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REGIONAL INNOVATION PERFORMANCE IN EUROPE

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Regional innovation performance in Europe

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Abstract

Europe 2020 strategy and the initiative "Innovation Union" call for a particular attention at the territorial dimension of innovation and knowledge creation. The heterogeneity across regions in their capacity to create knowledge and innovation, but also in their abilities to exploit ideas and technologies available across the European territory, motivates in-depth analyses of the territorial dimension of the knowledge economy.

This paper investigates the nature of knowledge production and diffusion among regions in 29 EU countries and tries to assess its effectiveness. The analysis follows a two-step analytical route. Firstly, as a preliminary analysis, we estimate a knowledge production function (Griliches, 1979 and many others) with the usual parametric methods, in order to find out which are the main determinants of knowledge production at the regional level in Europe. Secondly, based on these findings, we apply DEA to assess the degree of efficiency of European regions in their use of internal and external inputs for the production of new knowledge and ideas. This allows to provide a ranking of the innovative performance of EU regions for two points in time, the beginning of the current century and the second part of this decade. Such rankings will be evaluated thanks to the Malmquist productivity index in order to assess the relative importance of its main components.

According to the Data Envelopment Analysis, we found further evidence of a dualistic (centre vs periphery) pattern in the regional innovation activities, with the highest efficient territories located in the most central or economically strategic areas of the continent. On the contrary, the application of the Malmquist productivity index shows that productivity dynamics has been extremely differentiated across regions in terms of both magnitude and intrinsic features. We, again, observe important differences between the core and periphery of Europe and most specifically between the countries which are rich and industrialized and form the so called "Old Europe" and those which are relatively poor and have entered the European Union quite recently.

Keywords: innovation, human capital, spatial spillovers, European regions, DEA

JEL code: R11, 033, C31, C61

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1. Introduction[1]

Europe 2020 strategy and the consequential initiative "Innovation Union" call for a particular attention at the territorial dimension of innovation and knowledge creation (European Commission, 2011). The heterogeneity across regions in their capacity to create knowledge and innovation, but also in their abilities to exploit ideas and technologies available across the European territory, motivates in-depth analyses of the territorial dimension of the knowledge economy. The importance of the regional dimension in the study of innovation and economic performance in a globalizing economy has been the object of several studies in the latest years (starting with Camagni, 1991). As a result the concept of regional innovation systems (RIS) has been proposed to emphasize the importance of the regional scale and of specific local resources in enhancing the innovation performance of regions (Braczyk et al., 1998 and Malmberg and Maskell, 2002).

This paper follows this research path and in particular the rich tradition of studies pioneered by Jaffe (1989) on regional knowledge production function (KPF) with a methodological tool, Data Envelopment Analysis (DEA), firstly proposed by Farrell (1957), which has been rarely applied for regional analysis (partial exceptions for Europe being Zabala-Iturrigagoitia et al., 2007 and Enflo and Hjertstrand, 2009). Originally, DEA, like other frontier models, was used in productivity analysis at the micro-level, but it has recently become increasingly popular at the macro-level as a non-parametric alternative to parametric estimation. DEA, as a matter of fact, is instrumental to investigate not only the nature of the process under examination but mainly its effectiveness and efficiency with respect to a production frontier across a set of economic units, regions in this case. DEA is more adequate for benchmarking analysis, as it permits to identify the best performing units within a given set of entities whilst regression models are particularly suitable to measure central tendencies of a given phenomenon. DEA can, therefore, be particularly attractive for measuring efficiency in knowledge production without requiring specific assumptions on the behavior of regional innovation systems. Furthermore, thanks to the application of the Malmquist index (Coelli et al., 1998), we provide evidence on the contribution of efficiency or technological change to knowledge productivity variations, since it allows

[1] Thanks to Emanuela Marrocu, Raffaele Paci, Roberta Capello, Camilla Lenzi for helpful comments on previous versions of this work.

for the presence of time varying technical inefficiencies. This index can, thus, provide important insights thanks to its decomposition into two components, one that measures changes in technical efficiency (i.e. whether firms are getting closer to the production frontier over time) and one that measures changes in technology (i.e. whether the production frontier is moving outwards over time). This decomposition is one of the main desirable features of frontier models because they may provide useful information to the policy maker for analyzing the results of past productivity-enhancing strategies and for designing better ones for the future. In particular, this may prove essential in Europe where Cohesion policies, which were set to reduce economic imbalances mainly due to technology gap across regions, are currently under profound revision (see Barca, 2009).

The analysis follows a two-step analytical route. Firstly, we estimate a knowledge production function (Griliches, 1979 and many others) with the usual parametric methods, in order to find out which are the main determinants of knowledge production at the regional level in Europe. We adopt an empirical spatial specification (as in Moreno et al., 2005 and Marrocu et al., 2011a), which allows us to assess the presence of geographical technological spillovers across regions. As a result we find that main determinants, in accordance with previous literature, can be divided at least into two types: internal and external. Among the former we include investments in research and development and human capital, while among the latter we consider potential externalities coming from other regions. Secondly, based on these findings, we apply DEA to assess the degree of efficiency of European regions in their use of internal and external inputs for the production of new knowledge and ideas. This allows us to provide a ranking of the innovative performance of EU regions for two points in time, the beginning of the current century and the second part of this decade. Such rankings will be evaluated thanks to the Malmquist productivity index in order to assess the relative importance of its main components.

Important differences arise between the core and periphery of Europe and most specifically between the countries which are rich and industrialized and form the so called "Old Europe" and those which are relatively poor and have entered the European Union quite recently. As for the latter, productivity change is mainly due to a reduction of technology gap, whilst for the former countries the productivity is mainly changing thanks to efficiency improvements rather than an increase of technological capabilities. This can have important implications for the design of innovation and cohesion policies which are going to be discussed in the conclusions.

The paper is organized as follows. The next section provides a thorough review of the empirical literature on the analysis of knowledge production across regions and in particular on the few studies which have utilized DEA as their main analytical tool. The third section describes the methodology and its implementation. The fourth section presents data and the preliminary analysis based on parametric methods. The fourth section presents and discusses the main results of DEA and the final section concludes with some tentative policy implications.

2. Background literature

The KPF model (Griliches, 1979) has for long inspired scholars interested in the determinants of innovative activity at firms and regional level. The standard application of this model is the estimation of a function where the innovative output, often measured by patenting activity, depends on a series of inputs. Among such inputs the most important, and recurrent, is the expenditure in R&D, usually associated to the level of human capital as an additional input, given its well known effects on knowledge creation. This latter factor is essential if one wants to consider those cases where innovation is not solely the result of a formal investment in research but can derive also from informal processes of learning by doing (Nelson and Winter, 1982) and from the absorption of external knowledge (Abreu et al., 2008). As a matter of fact the ability to understand, interpret and exploit external knowledge relies on prior experiences embodied in individual skills and, more generally, in a well educated labour force (Engelbrecht, 2002 and Archibugi and Filippetti, 2011). This is why the latest contributions along this research path have often considered not only internal factors but also external ones, as potential determinants of innovative activity. Our work moves along this line of investigation and considers the presence of external factors coming from "proximate" regions, first of all, in the regression model and, most importantly, in the DEA application.

