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Technological catching up among European regions. Lessons from Data Envelopment Analysis

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Abstract

Europe's 2020 strategy and the initiative "Innovation Union" call for a particular attention to the territorial dimension of innovation and knowledge creation. To this end, this paper investigates the nature of knowledge production and diffusion among regions in 29 EU countries and tries to assess its effectiveness. Data Envelopment Analysis is thus applied to assess how efficiently European regions use internal and external inputs for the production of new knowledge and ideas. The analysis produces 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. This ranking is then evaluated through the Malmquist productivity index in order to assess the relative importance of its main components.

The Data Envelopment Analysis provides further evidence of a dualistic (centre vs. periphery) pattern in the regional innovation activities, with the most efficient territories located in the most central or economically strategic areas of the continent. The application of the Malmquist productivity index shows that both the magnitude and intrinsic features of the productivity dynamics are extremely differentiated across regions. Again, we observe important differences between the core and periphery of Europe and, more specifically, between the rich and industrialized countries which form the so called "Old Europe" and the relatively poorer ones which have entered the European Union quite recently.

This scenario provides some interesting lessons for European neighbouring countries and regions which are going to play the role of the New Europe in the foreseeable future.

Keywords: innovation, human capital, spatial spillovers, European regions, DEA
JEL code: R11, 033, C31, C61

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1. Introduction

Europe's 2020 strategy and the resulting initiative "Innovation Union" call for a particular attention to 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, is the rationale for 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 an unusual methodological tool: Data Envelopment Analysis (DEA). DEA was firstly proposed by Farrell (1957) and originally mainly used, like other frontier models, in productivity analysis at the micro-level. Recently, it has become increasingly popular at the macro-level as a non-parametric alternative to parametric estimation. Regional applications at the European level have been quite rare, with some exceptions, such as Zabala-Iturrigagoitia et al., (2007) and Enflo and Hjertstrand (2009).

The main aim of this paper is to assess, by means of DEA, the degree of efficiency with which European regions use internal and external inputs for the production of new knowledge and ideas. DEA allows to compute for the first time a regional ranking of the innovative performance within the EU in the first years of the current century. The evolution of such rankings is also evaluated thanks to the Malmquist productivity index (Coelli et al., 1998) in order to assess the relative importance of different factors.

Contrary to the usual econometric analysis, DEA is instrumental to investigating not just 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, consequently, more adequate for benchmarking analysis, as it permits to identify the best performing units within a given set of entities, while regression models are particularly suitable to measure central tendencies of a given phenomenon. DEA can be particularly attractive for measuring efficiency in knowledge production without requiring specific assumptions on the behavior of regional innovation systems. Furthermore, with the application of the Malmquist index, which allows for the presence of time-varying technical inefficiencies, we directly investigate the contribution of either efficiency or technological change to knowledge productivity variations. This index can be decomposed 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, as it offers useful information to the policy maker, who can thus analyze the results of past productivity-enhancing strategies and design better ones for the future. Most importantly, this decomposition allows to focus on the differences between those 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. This distinction is particularly informative with respect to the prospective potential evolution of European Neighbouring Countries which can be assimilated to the past dynamics of Eastern European regions. Finally, it may offer useful hints for designing a new innovation policy, as advocated by Camagni and Capello (2013), which replaces the "one size fits all approach" with a strategy built on the smart specialization of R&D activities in different regions (Foray, 2009).

As a matter of fact, results show that the relative efficiency in knowledge production is extremely heterogeneous across regions. We focus mainly on the differences between those 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. For the latter, productivity change appears to be mainly due to a reduction of technology gap, whilst for the former countries productivity is mainly changing through efficiency improvements rather than an increase of technological capabilities.

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 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 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. The most important input is the R&D expenditure, usually associated with the level of human capital as an additional input, given its well known effects on knowledge creation. This 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). Indeed, 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 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, 2011 are among the latest contributions). The only contributions which analyze different continents at the regional level are Crescenzi et al. (2007) for the 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. In this paper, since 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. The only partial exception is the study by Zabala-Iturriagagoitia et al. (2007) which tries to assess

European regional efficiency in innovation using DEA. This paper applies DEA 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 are considered to be an input rather than an output, following Azagra-Caro et al. (2003). Actually, regional GDP per capita is used as the dependent variable and consequently as the output measure of the regional innovation system[1] and this makes this study analogous to a growth accounting study rather than a KPF analysis. The only study which follows more closely the common functional model of a regional KPF is due to Roman (2010), who studies local innovation performance measured by patents, even though his analysis is applied to the limited local context of 14 regions of Bulgaria and Romania.

