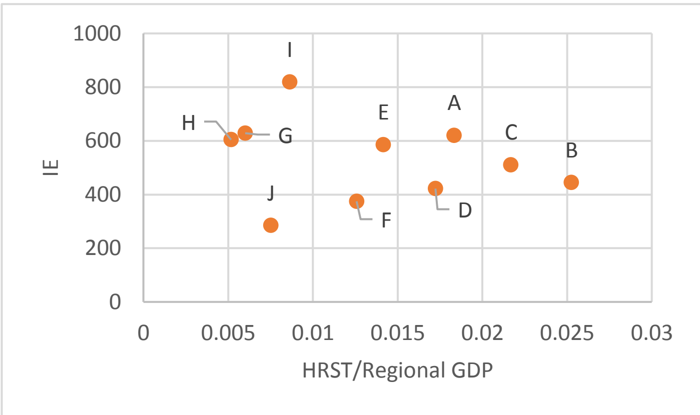


Chart 7. Region Position during-crisis - HRST (UK)



Note: A – Northen Ireland; B – West Midlands; C – West Yorkshire; D – Essex; E – South Yorkshire; F – Tees Valley and Durham; G – Cornwall and Isles of Scilly; H – Cumbria; I – East Yorkshire and Northen Lincolnshire; J – Lincolnshire;

Source: Our Elaboration

Specifically, Charts 6 and 7 represent the Top 10 UK regions, under the VRS assumption, in the pre-crisis period (Chart 6) and in the during-crisis period (Chart 7) corresponding to the relationship between the HRST/regional GDP and IE. As can be seen the regions are more concentrated in the left side, in the pre-crisis period. This means that these regions have lower levels of HRST but even so, the same regions have higher levels of IE, for example, Cornwall and Isles of Scilly, Cumbria and Lincolnshire. These last regions are also considered as the most efficient in the Top 10. West Midlands is the regions that show highest levels of HRST ratio. Somehow, these results are in line with the EU reports, showing that the UK is well positioned in all regions under study and thus presents high levels of HRST, namely in southern and eastern regions.

On the other hand, the UK is included in the Declining group which means that this country is efficient and has a strong National Innovation System but doesn't investment in innovation. In times of crisis, the UK tends to move to the right side because it benefits from National Systems of Innovation (NSI). Furthermore, according to Filippetti and Archibugi (2011) the NSI shows the importance of human resources for enterprises, namely in the UK.

Chart 8. Region Position pre-crisis - GVA Industry (UK)

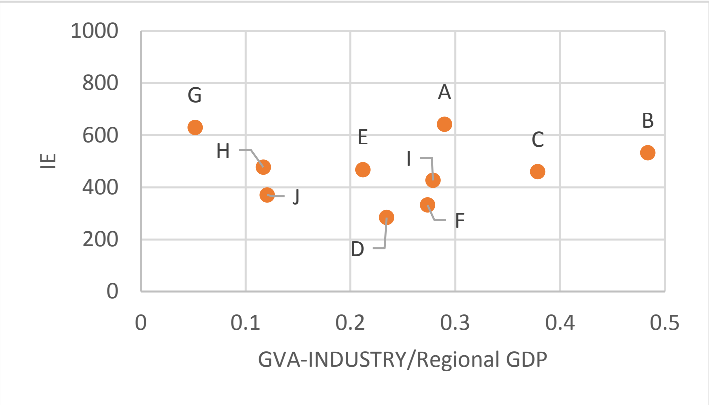
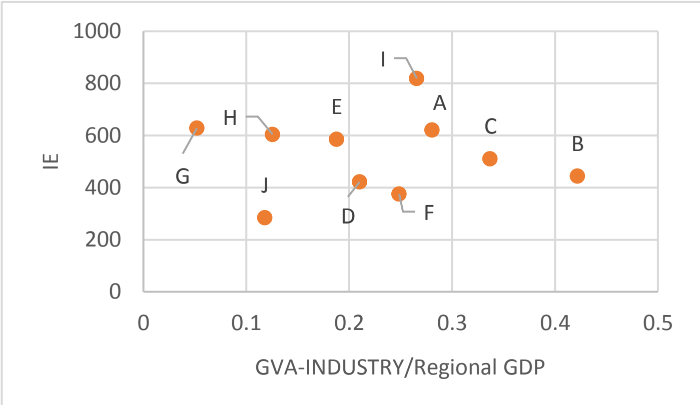


Chart 9. Region Position during-crisis - GVA Industry (UK)



Note: A – Northen Ireland; B – West Midlands; C – West Yorkshire; D – Essex; E – South Yorkshire; F – Tees Valley and Durham; G – Cornwall and Isles of Scilly; H – Cumbria; I – East Yorkshire and Northen Lincolnshire; J – Lincolnshire;

Source: Our Elaboration

Charts 8 and 9 show the relationship between the GVA Industry ratio and the IE ratio for the Top 10 UK regions; these regions are more concentrated in the middle of the charts, which means the levels of GVA are higher compared with the previous charts showing the Top 20. When compared, this two charts show that some regions decreased a little concerning Innovation Efficiency, however, this decrease is not significant. Once again, this relationship between Innovation Efficiency and in this case GVA of industry is assured by the National Innovation System and by government support.

The following Charts 10 and 11 represent the Top 10 NUT-II Regions in Spain.

Chart 10. Region Position pre-crisis - HRST (Spain)

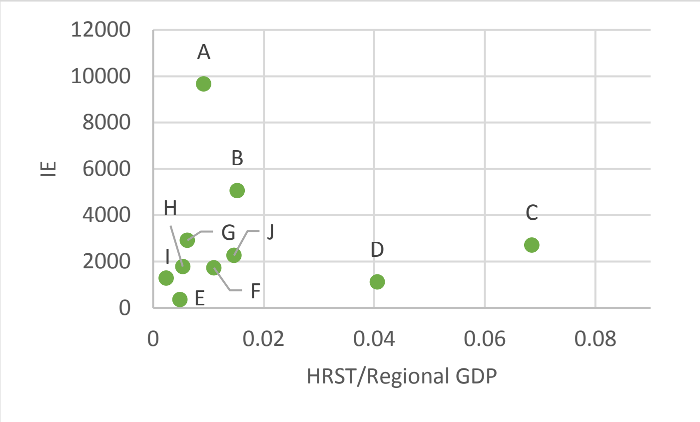
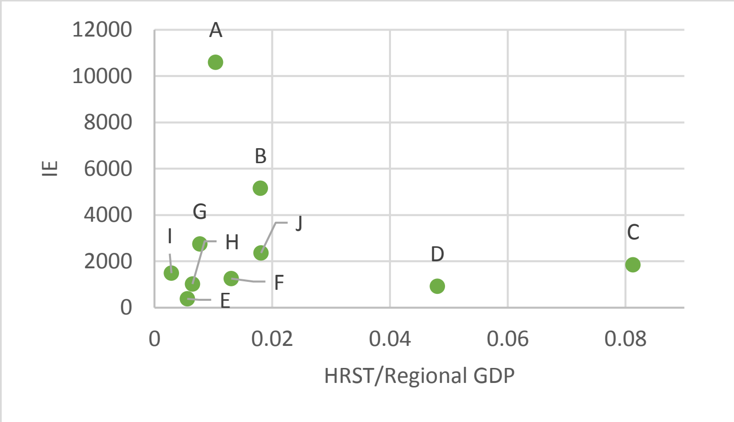


Chart 11. Region Position during-crisis - HRST (Spain)



Note: A – Extremadura; B – Canarias; C – Andalucia; D – Comunidad Valenciana; E – Comunidad Foral de Navarra; F – Region de Murcia; G – Illes Balears; H – Cantabria; I – La Rioja; J – Castilla – La Mancha;

Source: Our Elaboration

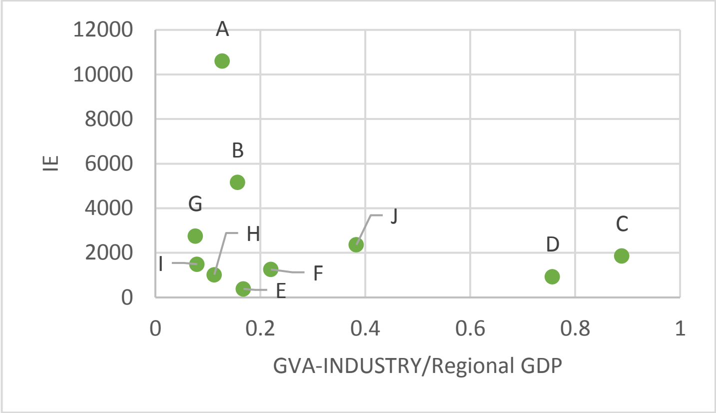
Charts 10 and 11 show the relationship between HRST and IER based on GDP. These Charts allow concluding that the most efficient regions considered by the DEA methodology are more concentrated on the left side. Extremadura is the region with higher levels of Innovation Efficiency and La Rioja has the lower levels of HRST. Finally, Comunidad Foral de Navarra has lowest levels of HRST and IER and Andalucia the highest values of HRST ratio, although with a low IE ratio.

In fact, Spain is included in the Lagging-behind group where the level of investment on R&D is low, and productivity levels and NSI are also low. Hence, the levels of HRST are low and during the financial crisis the regions tend to move to the right side, which means that although GDP decreases, the number of human resources (HRST) increases slightly.

On the other hand, the Regional Innovation Scoreboard (RIS) (European Commission, 2017), considered the regions of Spain as a moderate innovators, and the region that stands out most is Pais Vasco. Furthermore, Cataluña, Comunidad de Madrid and Comunidad Foral de Navarra are in the Top 10 of the Moderate Innovators and Canarias is in the Top 10 of Modest Innovators.