The point of departure is the seminal paper by Jaffe (1989), who proves the existence of geographically mediated spillovers from university research to commercial innovation in US metropolitan areas. The main results of his paper have been later extended and strengthened by many other authors who observe the presence of local externalities both within and across regions in the USA (Acs et al., 1992; Anselin et al., 1997; O´hUallacha´in and Leslie, 2007). Most of these studies introduce the concept of geographical proximity and test its importance by means of spatial econometric techniques. Along the same vein, several studies have been proposed for the EU regions (Tappeiner et al., 2008; Acosta et al., 2009; Buesa et al., 2010, Marrocu et al, 2011a,b are among the latest contributions). The only contributions which analyze different continents at the regional level are Crescenzi et al. (2007) for US and EU, with data coming from USPTO and EPO respectively, and Usai (2011) on OECD regions with homogenous information coming from the Patent Cooperation Treaty.

A common finding of all these papers is that innovation performance is partly due to internal factors and partly to spillovers which flow from one region to another, especially when they are geographically proximate. However, some studies on European regions have started adding other possible dimensions of proximity and assessing their role on knowledge production. In particular, Bottazzi and Peri (2003), Greunz (2003) and Moreno et al. (2005) investigate inter-regional knowledge spillovers across European regions, testing to what extent technological proximity together with geographical proximity is important in the creation of new knowledge within European regions. Furthermore, all these studies consider institutional proximity (measured by means of country dummies) and find it relevant in indentifying the more and less innovative regions. More recently the set of proximity dimension which may influence innovative activity has widen to include also organizational and social proximity (Marrocu et al., 2011). In this paper, due to the fact that the main focus is the analysis based on DEA, we implement the standard simplified model where all these dimensions are proxied by geography.

While the application of parametric, i.e. econometric, techniques to the study of regional economic and innovative performance has become standard, the implementation of non parametric methods is still quite rare. Especially in the analysis of regional innovation systems' performance. A partial exception is the study by Zabala-Iturriagagoitia et al. (2007) which tries to assess European regional efficiency in innovation thanks to DEA. This paper applies this methodology based on information provided by the European Innovation Scoreboard (EIS) for 2002 and 2003. However, the analysis is not performed within the usual setting of the KPF, since patents, following Azagra-Caro et al. (2003), are considered to be an input rather than an output. Actually, regional GDP per capita is used as the dependent variable and consequently as the output measure of the regional innovation system[2] and this makes this study analogous to a growth accounting study rather than to a KPF analysis. The only study which follows more closely the common functional model of a regional KPF is due to Roman (2010), who apply DEA to study local innovation performance measured by patents, even though with reference to the limited local context of 14 regions of Bulgaria and Romania. Another interesting recent study is Charlot et al. (2012) who adopt a semi-parametric approach, which, while relaxing any arbitrary assumption on the 'shape' of the KPF, allows for the presence of heterogeneity in the impact of R&D and Human Capital between 'core' and 'peripherial' regions in EU.

An analogous setting has been, however, implemented in several studies which investigate knowledge production at the national level as in Wang (2007), Wang and Huang (2007) and Sharma and Thomas (2008) who have recently followed the pioneering contribution by Rousseau and Rousseau (1998). They all use granted patents as the measure of output of the knowledge production process and, in some cases, publications counts, too. Moreover, since the availability of national data is higher, these national analyses manage to implement richer models in order to test some interesting additional hypotheses. This is done in Schmidt-Ehmcke and Zloczysti (2009), who discriminate knowledge production across sectors and Cullmann et al. (2009) who distinguish the impact of private and public R&D and of different institutional and regulatory frameworks.

A common weakness of all studies above is that they provide a static point of view without investigating the dynamic evolution of regional productivity. This can be done thanks to the implementation of

[2] The indicators employed in the efficiency model are those provided by the European Innovation Scoreboard. Thus, the indexes considered as inputs for the frontier model are: higher education (the percentage of the population between 25 and 64 years of age with a higher education), lifelong learning (the percentage of the population between 25 and 64 years of age participating in lifelong learning activities), medium/high-tech employment in manufacturing (the percentage of the total workforce), high-tech employment in services (the percentage of the total workforce), public R&D expenditure (the percentage of GDP), business R&D expenditure (the percentage of GDP), and high-tech patent applications to the European Patent Office (EPO) per million population.

the Malmquist index[3] which allows for decomposing productivity changes into their main components. However, this growth accounting exercise has been so far carried out only in some parallel studies on productivity growth and convergence among European regions by Enflo and Hjertstrand (2009) and Filippetti and Peirache (2012). Both studies decompose labour productivity into efficiency change, technical change and capital accumulation in order to analysis the main reasons behind the differentiated dynamics of European regions in the latest decades. Enflo and Hjertstrand (2009) shows that most regions, within their sample of 67 Western European regions, have fallen behind the production frontier in efficiency and that capital accumulation has had a diverging effect on the labour productivity distribution. Nonetheless, the economic hierarchy of the regions remained surprisingly stable over time, as only eight out of 69 regions improved their relative efficiency and manage to close the technological gap with the leading regions. Filippetti and Peirache (2012) enlarge the sample to Eastern European regions and, not surprinsingly, find that there has been overall convergence in labour productivity growth which has been driven by capital accumulation and exogenous technical change. Further, the lack of convergence of some backward regions is, in their opinion, to be attributed mainly to a shortage of endogenous technological capabilities.

This literature background provide a fertile and motivating scenario for the implementation of DEA and the Malmquist index for the analysis of regional knowledge production in Europe. Our aim is to contribute to the research agenda started by Zabala-Iturrigagoitia et al. (2007) mainly in four ways. Firstly, we update and enlarge the regional sample in order to take into account the EU enlargement process by distinguishing between the rich group of the EU15 (plus Norway and Switzerland) and that of the relatively backward EU12 new entrant countries. Secondly, we investigate with a non parametric frontier model a typical knowledge production function, as it has been done so far only at the national level, in order to provide a common ground of analysis with respect to the rich earlier literature based on parametric methods. Thirdly, we exploit the availability of a two-period panel dataset in order to apply the Malmquist index and provide additional insights since this

[3] It is worth observing that other methods to make DEA dynamic have been proposed in the literature, such as window and sequential DEA (see Cook and Seiford, 2009). Malmquist index has been preferred since it allows a useful decomposition of the productivity change.

can be decomposed into two components, one which measures changes in technical efficiency and one which measures changes in technological capability. Finally, we insert an index which measures potential spillovers coming from nearby regions which may affect the knowledge production process, as it is hypothesised in the theoretical literature on RIS and confirmed empirically in this paper as in many previous ones. This specific problem is acknowledged and dealt with also by Enflo and Hjertstrand (2009), who, however, control for possible spatial autocorrelation drawing blocks of observations from the dataset which are within the same national borders. However, this correction is bound to fail to discriminate at least two distinct dimensions of proximity: the institutional and the geographical one (Boschma, 2005).

3. Methodological issues

In this section we describe and discuss the methodological tools adopted for the analysis of innovative performance in European regions in terms of new knowledge creation. Our empirical strategy is based on a two step procedure: as a preliminary analysis, we perform the usual econometric estimation and secondly, we use DEA to construct a nonparametric production frontier for European regions which is going to be analyzed from both a static and a dynamic perspective.

The preliminary analysis, therefore, entails the estimation of a standard KPF with the usual estimation based on regression parametric methods. These are well-known and in what follows we only discuss our estimation model and in some detail the distinctive features of the spatial specification. Our preliminary aim is to identify the main determinants which characterize the process of knowledge production in European regions to be used later in the DEA application. In light of the theoretical literature and the many previous empirical studies on KPF we assume that the creation of new ideas is the result of internal and external factors. Consequently, we are going to estimate a Spatial Autoregressive Model (SAR) as follows:

$$y_{it} = \beta X_{it} + \varrho W y_{it} + u_{it} \qquad (1)$$

where y is the dependent variable, X is a set of explanatory variables which measures internal characteristics and W is the matrix of spatial weights (multiplied by the dependent variable after its normalisation) used to describe the geographic interconnectivity among regions. This is meant to explicitly capture possible cross-border externalities in the form of spillovers coming from other regions. Finally, u is a i.i.d error process. It is important to note that in our case each entry of W is the inverse of the distance between a given pair of regions; Spillovers are, thus, believed to lose force and to fade away as the distance among regions increases. Finally, it is worth emphasizing that in all the estimation and testing procedures the W matrix is max-eigenvalue normalized.