An analogous setting, however, has been 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, also publications. Moreover, since national data is more readily available, 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 the Malmquist index which can decompose productivity changes into their main components.[2] However, this kind of 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 analyze the main reasons behind the differentiated dynamics of European regions in the latest decades. Enflo and Hjertstrand (2009) show that most regions, within their sample of 69 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 leaders. Filippetti and Peirache (2012) enlarge the sample to Eastern European regions and, not surprisingly, 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 provides a fertile and motivating scenario for the implementation of DEA and the Malmquist index on the analysis of regional knowledge production in Europe. Our aim is to contribute to the research agenda started by Zabala-Iturrigagoitia et al. (2007) in four main ways. Firstly, we update and enlarge the regional sample in order to take into account the EU enlargement process, and separate the rich group of the EU15 (plus Norway and Switzerland) and

[1] 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.

[2] 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). The Malmquist index has been preferred since it allows a useful decomposition of the productivity change. Moreover, thanks to large number of DMUs in our sample, we avoid the usual weakness of the Malmquist index, that is its poor performance in dealing with slacks in the frontier.

that of the relatively backward EU12 new entrant countries. Secondly, we investigate a typical knowledge production function with a non parametric frontier model, 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 to apply the Malmquist index and thus provide additional insights by splitting the index into two components, one which measures changes in technical efficiency and one which measures changes in technological capability. In the latter case, we can assess if regions lagging behind the technological frontier are benefiting from the process of catching up through the diffusion of innovations created in richer countries, as suggested by the technology gap theory by Abramovitz (1986) and Verspagen (1991). 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 by 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: first, 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. The second step consists of evaluating such rankings with the Malmquist productivity index in order to assess the relative importance of its main components.

The first step consists of the application of the non parametric tools to the set of output and inputs traditionally used to estimate a KPF model. 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. 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.[3] We choose to implement the non-parametric 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 outputs. 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 the selection of 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), a term

[3] As a preliminary analysis, we estimate a knowledge production function (Griliches, 1979 and many others) with the usual parametric methods, in order to identify the main determinants of knowledge production at the regional level in Europe. Results show the expected positive sign and also that the human capital elasticity turns out to be higher than the research and development 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 across regions spillovers. These results are the basis for the specification to be used in the DEA analysis.

coined by Charnes et al. (1978). The best performance is characterized in terms of efficiency, so that the top 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 assessed by calculating their distance from the frontier.

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:

$$TE_0^t(output_i, inputs_i) = max\{\theta_i(output_i, inputs_i) \in P^t\} = D_0^t(output_i, inputs_i)^{-1} \quad (1)$$

θ 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 θ = 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 the Malmquist index to incorporate the influence of scale economies, as a departure of the best practice technology from the benchmark technology.

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.

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

$$M_o^t\ (input^t, output^t, input^{t+1}, output^{t+1})_i = \left(\frac{D_o^t(input^{t+1}, output^{t+1}}{D_o^t(input^t, output^t}\right) \quad (2)$$

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

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

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

$$= \left[\left(\frac{\mathrm{D_o^t(input^{t+1}, output^{t+1}}}{\mathrm{D_o^t (input^t, output^t}}\right)\left(\frac{D_o^{t+1}(input^{t+1}, output^{t+1}}{D_o^{t+1}(input^t, output^t}\right)^{1/2}\right] \quad (3)$$

$M_o^t\ (input^t, output^t, input^{t+1}, output^{t+1})_i$ 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)

All in all, productivity change, i.e. the Malmquist index, is decomposed in three components. The first one measures the change in scale efficiency over two periods (i.e. how closer a DMU gets to its most efficient scale size); the second component measures the pure efficiency change, (i.e. the efficiency increases with constant returns to scale); and the third component refers to 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 is less than one, it signifies productivity is increasing. The same applies to any of its components.

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 on some contextual phenomena, such as other regions innovative performance. Nonetheless, we cannot neglect 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)[4].

