European Regional Productive Performance under a Metafrontier Framework. The role of patents and human capital on technology gap?

Kostas Kounetas and Oreste Napolitano and Spyridon Stavropoulos and Martijn Burger

University of Patras, Rio, Greece Department of Economics, University of Naples, Parthenope, Italy Department of Business and Economics, Department of Applied Economics and Erasmus Happiness Economics Research Organisation (EHERO), Erasmus University Rotterdam and Tinbergen Institute, Rotterdam, The Netherlands, Department of Applied Economics and Erasmus Happiness Economics Research Organisation (EHERO), Erasmus University Rotterdam and Tinbergen Institute, Rotterdam, The Netherlands

6 January 2018

European Regional Productive Performance under a Metafrontier Framework. The role of patents and human capital on technology gap?

Kostas Kounetas[a,b], Oreste Napolitano [a], Spyridon Stavropoulos[c] and Martijn J. Burger[c],

[a]University of Naples, Parthenope, Italy Department of Business and Economics

[b] University of Patras, Rio, Greece Department of Economics

[c]Department of Applied Economics and Erasmus Happiness Economics Research Organisation (EHERO), Erasmus University Rotterdam and Tinbergen Institute, Rotterdam, The Netherlands

Abstract: Assessing regional convergence is an important issue both at the national and at the supranational level, such as the level of European regions. Regional convergence and productivity growth are also principles of the European regional policy. This paper studies regional productivity convergence among 232 NUTS-2 European regions for the period 2003-2011. Despite the European regional policies implemented in the last two decades, the technology gap between European regions has only increased. The objective of this paper is to provide new evidence on production efficiency and the technology gap in European regions. We present a two-stage model of regional productive performance using a meta-frontier framework and a PVAR analysis. The main conclusion is that there exist significant differences in productive performance that confirm the North-South division in Europe. Finally, the results from the PVAR model provide robust evidence for the role played by human capital and innovation activity through patent realization in the technology gaps at the regional level in Europe.

Key words: Meta-frontier, DEA bootstrap, PVAR, Spillovers, European Regions.

JEL classification codes: C15,D24,O47,R11

1. Introduction and motivation

Convergence and cohesion among European regions has been one of the most crucial objectives of the European Union since the Treaty of Rome in 1957. The creation of a common market and economic and monetary unification strengthened the need for this convergence. This goal has been reaffirmed in the subsequent steps towards the European enlargement of 2004 and deeper integration. Moreover, to fulfill convergence and cohesion targets, the European Commission devised several policies and mechanisms to help lagging regions catch up with the richest ones, with the aim of improving their productive performance and narrowing the existing technology gap in Europe. During the period of 2007–2013, economic convergence was one of the three objectives of the European Union regional policy and was pursued through the European Fund for Regional Development (EFRD), the European Social Fund (ESF) and the Cohesion Fund. These funds aimed at improving productivity and growth for the lagging regions. However, because of the existence of significant regional productivity differentiations, many authors question the effectiveness of these policies (e.g., Boldrin and Canova, 2001).

At the same time, growth and productive performance have attracted the attention of economists, policy makers and experts in many countries that have elevated productivity and efficiency performance to the status of a core issue for modern economies. While these studies have mainly concentrated on firms, industries and/or countries, a limited number of studies have been devoted to the regional level. In the European Union (EU), the issue of productive performance has been taken under serious consideration since the formulation of the Lisbon Strategy in 2000. This development plan was fueled by recent studies that revealed the existence of significant variations in productive performance levels and groups (i.e., North vs South).

The idea of European regional growth divergence is not only a theoretical one stemming from academic notions (Fagerberg et al., 1997) but also a phenomenon with real dimensions, as studies have confirmed its existence (Fagerberg and Verspagen, 1996; Fagerberg et al. 1997). Commonly used phrases such as “Europe at different speeds” indicate a general concern about divergent regional growth patterns. One of the drivers of this gap is the increasing technology heterogeneity between regions; while some regions are highly developed in terms of level of technology, others lag behind considerably.

In this line, regional differences have become the main source of national differences since firms and organizations at the regional level have emerged as core economic units. The heterogeneity across regions in their ability to generate knowledge and innovation and to share or adapt new technologies available across the Euro zone calls for further investigation concerning productive performance aspects. However, ignoring the national production structures and the already existing heterogeneity across European regions could lead to biased estimates of production functions and misleading policy recommendations. Hence, two questions arise: to what extent do country-specific regions encapsulate technological characteristics of European meta-technology improving their productive performance, and what are the possible drivers for reducing the technology gap? This is an important pair of questions that has — to the authors’ best knowledge — been relatively little explored in the regional economics literature.