The second step is the main original contribution of this paper and consists of the application of the non parametric tools to the set of output and inputs which have been singled out thanks to the regression analysis based on parametric methods. Among non parametric methodologies, we choose to implement the DEA approach, firstly developed by Farrell (1957), and based on mathematical programming techniques. While with a regression model, one estimates the average behavior of the phenomenon at hand, the DEA method aims at identifying the best performing units (regions in our case) among a set of entities whose objective is to convert multiple inputs into multiple output. In recent years DEA has been applied to analyze the behavior of entities involved in a wide range of activities and contexts, such as firms, hospitals, universities, cities, regions and countries. Thanks to its high flexibility DEA has been proved successful in identifying various sources of inefficiency, in particular in studying benchmarking practices.

One of the essential features of DEA, which makes this tool particularly suitable in this kind of analysis is that it does not require to choose a specific functional form for the relation linking inputs to outputs. Such inputs and outputs can be multiple and can be expressed in different units of measurement, as long as they are the same for all the decision making units (DMUs), the term coined by Charnes et al. (1978). The best performance is characterized in terms of efficiency, so that the most performing units define the efficient frontier, which "envelope" all the other units. The technology frontier (efficiency frontier) is then defined as the maximum output attainable from each input level (see Coelli et al., 2005) and regions may or may not be on the frontier of this technology. Regions are therefore evaluated by calculating their distance from the frontier.

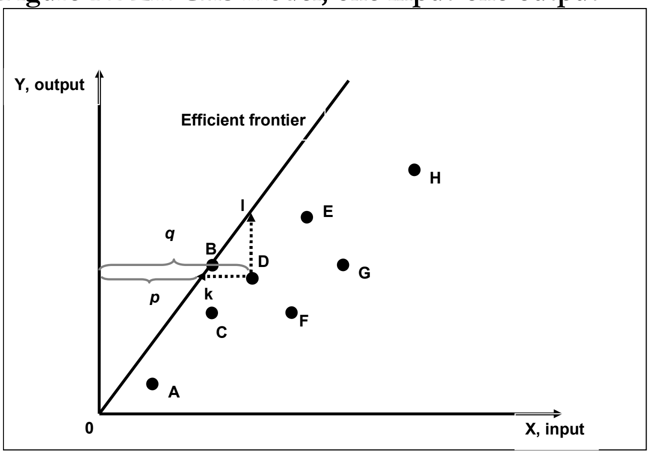
To illustrate how the DEA approach[4] operates we consider Figure 1 where we report different units labeled from A to H. If we

[4] This description is mainly based on Coelli (1996) and Cooper et al. (2007).

assume constant return to scale (CRS), the frontier is identified, on the basis of the available empirical information, by DMU B, which is fully efficient. According to Cooper et al. (2007) a DMU is said to be fully (100%) efficient if the performance of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs. Note that this notion refers to "technical" efficiency and it does not require a priori information on prices or weights accounting for the relative importance of inputs or outputs.

Accordingly, DMU D which is not on the frontier will have an efficiency level proportional to its distance to DMU B. This measure is given by the ratio p/q, which is equal to 0.75 and it implies that if DMU D proportionally reduces all the inputs to the 75% of the their actual amounts, it could still produce the same level of output. In this way DMU D would be projected horizontally towards the efficient frontier. Under the assumption of constant returns to scale (CRS), the same efficiency gain would be obtained by a vertical projection, in this case with the same input amount DMU D could produce a level of output 33% (1/0.75=1.33) greater with respect to the previous one and move vertically towards efficient frontier, at point I. DMU B is called the benchmark or reference unit for DMU D.

Figure 1 DEA-CRS model, one input-one output



In the former case we talk of input-oriented measures of efficiency, whilst in the former case the measure is an output-oriented one. Note that under the assumption of CRS the two orientation identify the same frontier and the same set of efficient DMUs, only the measures associated with the inefficient DMU can be different. Note also that in the case of DMU D efficiency can be achieved by each movement in the area k-D-l (Figure 1).

Following Charnes et al. (1978) the maximization problem for each DMU is based on the ratio of outputs to inputs, which is used to measure the efficiency of a DMU with respect to all other DMUs. When the output to inputs ratio is maximized the model is referred to as input-oriented model; conversely, we have an output-oriented model when the ratio is inverted and a minimization problem is solved.

Since the assumption of constant returns to scale is rarely attainable in real-world situations as it requires that each DMU is operating at an optimal scale, in what follows we briefly describe the Varying Return to Scale (VRS) model, suggested by Banker et al. (1984). With respect to the CRS model the linear programming problem is augmented with an additional convexity constraint. The VRS approach allows to envelop the data more tightly so that technical efficiency measures are always greater or equal to the ones obtained under the assumption of CRS. The aim is to isolate "pure" technical inefficiency from "scale" inefficiency. Operationally this is done by carrying out both a CRS and VRS DEA, if for a given DMU there is a difference in the technical scores this is interpreted as evidence of scale inefficiency.

We use the Farrell-type output oriented technical efficiency index which is equivalent to the inverse of the Shepherd output distance function:

$$TE_0^t(output_i, inputs_i) = \max\{\theta : (output_i, \theta inputs_i) \in \mathrm{P}^{\mathrm{t}}\} = D_0^t(output_i, inputs_i)^{-1} \qquad (2)$$

measures the radial distance between the observation and the efficiency frontier, and P is the production technology available at time *t* for each region. The efficiency score is the point on the frontier characterized by the level of inputs that can be reached if the region is efficient (Simar and Wilson, 1998). A value of □ = 1 indicates that a region is fully efficient and thus is located on the efficiency frontier based on the technology set P, which is unobserved and is thus estimated thanks to DEA. Using *t+1* instead of t for the above model, we get $D_o^{t+1}(output_i, inputs_i)$, that is the technical efficiency score for our region at t+1.

Finally, when a panel of data is available, changes in productivity over the period under consideration can also be calculated using the Malmquist productivity change index. Originally, Malmquist (1953) proposed a quantity index for measuring the standard of living, but, later on, his index and its variations have mainly been used in the field of production analysis to explore total factor productivity (TFP) growth. The Malmquist productivity index is defined on a benchmark technology satisfying constant returns to scale, which is to be distinguished from a best practice technology allowing for variable returns to scale. This convention enables it to incorporate the influence of scale economies, as a departure of the best practice technology from the benchmark technology.