4. Data and preliminary analysis

The empirical strategy used here consists of a two-step process based on non parametric methods. We perform, in the first step, the Data Envelopment Analysis (DEA) and to build, in the second step, the Malmquist index. We can thus 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: the EU15 which have formed the core of EU in the eighties and in the nineties, plus Norway and Switzerland; and EU12, that is, the eastern countries which have entered EU in more recent years.

[4] 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.

Table 1. Regions at NUTS 2 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.[5] 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), input 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 input variables refer 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 input variables.

[5] Results are robust with respect to the use of indicators for averages of three years.

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 output variable to proxy innovative performance is given by the amount of patent activity in a region[6] in a certain period (*pat*). In 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, the effectiveness of this investment may crucially depend 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

$$output = f(inputs) \tag{4}$$

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

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

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*.

[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, patents are considered the best indicator of research output and have been widely used since they are an objective and standardized measure. Second, data on patent applications at EPO are easily accessible 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 the 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).

Note, again, that all the input 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 provides 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 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 Western Europe produce on average more than 250 patents in both periods, Eastern regions manage to get around 10. This considerable technological gap is slowly changing since, while Western production has been rather stable, inventive output by EU12 countries has increased of about 20% from 9.8 to 11.6. Nonetheless, it should be noted that at this pace the catching-up would take almost two hundred years. Eastern regions and countries need to accelerate their technological convergence if they want to be more competitive in the knowledge economy.

The comparison of output and input indicators reported in table 4 may provide some preliminary hints on the origins of such a gap. As a matter of fact, we discover that for each patent in EU12 countries there are at least 25 in EU15+2 countries, while 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 gaps between the two systems are even smaller for the last three indicators. In particular, human capital in Eastern regions is only one third of the human capital available in Western Europe while average population in EU15+2 regions is even slightly lower than the average in the 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 can be interpreted as an indication that most EU12 countries and regions are inefficient in knowledge production. 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 (lower than the one available for EU15 countries), due to a pure technology gap problem. The application of the DEA and the Malmquist index in the following section should help us to discriminate between these two possible causes to explain the recent dynamics in knowledge productivity of European regions. Most importantly it may offer some hints on how this evolution, which is currently too slow to warrant convergence in a reasonable time, can be improved.

5. DEA results

DEA models can be distinguished according to whether they are *input*- or *output*-oriented. The former are closely related to operational and managerial issues and imply short term objectives, whilst the latter are more related to planning and macroeconomic strategies typically referred to a long time horizon. Cullinane et al. (2005) explain that input-oriented models are more suitable when the output is roughly fixed within a certain constrained range for some time and the key issue is how to efficiently use inputs. On the contrary, output oriented models provide a more appropriate analytical scenario when inputs can be considered as given and economic agents and/or policy makers aims at maximizing the productive performance in the medium/long run future. We choose the output-oriented approach, since the objective of investment in R&D and human capital is to permanently increase local innovative output so as to improve regional competitive position in the long term.

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 the first and second 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 industrialized 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, three Greek regions and the Finnish insular region of Åland. These regions have a rather low patent production but represent the efficient benchmark for those least inventive regions positioned on the left hand side of the knowledge production frontier. The most efficient regions are followed by a group of 13 regions belonging to Germany, Austria, Switzerland, Finland but also Malta and Bulgaria which are pretty close to the frontier as they show high technical scores. On the contrary, the lowest scores are shown mostly 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 increases 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 highest 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 short a time for the pattern of the knowledge creation process to change. It is well-known that this 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 unravel 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. 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 in 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 whole sample and then split in two main group of countries: one includes regions belonging to EU15 and the two EFTA countries Switzerland and Norway, the richest regions in the EU, whilst the latter group includes regions belonging to the 12 new entrant countries mainly located in the eastern part of Europe.

Table 4 Technical and Scale efficiency

Technical Efficiency (CRS 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 4 shows that the average values are quite low both for technical and for pure technical efficiency. This result can be explained by observing that we are dealing with a sample of 271 regions, a large number compared to the sample of 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 these studies we see that when the sample is smaller and therefore more homogeneous, higher efficient values ensue. Moreover, we have already remarked in our comments to Table 3, that our sample is characterized by a high degree of heterogeneity. As a matter of fact, results classify as efficient regions only 15 regions for the first period and 18 for the second one over a total amount of 271 regions. The vast heterogeneity of input and output indicators 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 out of 271regions have an index of pure technical efficiency above 0.5 in the first period and they only increase to 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 from 0.85 to 0.80 for the whole sample, a decrease of -7% which doubles up to -14% when one considers only the EU12 new entrant countries. Table 4 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, appears to be slightly expanding.