Chart 12. Region Position pre-crisis -GVA Industry (Spain)

Chart 13. Region Position during-crisis - GVA Industry (Spain)



Note: A – Extremadura; B – Canarias; C – Andalucia; D – Comunidad Valenciana; E – Comunidad Foral de Navarra; F – Region de Murcia; G – Illes Balears; H – Cantabria; I – La Rioja; J – Castilla – La Mancha;

Source: Our Elaboration

Charts 12 and 13 show the relationship between the GVA industry ratio and IE ratio and indicate that regions are more dispersed but more concentrated at the bottom and left side. Furthermore, the regions considered more efficient are on the left side, with Comunidad Foral de Navarra having low levels of Innovation Efficiency, and Extremadura having high levels of IE. From the pre-crisis period to the during-crisis period, the regions move further to the right side, which means that the regions recover soon after the crisis.

The following Charts, 14 and 15, show the position of the Top 10 NUT-II regions in Poland.

Chart 14. Region Position pre-crisis - HRST (Poland)

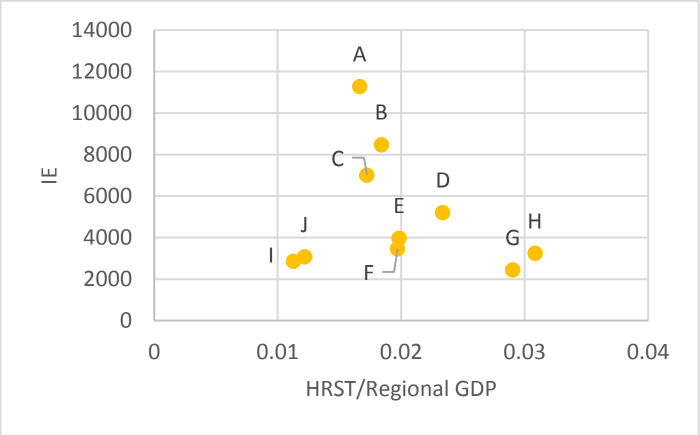
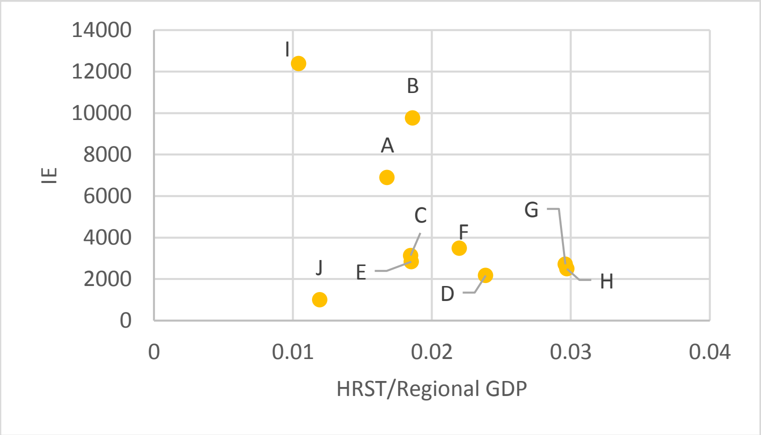


Chart 15. Region Position during-crisis - HRST (Poland)



Note: A –Podlaskie; B – Warminsko-Mazurskie; C – Swietokrzyskie; D – Pomorskie; E – Zachodniopomorskie; F – Kujawsko-Pomorskie; G – Podkarpackie; H – Wielkopolskie; I – Opolskie; J – Lubuskie;

Source: Our Elaboration

Charts 14 and 15 show the relationship between HRST and IE ratios. It is possible to verify that the regions are more concentrated in the middle of the chart, meaning that these regions have high levels of Innovation Efficiency and the HRST ratio is relatively low. Opolskie and Podlaskie are the regions that decreased the most the IE ratio from the pre-crisis period to the during-crisis period. In fact, Poland is considered a catching-up Country, since Poland invests significantly in R&D, yet doesn't receive much support from the NSI. These are some of the characteristics of the New Member States in the European Union included in the Catching-up Group defined by Filippetti and Archibugi (2011).

Chart 16. Region Position pre-crisis -GVA Industry (Poland)

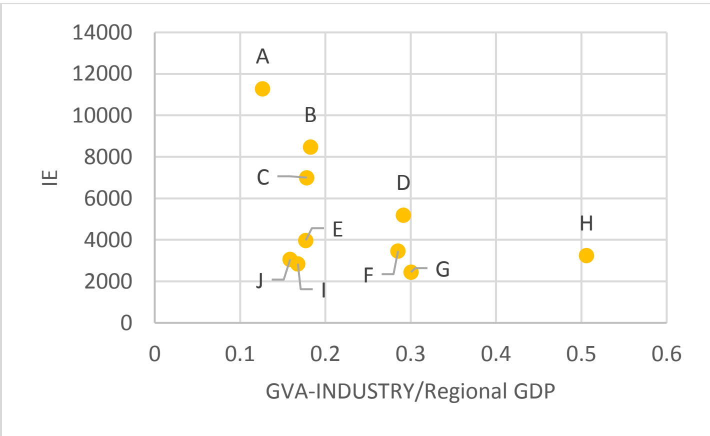
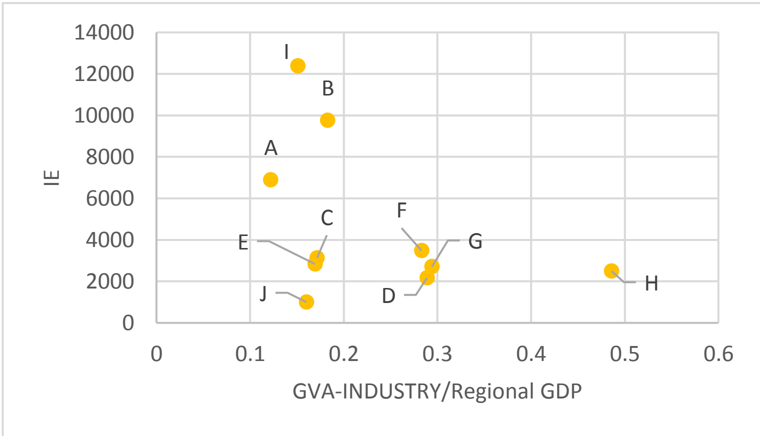


Chart 17. Region Position during-crisis - GVA Industry (Poland)



Note: A –Podlaskie; B – Warminsko-Mazurskie; C – Swietokrzyskie; D – Pomorskie; E – Zachodniopomorskie; F – Kujawsko-Pomorskie; G – Podkarpackie; H – Wielkopolskie; I – Opolskie; J – Lubuskie;

Source: Our Elaboration

To conclude the analysis of the position of the Top 10 Poland regions, Charts 16 and 17 show the relationship between GVA industry and IE ratios. Contrary to the previous Charts of Poland, the regions are more dispersed but more on the left side. The regions considered more efficient by the DEA methodology are Opolskie, Podlaskie and Lubuskie, more concentrated on the left side. This means that the ratio of GVA industry and GDP is low. During the financial crisis it is possible to detect that regions decrease their levels of IER and they move further downwards in response to the crisis, except Opolskie, which increased the levels of IE, since the Regional GDP increased for Opolskie.

Also, the regions from Poland are considered Modest Innovators by RIS (European Commission, 2017). Even so, Wielkopolskie, Lubelskie, Podlaskie and Opolskie are included in the Top 10 of Modest Innovators. Notwithstanding, the Eurostat report (2017) shows that Poland regions tend to recover more easily in the during-crisis period.

Beside this, it is also important to analyse the same factors, considered for the discussion, i.e. the HRST and GVA-Industry for Romania and Bulgaria that are also considered Catching-up countries:

Chart 18. Region Position pre-crisis - HRST (Romania)

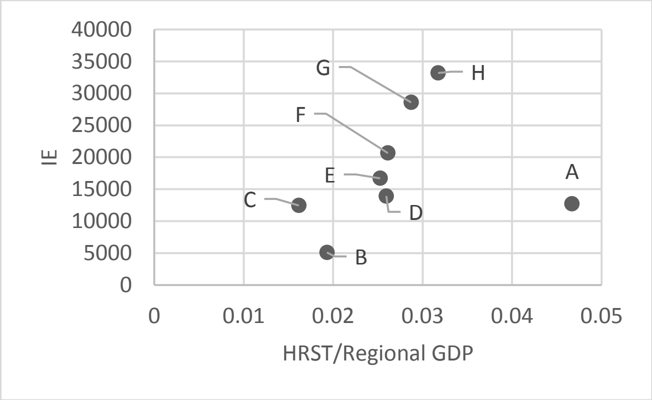
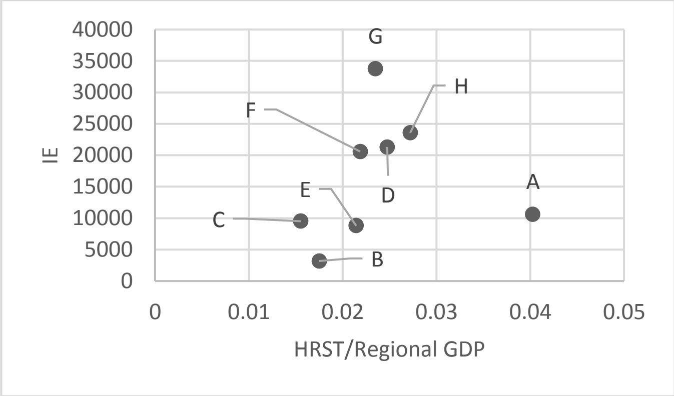


Chart 19. Region Position during-crisis - HRST (Romania)



Note: A – Nord-Est; B – Bucaresti-Ilfov; C – Vest; D – Nord-Vest; E – Centru; F – Sud-Vest Oltenia; G – Sud-Est; H – Sud-Muntenia

Source: Our Elaboration

Charts 18 and 19 show the relationship between HRST and IE ratios for the Romania regions. It is possible to verify that the regions are more concentrated in the middle of the chart showing high levels of IER and the levels of HRST are also high comparatively with other regions, such as, UK regions. During the crisis the regions move further downwards, decreasing the levels of IER, even though, the levels of HRST don't decrease in the same proportion.

