Regional Efficiency, Innovation and Productivity

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A discussed issue in the regional innovation systems (RIS) literature is the performance of the geographical ñsystemsò themselves, consisting in the ex-post measurement of the efficiency reached in terms of innovation, productivity growth and global economic performance. Our study evaluates the ex-post technical efficiency of innovation in a sample of EU regions by means of a DEA (Data Envelopment Analysis) methodology and relates the results to productivity at regional level. We find that innovation inputs and outputs are positively linked to productivity, although patents, the most commonly adopted output of the innovation process, are a very imperfect measure for innovation. The policy implications are of uttermost relevance for local governments and administrations, especially when evaluating the leverage given by the inputs in the knowledge production function, and since, increasingly, RIS are seen as a target for economic policy while pursuing the more general objective of competing in the global innovation economy.

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1. Why Regional Efficiency?

In the wide literature on Regional Innovations Systems (RIS) a pivotal issue concerns the efficiency of the system in itself. Given the variety of theoretical perspectives and approaches that can be taken in order to analyzes local geographical systems of innovation (from bottom ï up to top down to evolutionary theories), the critical points that researchers and scholars need to face are essentially two: first, devise new and comprehensive indicators for the innovation performance; secondly, to melt and use these indicators to provide useful, flexible results for the policy maker.

The search for new indicators is constantly carried by statistical institutes and research centres at universities, providing through time increasingly detailed data series on local basis. For instance, the OECD Regional Innovation database represents a concrete effort to put together several local indicators and make regions comparables in a worldwide perspective. The Regional Innovation Scoreboard is an invaluable contribution for the comparison of EU regionsô innovative performance. But, no brand new indicators for innovation performance have appeared in recent years; only more detailed data on the ñoldò R&D expenditure, employees in R&D sectors, patents, and so on, are being provided.

Though, the topic of measuring performance remains on the political agenda of national and local administrations, even more under the pressure of the current economic crisis. In an ever-changing environment where new players emerge, finding the right formula to boost knowledge creation has become the key to long term development and sustainability for both developed and developing countries.

The economic structure of businesses, by means of international alliances and multinational enterprises (MNE) , has crossed over the boundaries of national states to give birth to dynamic, transnational emerging locations. Such areas have regional features rather than national, in that the importance of linkages and learning by interacting provides these areas (e.g. clusters, districts, special economic zones) with an intangible asset that can be called either ñshared tacit knowledgeò and/or òspilloversò of various nature. In a regional context, innovation can also mean ósoftô use of knowledge in business activities, resulting in higher productivity and performance. And while emerging economies increasingly become the favored location for R&D by MNE, once performed in home countriesô headquarters, we are witnessing the shift from global production networks to global innovation networks.

Whatôs the advantage of translating the original concept of national innovation system into a regional, local, dimension? ñThe performance of national economies cannot be explained only in terms of strategies and performance of firms. There are other factors and actors that play vital roles in favoring the generation and diffusion of knowledge, including: inter-organization networks, financial and legal institutions, technical agencies and research infrastructures, education and training systems, governance structures, innovation policies, etc.ò (Iammarino, 2005, p. 499).

The measurement and evaluation of these factors can only be appreciated at local level, because of the natural embeddedness of economic activities in the society. As an example, the increasing attention to social capital in local development studies are example of the key role played by the quality of education, networks and personal relations between individuals, firms and institutional players in the generation, diffusion and absorption of new knowledge.

Notwithstanding, the traditional bane of regional economists and geographers is the lack of meso-economic data on these variables, so important for the performance and ñefficiencyò of the regional innovation systems. Why is efficiency important? Because of the search for best practices that should become the *blueprint* for policy makers.

Our study uses ñclassicalò innovation indicators in a DEA framework: the Data Envelopment Analysis (DEA) approach. This mathematical, linear approach presents some advantages with respect to the usual linear production function approach since it does not depend on specific hypotheses on the innovation process and only relies on data to provide a measure of technical efficiency derived by a simple measurement of industrial efficiency of production processes (see below).

The idea of a DEA approach, already found in the literature (Zabala-Iturriagagoitia, et al., 2007; Fu, 2008) has been welcomed as having certain advantages in the public sector analysis (Charnes et. al., 1994; Martinez Cabrera, 2003) and semi-public activities as RIS. In particular, the DEA analysis is particularly fit to evaluate best practices, since it is an extreme-points approach specifically aimed at creating benchmarks.

The DEA analysis allows for the ranking of regions according to the classical inputs (as R&D expenditure and employees) and output (patents, regional GDP) of the innovation production function (Fritsch, 2002; Fritsch and Slavtchev, 2007); as a second step in our investigation, we adopt the innovation production approach to compare the results from linear regressions with the DEA results, and finally, as suggested by OECD (2009), we correlate the lagged pattern of technical efficiency of regions with changes in regional productivity.

The idea underlying this step stems from OECD (2009), where evidence is provided of a positive correlation between innovativeness of regions and labor productivity. Consistently with the fundamentals of economic growth theories, innovation is acknowledged as the essential engine for long term growth. In particular, innovation and the adoption of new technologies are considered major determinants of productivity growth, especially of the multi-factor productivity. A positive correlation is found among the OECD regions fast-growing in labor productivity (larger than their national labor productivity growth) and in regional patenting activity, which confirms the positive impact of knowledge-oriented activities and innovation systems on productivity.

The study is organized as follows. In the next section we discuss the relevant literature on RIS efficiency measurement and its possible relationship with productivity gains according to various methodological approaches. In the third section, we present the data (Eurostat) with some descriptive statistics and introduce the DEA methodology to evaluate and rank the regions according to their innovation performance. In the fourth section we adopt the innovation production function approach to compare the results from linear regressions with the DEA results. In the fifth section we graphically correlate productivity with the innovative activity of regions (as a method to at least partially rule out the endogeneity of innovation and productivity). The sixth section contains an alternative approach to evaluate the impact of innovation inputs of regional GVA. The last paragraph concludes.

2. Background literature

In recent years, the innovation system approach has been increasingly applied to the analysis of innovation activities in both national and regional contexts (Cooke 1998; Lundvall 1992; Edquist 1997). Regional systems of innovation may constitute an adequate approach for the analysis of innovation activities if spatial proximity matters and the effect of certain influences is limited to a particular region.

Modern efficiency measurement starts with Farrell (1957) who drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency which could account for multiple inputs. He proposed that the efficiency of a firm consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. These two measures are then combined to provide a measure of total economic efficiency.

Reasons for technical inefficiency can be manifold and comprise all sorts of mismanagement such as inappropriate work organization and improper use of technology, scarcity of inputs as well as X-inefficiency as exposed by Leibensteinῲs (1966) seminal work.

Applying this definition to the concept of a regional innovation system means that a region is technically efficient if it is able to produce the possible maximum of innovative output from a given amount of innovative input. Accordingly, a RIS is regarded as technically inefficient if its output falls below the maximum possible value (Fritsch and Slavtchev, 2007). Moreover, RIS have increasingly been recognized as a fruitful alternative analytical framework and tool for generating economic policies (De Bruijn and Lagendijk, 2005; Asheim and Jan, 2006). Of course, the RIS that reaches the theoretical optimum can be considered a benchmark for future policies, targeting innovation at firm level or the educational system, for instance.

The idea of a knowledge production function and ideas-driven growth is empirically tested in Furman, Porter and Stern (2002), where a great deal of variability of innovation activity across countries is due to differences in the level of inputs devoted to innovation (R&D manpower and spending). Fritsch (2002) and Fritsch and Slavtchev (2007) adopt the knowledge production function approach, where the R&D expenditure is the main input while the number of patents granted to a given geographical area is the output.