Using the period t benchmark technology, the output-oriented productivity index is written as:

$$M_o^t\ (input^t, output^t, input^{t+1}, output^{t+1})_i = \left(\frac{D_o^t(input^{t+1}, output^{t+1}}{D_o^t(input^t, output^t}\right) \qquad (3)$$

However, defining the benchmark either at t or at t+1 is arbitrary and therefore it is conventional to define the Malmquist productivity index as the geometric mean of the two, and so

$$\mathrm{M_o^t}\ (\mathrm{input^t}, \mathrm{output^t}, \mathrm{input^{t+1}}, \mathrm{output^{t+1}})_\mathrm{i} =$$

$$= [\mathrm{M_o^t}(\mathrm{input^t}, \mathrm{output^t}, \mathrm{input^{t+1}}, \mathrm{output^{t+1}})_\mathrm{i} \times \mathrm{M_o^{t+1}}(\mathrm{input^t}, \mathrm{output^t}, \mathrm{input^{t+1}}, \mathrm{output^{t+1}})]^{1/2} =$$

$$= \left[\left(\frac{\mathrm{D_o^t}(\mathrm{input^{t+1}}, \mathrm{output^{t+1}}}{\mathrm{D_o^t}(\mathrm{input^t}, \mathrm{output^t}}\right)\left(\frac{D_o^{t+1}(input^{t+1}, output^{t+1}}{D_o^{t+1}(input^t, output^t}\right)^{1/2}\right] \qquad (4)$$

$M_o^t\ (input^t, output^t, input^{t+1}, output^{t+1})_i$ greater or smaller than one implies growth or decline, whilst a value equal to one signals stagnation between periods t and t+1.

Productivity change can be explained either in terms of technological change (i.e. whether the production frontier is moving outwards or inwards over time) or thanks to contribution of technical efficiency change (i.e. whether DMU are getting closer or more distant to the production frontier over time). Therefore, we can briefly determine the total productivity change in a successive period of time with the following equation:

Productivity change (PC) = Technical efficiency change (TEC)* Technological changes (TC)

Fare et al. (1994a, b) further decompose technical efficiency changes to distinguish scale efficiency (how much a unit gets closer to its most productive size under VRS) and pure efficiency components (efficiency gains under the hypothesis of CRS). Therefore productivity changes and its main elements can be calculated separately with the following equation:

PC = Scale efficiency change (SE)* Pure efficiency change (PE)*Technological change (TC)

Compared to other indices (Törnqvist-Theil and Fisher Ideal indexes), the Malmquist indexes have some desirable features and properties (Grifell-Tatjé and Lovell 1996). They do not require behavioral assumptions, such as cost minimization or profit maximization, which makes them useful in situations in which DMUs' objectives differ or are unknown. Furthermore, they do not require price information which implies that they can be used in situations where either prices do not exist, are distorted or have little economic meaning.

All in all, three aspects of the efficiency will be considered: technical efficiency, i.e. the efficiency with which inputs are converted into output; scale efficiency, i.e. how close a DMU is to its most efficient scale size; and productivity growth, i.e. the change in output which is not a consequence of growth in input quantities. The last one can be decomposed in two components. The first one measures the change in technical efficiency over two periods (i.e. whether or not the unit is getting closer to its efficiency frontier over time) and the second component measures the change in technology over the two time periods (i.e whether or not the frontier is shifting out over time). If Malmquist index, on the basis of minimization of production factors, is less than one, it indicates that productivity decreases, on the contrary, if on the basis of maximization of production factors, the Malmquist index or any of its elements were less than one, it signifies productivity is getting bigger.

In conclusion, DEA is certainly a useful method for investigating regional performance in the production of new knowledge without imposing assumptions about the functional form of the technology or assuming that all regions produce ideas efficiently. Regions represent the decision making units which are in control of the main inputs, such as investments in research and development and human capital skills, and whose result may also depend by some contextual phenomena, such as other regions innovative performance. Nonetheless, we cannot overlook some weaknesses of this methodology. First of all, this method is based merely on input and output data and, as a result, the technological frontier is only defined relative to the best-practice observations in the sample and therefore it ignores the potential existence of more efficient regions outside the sample data. Secondly, the estimator is purely deterministic, as no additive stochastic term is included in the linear programming approach, this implies that any discrepancy between actual and potential output is necessarily attributed to inefficiency (Del Gatto et al., 2011)[5].

4. Data and preliminary analysis

The empirical strategy used here consists of a two-step process which combines parametric and non parametric methods.

As far as the parametric methods are concerned, the basic KPF model is initially estimated for two different periods: the beginning of the current century and the middle of its first decade. As regards the non parametric methods, the same variables are then used in order to perform the Data Envelopment Analysis (DEA) and to build the Malmquist index in order to see how productivity has changed along the years and what has caused such changes, if any.

Data refer to 271 EU regions in 29 countries for the period going from 2000 until 2007. A list of the indicators and the sources of data are reported in Table 1. Another list, in table 2, presents the 29 EU countries together with the relative number of NUTS2 regions in each country. Countries are divided into two groups: EU15 which have

[5] In this respect, Simar and Wilson (1998, 2000) have introduced bootstrapping techniques into the DEA framework to overcome this and other associated shortcomings. Within the background literature presented above, Enflo K. and Hjertstrand P. (2009) apply this methodology to build confidence intervals in order to assess the statistical significance of their results.

formed the core of EU in the eighties and in the nineties, plus Norway and Switzerland; and EU12, that is eastern countries which have entered EU in more recent years.

Table 1. Regions and NUTS level

Code	Country	Number of regions
AT	Austria	9
BE	Belgium	11
BG	Bulgaria	6
CH	Switzerland	7
CY	Cyprus	1
CZ	Czech Republic	8
DE	Germany	39
DK	Denmark	5
EE	Estonia	1
ES	Spain	16
FI	Finland	5
FR	France	22
GR	Greece	10
HU	Hungary	7
IE	Ireland	2
IT	Italy	21
LT	Lithuania	1
LU	Luxembourg	1
LV	Latvia	1
MT	Malta	1
NL	Netherlands	12
NO	Norway	7
PL	Poland	15
PT	Portugal	5
RO	Romania	7
SE	Sweden	8
SI	Slovenia	2
SK	Slovakia	4
UK	United Kingdom	37
Total		271

The values for all variables are computed as two-years average. Further, since the production of knowledge is characterized by a delay with respect to the investments in either R&D or human capital and since the production of ideas is formalized through the application for a patent (Jaffe, 1986 and 1989), explanatory variables are included with a lag of two years with respect to the year of the dependent variable. It means that for the first period the dependent variable, that is the number of patents, refers to the 2003-2004 interval while the explanatory variables to the two-year period 2000-2001. For the more recent period we use the average values for 2006-2007 for the dependent variable and, consequently, average values for 2003-2004 for explanatory variables.

Table 2. Definition of inputs and output

Variable name	Definition	Source
pat_	Number of EPO patent applications per priority year & residence region of inventors.	CRENoS elaboration on OECD REGPAT database
rdexp_	Total intramural R&D expenditure (Millions of euro)	Eurostat
hkth_	Economically active population with Tertiary education attainment - 15 years and over (Thousand population)	Eurostat
popth_	Number of people at 1st January (Thousand of population)	Eurostat
wypat_	Spatially lagged variable for patents (described above)	CRENoS elaboration on OECD REGPAT database

Following the well-established literature on the estimation of knowledge production functions, as already emphasized in the previous section, the dependent variable to proxy innovative performance is given by the amount of patent activity in a region[6] in a certain period (*pat*). In

[6] Patent applications are often criticized as they represent a biased component of the innovative output since not all inventions are patented and not all patents transform into innovations. Moreover, the value of patents is skewed to the right, with only a few patents being highly valuable. Despite this criticism, nonetheless, patents are the best indicator of research output and have been

particular, we use EPO applications[7], which are associated to regions on the basis of the inventors' addresses[8] as this is more indicative of the location where the invention occurred[9]. Applications are referred to the sum of two year periods to ensure that the number of zero values is kept to a minimum. Another conventional proxy used in the literature is the expenditure in R&D which is considered the principal input in the KPF. The research and development (*rd*) effort is measured by the total intramural R&D expenditure in millions of euro. Moreover, many authors (Cohen and Levinthal, 1990) observe that the effectiveness of this investment depends crucially on the absorptive capacity of a territory, which, in turn is linked to the availability of skilled human capital. For this reason, we augment the traditional KPF model by including also the human capital endowment (*hk*), measured by the number of economically active individuals with at least a tertiary education degree (ISCED 5-6).[10]

Thus, the general form of the empirical model for the KPF is as follows

$$output = f(inputs) \tag{5}$$

Finally, we also include the resident population (*pop*) as a control variable to account for the relative dimension of the regions and country dummies (*ND*) to take into account for idiosyncrasies across countries

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widely used since they are an objective and standardized measure. Second, data on patent applications at EPO are widely available and since the process of obtaining a patent at this international office is quite costly we may reasonably assume that they are presumed to have a value above a certain threshold.