Chart 20. Region Position pre-crisis -GVA Industry (Romania)

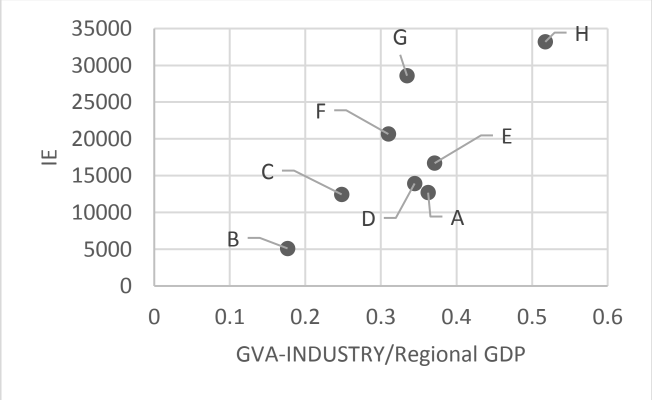
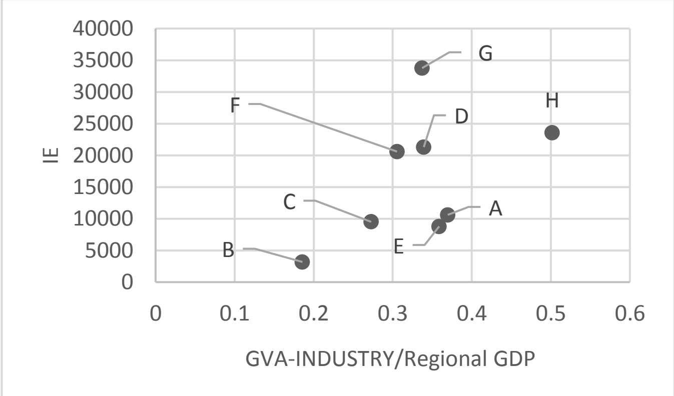


Chart 21. Region Position during-crisis -GVA Industry (Romania)



Note: A – Nord-Est; B – Bucaresti-Ilfov; C – Vest; D – Nord-Vest; E – Centru; F – Sud-Vest Oltenia; G – Sud-Est; H – Sud-Muntenia

Source: Our Elaboration

Charts 20 and 21 show the relationship between GVA-Industry and IER for Romania regions and it is possible to verify that regions are concentrated in the middle of the charts with similar levels of GVA-Industry comparatively with the regions of the other countries analysed. Once again, it is possible to see that the regions tend to move further downwards during the crisis period.

Chart 22. Region Position pre-crisis - HRST (Bulgaria)

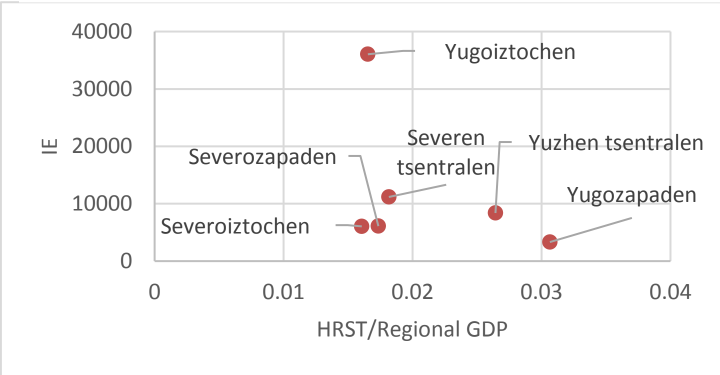
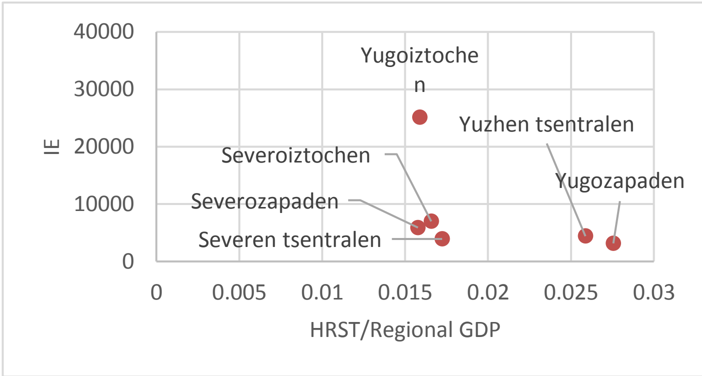


Chart 23. Region Position during-crisis - HRST (Bulgaria)



Source: Our Elaboration

Charts 22 and 23 show the relationship between HRST and IER for Bulgaria regions. Bulgaria are represented in this sample with 6 regions and Yugoiztochen is the region with higher levels of IER. The levels of HRST are low and tend to decrease from the pre-crisis period to during-crisis period.

Chart 24. Region Position pre-crisis -GVA Industry (Bulgaria)

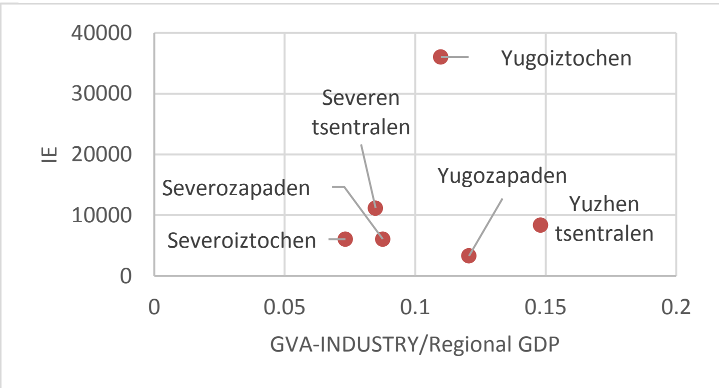
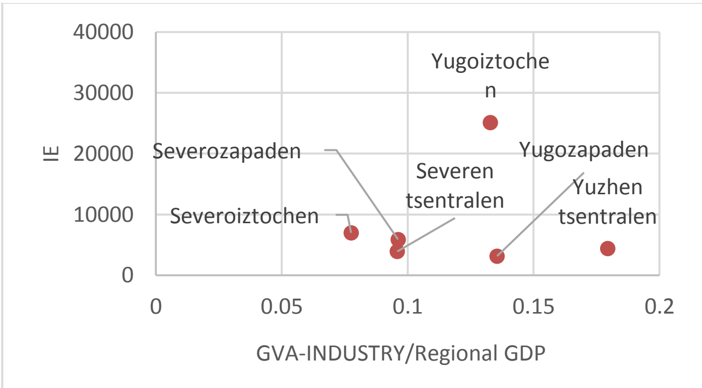


Chart 25. Region Position during-crisis -GVA Industry (Bulgaria)



Source: Our Elaboration

Charts 24 and 25 show the relationship between GVA-Industry and IER. It is possible to see that the levels of GVA-Industry are relatively low and Yugoiztochen is, once again, the region that stands out the most. From the pre-crisis period to during-crisis period the regions move further downwards.

In fact, Romania and Bulgaria are considered as modest innovators and are the less developed countries of UE, however the results of DEA application show high scores on innovation efficiency for their regions, namely for Romania. The truth is that Romania, shows high levels of HRST comparatively with other regions analysed and this can be a reason for the high levels of IER, that is, the fact of Romania show high levels of HRST allows it has a bigger absorption capacity where the knowledge spillovers play a fundamental role and without this the regions of Romania don't innovate.

This analysis impacts public policies because as aforementioned, human resources play a key role towards the innovation process, namely during crisis, because they reduce the effects from crisis (Crescenzi et al., 2016; Kalapouti et al., 2017).

On the other hand, the regions that suffer the most due to financial crisis are those from countries with the lowest levels of government support to innovation, namely New Member States and Poland.

Furthermore, the results indicate persistency on innovation process over time, which means that in time of crisis, the regions choose technological accumulation. This doesn't mean the regions follow the same sectors of innovation. In fact, financial crisis may represent an opportunity for government support, especially concerning new sectors such as environmental issues.

5. Conclusions and limitations

The main goal of this thesis is to measure the efficiency in terms of innovation of EU regions and understand the impact of innovation in EU regions, namely during the recent global financial crisis. The second goal is to organize an up-to-date ranking with the most efficient regions in the EU. To achieve these goals the methodology used included the DEA methodology with a new indicator, Innovation Efficiency Ratio, the PCSE methodology and the GMM estimations for 104 EU NUT-II regions during the period of time from 2006 to 2012. The results indicate that Romania is one of the countries with more regions on the Top 20 ranking, followed by Bulgaria.

Answering the questions that were posed at the beginning, the most efficient regions are the Sud-Est and Sud-Muntenia in Romania, Yougoiztochen, Severozápaden and Severen Tsentralen in Bulgaria, the Province of Luxembourg in Belgium and the Algarve in Portugal.

The results from the different Eurostat reports (2011; 2017) and reports from the European Commission (2017) do not support the present results. In fact, the regions from Romania are considered the most modest in terms of innovation, although present results indicate they are the most efficient regions.

On the other hand, it is important to take into account that in this study the majority of the regions are located in the Southern and Eastern EU, precisely the regions that according to previous reports have lower scores in wealth creation and innovation.

Regarding the main factors affecting innovation and efficiency these include HRST supporting conclusions by Crescenzi et al. (2016), Filippetti and Archibugi (2011), Kalapouti et al. (2017) and Patra and Krishna (2015). Effectively, in this study, the HRST have proved to be the most significant factor that affects the Innovation Efficiency positively. In this way, the qualified human resources are a key-factor for innovation, namely in time of crisis. Therefore they should be part of any strategy towards innovation because they are able to improve and innovate. On the other hand, the Gross Value Added of Industry affects negatively the Innovation Efficiency.

Thirdly, the crisis accentuated disparities between the regions. The results obtained allow confirming that regions from Spain, such as Illes Balears, La Rioja, Andalucia e Region de Murcia were those that decreased the most in efficiency scores from 2008 to 2009, also, some regions from Poland, such as Podlaskie and Lubuskie and from the UK, Northern Ireland was the worst from 2008 to 2009. Moreover, in the Top 20, Yugoiztochen (Bugaria) and Centru (Romania) also decreased their levels of efficiency from 2008 to 2009.

However, all these regions had a good recovery between 2009 and 2012 improving their efficiency levels.