Rodriguez-Pose and Crescenzi (2008) tried to unify several theoretical approaches by means of principal component analysis on EU 25 regional data, underlying the importance of proximity and distance when regions need to source externally knowledge and innovation.

A DEA methodology is adopted in Zabala-Iturriagagoitia, Voigt, Gutiérrez-Gracia and Jiménez-Sáez (2007), that use the European Innovation Scoreboard data to assess the technical efficiency of EU regions. The DEA approach is also used by Fu (2008), that assess the performance of regional innovations systems in China in relation to their absorptive capability and foreign direct investment. The discussion on the importance of MNE in the European RIS has been investigated by Cantwell and Iammarino (2003). Xibao (2006) adopts a stochastic frontier specification to analyze the effect of region-specific factors on the efficiency of innovation systems.

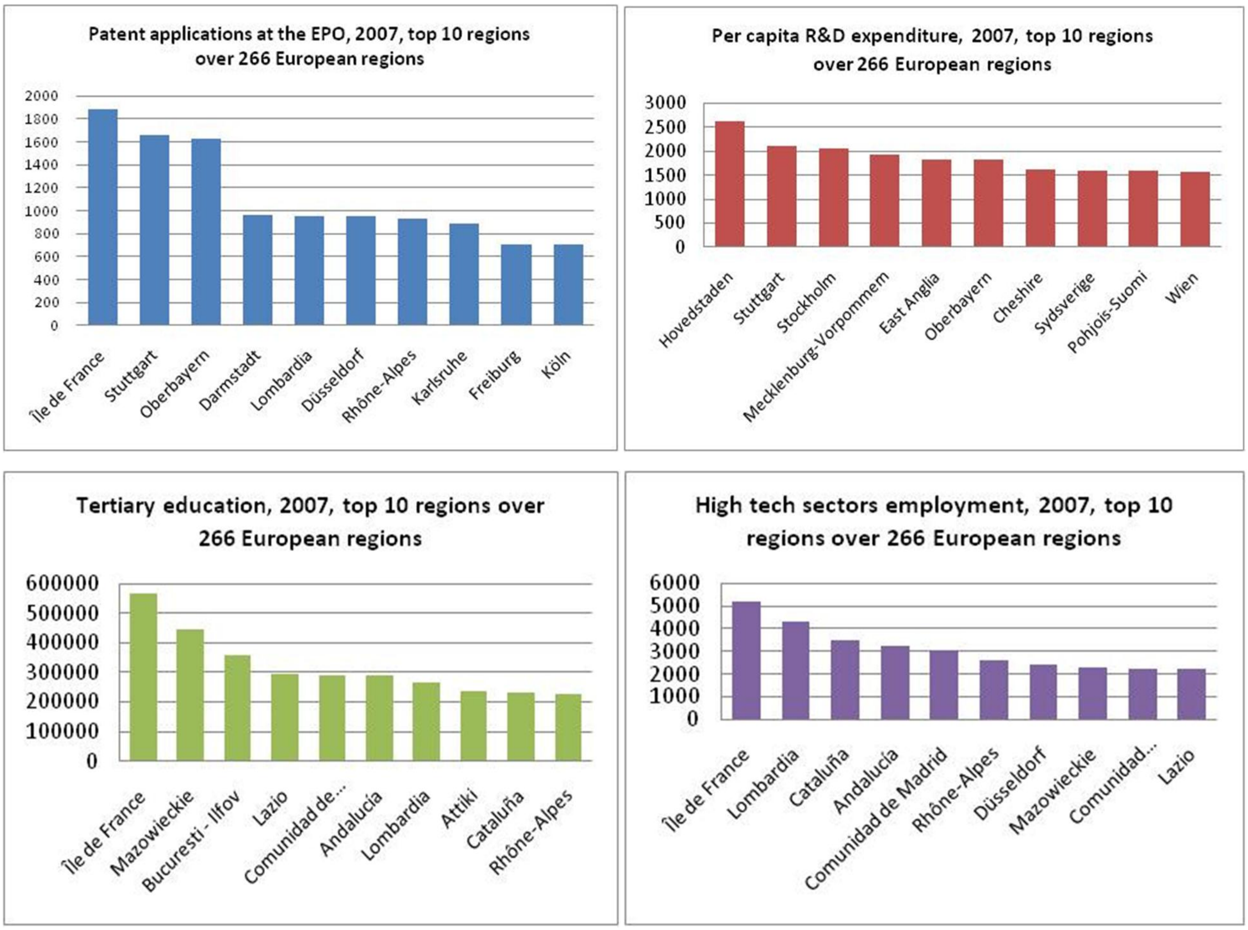
The step that specifically links the performance of regional innovation systems to productivity growth has been relatively neglected . The obvious difficulty lies in the simultaneity of productivity and innovation performance at regional level together with the usual lack of comprehensive meso-economic data. Usually, studies concentrate on firm level analyses (Griffith, Huergo, Mairesse and Peters, 2006), where data on the different types of innovation (product and process) are available;

most macro-level studies rely on classical innovation indicators with regression analysis, leading to mixed results as for the role, for example, of GDP per capita and GDP at regional level.

3. Data and methodological approach

The data we use come from the Eurostat Regional database and concern all NUTS2 regions from 1995 to 2007. We use annual data for patent applications to the European Patent Office by priority year, gross value added at basic prices, employment in technology and knowledge-intensive sectors, total intramural per capita R&D expenditure (GERD), total R&D personnel and researchers, number of students at the tertiary education - levels 5-6 (ISCED 1997), population and labor productivity (computed as regional gross value added divided by the regional employment). Figure 1 provides an overview of the top performing regions in 2007 according to the various indicators considered here.

Figure 1. Top performing regions in 2007.



Source: elaboration on Eurostat data

Figure 2 provides a panorama of European regions according to the most commonly adopted indicator for innovation output, patents.