7 We date patent applications using the priority date instead of the usual application date since it is the date closest to the date of invention and the decision to seek patent protection.

8 If there are multiple inventors, the application is divided equally among all their respective regions (fractional counting), avoiding thus double counting. Data comes from REGPAT, a database made available by OECD.

9 The alternative being to refer to the residence of the applicant which usually corresponds either to the legal location of the firm or to the headquarter and not necessarily to the place where production and innovation (or only the latter) take place.

10 For a general overview of the territorial pattern of human capital and R&D in the enlarged Europe see Colombelli et al. (2011).

due to institutional differences. Most importantly, as announced above and reported in equation (1), we include a lag of the spatial dependent variable in order to identify potential influences, that is spillovers, coming from nearby regions.

$$output = f(inputs, controls, spillovers) \quad (6)$$

Where *output* is proxied by *pat*, the *inputs* are *rd* and *hk* and spillovers are proxied by the spatial lag of the dependent variable *Wpat*. Controls, that is contextual phenomena which are not determined by the DMU, are *pop* and *national dummies*. As a result, (2) can be formalized, as the log transformation of a Cobb-Douglas function, as follows:

$$pat_{it} = \alpha + \beta_1 rd_{it-s} + \beta_2 hk_{it-s} + \beta_3 pop_{it-s} + \beta_4 ND_i + \rho W pat_{it} + \varepsilon_{it} \quad (7)$$

where i=1,…271 and t as explained above;

Note, again, that all the explanatory variables included in the model are lagged (t-s) and averaged over the two-year period to smooth away cycle effects and to avoid potential endogeneity problems.

Table 3 provide some descriptive statistics of the main indicators used in the empirical analysis in order to appraise and assess the knowledge and technology gap between the two main groups of countries in Europe: western rich and eastern backward economies. Moreover the comparison of such indicators along the two periods allows for a preliminary analysis of how this gap has changed in the recent times.

Table 3. Descriptive statistics for the inputs and outputs

			Patents	R&D	HK	Population	W*patents
1st period	All sample (n=271)	Mean	207.3	672.6	173.4	1792.1	230.4
		Sd	387.1	1212.8	178.9	1425.5	62.3
	EU15+2 (n=217)	Mean	256.4	824.4	186.1	1772.3	246.6
		Sd	418.4	1311.5	192.5	1511.9	57.7
	EU12 (n=54)	Mean	9.8	62.3	122.3	1871.6	165.2
		Sd	16.0	96.3	93.9	1013.4	28.3
2nd Period	All sample (n=271)	Mean	208.1	740.5	196.2	1810.6	230.3
		Sd	372.1	1290.6	196.9	1454.8	61.2
	EU15+2 (n=217)	Mean	257.0	906.6	210.4	1799.7	245.5
		Sd	401.2	1392.9	212.5	1547.5	57.4
	EU12 (n=54)	Mean	11.6	72.9	138.9	1854.3	169.1
		Sd	16.5	105.8	97.0	1009.8	29.8

From the table above it is clear that innovative performance is a dualistic phenomenon: while regions in the Western Europe produce on average more than 250 patents in both periods, Eastern regions manage to get around 10. Nonetheless this dual system is currently slowly changing since while Western production is rather stable, the one by EU12 countries has increased of about 20% from 9.8 to 11.6.

If one compare output and input indicators, we discover that for each patents in EU12 countries there are at least 25 in EU15+2 countries, whilst the distance is much lower when we look at the investments in innovation: for each euro spent in R&D in EU12 there are almost 13 spent in the EU15+2. The gap between the two systems are even smaller in the last three indicators. In particular, human capital in Eastern regions is only one third of the one which is available in Western Europe while average population in EU15+2 regions is even slightly lower than the average population in EU12 regions. Finally, the potential for spillovers from proximate regions is higher in EU15+2 regions with respect to EU12 but the gap is not very large: in both periods the average production of neighboring regions was around 245 in EU15+2 and about 170 in EU12 regions.

All these indicators may be interpreted as an indication that most EU12 countries and regions are inefficient. This inefficiency may be due either to technical inefficiency with respect to a common technological frontier, or, if EU12 countries have a different technological frontier (below the one available for EU15 countries), due to a pure technology gap problem. The application of the DEA in the following section aims at helping us to discriminate between these two possible causes to explain the recent dynamics in knowledge productivity of European regions.

In Table 4 we present the results for the parametric analysis for the two periods. In both periods, we first present the OLS specification (column one and three), which allow for testing the presence of spatial dependence. According to the robust LM tests (bottom panel), as a matter of fact, we find evidence of spatial dependence for both periods. For this reason, column two and four present the estimation of the spatial specifications.

Table 4. Regression analysis

Dependent Variable: Patents

	first period		second period	
Model	**Pooled**	**SAR**	**Pooled**	**SAR**
Estimation method	OLS	ML	OLS	ML
R&D	0.521 ***	0.464 ***	0.584 ***	0.516 ***
	(0.067)	(0.058)	(0.062)	(0.053)
Human Capital	0.656 ***	0.764 ***	0.424 ***	0.579 ***
	(0.209)	(-0.178)	(0.196)	(-0.168)
Spillover		0.934 ***		0.924 ***
		(0.061)		(0.068)
Constant	Yes	Yes	Yes	Yes
Adj R-squared	0.913		0.926	
Sigma		0.500		0.450
Diagnostics				
Moran's	10.32		10.23	
p-value	0.000		0.000	
Robust LM test - No spatial lag	49.57		47.66	
P-value	0.000		0.000	
LM test - No Spatial lag	56.70		54.63	
P-value	0.000		0.000	
Robust LM test - No Spatial error	0.15		0.05	
P-value	0.698		0.822	
LM test - No Spatial error	7.29	-1936	7.02	6187.6
P-value	0.007	1.000	0.008	0.000

Estimation for 271 regions.

Control variables: population and country dummies

Focusing on the first period, we observe that both *rd* and *hk* show the expected positive sign and also that the *hk* elasticity turns to be higher than the *rd* elasticity confirming the absolute relevance of skilled workers for the knowledge process. The coefficient associated with the spatially lagged dependent variable is significant and its magnitude highlights the economic relevance of knowledge spillovers: for the same endowments of R&D and human capital, the closer is a region to the most innovative areas, the higher the benefit in terms of new knowledge creation. Results are confirmed in the second period: we can also confirm the importance of *hk* with respect to *rd* even if the elasticities' difference is now smaller than for the first period estimates.

These results are the base for the definition of the specification to be used in the DEA analysis, whose results are presented in the following section.

5. DEA results

Following Cullinane et al. (2004), in carrying out the data envelopment analysis to investigate the innovative performance of European regions we adopt the *output*-oriented approach, since the objective of R&D is to increase innovative output so as to improve regional competitive position. As a result this approach is more suitable when the analysis serves as the basis for defining planning and policy strategies, which is commonly the case for geographic units, such as areas, regions or countries. On the other hand, the input orientation is more adequate when operational and managerial objectives are involved.