An interesting aspect is that regions considered 100% efficient before the crisis tend to keep these scores during the financial crisis, and most of the regions in the Top 20 tend to increase efficiency levels after 2008. Hence, disparities between regions do persist, as among regions within the same country. The effect of crisis in the different EU countries is different because it depends on factors such as fiscal systems, capital flows and credit markets. Ultimately, the investment reduction on innovation is the main consequence of such factors.

To sum up, there are significant divergences between EU regions and the financial crisis has hindered bridging such gaps, because the most vulnerable countries reduced their investment on innovation (Archibugi & Filippetti, 2011). Innovation efforts are not yet translated into results, and as a consequence southern regions are still far behind northernmost regions. In addition, the disparities among regions from the same country still persist, especially peripheral regions, more distant from capital city regions. Concerning the regions from Poland, Spain and Romania, there are serious disparities when compared with regions from Germany, France, Finland or Sweden. Hence, full recovery from the crisis by all EU regions is only possible in the long term, which constitutes an additional obstacle to convergence among regions. These differences impact the EU as a whole because the EU also moves away from other world leading economies such as the USA, Japan, India or China, meaning the European economy will not be so attractive on a global scale.

Focusing on regional innovation may constitute a solution for regional disparities, as well as government investment at a regional level, with the support from the EU and specific innovation policies, directed related to NSI and human capital, to allow convergence among regions regarding efficiency.

Finally, this study presents some limitations. The first limitation concerns data collection, since there is a limited amount of data available since 2012, particularly regarding patents and other variables such as number of publications or exports of medium and large enterprises. In addition, some regions from Germany and France, the main powers of the European Union, could not be considered in this study due to lack of data regarding the selected timeframe. Also, the different types of innovation were not contemplated. One the other hand, the number of patents is an imperfect variable to measure the Innovation Efficiency because it doesn't capture much of innovation because it is not always patented.

For future research, it would be interesting to obtain more updated data and for more regions in order to re-compare them and use other variables as proxy of innovation, such as Intellectual Property Rights, more specifically, the European Union Trademarks applications and Community Design Applications. Furthermore, it would be also interesting to consider the targets and benchmarks of the results of DEA in the study, as well as to focus more in the super-efficiency results. Last but not least, it would be interesting analyse the several strategies of innovation in territorial terms with the aim of re-orienting them, based on this study.

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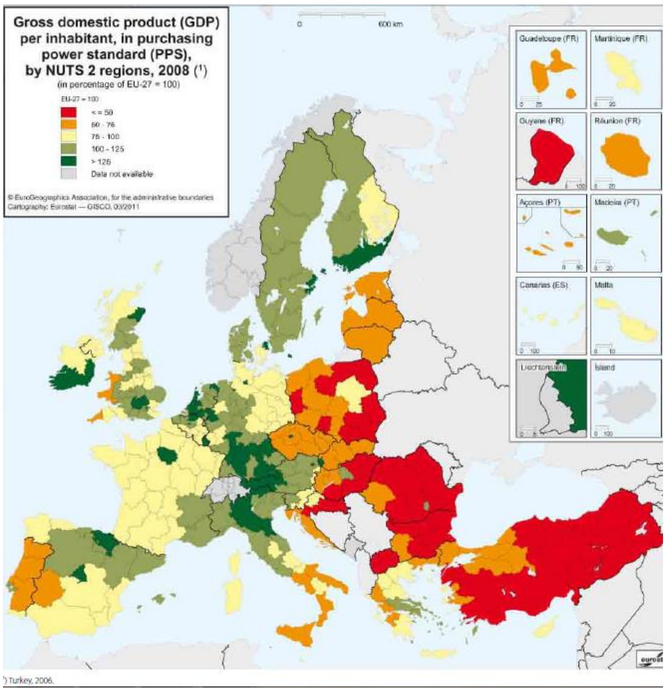
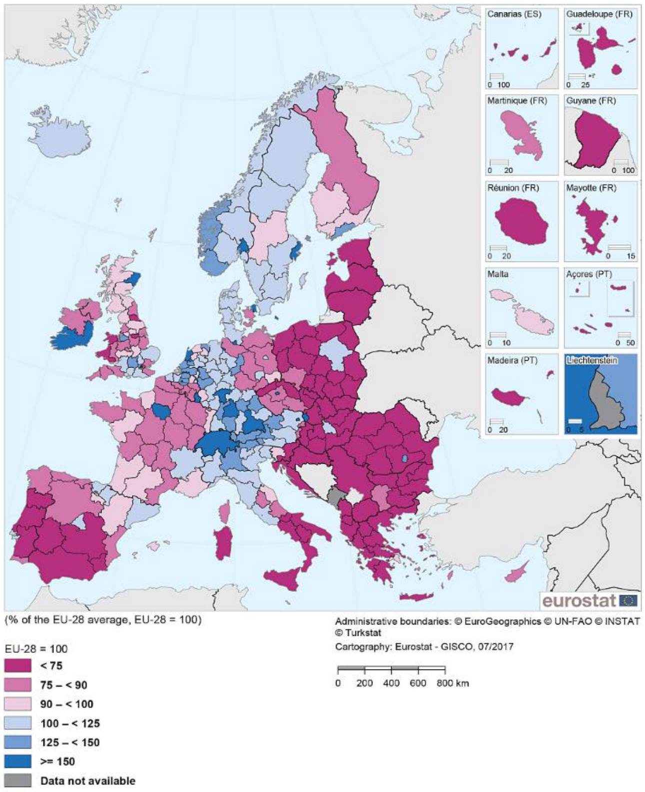
Annex

Figure A1. Gross domestic product (GDP) per inhabitant, in purchasing power standard (PPS), by NUTS 2 2008 (Turkey, 2006) (in percentage of EU-27 = 100)



Source: Eurostat (online data code: nama_r_e2gdp).

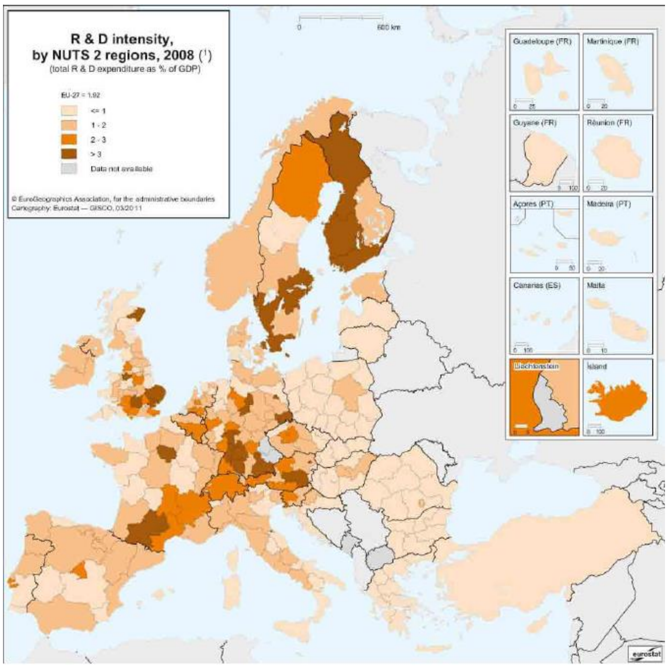
Figure A2. Gross domestic product (GDP) per inhabitant in purchasing power standards (PPS) in relation to the EU-28 average, by NUTS 2 regions, 2015 (% of the EU-28 average, EU-28 = 100)



Notes: Ireland, Norway and Albania: 2014. Switzerland and Serbia: national data. Switzerland: provisional.

Source: Eurostat (online data codes: nama_10r_2gdp and nama_10_pc)

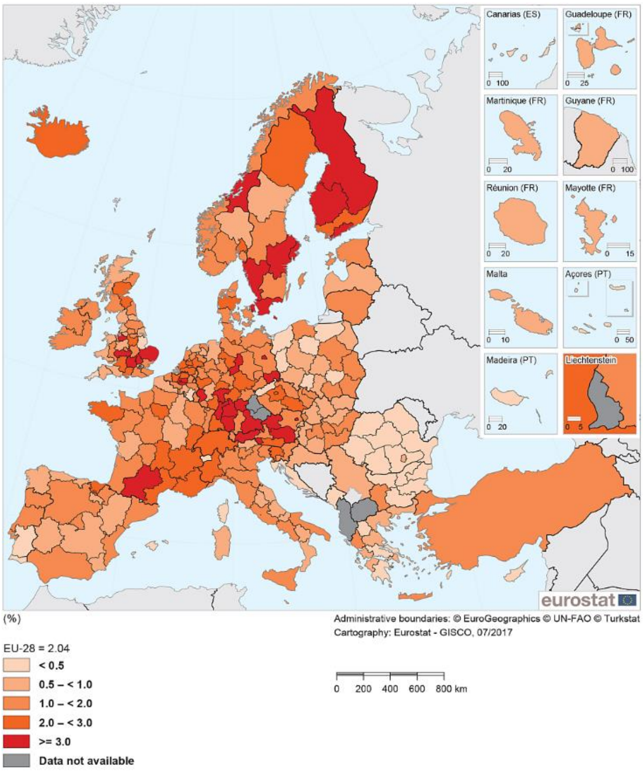
Figure A3. R & D intensity, by NUTS 2 regions, 2008(1) (total R & D expenditure as % of GDP)



Notes: (1) EU-27, Eurostat estimate; Belgium, Denmark, Germany, Ireland, Netherlands, Austria and Sweden, 2007; Greece, 2005; France, 2004; Belgium, Départements d'outre-mer (France) and Croatia, by NUTS 1 regions; Norway, Switzerland and Turkey, national level; Niederbayern and Oberpfalz (Germany), confidential data; Estonia, Ireland, Luxembourg and Malta, provisional data; Netherlands, estimate; Sweden, in some cases researchers are allocated to the head office; Denmark, break in series with previous year for which data is available.

Source: Eurostat (online data code: rd_e_gerdreg).