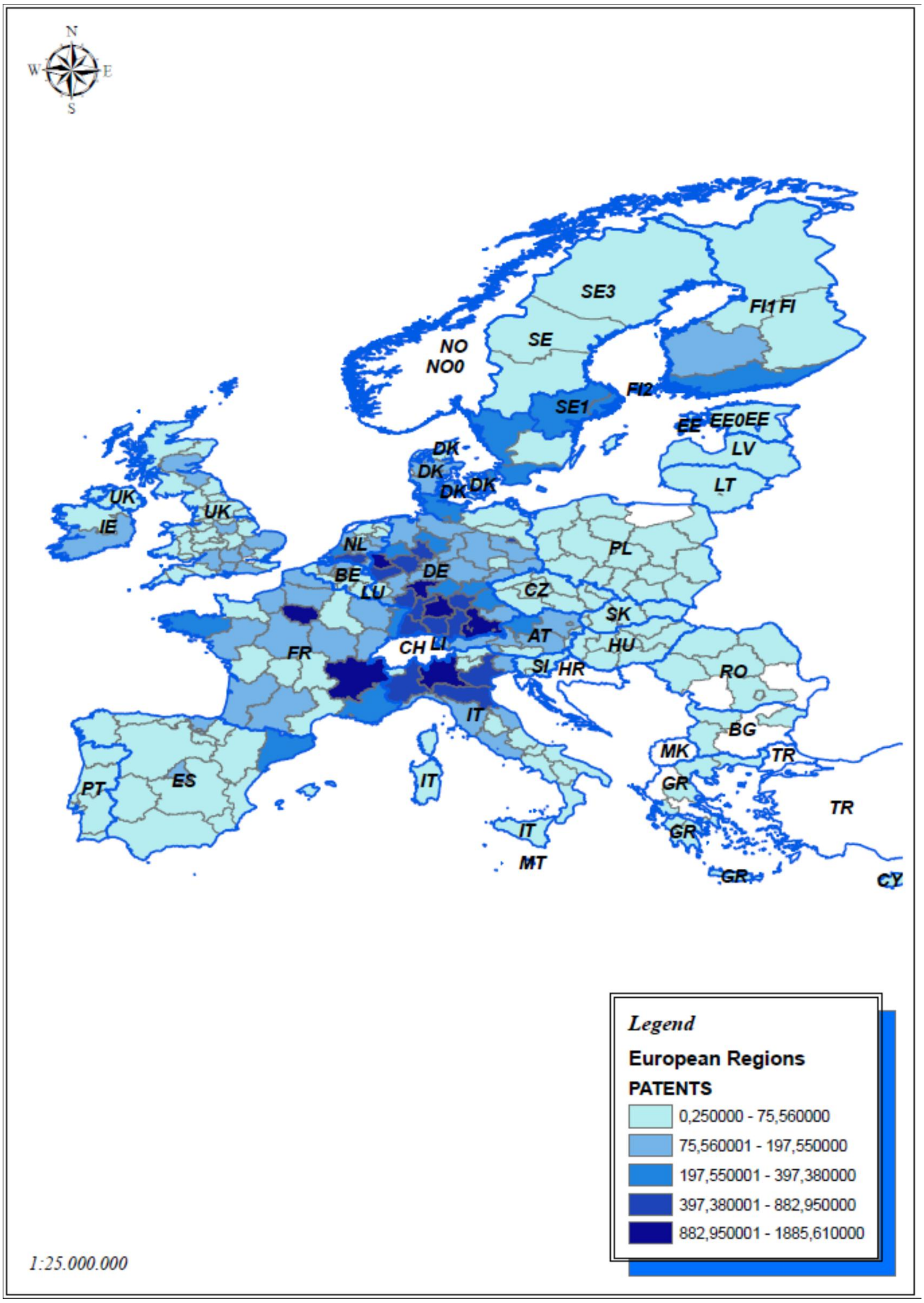
Following former DEA studies (Zabala-Iturriagagoitia et al., 2007; Fu, 2008) we opted for setting some of these variable as inputs for the innovation production process which efficiency we want to measure, and some of the others as outputs. In particular, the debate is open since most the variables commonly considered as output are also an input in the continuous production process of new knowledge. So, for instance, more R&D employees will likely be related to more R&D expenditure; more R&D expenditure will likely lead to more high-tech job places and probably to higher gross value added. On the other hand, those areas with higher gross value added will be likely investing more in R&D and in tertiary education. Patents only capture a small fraction of the complex innovation process and represent probably better the strength of the potential technological endowment of a country, though their commercial value and therefore their impact on the market is hardly measurable. A few regions in Europe (mostly in Germany, together with Lombardy, Rhone ï Alpes and Ile de France) concentrate the highest number of patent applications, with peripheral regions lagging far behind (see Figure %%); Europe has a typical hub-and-spoke structure in terms of patent applications.

Classical methodological approaches always consider patents as an output of the innovation production process, but also gross value added and high-tech employment. We therefore stick to this classification and use variables on tertiary education, R&D expenditure and R&D employment as inputs of the innovation production process to be evaluated by a DEA approach.

The DEA has become popular especially when the aim is to evaluate the relative performance in terms of profits for a sample of firms, as it consists of a non-parametrical mathematical programming approach to frontier estimation. The key paper introducing the term DEA dates back to 1978 (Charnes, Cooper and Rhodes, 1978), where they coined the DEA term and set up an input ï oriented (as opposed to the dual problem, output oriented) model with constant returns to scale.

DEAös empirical orientation and the absence of a need for the numerous a priori assumptions that accompany other approaches (such as standard forms of statistical regression analysis) have resulted in its use in a number of studies involving efficient frontier estimation in the governmental and nonprofit sector, in the regulated sector, and in the private sector. Formally, DEA is a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data as in statistical regression, for example, one ófloatsô a piecewise linear surface to rest on top of the observations. Because of this perspective, DEA proves particularly adept at uncovering relationships that remain hidden from other methodologies.

Figure 2. Regional patent application at the European Patent Office, 2007.



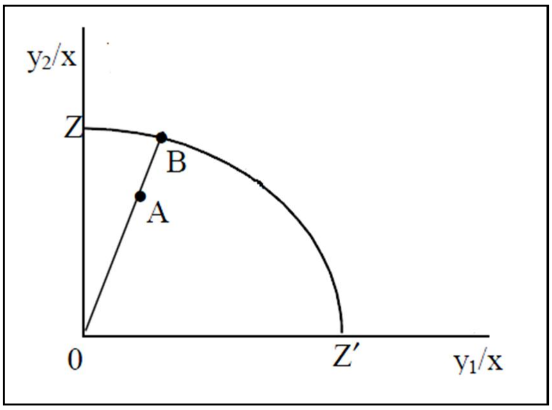
Source: elaboration on Eurostat data

DEA models can rely on a series of hypotheses concerning the returns of the underlying production function (increasing, decreasing or constant) and can be either input or output oriented. It is important to underline that under constant returns to scale, the output and input orientated models will estimate exactly the same frontier and therefore, by definition, identify the same set of units as being efficient. It is only the efficiency measures associated with the inefficient units that may differ between the two methods. From Coelli (1996) :

ñThe input-orientated technical efficiency measure addresses the question: ñBy how much can input quantities be proportionally reduced without changing the output quantities produced?ò One could alternatively ask the question: ñBy how much can output quantities be proportionally expanded without altering the input quantities used?òò.

As an example, suppose production involves two outputs (y_1 and y_2) and a single input (x_1). Under constant returns to scale, we can represent the technology by a unit production possibility curve in two dimensions. In figure 3, the ZZô line is the unit production possibility curve and the point A corresponds to an inefficient firm. The inefficient point A lies below the curve since Zô represents the upper bound of production possibilities.

Figure 3. Output orientation, technical and allocative efficiencies



The Farrell output-orientated efficiency measures would be defined as follows. In figure 3, the distance AB represents technical inefficiency. That is the amount by which outputs could be increased without requiring extra inputs. Hence a measure of output-orientated technical efficiency is the ratio TE0 = 0A/0B. The formal maximization problem to be solved in order the get values of the efficiency measures for the various units under analysis can be found in Coelli (1996); Cooper, Seiford and Zhu (2008).

We use the programmable free software DEAP made available from the Centre for Efficiency and Productivity Analysis, School of Economics, University of Queensland (Australia). Since regions have a number of missing data and the software treats as ñ0ò a missing value, we computed the average values of variables from 1995 through 2007 and then dropped missing values. This unfortunately led us to lose some information on a certain number of regions, but we got rid of any cyclical effect that might have affected regions in given years, obtaining a more enlarged perspective. The results of the DEA output oriented analysis is graphically represented in Table 1.

The regions associated with an efficiency parameter of ñ1ò represent the benchmark; that is, the set of units whose efficiency in producing a given level of output with their available inputs is better. The other regions are those that could definitely improve their performance by adjusting their technical ñmethodologyò in the use of inputs.