This reading is, however, contrasted when, thanks to the Malmquist index, we focus on the dynamics of productivity along the years under analysis. Table 5 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 changes 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 of 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 make up 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, implying 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 by almost 11% (PE=1.108) whilst the latter diminishes by nearly 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 gap with respect to Western regions. These indications of technological catching up may be mainly the result of the implementations of modern techniques embodied in foreign direct investments which have delocalized traditional sectors from the Old to the New Europe during the transition (Burda and Severgnini, 2009). This may also explain the improvements in terms of pure efficiency. As far as the movement away from the optimal scale of production, this, on the contrary, can be attributed to the transformations of the production structure of these countries during the transition: they have been shifting, more or less gradually, from an economic system based on large scale firms owned by the state to a more diversified system of small, medium and big enterprises within an emergent private sector (Marrocu et al, 2012). It is possible that such transformation has produced R&D investments which are allocated over a relatively large number of programs and projects that do not exploit the important economies of scale due to large fixed research costs (Foray, 2009).

Table 5. Malmquist index decomposition

	Technological Change (TC)	**Technical Efficiency Change (TEC)**			**Productivity Change (PC)**
		Pure Efficiency (PE)	*Scale Efficiency (SE)*	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 by more than 10% (TE=1.104). An achievement which is due to a strong progress in pure efficiency (PE=1.159) and a partial regress in scale efficiency (SE=0.953).

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 they apply it to labour instead of knowledge productivity. In particular, they analyze 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 about the two macro areas of Europe described above is, needless to say, quite intriguing since it provides a clear-cut picture of the 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, as clearly suggested by the taxonomies recently offered by Hollanders et al., (2009) and Capello and Lenzi (2012). Foddi et al. (2012) apply DEA not only on knowledge production but also on economic production and conclude that heterogeneity is much higher in knowledge than in economic production. An indication of the fact that combining and using knowledge inputs efficiently is much more difficult than obtaining an efficient combination and use of production factors.

An attempt to offer some further evidence of such regional heterogeneity in knowledge production is given in 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 colored regions, those with the highest values of productivity change, are mostly located in Eastern countries such as the Czech Republic, Poland, Romania and Slovakia. There are, however, some other dark regions which are located in the southern countries of Europe, such as Greece, Portugal, Spain and Southern Italy. All in all, these regions are characterized by low productivity of knowledge (both in the EU15+2 and in the EU12 areas) and are undergoing a process of very gradual convergence with respect to high-productivity regions. In the middle group, 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 either 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 for gaining 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 analyze 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 in 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 since they appear, especially after the enlargement, 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 convergence process. Convergence may be obtained either through technological transfer or 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.

The analysis follows two steps. Firstly, we implement a DEA, which provides evidence of a dualistic (centre vs. periphery) pattern in the regional innovation activities, with the most 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, the application of the Malmquist productivity index, in the second part of the analysis, 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 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. The former regions are those who create most innovations whilst the latter regions are those which lag behind and can eventually exploit the diffusion of such innovations.

As a matter of fact, results show that there has been a process of knowledge productivity convergence, albeit slow, and that such a convergence is mostly attributable to a closing up of the technology gap and to an significant enhancement in pure efficiency. On the contrary, the efficiency component due to the scale dimension has been decreasing for all regions in Europe and in particular in new entrant countries. For the future, however, we expect that potential gains due to reductions of the technology gap and inefficiencies are going to be limited, due to the fact that, from now on, backward regions are going to be closer to the frontier. This reasoning should lead to a future strategy which abandons the idea of R&D expenditure and human capital as the only way to boost innovation processes and productivity enhancement. The differentiated specialization models along diverse stages in the development process suggest a very heterogeneous pattern in the exploitation of technological externalities both at the regional and at the interregional level (as shown in Brülhart and Mathys (2008), Foster and Stehrer (2009) and Marrocu et al., 2012). At the same time, the diverse phases of the innovation process also show varying performances, making the pathway to technological progress and economic growth specific to local and contextual characteristics (Capello and Lenzi, 2012).