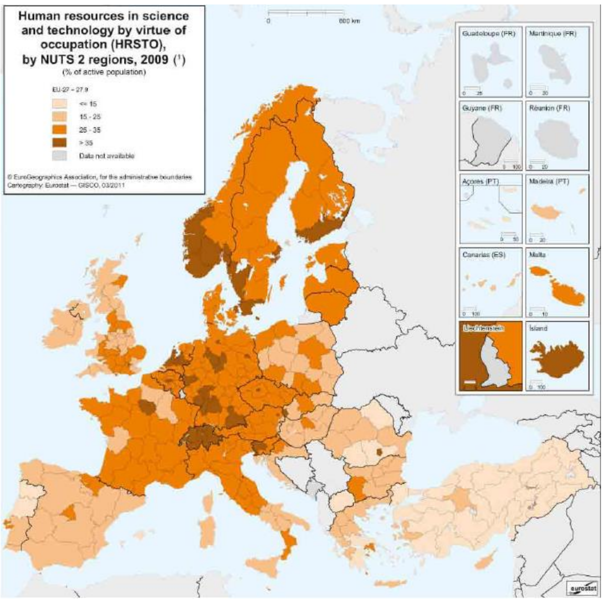
Figure A4. R & D intensity — gross domestic expenditure on R & D (GERD) relative to gross domestic product (GDP), by NUTS 2 regions, 2014 (%)



Notes: Départements d'outre-mer (FR): NUTS level 1. Switzerland, Serbia and Turkey: national data. Belgium, Germany, Ireland, Greece, France, Austria, Finland, Sweden and Norway: 2013. Switzerland: 2012. Italy and the United Kingdom: estimates.

Source: Eurostat (online data code: rd_e_gerdreg)

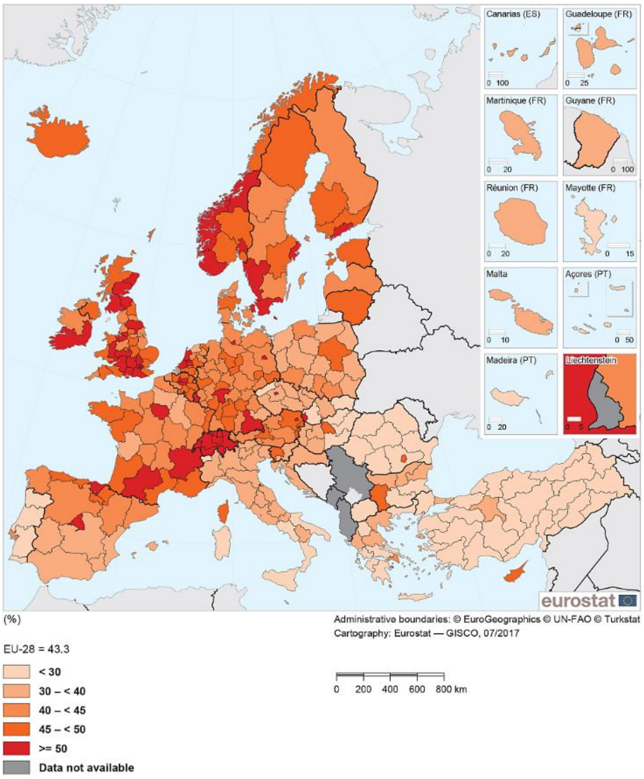
Figure A2. Human resources in science and technology by virtue of occupation (HRSTO), by NUTS 2 regions, 2009 (1) (% of active population)



Notes: (1) Corse (France) and Åland (Finland), data lack reliability due to reduced sample size, but publishable.

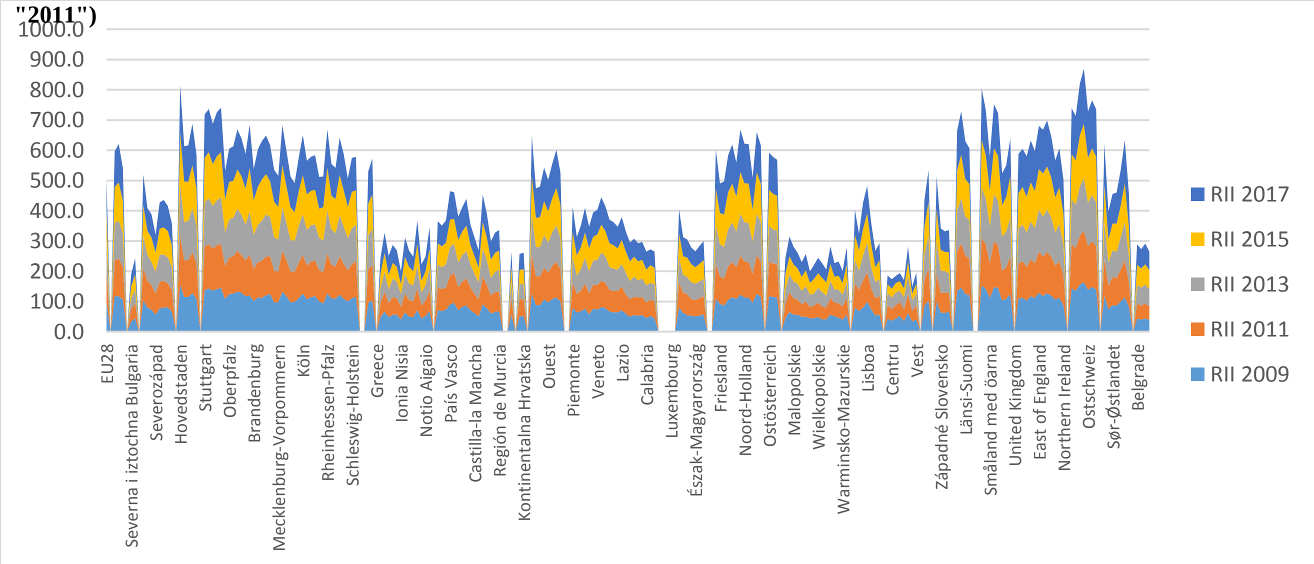
Source: Eurostat (online data code: hrst_st_rcat).

Figure A1. Share of human resources in science and technology (HRST) within the economically active population, by NUTS 2 regions, 2015 (%)



Source: Eurostat (online data code: hrst_st_rcat)

Chart A26. Evolution of Regional Innovation Index over time by NUT-II regions of Europe (Relative performance to EU in "2011")



Source: Our elaboration
Data: Regional Innovation Scoreboard (Available on: http://ec.europa.eu/growth/industry/innovation/facts-figures/regional_en)

Chart A2. Population with tertiary education - RIS 2017

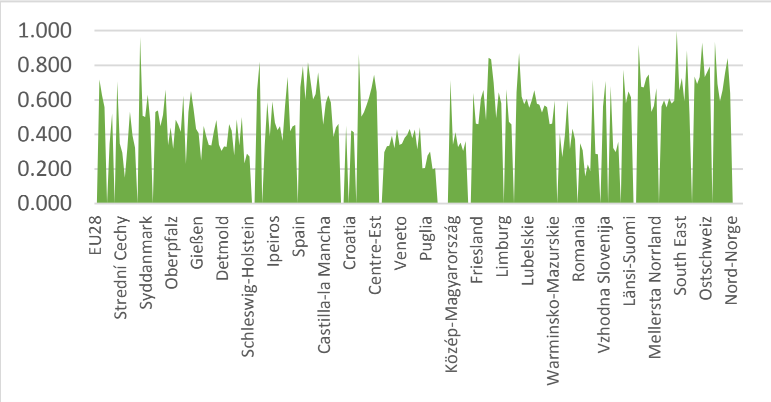
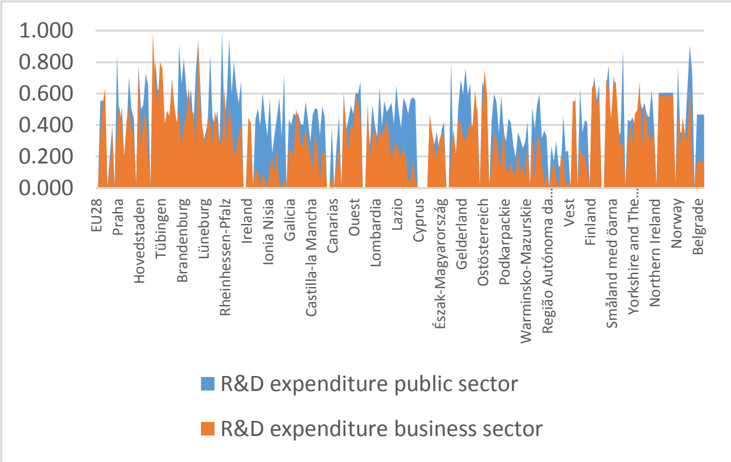


Chart A3. R&D expenditures - RIS 2017



Source: Our elaboration
Data: Regional Innovation Scoreboard (Available on: http://ec.europa.eu/growth/industry/innovation/facts-figures/regional_en)

Chart A4. EPO patent applications - RIS 2017

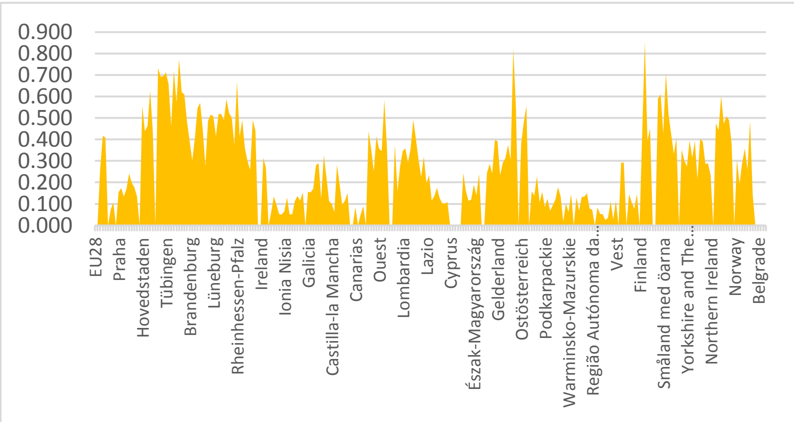
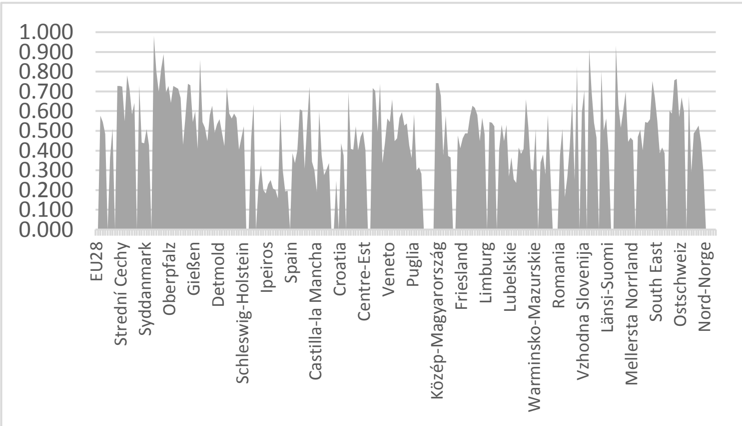