Based on the analysis above in our empirical DEA, R&D investments and human capital serve as internal inputs, spatially lagged patents serve as external inputs, while patent applications are used to approximate innovative output. Population controls for differences in the regional dimensions.

Maps 1 and 2 show an overview of the main results of the application of the DEA to our sample of European regions. In particular they allow to examine the geographical distribution of the regional efficiency measures for the knowledge production function calculated for 1st and the 2nd period, respectively. Fully efficient regions, in terms of converting R&D and human capital inputs into patents, have a technical efficiency score of 1 (red colored in the maps); these are the best performing areas in innovation activity, given their inputs, and therefore they define the production possibility frontier.

[Insert about here map1 and map2]

For the first period, we can observe in map 1 that there are 15 efficient regions out of 271 and that among them there are territories where important cities are located (such as Île de France) and strongly industrialised areas such as Stuttgart in Germany or Noord-Brabant in the Netherlands. Nonetheless, we notice that there are also regions belonging to less economically strategic areas, such as three Bulgarian regions, 3 Greek regions and the Finnish insular region of Åland. The most efficient regions are followed by a group of German and North Italian regions, which are pretty close to the frontier as they show high technical scores. On the contrary, the most lowest scores are shown by regions located in European peripheral areas, especially in the new accession countries and in the South of Europe.

If we focus on the DEA results for the second period, we can observe that in this case the number of efficient regions increase thanks to three more German regions which enter this group. All other efficient regions are the same as in the first period. The overall geographical distribution of the efficiency scores is very similar to the first period: regions showing the higher efficiency values are mainly located in the Centre and in the North of Europe, whilst most peripheral areas show lowest efficiency values. This analysis confirms the presence of a dualistic – centre *vs* periphery – pattern in the innovation activity. Moreover the geographical distribution of high and low efficiency scores shows the evidence of a strong spatial pattern supporting the hypothesis of the relevance of spatial concentration and possibly spillovers.

When one compares the two maps the overall picture does not seem to change appreciably, this is obviously due to the fact that a three-year lag is probably too limited in time for the pattern of the knowledge creation process to change. It is well-known that such a process is quite persistent as it requires considerable efforts on the investment side, both for R&D expenditure and, especially, for human capital, whose economic returns and effects occur completely only over long run horizons. Nonetheless, it is important to emphasize the fact that the phenomenon under examination, that is innovation activity, is on the rise within this time interval, albeit short. Moreover, in both periods, the most efficient territories exhibit a great deal of heterogeneity. Despite the fact that the majority of the efficient regions are located in the most central and rich areas of the continent, due to the particular features of the DEA methodology which selects efficient units also at a low scale, we find high efficiency scores also in small, peripheral and relatively backward regions.

The presence of a dual innovation system in Europe is further analyzed thanks to Table 5 where results are distinguished into three components, technical efficiency (which corresponds to the hypothesis of constant return to scale), pure technical efficiency (which corresponds to the hypothesis of varying return to scale) and scale efficiency (obtained by comparing the two previous indexes). Such indexes are provided for the all sample and then distinguished in two main group of countries: the former includes regions belonging to EU15 and the two EFTA countries of our sample that is Switzerland and Norway, that is the richest ones in EU, whilst the latter group includes regions belonging to the 12 new entrant countries mainly located in the eastern part of Europe.

Table 5 Technical and Scale efficiency

	1st period			2nd Period		
	All sample	EU15+2	EU12	All sample	EU15+2	EU12
Min	0.007	0.012	0.007	0.008	0.015	0.008
SD	0.230	0.235	0.136	0.249	0.254	0.067
Geom Mean	0.205	0.245	0.099	0.219	0.270	0.094

Pure Technical Efficiency (VRS Efficiency)

	1st period			2nd Period		
	All sample	EU15+2	EU12	All sample	EU15+2	EU12
Min	0.008	0.013	0.008	0.011	0.024	0.011
SD	0.257	0.250	0.262	0.266	0.263	0.218
Geom Mean	0.240	0.278	0.133	0.275	0.322	0.147

Scale Efficiency

	1st period			2nd Period		
	All sample	EU15+2	EU12	All sample	EU15+2	EU12
Min	0.029	0.029	0.225	0.015	0.015	0.154
SD	0.171	0.153	0.199	0.187	0.157	0.227
Geom Mean	0.853	0.881	0.749	0.796	0.840	0.641

Table 5 shows that the average values are quite low both for technical and for pure technical efficiency. This results can be explained by observing that we are dealing with a sample of 271 regions, quite a large number compared to most similar DEA analyses presented in the recent literature (Enflo and Hjertstrand, 2009; Roman, 2010; Jimenez-Sàez et al., 2011; Zabala-itirriagagoitia et al., 2007). From this studies we see that when the sample is smaller and therefore more homogeneous, this ensures higher efficient values. Moreover, we have already remarked while commenting Table 3, that our sample is characterized by a high degree of heterogeneity. As a matter of fact, results classify only 15 regions for the first period and 18 for the second one as efficient regions over a total amount of 271 regions. The large input and output indicators heterogeneity could explain the distance of some regions, from the frontier and therefore such low values for technical efficiency. In the same vein, it is worth noting that only 50 regions, out of 271, have an index of pure technical efficiency above 0.5 in the first period and they become just 60 in the second period. This implies that technical efficiency slightly increases from the first to the second period (from 0.20 to 0.22) and the same happens for the pure efficiency (from 0.24 to 0.27). On the contrary, scale efficiency shrinks going from 0.85 to 0.80 for the whole sample, a decrease of -7% which doubles up to -14% when one considers only the new entrants EU12 countries. Table 5 also shows that, as expected, the group of richest regions shows the highest efficiency scores for the three measures considered in both periods. Most importantly, and somewhat surprisingly, the efficiency gap between Western and Eastern regions is not closing up but, on the contrary, it is slightly expanding.

This reading is, however, contrasted when, thanks to the Malmquist index, we focus on the dynamic of productivity along the years under analysis. Table 6 synthesizes the main outcome for the decomposition provided by the procedure described in section four. The most important result is reported in the last column, where one finds that the total productivity change has been on average almost null. This result is however quite different when one refers either to the EU15+2 regions, where productivity change has been negative (-2%) or to EU12 new entrant regions, where productivity has increased by almost 3%. As a matter of fact the productivity change index has been above one for 28 out 54 regions in EU12 (52%) and for just 88 out 217 in the Western EU15+2 regions (40%).

This contrasted evolution is the result of a very complex composition of the different pieces which makes such an index. Most of the increment in the productivity index for the EU12 new entrant regions is, in fact, due to technological change which has an index of 1.086, which implies a positive change of almost 9%. This increment is partially compensated by a decrease of the total efficiency in Eastern regions of around 5% (TC is 0.946). A decrease which can be, in turn, decomposed in pure and scale efficiency change which have opposite dynamics. The former increases of almost 11% (PE=1.108) whilst the latter diminishes of almost 15% (SE=0.854).

In a nutshell Eastern regions have on average moved their technological frontier upwards and have therefore reduced their technology gap which is the main cause of their productivity disparity with respect to Western regions. A disparity which is currently being closing down. At the same time there has been a recovery in terms of pure efficiency too, even though this has been associated to a movement away from the optimal scale of production. This can be due to the great changes in the production structure of this countries during the transition: they are in fact moving from an economic system based on big scale firms owned by the state to a more diversified system of small, medium and big enterprises within an emergent private sector (see Marrocu et al., 2012).