We find that even small and relatively poor and peripheral regions such as Corse are technically efficient, more than other bigger and richer regions. The idea is: how well are you using your endowment of R&D and human capital with respect to the best performing regions in technical efficiency terms? So, even if on average we should expect that richer or more productive regions should be the more efficient, it is also possible that smaller regions are adopting good practices in the innovation management of their territory. As a results, among the regions outperforming the others we find, for the case of Italy for instance, Lombardy, one of the richest and more innovative regions, but also the autonomous province of Bolzano and Valle dôAosta, those are small but evidently efficient, northern regions in the Alps area.

The message we can draw from these results is the following: when we look at the efficiency of a local system, it is convenient to study and analyze the quality of and management of innovation of the best performing regions in order to reach higher level of efficiency in the ñproductionò of innovation. So, it may not be the quantity of investment in tertiary education and R&D employment that can be conducive to higher performances, but the procedures adopted and the presence of shared approaches and beliefs in local communities.

Table 1. Output-oriented DEA efficiency analysis; 185 EU regions, averages 1995 -2007.

Region	Efficiency parameter	Region	Efficiency parameter	Region	Efficiency parameter
Burgenland (AT)	1	*Bretagne*	0.595	*Midtjylland*	0.375
Corse	1	*Haute-Normandie*	0.585	*Východné Slovensko*	0.375
Drenthe	1	*Basse-Normandie*	0.581	*Région de Bruxelles-Capitale*	0.373
Lombardia	1	*Alsace*	0.573	*Campania*	0.372
Luxembourg	1	*Pays de la Loire*	0.571	*Región de Murcia*	0.372
Niederösterreich	1	*Sjælland*	0.56	*Västsverige*	0.372
Noord-Brabant	1	*Vest*	0.56	*Cantabria*	0.368
Notio Aigaio	1	*Toscana*	0.555	*Jihozápad*	0.368
Peloponnisos	1	*Észak-Magyarország*	0.547	*Severoiztochen*	0.368
Provincia Autonoma Bolzano/Bozen	1	*Puglia*	0.544	*Észak-Alföld*	0.368
Severozapaden	1	*Friuli-Venezia Giulia*	0.542	*Auvergne*	0.364
Severozápad	1	*Cataluña*	0.532	*Andalucía*	0.363
Sterea Ellada	1	*Norte*	0.532	*Severovýchod*	0.362
Strední Cechy	1	*Noord-Holland*	0.527	*Galicia*	0.36
Sud-Est	1	*Nyugat-Dunántúl*	0.526	*Zachodniopomorskie*	0.36
Valle d'Aosta/Vallée d'Aoste	1	*Zuid-Holland*	0.526	*Östra Mellansverige*	0.359
Vorarlberg	1	*Lorraine*	0.525	*Strední Morava*	0.358
Åland	1	*Região Autónoma dos Açores (PT)*	0.525	*Etelä-Suomi*	0.357
Île de France	1	*Sachsen-Anhalt*	0.52	*Principado de Asturias*	0.357
Nord-Est	0.985	*Molise*	0.515	*País Vasco*	0.351
Piemonte	0.981	*Alentejo*	0.502	*Castilla y León*	0.342
Illes Balears	0.95	*Hamburg*	0.493	*Kujawsko-Pomorskie*	0.341
Veneto	0.947	*Midi-Pyrénées*	0.493	*Aragón*	0.339
Sud-Vest Oltenia	0.926	*Sardegna*	0.489	*Canarias (ES)*	0.337
Flevoland	0.865	*Warminsko-Mazurskie*	0.485	*Dél-Alföld*	0.331
Schleswig-Holstein	0.857	*Vzhodna Slovenija*	0.484	*Languedoc-Roussillon*	0.331
Småland med öarna	0.856	*Közép-Dunántúl*	0.483	*Attiki*	0.33
Sud - Muntenia	0.824	*Liguria*	0.477	*Utrecht*	0.329
Emilia-Romagna	0.821	*Abruzzo*	0.476	*Lódzkie*	0.323
Thüringen	0.814	*Franche-Comté*	0.474	*Lubelskie*	0.322
Zeeland	0.813	*Limburg (NL)*	0.472	*Slaskie*	0.322
Calabria	0.799	*Limousin*	0.472	*Steiermark*	0.322
Ionia Nisia	0.793	*Sicilia*	0.469	*Comunidad Foral de Navarra*	0.32
Saarland	0.793	*Kärnten*	0.468	*Länsi-Suomi*	0.317
Swietokrzyskie	0.785	*Severen tsentralen*	0.467	*Bremen*	0.306
Basilicata	0.784	*Opolskie*	0.465	*Wielkopolskie*	0.304
Champagne-Ardenne	0.778	*Lazio*	0.456	*Kentriki Makedonia*	0.292
Rhône-Alpes	0.771	*Sydsverige*	0.453	*Övre Norrland*	0.289
Friesland (NL)	0.75	*Umbria*	0.442	*Itä-Suomi*	0.278
Provence-Alpes-Côte d'Azur	0.724	*Aquitaine*	0.437	*Latvija*	0.278
Centre (FR)	0.709	*Gelderland*	0.435	*Kriti*	0.271
Salzburg	0.707	*Centro (PT)*	0.434	*Lisboa*	0.27
Mellersta Norrland	0.706	*Malta*	0.434	*Ipeiros*	0.269
Castilla-la Mancha	0.705	*Nordjylland*	0.433	*Groningen*	0.268
Algarve	0.701	*Overijssel*	0.429	*Lietuva*	0.258
Kypros/Kibris	0.699	*Comunidad Valenciana*	0.427	*Dytiki Ellada*	0.253
Bourgogne	0.698	*Západné Slovensko*	0.427	*Wien*	0.253
Norra Mellansverige	0.693	*Podlaskie*	0.425	*Pomorskie*	0.248
Dytiki Makedonia	0.684	*Provincia Autonoma Trento*	0.424	*Dolnoslaskie*	0.247
Yuzhen tsentralen	0.677	*Extremadura*	0.417	*Jihovýchod*	0.247
Nord - Pas-de-Calais	0.675	*Northern Ireland (UK)*	0.411	*Hovedstaden*	0.225
Thessalia	0.649	*La Rioja*	0.408	*Pohjois-Suomi*	0.205
Lubuskie	0.645	*Tirol*	0.408	*Eesti*	0.201
Syddanmark	0.638	*Border, Midland and Western*	0.4	*Közép-Magyarország*	0.199
Oberösterreich	0.631	*Comunidad de Madrid*	0.397	*Malopolskie*	0.194
Centru	0.629	*Stredné Slovensko*	0.396	*Yugozapaden*	0.16
Podkarpackie	0.624	*Anatoliki Makedonia, Thraki*	0.395	*Zahodna Slovenija*	0.154
Southern and Eastern	0.624	*Dél-Dunántúl*	0.393	*Mazowieckie*	0.142
Marche	0.621	*Mecklenburg-Vorpommern*	0.385	*Praha*	0.108
Picardie	0.616	*Stockholm*	0.384	*Bratislavský kraj*	0.099
Poitou-Charentes	0.603	*Moravskoslezsko*	0.378	*Bucuresti - Ilfov*	0.093
Nord-Vest	0.597	*Berlin*	0.377		

4. Knowledge production function: regression analysis

We can now compare the results above from the DEA analysis with the linear regression analysis of the knowledge production function, as presented in Fritsch (2002):

$$\text{R\&D output} = f\,(\text{R\&D expenditure, Tertiary education})$$

We consider as inputs, in turn, the total R&D expenditure over GDP by region and the Tertiary Education and as output the number of patent application by region: to remain consistent with the DEA approach and since the panel structure we would have is heavy unbalanced, we cannot use a panel data approach and therefore adopt the pooled values of the variables from 1995 to 2007. Taking the Cobb-Douglas production function as a framework, the basic relationship is:

$$\text{R\&D output} = a\ \text{R\&D input}^{b}$$

with the term a representing a constant factor and b giving the elasticity by which R&D output varies in relation to the R&D input. For estimation with standard regression methods, we take the natural logarithms of both sides:

$$\ln \text{R\&D output} = \ln a + b \ln \text{R\&D input} + e$$

where the b parameter represents the marginal contribution of R&D inputs ï expenditure and education ï to the innovation output, measured by patents, and e is an error term. The aspect under which our analysis differs from Fritsch (2002) is that we rely on the Eurostat regional data on innovation, while his sample was made of firm-level survey data, and therefore probably the difference is that we should find less variance with a smaller number of cases.