Chart A5. Employment medium and high tech manufacturing & knowledge-intensive services - RIS 2017



Source: Our elaboration
Data: Regional Innovation Scoreboard (Available on: http://ec.europa.eu/growth/industry/innovation/facts-figures/regional_en)

The results of application of DEA methodology in Model 1 are presented in the tables below:

Table A1. Top 20 of Efficient Regions (Model 1 – CRS) – All Regions

Model 1 - CRS								
All regions - Top 20								
		Before			During			
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Belgium	Prov. Luxembourg (BE)	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Spain	Comunidad Foral de Navarra	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Poland	Lubuskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Portugal	Algarve	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
UK	Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Spain	La Rioja	99.4%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Belgium	Prov. Brabant Wallon	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	87.9%	98.0%
Belgium	Prov. West-Vlaanderen	**100.0%**	91.8%	99.4%	**100.0%**	**100.0%**	91.0%	**100.0%**
Romania	Sud-Est	84.9%	**100.0%**	**100.0%**	87.1%	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Severen tsentralen	83.9%	**100.0%**	**100.0%**	78.1%	**100.0%**	99.9%	**100.0%**
Spain	Illes Balears	**100.0%**	90.9%	92.2%	**100.0%**	83.5%	84.3%	95.3%
Romania	Vest	61.0%	53.0%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
UK	Lincolnshire	89.9%	**100.0%**	70.7%	**100.0%**	86.1%	73.4%	79.1%
Spain	Región de Murcia	82.3%	**100.0%**	92.3%	81.5%	83.6%	77.0%	81.2%
Belgium	Prov. Limburg (BE)	95.3%	94.0%	75.7%	79.5%	88.0%	81.6%	75.5%
Poland	Opolskie	80.7%	86.5%	83.9%	65.8%	**100.0%**	81.5%	89.9%
Bulgaria	Yugoiztochen	70.9%	83.9%	88.7%	81.2%	74.0%	93.3%	89.8%
Bulgaria	Severozapaden	68.2%	70.2%	82.5%	68.8%	99.8%	**100.0%**	88.4%
UK	East Anglia	65.6%	77.0%	74.9%	82.1%	94.5%	90.7%	88.4%
Belgium	Prov. Oost-Vlaanderen	77.0%	93.2%	76.4%	68.6%	75.7%	73.0%	98.1%
Annual Average – 104 regions		**62.2%**	**63.1%**	**63.2%**	**62.4%**	**61.0%**	**60.4%**	**62.8%**

Source: Our Elaboration

As can be seen, under the CRS assumption the most efficient region in the European Union are the Province of Luxembourg in Belgium, Comunidad Foral de Navarra (Spain), Lubuskie (Poland), Algarve in Portugal and Cornwall and Isles of Scilly (UK). These regions present 100% of efficiency in all time period. Furthermore, Severen tsentralen (Bulgaria),

Región de Murcia (Spain), Opolskie (Poland), Severozapaden (Bulgaria) and Prov. Oost-Vlaanderen (Belgium) were the regions that most suffered in terms of efficiency when are analysed the time period before and during financial crisis. Others, like East Anglia (UK) have a higher score in 2009. It is possible to observe that in this Top 20 Belgium and Spain are the countries with more regions represented.

Table A2. Top 10 of Efficient Regions (Model 1 - CRS) - UK, Spain and Poland

Model 1 - CRS							
UK, Spain and Poland - Top 10							
	Before			During			
UK	2006	2007	2008	2009	2010	2011	2012
Cumbria	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Lincolnshire	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
East Anglia	**100.0%**	**100.0%**	**100.0%**	92.8%	**100.0%**	**100.0%**	97.4%
East Yorkshire and Northern Lincolnshire	90.2%	98.4%	91.5%	**100.0%**	**100.0%**	91.5%	94.0%
Berkshire, Buckinghamshire and Oxfordshire	87.5%	71.1%	**100.0%**	**100.0%**	89.3%	**100.0%**	**100.0%**
West Yorkshire	76.9%	64.0%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Tees Valley and Durham	92.4%	60.0%	**100.0%**	98.0%	97.6%	**100.0%**	91.1%
Derbyshire and Nottinghamshire	89.8%	79.7%	91.6%	83.5%	98.2%	**100.0%**	81.5%
Herefordshire, Worcestershire and Warwickshire	95.2%	57.9%	85.6%	**100.0%**	**100.0%**	86.7%	81.6%
Annual Average – 29 regions	**78.5%**	**72.3%**	**82.1%**	**80.7%**	**82.8%**	**80.4%**	**81.3%**
Spain							
Comunidad Foral de Navarra	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
La Rioja	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Aragón	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Illes Balears	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Región de Murcia	82.5%	**100.0%**	**100.0%**	97.2%	**100.0%**	**100.0%**	**100.0%**
Canarias (ES)	65.9%	93.8%	95.5%	89.7%	**100.0%**	**100.0%**	98.2%
Cantabria	90.7%	84.0%	85.2%	91.0%	75.0%	80.4%	79.8%
Extremadura	61.7%	72.3%	74.0%	98.5%	76.4%	87.6%	98.2%
Cataluña	**100.0%**	82.4%	85.9%	74.0%	72.7%	56.0%	69.8%
Castilla-la Mancha	83.9%	80.3%	78.9%	75.2%	73.7%	73.5%	72.8%
Annual Average – 17 regions	**77.1%**	**80.6%**	**80.5%**	**81.5%**	**77.7%**	**78.3%**	**79.4%**
Poland							
Lubuskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Opolskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Wielkopolskie	78.2%	88.8%	87.6%	**100.0%**	**100.0%**	**100.0%**	98.2%
Swietokrzyskie	**100.0%**	**100.0%**	**100.0%**	98.3%	83.6%	86.5%	81.7%
Podlaskie	77.0%	72.9%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Pomorskie	52.4%	79.5%	**100.0%**	95.8%	86.4%	**100.0%**	**100.0%**
Podkarpackie	**100.0%**	77.2%	96.6%	94.8%	85.1%	68.4%	62.5%
Kujawsko-Pomorskie	76.5%	98.3%	85.2%	69.8%	77.4%	85.2%	75.6%
Zachodniopomorskie	61.4%	58.9%	**100.0%**	93.5%	86.2%	77.4%	78.6%
Lódzkie	84.8%	91.2%	75.8%	**100.0%**	65.5%	59.6%	75.5%
Annual Average – 16 regions	**79.1%**	**81.9%**	**87.7%**	**83.5%**	**78.1%**	**79.1%**	**77.2%**

Source: Our Elaboration

Specifically, this Table 2 confirms that the regions in the Top 20 in the global ranking are part of this Top 10 of each country and almost all of them are considered 100% efficient. It is also important to note the regions Cumbria (UK) and Aragón (Spain) that have a value of 100% but do not appear in the Top 20. Here, it is possible to confirm the lower score of Region de Murcia (Spain) from 2008 to 2009.

Table A3. Top 20 of Efficient Regions (Model 1 - VRS) - All Regions

Model 1 - VRS								
All regions - Top 20								
		Before			During			
Country	Region	2006	2007	2008	2009	2010	2011	2012
Belgium	Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Belgium	Prov. Brabant Wallon	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Belgium	Prov. Luxembourg (BE)	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Severozapaden	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Severen tsentralen	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Spain	Comunidad Foral de Navarra	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Spain	La Rioja	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Spain	Illes Balears	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Poland	Lubuskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Portugal	Algarve	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Romania	Sud-Est	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Slovakia	Bratislavský kraj	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
UK	Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Belgium	Prov. West-Vlaanderen	**100.0%**	99.5%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
UK	Berkshire, Buckinghamshire and Oxfordshire	**100.0%**	96.8%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Bulgaria	Yugoiztochen	97.1%	**100.0%**	**100.0%**	**100.0%**	94.9%	**100.0%**	**100.0%**
Belgium	Prov. Vlaams-Brabant	90.1%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Poland	Opolskie	**100.0%**	97.4%	88.8%	79.9%	**100.0%**	86.1%	90.3%

Bulgaria	Severoiztochen	96.2%	93.6%	94.3%	89.6%	86.2%	80.9%	94.1%
Poland	Podlaskie	82.2%	77.2%	**100.0%**	95.3%	87.5%	89.9%	97.1%
	Annual Average – 104 regions	**70.0%**	**69.7%**	**69.7%**	**68.9%**	**67.6%**	**65.7%**	**67.7%**

Source: Our Elaboration

Firstly, it is possible to observe that the number of regions 100% efficient is bigger with the VRS assumption and all the regions in this ranking have a higher value under this assumption. This happens because the variables considered are almost all in ratio. Once again, Belgium is the country with more regions in this ranking. However, some of the regions considered in the Top 20 with the CRS assumption don't appear in this Top 20, for example the Province of Limburg (Belgium) and Región de Murcia (Spain). Additionally, Opolskie (Poland), Severoiztochen (Bulgaria) and Podlaskie (Poland), are the only regions in this ranking with lower ranking from 2008 to 2009, i.e. during the financial crisis.