Table 6. Malmquist index decomposition

	technological change	**efficiency change**			**productivity change**
		pure efficiency	*scale efficiency*	total	
All sample	0.928	*1.148*	*0.933*	1.071	**0.994**
EU15+2	0.892	*1.159*	*0.953*	1.104	**0.986**
EU12	1.086	*1.108*	*0.854*	0.946	**1.027**

A different picture emerges when we refer to Western regions. In this case there has been a downward movement of the frontier since the technological change index is below unity (TC= 0.892). At the same time there has been a great jump of total efficiency, which has increased of more than 10% (TE=1.104). An achievement which is due to a partial regress in scale efficiency (SE=0.953) and a strong progress in pure efficiency (PE=1.159).

It is interesting to note that these results are compatible with the recent work by Filippetti and Payrache (2012) who are the only scholars to provide the Malmquist decomposition for European regions, even though for labour instead of knowledge productivity. In particular, they analyse the contribution of capital deepening and total factor productivity as drivers of labour productivity growth and catch up in Europe. They find that the Old Europe presents a decreasing dynamics for technological change and a positive one for efficiency change. The opposite is true for the new entrant regions which experience an increase in their technological capabilities and a slight decrease in efficiency.

[Insert about here map3]

The scenario described above about the two macro areas of Europe is, needless to say, quite intriguing since it provides a clear-cut picture of some phenomena dynamics across European regions. However, we have to remember that such macro-areas contain very differentiated sub territories which are difficult to classify according to just one dimension. According to Capello and Lenzi (2012), for instance, the different dimensions of knowledge and innovation can give rise to a very fragmented picture of Europe. An attempt to offer some evidence of such regional heterogeneity is given thanks to Map 3, where we can observe the spatial distribution of productivity change (PC) values for our regions' sample. This map, in other words, gives a detailed account of individual region dynamics in productivity in the first part of the latest decade.

It is not surprising that dark red colored regions, those with the highest values of productivity change, are mostly located in Eastern countries such as Czech Republic, Poland, Romania and Slovakia. There are, however, some red regions which are located in the southern countries of Europe, such as Greece, Portugal and Spain. All in all, these are all regions which are characterized by a low productivity of knowledge (both in the EU15+2 and in the EU12 areas), which are undergoing a process of convergence with respect to high-productivity regions. In the middle class, furthermore, we find those regions with stable productivity since PC is around zero (that is a Malmquist index value close to 1). This class includes mainly regions which belong to the core of the richest countries of the EU15+2 macro-area. In the last two classes we find those regions which have experienced a decline in their capacity to produce ideas (that is patents). The spatial pattern of such classes is more difficult to define precisely since these regions are spread all over Europe. In this group we can find both industrialized rich regions which are losing a slice of their technological leadership and some backward regions which are not managing to converge in terms of technological change and in terms of efficiency towards the highest frontier in knowledge production.

6. Conclusions

Knowledge and innovation are crucial determinants of economic growth. Understanding the sources and patterns of the production of knowledge is, therefore, fundamental to have a complete appreciation of this process, its strengths as much as its deficiencies and inefficiencies.

Our study aims at providing some evidence on this issue with an analysis of knowledge production at the regional level in Europe by means of a non parametric method, i.e. Data Envelopment Analysis. This method, as a matter of fact, allows to analyse and assess the level of efficiency of a set of economic units, European regions in our case, in the use of inputs/resources devoted to the production of knowledge. The implementation of the Malmquist index, moreover, allows also to study the dynamics of productivity changes along time, providing useful indications in order to appraise those policies which are aimed at either incrementing or directing this process. This is particularly important for the case of European regions. As a matter of fact, European regions, especially after the enlargement, appear extremely polarized in terms of innovation and knowledge production (Hollander et al., 2009). EU policies are clearly aimed at trying to lessen such concentration while favoring a convergent process. Such a convergence may be due thanks to technological transfer or to an endogenous process, accompanied by an efficient use of scarce resources. Our study aims at assessing the role of these different elements in the dynamics of knowledge production of European regions in the latest years.

Our analysis is based on two steps. Firstly, as a preliminary analysis, we estimate a knowledge production function with the usual parametric methods, to find out that returns of R&D expenditures and human capital on regional innovative capacity have a strong role in fostering innovation and knowledge creation. Most importantly, the presence of a qualified and skilled labour force proves to be a crucial factor, even more than direct investment in R&D. Results also reveal the presence of a strong spatial pattern of innovation activity enhancing spillovers.

Based on these results we have, as a second step, implemented a DEA, according to which there is evidence of a dualistic (centre vs periphery) pattern in the regional innovation activities, with the highest efficient territories located in the most central or economically strategic areas of the continent. Conversely, the lowest efficiency scores are shown by regions located in European peripheral areas, especially in the new accession countries. Further, apparently this picture does not change very much along time.

On the contrary, the application of the Malmquist productivity index shows that productivity dynamics has been extremely differentiated across regions in terms of both magnitude and intrinsic features. We, again, observe important differences between the core and periphery of Europe and most specifically between the countries which are rich and industrialized and form the so called "Old Europe" and those which are relatively poor and have entered the European Union quite recently.

Results show that there is been a process of knowledge productivity convergence along time and that such a convergence is mostly attributable to a closing up of the technology gap and thanks to an important enhancement in efficiency. The efficiency component due to the scale dimension has been on the contrary decreasing for all regions in Europe and in particular in new entrant countries.

For the future, we can expect that potential gains due to technology gap and inefficiencies are going to be reduced due to the fact that from now on backward regions are going to be closer to the frontier. Nonetheless, there is still some room for improvement and it is probably necessary that this process of narrowing the technology gap and of reducing inefficiency is helped through appropriate measures by the EU.