Since the dispersion of data is high, in order to focus our analysis we concentrate on the best performing regions according to the analysis.

We run an OLS regression with regional dummies for those regions whose efficiency indicator, computed on the 1995 -2007 average performance, is equal to 1. We have 19 regions in the subsample, among which features as GDP per capita, size and so on differ a lot. The result for estimating the above equation, using in turn R&D expenditure and Tertiary education as regressors, is shown in Tables 2a and 2b. In a sense, running an OLS regression over best performing regions can be interpreted as a further screening process to get rid of averages noises and actually detect the regions whose performance was acknowledged by a double filter.

Table 2a. Efficiency equations for best performing regions, R&D Expenditure

Dependent Variable:		Patent Applications				
Region/Indipendent variables	*Coef.*	*Std. Err.*	*t*	*P>|z|*	*[95% Conf.*	*Interval]*
R&D expenditure	.3268899	.2928614	1.12	0.267	-.2552993	.9090791
Corse	1573462	2308856	0.07	0.946	-4432507	474.72
Drenthe	-1067271	1279268	-0.08	0.934	-2649828	2436374
Lombardia	**1249703**	**1405278**	**8.89**	**0.000**	**9703428**	**1529063**
Luxembourg	-2368368	3024845	-0.78	0.436	-8381562	3644826
Niederösterreich	1313103	1372184	0.96	0.341	-1414707	4040914
Noord-Brabant	**1324562**	**2265137**	**5.85**	**0.000**	**8742674**	**1774856**
Notio Aigaio	-3255013	2293234	-0.14	0.887	-4884299	4233297
Peloponnisos	-2374635	1403193	-0.17	0.866	-3026919	2551992
Bolzano/Bozen	-6191268	1539844	-0.40	0.689	-3680236	2441982
Severozapaden	1442971	1298554	0.11	0.912	-2437143	2725737
Severozápad	1141052	1247755	0.09	0.927	-2366349	2594559
Sterea Ellada	751971	1544162	0.05	0.961	-2994495	3144889
Stredni Cechy	-5046257	128343	-0.39	0.695	-3056001	2046749
Sud-Est	1449647	1431248	0.10	0.920	-2700263	2990192
Valle d'Aosta/Vallée d'Aoste	-6673409	1235438	-0.54	0.590	-312331	1788628
Vorarlberg	2131815	1549168	0.14	0.891	-2866464	3292826
Åland	2387552	1178329	0.02	0.984	-2318566	2366317
Île de France	**2751214**	**1146755**	**23.99**	**0.000**	**2523247**	**2979181**
constant term	-1440462	9811796	-0.15	0.884	-2094567	1806474
Number of observations		106		F(19.86)		99.7
R^2		0.9566		Prob > F		0.000

Table 2b. Efficiency equations for best performing regions, Tertiary Education

Dependent Variable:		Patent Applications				
Region/Indipendent variable	*Coef.*	*Std. Err.*	*z*	*P>|z|*	*[95% Conf.*	*Interval]*
Tertiary Education	-.0016731	.0025145	-0.67	0.507	-.0066612	.0033149
Corse	-1036046	9010175	-0.11	0.909	-1890981	1683772
Drenthe	1578596	8969007	0.18	0.861	-162135	1937069
Lombardia	**1702917**	**6469374**	**2.63**	**0.010**	**4195674**	**2986267**
Luxembourg	6024052	9555901	0.63	0.530	-1293229	2498039
Niederösterreich	1810384	931093	1.94	0.055	-3665363	3657423
Noord-Brabant	**1807303**	**202.82**	**8.91**	**0.000**	**1404963**	**2209644**
Notio Aigaio	-1797672	1957241	-0.09	0.927	-4062406	3702871
Peloponnisos	1734015	128339	0.01	0.989	-252856	2563241
Bolzano/Bozen	1086118	1052166	0.10	0.918	-1978603	2195826
Severozapaden	-172343	1130096	-0.15	0.879	-2414149	2069463
Severozápad	1871408	9921159	0.02	0.985	-1949377	1986805
Sterea Ellada	795792	1510383	0.05	0.958	-2916614	3075772
Stredni Cechy	-4266698	9562937	-0.04	0.965	-1939697	1854363
Sud-Est	5804532	1605868	0.36	0.719	-2605158	3766064
Valle d'Aosta/Vallée d'Aoste	-131881	9551783	-0.14	0.890	-2026698	1762936
Vorarlberg	1174946	9226527	1.27	0.206	-6553487	3005241
Åland	-1867019	1130258	-0.17	0.869	-2428829	2055425
Île de France	**3780332**	**1390224**	**2.72**	**0.008**	**1022501**	**6538163**
constant term	2133444	6532205	0.33	0.745	-1082469	1509158
Number of observations		121		F (109, 101)		139.09
R^2		0.9632		Prob > F		0.0000

The results from the tables above show that although some refinements must be implemented, a clear pattern highlights Lombardy, Noord Brabant and Ile de France as the best performing regions. In this case, there is no surprise since these regions are among the most dynamic in the European regional panorama, two of them belong to the ñFour Motorsò of Europe, (unfortunately, because of missing data we lack the information about German regions, but we would expect similar results).

The efficacy of the methodology of ñdouble filteringò for efficiency of the innovation process is moreover assessed by an identical pattern of statistical significance, when using two different innovation inputs.

These regions are the only ones for which the coefficients are positive and significant; the innovation production function is confirmed by the data. What about the remaining regions? These remaining regions are perhaps too heterogeneous to be captured by a regression analysis, but probably present some features to be investigated further.

The idea of selecting the best performing regions only is based on the OECD (2009) finding according to which there is a positive correlation between labor productivity growth and innovation are those where productivity is higher than the average value. This point is illustrated in the following section where we measure the correlation between productivity and innovation performance.