Table A4. Top 10 of Efficient Regions (Model 1 - VRS) - UK, Spain and Poland

Model 1 - VRS							
UK, Spain and Poland - Top 10							
	Before			During			
UK	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Cumbria	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Lincolnshire	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Berkshire, Buckinghamshire and Oxfordshire	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Surrey, East and West Sussex	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Cornwall and Isles of Scilly	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
East Anglia	**100.0%**	**100.0%**	**100.0%**	96.6%	**100.0%**	**100.0%**	**100.0%**
West Yorkshire	**100.0%**	94.2%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
East Yorkshire and Northern Lincolnshire	95.0%	**100.0%**	93.0%	**100.0%**	**100.0%**	**100.0%**	95.7%
North Yorkshire	**100.0%**	**100.0%**	95.2%	**100.0%**	**100.0%**	**100.0%**	86.0%
Tees Valley and Durham	**100.0%**	63.6%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Annual Average – 29 regions	**84.0%**	**81.5%**	**85.2%**	**84.4%**	**88.1%**	**87.2%**	**85.4%**
Spain							
País Vasco	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Comunidad Foral de Navarra	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
La Rioja	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Aragón	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Comunidad de Madrid	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Extremadura	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Illes Balears	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Región de Murcia	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Canarias (ES)	77.8%	99.4%	**100.0%**	95.1%	**100.0%**	**100.0%**	99.1%
Cataluña	**100.0%**	98.4%	86.9%	96.7%	89.5%	81.2%	94.6%
Annual Average – 17 regions	**89.7%**	**92.2%**	**90.7%**	**91.7%**	**88.0%**	**88.5%**	**88.7%**
Poland							
Mazowieckie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Wielkopolskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Lubuskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Dolnoslaskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Opolskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Pomorskie	94.5%	**100.0%**	**100.0%**	99.8%	94.9%	**100.0%**	**100.0%**
Slaskie	98.8%	**100.0%**	**100.0%**	93.1%	99.6%	93.8%	96.2%
Podlaskie	86.1%	85.8%	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Swietokrzyskie	**100.0%**	**100.0%**	**100.0%**	**100.0%**	84.3%	87.1%	87.2%
Lódzkie	95.9%	94.5%	**100.0%**	**100.0%**	**100.0%**	63.6%	**100.0%**
Annual Average – 16 regions	**92.2%**	**93.6%**	**97.7%**	**93.4%**	**88.7%**	**88.9%**	**88.8%**

Source: Our Elaboration

As in the previous Table the number of 100% efficient regions for each country is bigger. However compared with the Top 10 under CRS assumption, the 100% efficient regions are the same and compared with the Top 20 under VRS assumption, Podlaskie is not considered as 100% efficient in the Top 10. One the other hand it is possible to see that the regions considered 100% efficient before the crisis are the same regions 100% efficient after 2008, except for East Anglia (UK), Canarias (Spain) and Slaskie (Poland) because their score is lower from 2008 to 2009. Even so, East Anglia (UK) and Canarias (Spain) recover their efficiency score of 100% in the following years.

The results of super-efficiency of Model 1 are presented in following tables:

Table A5. Top 20 – Super-efficiency Analysis (Model 1 - CRS) - All Regions

Model 1 - Superefficiency CRS								
All regions - Top 20								
		Before			During			
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Belgium	Prov. Luxembourg (BE)	**196.7%**	**281.4%**	**436.7%**	**336.1%**	**269.7%**	**440.7%**	**374.2%**
Portugal	Algarve	**164.0%**	**182.1%**	**147.9%**	**136.2%**	**154.0%**	**143.4%**	**126.0%**

UK	Cornwall and Isles of Scilly	**179.6%**	**159.9%**	**146.4%**	**128.7%**	**132.9%**	**125.5%**	**109.0%**
Belgium	Prov. Brabant Wallon	**257.1%**	**156.1%**	**103.8%**	**103.8%**	**136.6%**	87.9%	98.0%
Spain	Comunidad Foral de Navarra	**131.6%**	**154.3%**	**154.4%**	**120.7%**	**123.4%**	**111.2%**	**115.9%**
Romania	Sud-Est	84.9%	**101.9%**	**105.3%**	87.1%	**126.4%**	**182.8%**	**194.0%**
Romania	Vest	61.0%	53.0%	**134.8%**	**189.5%**	**145.2%**	**141.5%**	**147.4%**
Poland	Lubuskie	**109.1%**	**121.7%**	**121.4%**	**145.4%**	**112.5%**	**110.0%**	**100.9%**
Romania	Bucuresti - Ilfov	24.4%	30.2%	**142.8%**	**126.4%**	**154.9%**	**155.4%**	**172.4%**
Spain	La Rioja	99.4%	**100.5%**	**135.1%**	**129.7%**	**106.5%**	**106.5%**	**118.3%**
Belgium	Prov. West-Vlaanderen	**123.1%**	91.8%	99.4%	**135.4%**	**135.6%**	91.0%	**105.4%**
Bulgaria	Severen tsentralen	83.9%	**125.0%**	**112.6%**	78.1%	**100.4%**	99.9%	**101.3%**
Spain	Illes Balears	**127.4%**	90.9%	92.2%	**102.8%**	83.5%	84.3%	95.3%
Spain	Región de Murcia	82.3%	**116.1%**	92.3%	81.5%	83.6%	77.0%	81.2%
UK	Lincolnshire	89.9%	**105.4%**	70.7%	**100.1%**	86.1%	73.4%	79.1%
Poland	Opolskie	80.7%	86.5%	83.9%	65.8%	**110.1%**	81.5%	89.9%
Belgium	Prov. Limburg (BE)	95.3%	94.0%	75.7%	79.5%	88.0%	81.6%	75.5%
Bulgaria	Severozapaden	68.2%	70.2%	82.5%	68.8%	99.8%	**104.4%**	88.4%
Bulgaria	Yugoiztochen	70.9%	83.9%	88.7%	81.2%	74.0%	93.3%	89.8%
UK	East Anglia	65.6%	77.0%	74.9%	82.1%	94.5%	90.7%	88.4%
Annual Average – 104 regions		**67.2%**	**67.9%**	**69.4%**	**67.8%**	**65.9%**	**66.3%**	**68.3%**

Source: Our Elaboration

With CRS assumption is can be seen that are only 3 regions with a score higher than 100% during all time period analysed, which are the Province of Luxemburg (Belgium), the most superefficient, that is, this region have the best performance on ranking of all regions, secondly, are Algarve (Portugal) and in third is Cornwall and Isles of Scilly. In this Top 20 Belgium and Spain stand out as being represented by a greater number of regions. Some other regions, namely the Comunidad Fural de Navarra decreased the score from 2006 to 2012, even with a score higher than 1. This decrease is most remarkable between 2008 and 2009.

Table A6. Top 10 – Super-efficiency Analysis (Model 1 - CRS) - UK, Spain and Poland

Model 1 - Superefficiency CRS							
UK, Spain and Poland - Top 10							
	Before			During			
UK	2006	2007	2008	2009	2010	2011	2012

Cornwall and Isles of Scilly	**239.1%**	**241.4%**	**269.9%**	**156.2%**	**285.9%**	**210.9%**	**167.8%**
Lincolnshire	**100.7%**	**124.1%**	**114.1%**	**196.5%**	**183.8%**	**138.6%**	**247.2%**
Cumbria	**126.7%**	**116.4%**	**133.1%**	**122.9%**	**123.2%**	**138.9%**	**141.3%**
East Anglia	**137.9%**	**135.0%**	**112.6%**	92.8%	**123.0%**	**100.8%**	97.4%
West Yorkshire	76.9%	64.0%	**102.0%**	**126.0%**	**102.8%**	**118.7%**	**114.0%**
Berkshire, Buckinghamshire and Oxfordshire	87.5%	71.1%	**113.3%**	**107.5%**	89.3%	**102.7%**	**108.5%**
East Yorkshire and Northern Lincolnshire	90.2%	98.4%	91.5%	**103.5%**	**108.4%**	91.5%	94.0%
Tees Valley and Durham	92.4%	60.0%	**109.4%**	98.0%	97.6%	**127.9%**	91.1%
West Midlands	53.2%	60.3%	85.9%	**105.3%**	99.0%	**102.4%**	**135.9%**
Herefordshire, Worcestershire and Warwickshire	95.2%	57.9%	85.6%	**123.7%**	**110.4%**	86.7%	81.6%
Annual Average – 29 regions	**85.9%**	**80.0%**	**91.8%**	**89.2%**	**95.2%**	**89.0%**	**92.2%**
Spain							
Comunidad Foral de Navarra	**313.8%**	**279.3%**	**407.5%**	**232.2%**	**288.7%**	**170.1%**	**207.8%**
La Rioja	**209.0%**	**205.6%**	**200.3%**	**183.8%**	**189.2%**	**205.6%**	**203.2%**
Illes Balears	**185.9%**	**194.5%**	**200.1%**	**188.0%**	**178.2%**	**185.2%**	**181.1%**
Aragón	**114.2%**	**144.4%**	**103.3%**	**149.2%**	**109.2%**	**259.0%**	**186.1%**
Región de Murcia	82.5%	**130.7%**	**103.5%**	97.2%	**106.1%**	**100.7%**	**105.6%**
Canarias (ES)	65.9%	93.8%	95.5%	89.7%	**120.5%**	**127.3%**	98.2%
Cantabria	90.7%	84.0%	85.2%	91.0%	75.0%	80.4%	79.8%
Extremadura	61.7%	72.3%	74.0%	98.5%	76.4%	87.6%	98.2%
Cataluña	**120.6%**	82.4%	85.9%	74.0%	72.7%	56.0%	69.8%
Castilla-la Mancha	83.9%	80.3%	78.9%	75.2%	73.7%	73.5%	72.8%
Annual Average – 17 regions	**103.2%**	**107.4%**	**110.8%**	**102.2%**	**100.8%**	**104.6%**	**102.0%**
Poland							
Lubuskie	**165.0%**	**166.5%**	**163.3%**	**503.9%**	**275.4%**	**399.5%**	**288.1%**
Opolskie	**111.1%**	**110.8%**	**176.4%**	**110.8%**	**117.1%**	**121.5%**	**108.6%**
Wielkopolskie	78.2%	88.8%	87.6%	**124.7%**	**147.4%**	**122.1%**	98.2%
Podlaskie	77.0%	72.9%	**111.6%**	**116.3%**	**107.9%**	**117.7%**	**130.8%**
Swietokrzyskie	**144.5%**	**114.1%**	**103.0%**	98.3%	83.6%	86.5%	81.7%
Pomorskie	52.4%	79.5%	**135.2%**	95.8%	86.4%	**108.3%**	**111.3%**
Podkarpackie	**108.5%**	77.2%	96.6%	94.8%	85.1%	68.4%	62.5%
Kujawsko-Pomorskie	76.5%	98.3%	85.2%	69.8%	77.4%	85.2%	75.6%
Zachodniopomorskie	61.4%	58.9%	**107.7%**	93.5%	86.2%	77.4%	78.6%
Lódzkie	84.8%	91.2%	75.8%	**110.8%**	65.5%	59.6%	75.5%
Annual Average – 16 regions	**87.1%**	**87.6%**	**104.7%**	**112.6%**	**93.6%**	**102.1%**	**92.1%**