In conclusion, the analytical scenario together with the empirical analysis offered in this study suggest a strategy which recognizes different regional specializations in specific knowledge production chains. This is instrumental to overcome the current catching up model, based on the technological gap, and opt for a development model more associated to economies of scale, which have been so far neglected. Economies of scale are crucial to allow each region to exploit the increasing returns to R&D due to the presence of high fixed costs in the innovation process (Foray, 2009). Europe 2020 and the Smart specialization strategy seems to provide (European Commission, 2010) interventions which attribute to each region its original innovation strategy in light of a specific specialization model, development stage and set of comparative advantages.

As for the European Neighbouring Countries, we expect that regions in this area are going to be able in the near future to exploit the same advantage of backward regions in Eastern countries. These regions have, in other words, a potential for catching up which is mainly due to the fact that they are far away from the technological frontier. This process can not, however, been taken for granted since the economies of ENC needs the necessary absorptive capacity to effectively use the knowledge and the technology already developed and applied in Western regions. This implies that the main preliminary step remains the accumulation of human capital stock.

Moreover, in these countries, similarly to Europe, we need interventions based on thematically/regionally focused innovation policies which are able to build for each region a specific innovation strategy based on a unique specialization model. A specialization model which is conditioned to the regional production structure, the development stage and the comparative advantages.