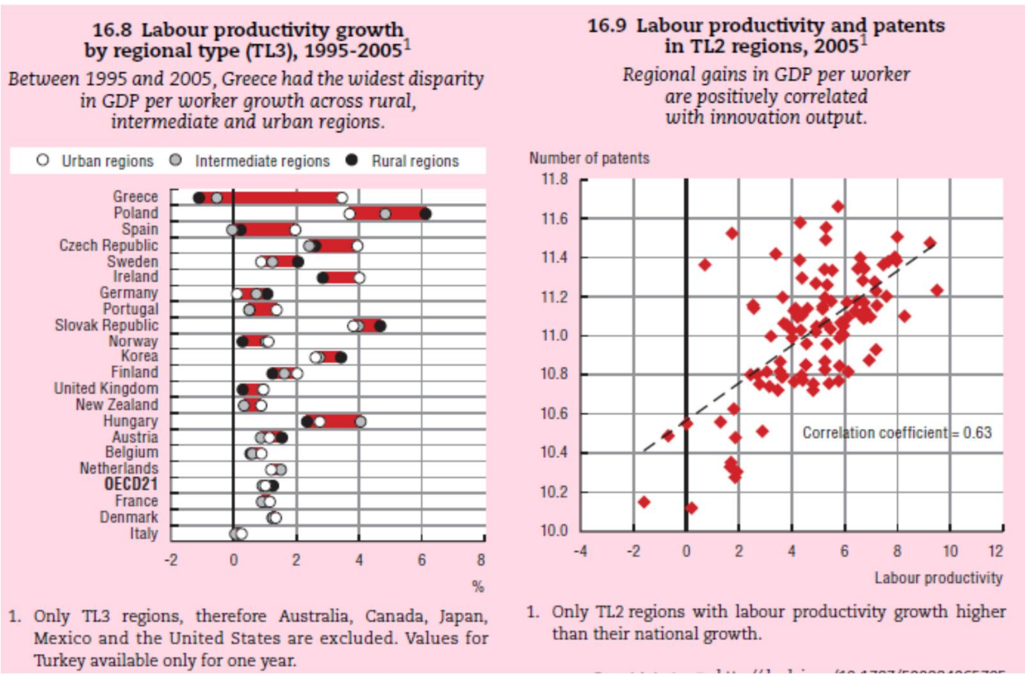
5. Innovation and productivity: looking for linkages

The accent put on innovation hides actually another concern for economists and politicians, that the contribution that innovation can give to productivity. The following section reports a focus by OECD (2009), that every two years produces a specific regional report with a section devoted to innovation. The next edition is forthcoming on July 22, 2011:

ñRegional differences in GDP per capita are mainly explained by productivity differentials among regions. Labor productivity growth is considered a key indicator to assess regional competitiveness. Regional living conditions are raised by continued gains in labor productivity, along with an increase in the labor force participation. In fact only economies which manage to simultaneously sustain employment and productivity growth will increase their competitiveness edge and maintain it in the long run. Between 1995 and 2005, OECD labor productivity increased on average 1.5% annually. While many regions in Poland and the Slovak Republic increased their labor productivity by more than 4 percentage points annually, labor productivity decreased in around 20% of OECD regions, most diffusely in Mexico, Greece, Italy and Spain. Rural regions on average increased their labor productivity more than urban regions (1.2% versus 1.0%) signaling that rural regions are in the process of catching up. Labor productivity gains were larger in rural regions than in urban or intermediate ones especially in Poland, Sweden, Germany, the Slovak Republic and Korea. The process of catching-up in the labor productivity growth for rural regions with a low base has been driven in many regions by a shift in employment towards higher-productivity activities. The reduction of employment in agriculture, forestry and fishing sector between 1995 and 2005 was especially intense more than 30%), in the Slovak Republic, Poland and Korea, all countries which experienced both positive productivity growth and larger growth in rural than urban regions (Figure 16.8).

Differences in labor productivity growth among regions are invariably the results of multiple factors, including labor market policies and institutions (taxes, labor cost and wages setting, relevance of the informal labor market, economic and institutional environment towards foreign investment and migration, policies and investment in R&D, etc.). Innovation and the adoption of new technologies are considered major determinants of productivity growth, in particular of the multi-factor productivity, that is to say the component of output and labor productivity that is not accounted for by factor inputs. A positive correlation is found among the OECD regions fast-growing in labor productivity (larger than their national labor productivity growth) and in regional patenting activity, which confirms the positive impact of knowledge-oriented activities and innovation systems on productivity (Figure 16.9)ò. Figure 16.8 and 16.9 are reported in Figure 4.

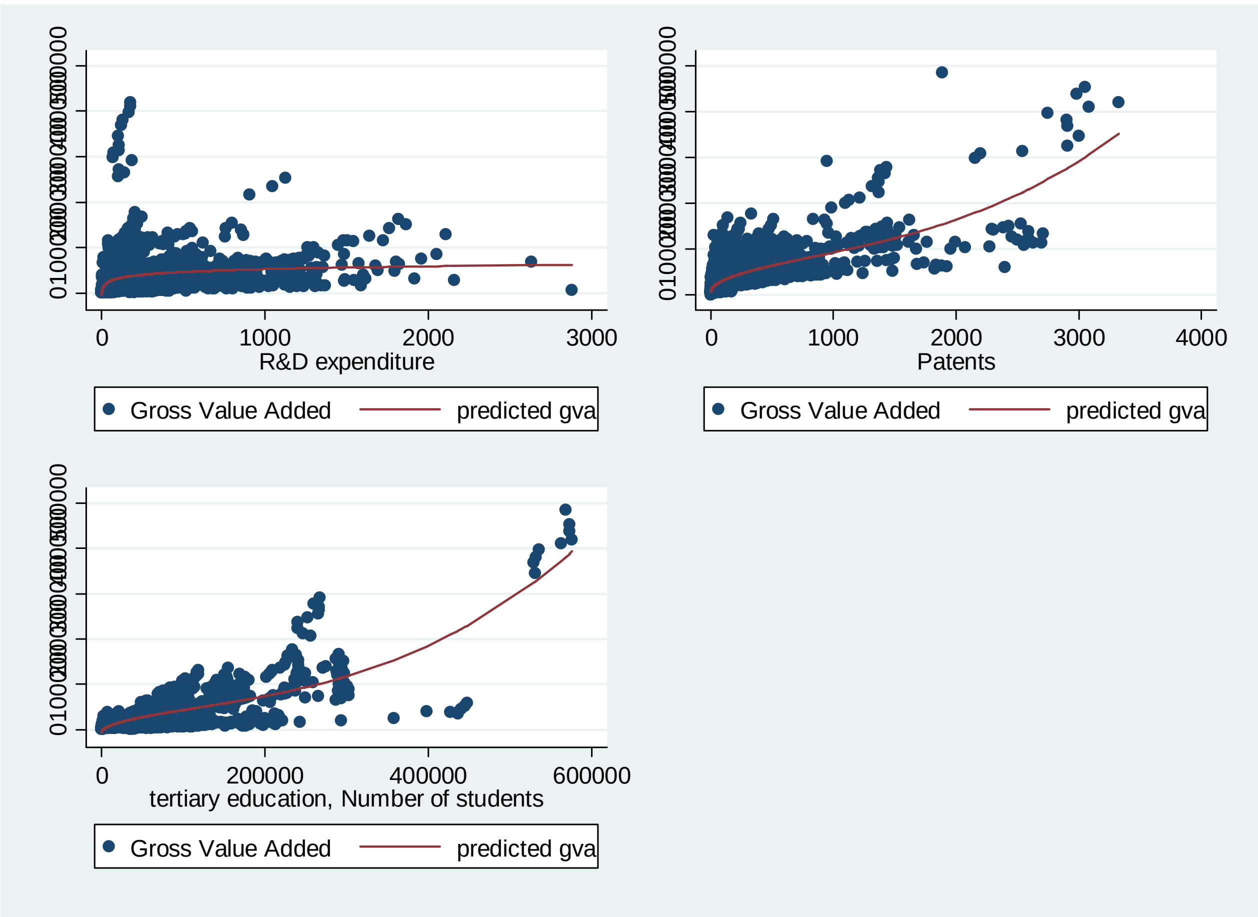
Figure 4. OECD Figures on labor productivity



The correlation depicted in Figure 16.9 above supports our idea that a large part of innovation contribute to labor productivity growth, therefore, those regions that register more patent application, should also register a higher labor productivity growth. In other words, we could estimate a different version of the knowledge production function above, by replacing the R&D output ñpatentsò, with the expected result from increased innovation, that is ñproductivity growthò. In that sense, by means of regression analysis we should be able to evaluate the marginal contribution of R&D expenditure and tertiary education to innovation captured by productivity growth.