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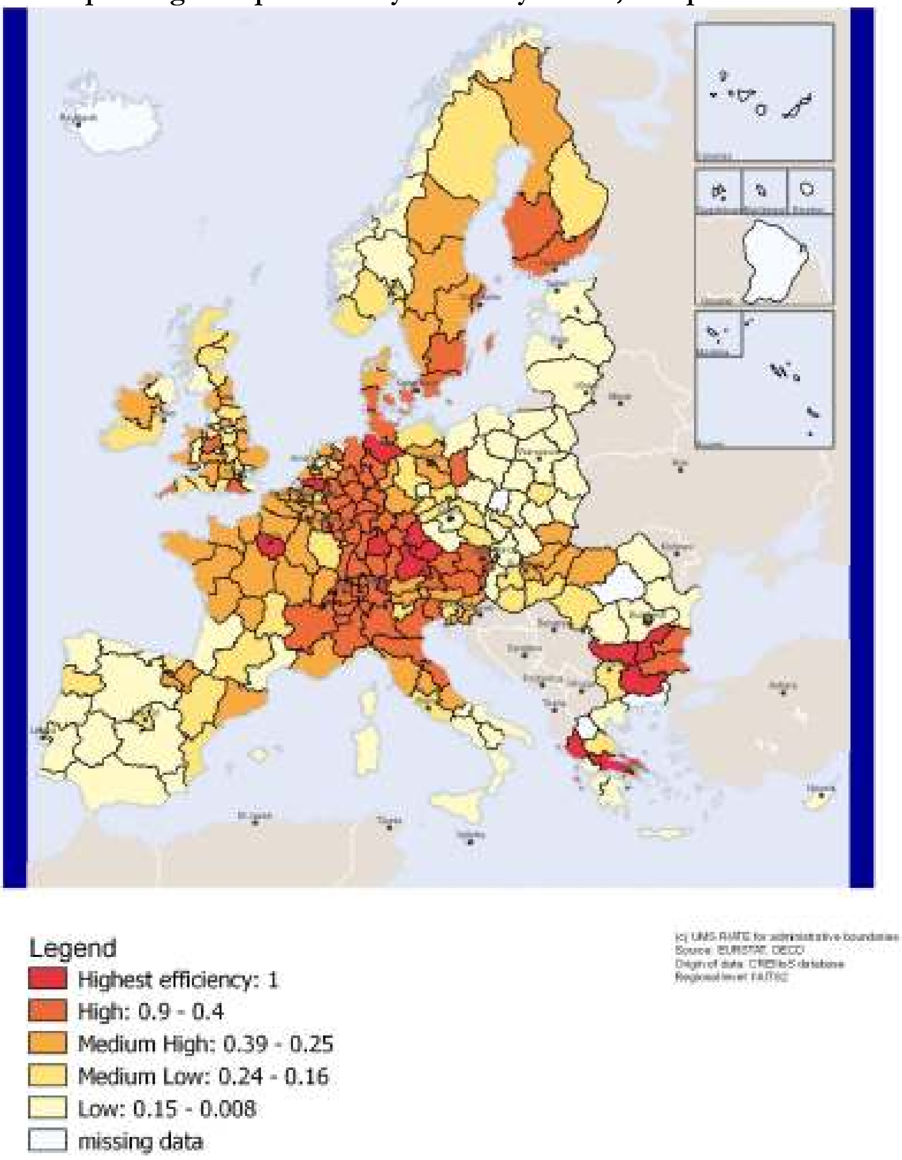
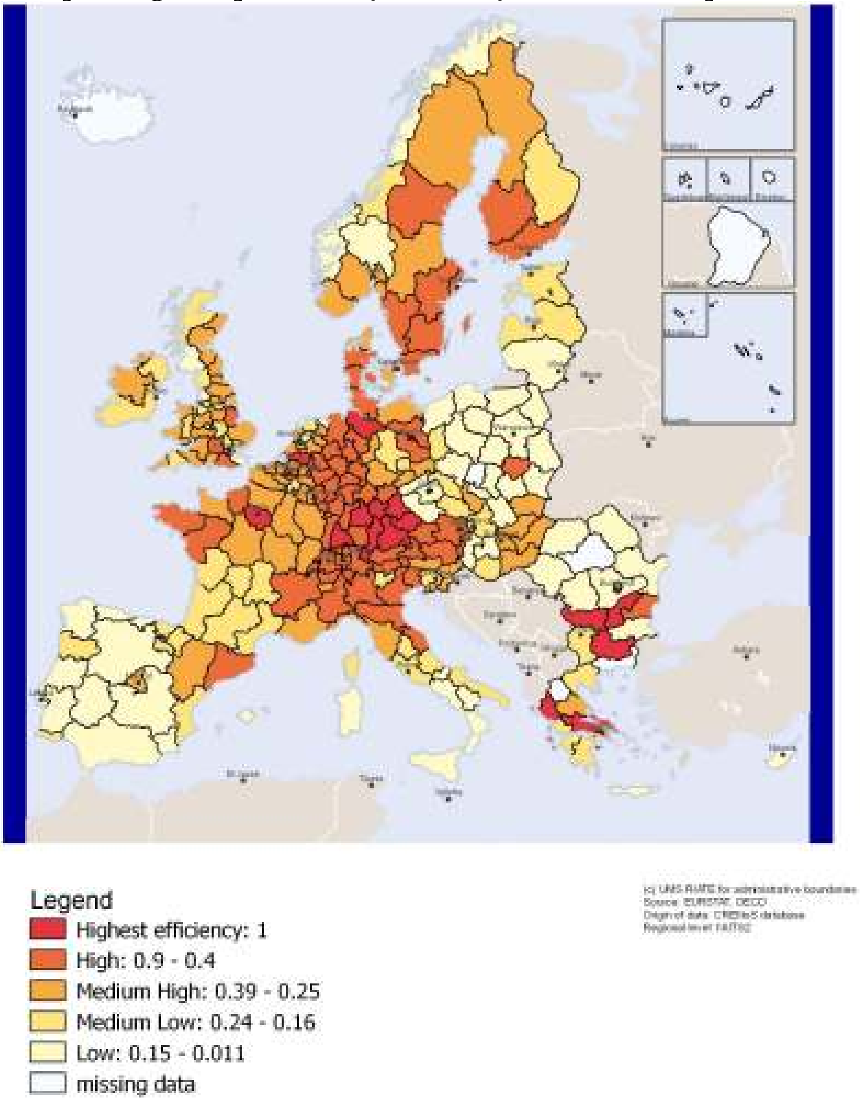
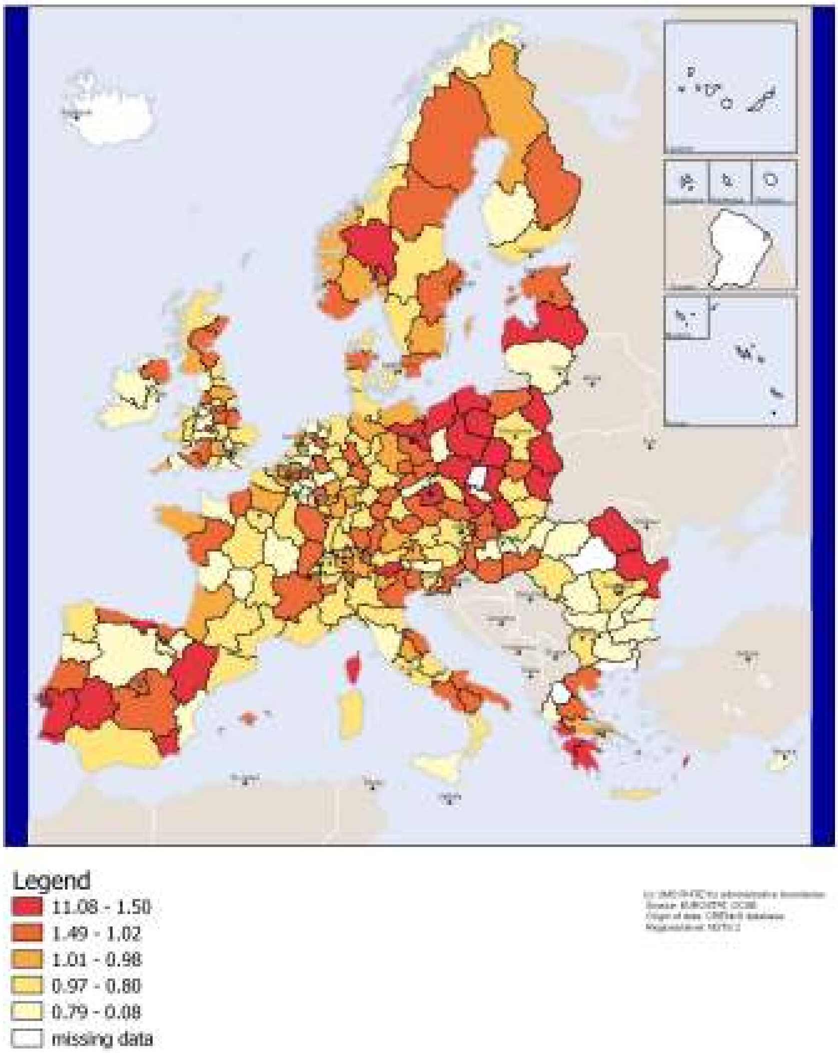
Map 1. Regional productivity efficiency scores, first period



Map 2. Regional productivity efficiency scores, second period



Map 3. Regional productivity change (Malmquist index)



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