Source: Our Elaboration

As expected, the regions with best efficiency performance on Top 20 are also represented in this Top 10 of each country. Effectively, Cornwall and Isles of Scilly (UK), Comunidad Foral de Navarra (Spain) and Lubuskie (Poland) are considered the regions with higher magnitude in terms of efficiency under the CRS assumption. One the other hand, Lubuskie is the only region that from 2008 to 2009 increased the score of efficiency of 163.3% to 503.9%.

Table A7. Top 20 – Super-efficiency Analysis (Model 1 - VRS) - All Regions

Model 1 – Super-efficiency VRS								
All regions - Top 20								
		Before			During			
Country	**Region**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Belgium	Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest	**big**	**big**	**big**	**big**	**big**	**big**	**big**
Belgium	Prov. Brabant Wallon	**big**	**big**	**big**	**261.2%**	**big**	**big**	**244.2%**
Belgium	Prov. Luxembourg (BE)	**199.1%**	**287.8%**	**562.0%**	**357.7%**	**287.6%**	**613.6%**	**764.8%**
Belgium	Prov. Vlaams-Brabant	90.1%	**147.7%**	**100.7%**	**big**	**136.8%**	**161.0%**	**big**
UK	Berkshire, Buckinghamshire and Oxfordshire	**101.7%**	96.8%	**141.6%**	**big**	**113.6%**	**141.8%**	**117.8%**
\UK	Cornwall and Isles of Scilly	**228.6%**	**205.1%**	**189.6%**	**169.0%**	**197.8%**	**153.0%**	**134.3%**
Portugal	Algarve	**164.2%**	**182.2%**	**149.6%**	**143.5%**	**164.8%**	**152.9%**	**136.7%**
Romania	Bucuresti - Ilfov	25.9%	34.4%	**170.5%**	**164.6%**	**202.0%**	**226.4%**	**261.1%**
Spain	Illes Balears	**204.3%**	**166.0%**	**150.6%**	**153.3%**	**129.1%**	**136.4%**	**139.3%**
Romania	Sud-Est	**105.5%**	**106.2%**	**122.2%**	**106.0%**	**144.2%**	**186.6%**	**244.7%**
Spain	Comunidad Foral de Navarra	**134.4%**	**164.4%**	**176.3%**	**136.9%**	**127.7%**	**119.5%**	**118.6%**
Romania	Vest	68.2%	59.7%	**140.6%**	**190.0%**	**169.7%**	**162.5%**	**149.3%**
Spain	La Rioja	**137.3%**	**125.7%**	**146.9%**	**137.1%**	**123.5%**	**126.2%**	**132.5%**
Slovakia	Bratislavský kraj	**100.6%**	**115.2%**	**132.8%**	**144.6%**	**152.0%**	**120.0%**	**118.2%**
Bulgaria	Severen tsentralen	**121.4%**	**179.2%**	**135.1%**	**115.7%**	**100.9%**	**106.3%**	**121.7%**
Belgium	Prov. West-Vlaanderen	**123.7%**	99.5%	**115.0%**	**150.0%**	**152.9%**	**103.3%**	**116.9%**
Poland	Lubuskie	**111.1%**	**133.0%**	**128.0%**	**153.3%**	**112.6%**	**111.2%**	**103.4%**
Bulgaria	Severozapaden	**102.6%**	**110.4%**	**112.2%**	**118.9%**	**118.1%**	**115.6%**	**112.8%**
Bulgaria	Yugoiztochen	97.1%	**113.7%**	**112.0%**	**112.4%**	94.9%	**105.3%**	**103.9%**
UK	Surrey, East and West Sussex	**145.0%**	**101.8%**	89.5%	**157.9%**	**106.9%**	43.2%	74.2%
Annual Average – 104 regions		**75.8%**	**76.3%**	**79.9%**	**78.7%**	**75.5%**	**75.4%**	**79.3%**

Source: Our Elaboration

Now, it is possible see the Top 20 under VRS assumption. So, Belgium is the country with the regions more developed in terms of efficiency and the two first regions that are

Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest and Province of Brabant Wallon are those that present best performance. One the other hand, all regions on this Top 20 are superefficient, on average.

Table A8. Top 10 – Super-efficiency Analysis (Model 1 - VRS) - UK, Spain and Poland

Model 1 – Super-efficiency VRS							
UK, Spain and Poland - Top 10							
	Before			During			
UK	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Berkshire, Buckinghamshire and Oxfordshire	**big**	**big**	**big**	**big**	**big**	**big**	**big**
Gloucestershire, Wiltshire and Bristol/Bath area	99.5%	94.5%	78.2%	87.4%	**100.5%**	**128.2%**	**big**
Cornwall and Isles of Scilly	**299.3%**	**244.0%**	**293.5%**	**191.6%**	**295.9%**	**213.0%**	**187.0%**
Lincolnshire	**101.0%**	**129.6%**	**114.6%**	**214.5%**	**188.8%**	**151.3%**	**321.7%**
Surrey, East and West Sussex	**185.9%**	**169.5%**	**165.6%**	**171.3%**	**146.2%**	**125.7%**	**145.6%**
Cumbria	**128.2%**	**118.5%**	**204.3%**	**151.2%**	**155.2%**	**155.1%**	**180.7%**
East Anglia	**154.6%**	**176.0%**	**116.3%**	96.6%	**131.3%**	**102.6%**	**100.5%**
North Yorkshire	**162.4%**	**148.4%**	95.2%	**102.4%**	**107.6%**	**113.5%**	86.0%
West Yorkshire	**109.2%**	94.2%	**106.1%**	**145.5%**	**103.4%**	**133.9%**	**121.1%**
East Yorkshire and Northern Lincolnshire	95.0%	**135.3%**	93.0%	**125.5%**	**114.2%**	**111.0%**	95.7%
Annual Average – 29 regions	**99.2%**	**95.9%**	**101.5%**	**100.2%**	**106.8%**	**101.2%**	**103.3%**
Spain							
Comunidad de Madrid	**big**	**big**	**big**	**big**	**big**	**big**	**big**
Comunidad Foral de Navarra	**big**	**big**	**big**	**big**	**big**	**327.9%**	**325.0%**
País Vasco	**114.6%**	**121.4%**	**171.6%**	**123.1%**	**big**	**big**	**big**
Aragón	**114.8%**	**145.5%**	**103.7%**	**150.0%**	**109.6%**	**big**	**192.2%**
Illes Balears	**306.1%**	**252.5%**	**260.8%**	**260.2%**	**231.7%**	**236.5%**	**243.1%**
La Rioja	**219.7%**	**213.1%**	**215.1%**	**193.5%**	**203.9%**	**218.6%**	**213.3%**
Región de Murcia	**107.6%**	**155.8%**	**124.6%**	**107.3%**	**119.4%**	**110.3%**	**123.5%**
Extremadura	**101.3%**	**108.7%**	**106.9%**	**127.1%**	**107.3%**	**118.8%**	**129.5%**
Canarias (ES)	77.8%	99.4%	**102.1%**	95.1%	**123.8%**	**128.8%**	99.1%
Cataluña	**131.3%**	98.4%	86.9%	96.7%	89.5%	81.2%	94.6%
Annual Average – 17 regions	**114.7%**	**117.6%**	**115.1%**	**114.7%**	**106.6%**	**125.8%**	**129.0%**
Poland							
Mazowieckie	**big**	**big**	**big**	**big**	**big**	**big**	**big**
Malopolskie	**big**	**178.3%**	**big**	94.3%	40.2%	**big**	75.7%
Lubuskie	**317.8%**	**233.8%**	**163.6%**	**509.0%**	**433.5%**	**400.7%**	**343.2%**
Lódzkie	95.9%	94.5%	**110.1%**	**big**	**109.8%**	63.6%	**155.7%**
Lubelskie	75.6%	90.7%	**big**	56.8%	58.7%	61.1%	45.5%
Opolskie	**121.9%**	**118.4%**	**241.8%**	**112.6%**	**119.8%**	**123.2%**	**111.6%**

Dolnoslaskie	**133.1%**	**159.8%**	**118.8%**	**117.0%**	**137.4%**	**146.1%**	**122.3%**
Wielkopolskie	**111.2%**	**112.7%**	**111.3%**	**133.8%**	**160.9%**	**134.9%**	**110.8%**
Podlaskie	86.1%	85.8%	**127.2%**	**136.5%**	**129.1%**	**136.9%**	**163.2%**
Pomorskie	94.5%	**145.5%**	**136.7%**	99.8%	94.9%	**110.5%**	**111.5%**
Annual Average – 16 regions	**117.1%**	**122.3%**	**124.0%**	**130.5%**	**121.2%**	**119.6%**	**116.0%**

Source: Our Elaboration

In particular, in the Top 10 of UK, Spain and Poland rankings, the regions with best performance have all of them *big*, namely Berkshire, Buckinghamshire and Oxfordshire (UK), Comunidad de Madrid (Spain) and Mazowieckie (Poland) and the other regions also have a high score.