Considering the whole of our dataset (4798 observations), we find that the correlation between patent application and regional gross value added (GVA) is about 77%. When plotting the relationship between regional GVA and patents, we find some interesting non-linearities (Figure 5):

Figure 5. Labor productivity against R&D expenditure, Patents and Tertiary education



Source: elaboration on Eurostat data

Figure 5 shows the pattern of labor productivity with respect to R&D expenditure, patents and tertiary education. While the first graph is somehow disappointing, hinting for no or almost no correlation between the two, the increasing pattern of the polynomial fitting line in the second and third graph seem to suggest that education and patents show increasing returns with respect to labor productivity. While for the case of R&D , we are only measuring how much is spent, but not in which projects and according to what modalities, education and patents seem to be building blocks for the increases in productivity. This results are of uttermost relevance when compared to previous OECD evidence in Figure 4 since not only we find a positive correlation patents and labor productivity, but also, while the OECD sample was made of those regions for which the labor productivity was higher than the average, here we took all regions for a long time spam, 1995 ï 2007. The presence of increasing returns with respect to labor productivity is a significant information in the perspective of formulation of economic and social policies.

6. Innovation and growth: assessing regional linkages

Several factors contribute to GDP growth and GVA growth. If we consider GVA growth as good proxy for global regional productivity, we may try and use innovation related variables (inputs and outputs) to assess the contribution of the innovative performance of regions to the regional global productivity. Following the growth model proposed by Fu (2008), we estimate the impact of innovation on regional economic growth by the following equations, in turn:

$$y_{it} = \alpha + \varphi P_{it} + \theta P_{it}^2 + \gamma L_{it} + \delta K_{it} + \varepsilon_{it} \qquad [1]$$

$$y_{it} = \alpha + \varphi R \& D_{it} + \theta R \& D_{it}^2 + \gamma L_{it} + \delta K_{it} + \varepsilon_{it} \quad [2]$$

$$y_{it} = \alpha + \varphi TE_{it} + \gamma L_{it} + \delta K_{it} + \varepsilon_{it} \quad [3]$$

Where y_{it} is the log of gross value added at time t for region i, P_{it} is the log number of patent applications at time t for region i, P^2_{it} is the square of the previous variable, L_{it} is log employment at time t for region i, K_{it} is the log gross fixed capital formation as a proxy for capital endowment. We use adopt two estimation techniques: an OLS estimate with regional dummies and random effect panel data estimation to take into account the longitudinal dimension that could provide some additional information. The results of estimation are reported in Table 6.

Table 6a. Equation [1], OLS with regional dummies

Dependent Variable	Log Gross Value Added					
Region/ Independent Variable	*Coef.*	*Std. Err.*	*t*	*P>|t|*	*[95% Conf. Interval]*	
Log Patents	0.44	0.07	6.24	0.00	0.30	0.58
Log Patents^2	-0.02	0.01	-2.27	0.03	-0.04	0.00
Log Employment	0.00	0.02	0.10	0.92	-0.04	0.04
Log Capital	0.39	0.04	9.89	0.00	0.31	0.47
Baden-Wuerttemberg	0.07	0.25	0.26	0.79	-0.43	0.57
Cataluna	-0.15	0.08	-1.81	0.07	-0.31	0.01
Ile De France	0.29	0.20	1.41	0.16	-0.11	0.69
Ita-Suomi	-1.72	0.21	-8.25	0.00	-2.14	-1.31
Kosep-Magyarorszag	-0.82	0.07	-11.45	0.00	-0.97	-0.68
Lisboa	0.01	0.06	0.09	0.93	-0.12	0.13
Lombardia	0.14	0.15	0.90	0.37	-0.16	0.44
Mazowieckie	-0.18	0.06	-2.92	0.00	-0.30	-0.06
Praha	-0.72	0.06	-11.34	0.00	-0.85	-0.60
South East	0.21	0.16	1.28	0.20	-0.11	0.53
Stockholm	-0.50	0.14	-3.59	0.00	-0.77	-0.22
Vlaams Gewest	-0.20	0.13	-1.59	0.11	-0.46	0.05
Wien	-0.44	0.08	-5.29	0.00	-0.61	-0.28
Constant	5.89	0.39	15.09	0.00	5.12	6.66
Number of observations	133		R-squared	0.9914		
F(17, 115)	783.22		Adj R-squared	0.9902		
Prob > F	0.00000		Root MSE	0.10988		

Table 6b. Equation [1], Random Effects

Dependent Variable	Log Gross Value Added					
Independent Variable	*Coef.*	*Std. Err.*	*t*	*P>|t|*	*[95% Conf. Interval]*	
Log Patents	0.40	0.07	5.38	0.00	0.25	0.55
Log Patents^2	-0.02	0.01	-2.11	0.04	-0.03	0.00
Log Employment	0.01	0.02	0.26	0.80	-0.04	0.05
Log Capital	0.46	0.04	11.89	0.00	0.39	0.54
Constant	5.02	0.39	13.03	0.00	4.26	5.77
Number of observations	133		R-sq: within	0.7584		
Number of groups	14		between	0.8645		
Wald chi2(4)	438.33		overall	0.8561		
Prob > chi2	0					

Table 6c. Equation [2], OLS with regional dummies

Dependent Variable	Log Gross Value Added					
Region/ Independent Variable	*Coef.*	*Std. Err.*	*t*	*P>|t|*	*[95% Conf. Interval]*	
Log R&D	(dropped)					
Log R&D Squared	0.22	0.03	7.61	0.00	0.16	0.28
Log Employment	0.31	0.08	3.76	0.00	0.15	0.48
Log Capital	0.16	0.03	4.82	0.00	0.09	0.23
Baden-Wuerttemberg	-0.13	0.14	-0.93	0.36	-0.41	0.15
Cataluna	0.00	0.06	-0.06	0.95	-0.13	0.12
Ile De France	0.01	0.15	0.08	0.94	-0.28	0.31
Ita-Suomi	-0.86	0.10	-8.24	0.00	-1.07	-0.65
Kosep-Magyarorszag	-0.49	0.08	-5.91	0.00	-0.66	-0.33
Lisboa	-0.12	0.06	-1.89	0.06	-0.25	0.01
Lombardy	*0.72*	*0.14*	*5.18*	*0.00*	*0.44*	*1.00*
Mazowieckie	-0.62	0.06	-10.71	0.00	-0.74	-0.51
Praha	-1.42	0.10	-13.70	0.00	-1.63	-1.21
South East	-0.15	0.12	-1.24	0.22	-0.40	0.09
Stockholm	0.18	0.24	0.77	0.45	-0.29	0.65
Vlaams Gewest	-0.03	0.10	-0.33	0.74	-0.24	0.17
Wien	-0.86	0.11	-8.06	0.00	-1.07	-0.64
Constant	5.24	0.31	16.94	0.00	4.62	5.86
Number of observations	74		R-squared	0.9974		
F(16, 57)	1390.14		Adj R-squared	0.9967		
Prob > F	0.00000		Root MSE	0.06605		