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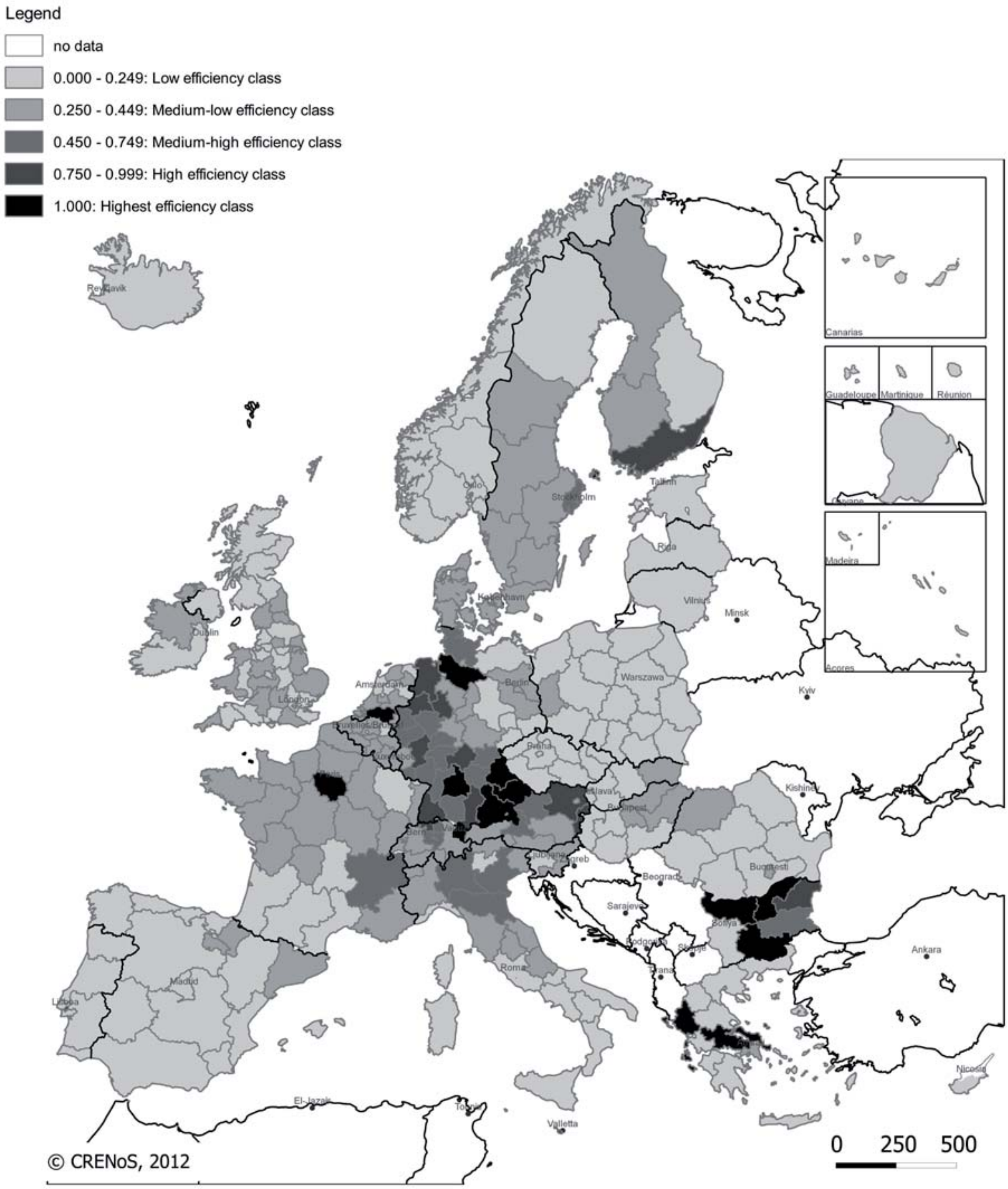
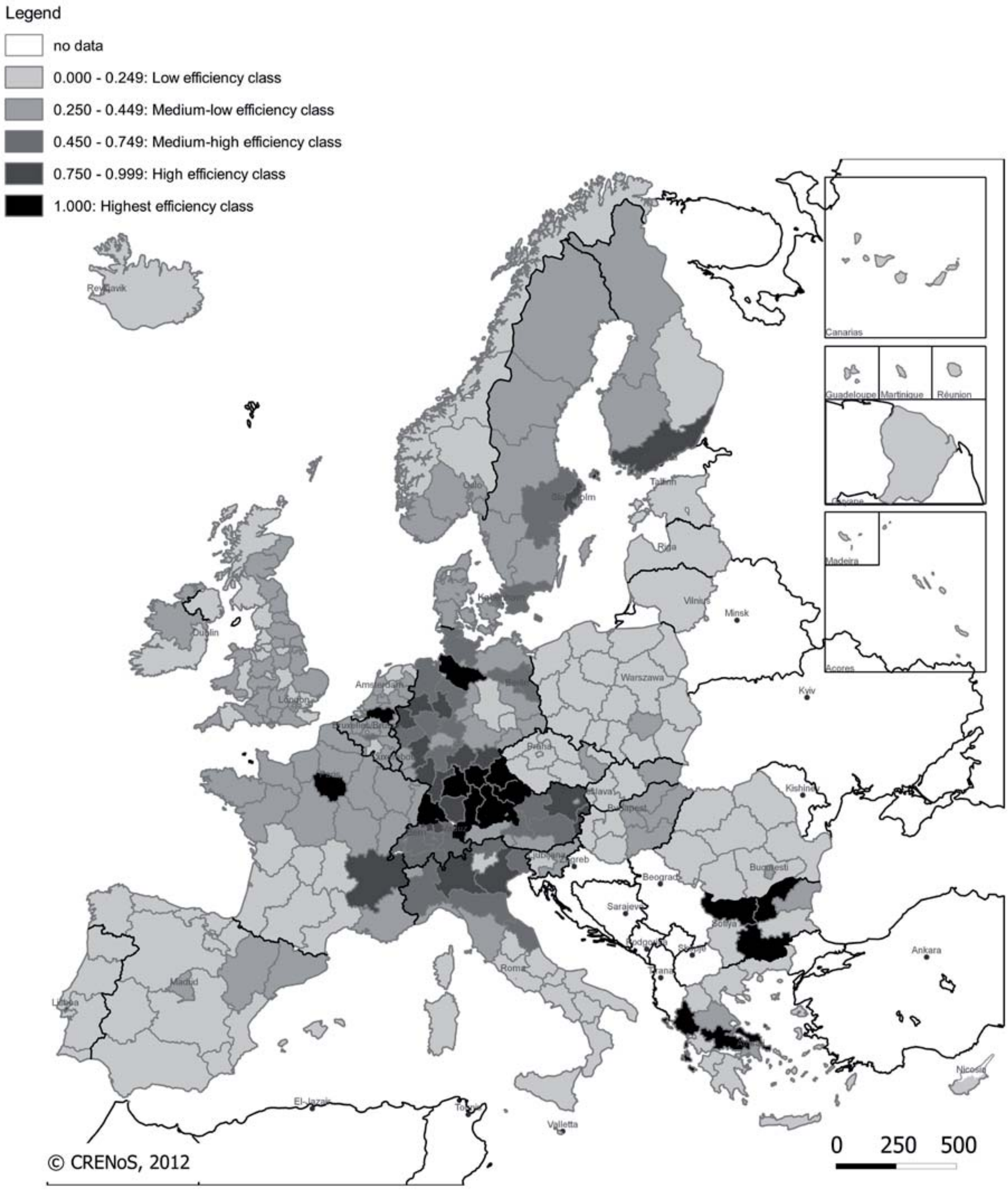
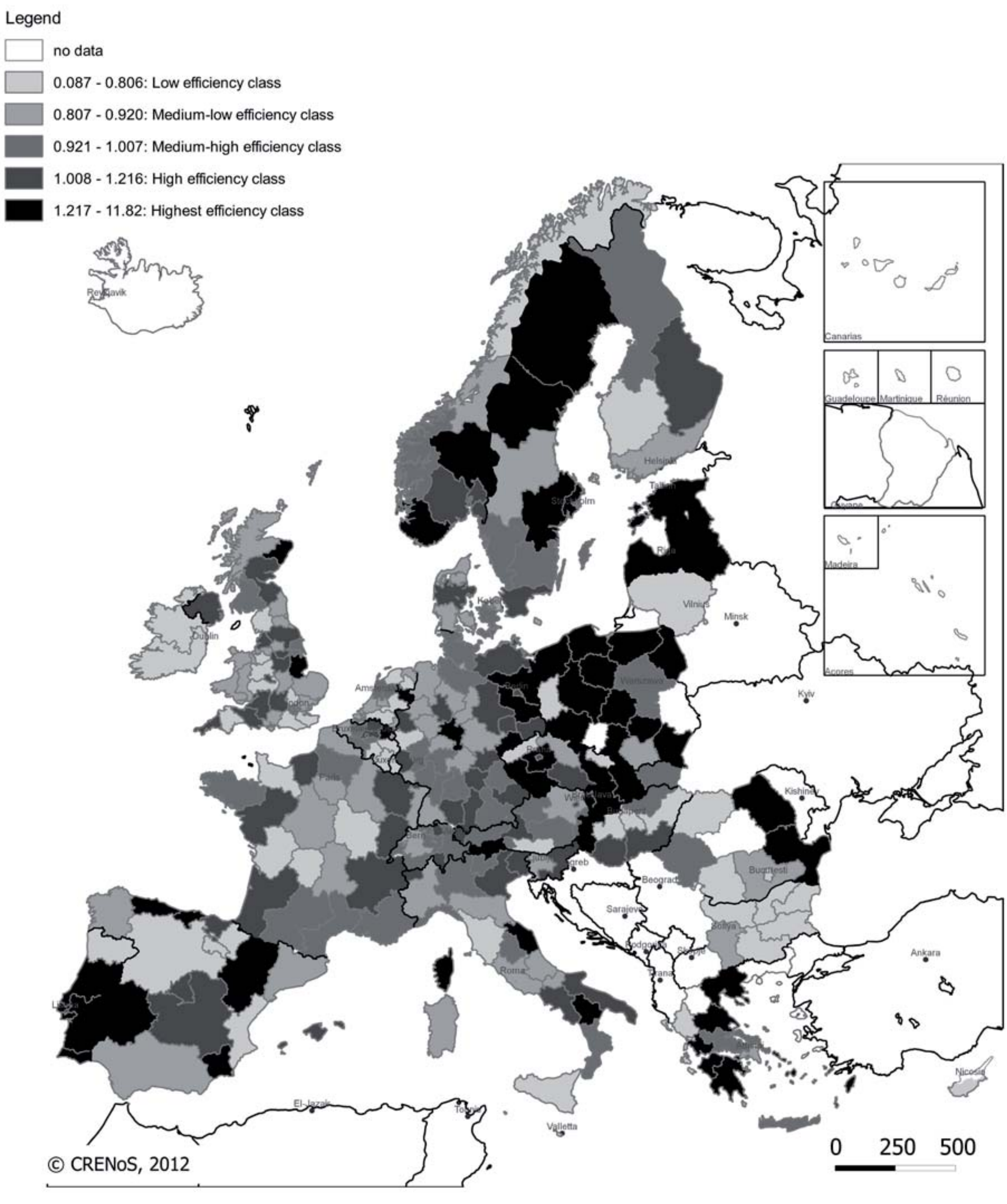
Map 1. Regional productivity efficiency scores, first period



Map 2. Regional productivity efficiency scores, second period



Map 3. Regional productivity change (Malmquist index)



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