Table 6d. Equation [2], Random Effects

Dependent Variable	Log Gross Value Added					
Independent Variable	*Coef.*	*Std. Err.*	*t*	*P>|t|*	*[95% Conf. Interval]*	
Log R&D	0.54	0.05	10.38	0.00	0.44	0.65
Log Employment	0.11	0.07	1.58	0.11	-0.03	0.24
Log Capital	0.19	0.04	5.09	0.00	0.12	0.26
Constant	4.78	0.35	13.48	0.00	4.09	5.48
Number of observations	74		R-sq: within	0.8319		
Number of groups	14		between	0.8805		
Wald chi2(3)	368.7		overall	0.9049		
Prob > chi2	0.0000					

Table 6.e, Equation [3], OLS with regional dummies

Dependent Variable	Log Gross Value Added					
Region/ Independent Variable	*Coef.*	*Std. Err.*	*t*	*P>|t|*	*[95% Conf. Interval]*	
Log Tertiary Education	0.35	0.09	3.86	0.00	0.17	0.53
Log Employment	0.04	0.03	1.31	0.20	-0.02	0.09
Log Capital	0.60	0.06	9.55	0.00	0.47	0.72
Baden-Wuerttemberg	0.26	0.13	1.94	0.06	-0.01	0.53
Cataluna	-0.09	0.10	-0.90	0.37	-0.28	0.10
Ile De France	0.23	0.16	1.39	0.17	-0.10	0.55
Ita-Suomi	-0.08	0.15	-0.55	0.59	-0.37	0.21
Kosep-Magyarorszag	-0.21	0.07	-3.08	0.00	-0.34	-0.07
Lisboa	-0.03	0.08	-0.37	0.71	-0.18	0.13
Lombardy	*0.63*	*0.11*	*5.70*	*0.00*	*0.41*	*0.85*
Mazowieckie	-0.35	0.05	-6.93	0.00	-0.45	-0.25
Praha	-0.47	0.10	-4.76	0.00	-0.66	-0.27
South East	0.15	0.13	1.16	0.25	-0.11	0.41
Stockholm	*0.35*	*0.07*	*4.98*	*0.00*	*0.21*	*0.49*
Vlaams Gewest	0.07	0.09	0.73	0.47	-0.12	0.25
Wien	*0.26*	*0.10*	*2.57*	*0.01*	*0.06*	*0.47*
Constant	0.66	1.10	0.60	0.55	-1.53	2.85
Number of observations	84		R-squared	0.9929		
F(16, 57)	589.68		Adj R-squared	0.9913		
Prob > F	0		Root MSE	0.09683		

Table 6.f, Equation [3], Random effects

Dependent Variable	Log Gross Value Added					
Independent Variable	*Coef.*	*Std. Err.*	*t*	*P>|t|*	*[95% Conf. Interval]*	
Log Tertiary Education	0.33	0.07	4.56	0.00	0.19	0.47
Log Employment	0.02	0.03	0.77	0.44	-0.03	0.07
Log Capital	0.71	0.06	12.58	0.00	0.60	0.82
constant	-0.02	0.67	-0.04	0.97	-1.33	1.28
Number of observations	84		R-sq: within	0.6955		
Number of groups	14		between	0.9575		
Wald chi2(3)	527.4		overall	0.9457		
Prob > chi2	0.0000					

From Table 6.a and 6.b we find that the contribution of patenting to Gross Value added is positive and significant, while the diminishing return is captured by the squared term that has a negative and significant sign. While employment is almost never significant in all estimation, the capital variable is always positive and significant. The interpretation for the employment variable to be so weak in our framework is puzzling. Since value added should be mainly related to the performance of the production function, where labor should play a major role with respect to capital, we would expect the two aggregate inputs to have almost the same weight in determining GVA. Instead, employment has a positive (slightly) and significant coefficient only once among our estimations. There could be inefficiencies in the labor market that hinder the reallocation of labor forces towards the more productive sectors, or there could be some undetected competition effects. These observations about employment capital hold through all the estimations. Using two different approaches allowed us to capture the single regionôs effect on gross value added and the longitudinal dimension with a panel data approach. Interestingly, when the patenting activity is considered, no single region has a positive and significant effect on gross value added, while many have a significant negative effect, in virtually all the newly EU entered regions (Kosep-Magyarorszag, Praha, Mazowieckie) but also Ita Suomi, Stockholm and Wien. As a general consideration, the goodness of fit is high in all estimations, no matter the technique being adopted. When analyzing Table 6.c and 6.d, we look at the first input-related aspect of innovation, that is R&D expenditure. In Table 6.c we find for the first time a region, Lombardy with a positive and significant coefficient on gross value added. This is a first indication of the already observed discrepancy between input and output related measures for innovation, under the DEA analysis: there is in general no connection between the performance in terms of the output ï patents ï and the input measures in the knowledge production function. Again, the same considerations for employment and capital hold (but for R&D squared dropped because of collinearity). When coming to Table 6.e and 6.f, we find a further indication for the signal preliminarily captured in Table 6.c. We have three regions (Lombardy, Stockholm and Wien) for which the dummies are positive and significant. This adds to the previous DEA findings and tells further that Education ï in our case, deliberately chosen at the highest level ï has an impact in the knowledge production function, in the sense that quality matters in basically quantitative evaluation of the knowledge production function.

7. Conclusions

The aim of our paper has been to move a step towards a relatively neglected field, that is the relation between regional innovation systems efficiency and productivity. In particular, we turned to different approaches in the effort of finding comparable measures for regional innovation performance (DEA and knowledge production function approach) and then trying to link regional innovation indicators (input and output based) with gross regional value added.

In the first part of this study, we adopted a DEa approach to evalutate the relative performance of European Regions with respect to standard innovation indicators, those are patents, R&D expenditure and tertiary education. Of course it is fairly likely that at aggregate level these variables are endogenous, though, policy makers and economists are struggling to find and adopt new methods and indicators to measure performance. The DEA approach is commonly adopted when measuring firmsô efficiency, but increasingly it is found in the literature concerning the performance of local administration of public management. In our case, we find that a group of regions perform better than the others and in a sense, that should be looked at as benchmarks. We find both rich, large regions but small regions as well. So, there is factor of competitiveness in the pooer regions stemming from the combinations of inputs to get a given output that put them high in the rank. Of course, as expected, two if the four motors of Europe as expected, belong to the best performing regions; among these, for Italy we have Lombardy but Valle dôAosta and Bolzano as well. Probably, their autonomous administration and their small size helps finding an efficient combination of inputs.

The production function approach implies comparing the innovation production with a generic production function. In this case, we are able to evaluate the marginal contribution to innovation (in terms of patents) of R&D and patents, separately. We find a positive contribution and results are consists with the DEA approach, though we have a lot of variation since we have some regions for so many years, we still find that positive dummies emerge again for Lombardy, Ile de France and Vlaams, three of the richest and dynamic regions in Europe.

Finally, we find a positive correlation between labor productivity and in turn, patents, R&D expenditure and tertiary education, with some interesting non-linearities hinting for increasing returns in tertiary education and patents, but not for the total R&D expenditure. To conclude, we run the Fu (2008) equation to assess the contribution of innovation inputs to gross value added at regional level. The specification of the final relationship between GVA, input factors and innovation indicators could be more deeply investigated. As an example, Fu also enters exports and FDI as productivity determinants for China regions. This research area surely deserves investigation. Moreover, no one can conclusively tell if input or output measures for innovation should be correctly considered in GVA determination, since in a global perspective the innovation function does not look like a linear process, but rather a circular one as what is output for one agent becomes input for the other. Our conclusion relies on the empirical evidence, consistent through different approaches: some variables have more leverage in generating innovation than others, and policy makers should focus on policies aimed at empowering the education system, for example, while the generic level of R&D expenditure, though important, does not assure efficiency in itself.

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