The objective of this paper is to fill this gap in the literature by providing new evidence on production efficiency and the technology gap in European regions using a meta-frontier framework. Thus, to shed light on these issues, we present a two-stage model of regional productive performance. In the first stage, we estimate regional efficiency related to the country’s level of technology and European meta-technology (meta-frontier approach). The introduction of the meta-frontier framework in this study provides the opportunity to estimate the associated technology gaps relative to the meta-technology available in European regions and investigate possible spillover effects (Tsekouras et al. 2016; 2017). Following this logic, we assume that the estimation of technology gaps for each region is related to the relevant distance from their country's level of technology. It is therefore worth noting that the constitution of the country frontier is an essential factor that needs to be taken into account.

Moving a step further, in a second stage of analysis, we assess the role of technological knowledge as measured by the stock of patents and human capital in shaping the technology gap between European regions over the period 2003-2011. Despite the apparent interest in investigating regional productive performance and the fact that a significant body of studies focused on productive performance determinants, to the best of our knowledge, there have been no empirical studies that assessed the determinants of technology gaps.

Finally, our contribution to empirical literature on regional performance lies not only in the significant role of knowledge spillovers but also in the causal relationship between such spillovers and their determinants. A dataset consisting of 232 European regions from 19 countries over the period 2003-2011 is used to address the different aspects of regional performance using a Bootstrap Data Envelopment Analysis (DEA) under a meta-frontier framework. In our study on the heterogeneous European regions, we will test the existence of significant differences in terms of productive performance confirming or disproving the North-South division. In addition, we will check the hypothesis that the economic hierarchy of the European regions remains stable over time and determine whether there are clubs of technology gap leaders and laggards. Finally, in our econometric analysis, we will provide evidence on the role of human capital and innovation activity through patents realization in the technology gaps at the regional level in Europe.

The rest of the paper is organized as follows. Section 2 presents a short literature review, while Section 3 summarizes the overall methodology and discusses the DEA of the efficiency measure. Section 4 gives a description of the data used for the analysis. Section 5 presents the results of the two-stage analysis. The final section provides conclusions and policy recommendations.

2. Short review of the literature

In this section, we present a brief, non-exhaustive overview of some works concerning regional productivity and its determinants. Recent empirical literature on country- and regional-level productivity has shown that differential behavior of individual production entities is mainly due to R&D efforts, innovation activity, and human capital. Concurrently, a stylized fact that has emerged from the empirical literature is that public capital and infrastructure play an important role in driving productivity differences.

Studies examining regional efficiency have investigated individual countries and focused on specific issues that may influence efficiency and/or production performance. For example, Bronzini and Piselli (2009) examined the role of R&D, human capital (Tzeremes, 2014) and public infrastructure in regional performance, while Percoco (2004) sought to determine the impact of public capital on regional productivity, suggesting that infrastructure plays an important role in driving productivity differences between Italian regions. Similarly, De Stefanis and Sena (2005) found a significant impact of public capital on regional efficiency, focusing their research on the industrial sector, while Maudos et al. (2013) used a DEA approach for Spanish regions to show the importance of productive specialization and sector inefficiencies. Moreover, Enflo and Hjertstrand (2009) used a bootstrap DEA approach to discuss the effect of labor productivity decomposition on efficiency and technological change and capital accumulation. Finally, Dettori et al. (2014) denoted the role of human capital but also of social and technological capital in total factor productivity for a significant dataset of European regions, while Lin and Chiang (2011) examined the information technology paradox for a variety of countries.

The common characteristic of all these studies is that they assume that there is homogeneity between the regions under evaluation (Dyson et al., 2001) or that all production entities share a comparable input-output mix. The “homogeneity assumption” (Haas and Murphy, 2003; Samoilenko and Osei-Bryson, 2010) appears to be one of the most controversial issues in efficiency and productivity analysis and is often treated with a type of statistical clustering (Kounetas, 2015). With respect to analogous works, our work takes into account the “technological isolation hypothesis” (Tsekouras et al. 2016;2017), thereby ignoring the diffusion of technological advancements and the corresponding peer (i.e., spillover) effects among the European regions within countries. Thus, using a meta-frontier methodology, we can compare the technical efficiency of regions that belong in different groups. In contrast to the parametric econometric techniques, the non-parametric techniques account for regional differences, as these methods permit examination of a production frontier across a set of economic units (Foddi and Usai, 2013). However, only a few studies have examined productivity efficiency at the regional level using meta-frontier techniques (Zabala-Iturrigagoitia et al 2007; Enfo and Hjerstrand, 2009; Foddi and Usai, 2013), and to our knowledge, no study has investigated the role of technology gaps considering the performance of individuals regions in terms of their national technology but also in terms of European technology (meta-technology).

3. Definitions, Notations and Modeling Issues

3.1. Definitions and notations

To present our methodology, let us begin with i regions, each producing M outputs using N inputs with $N = \{1,...,n\}$ and $M = \{1,...,m\}$ the input and output sets. We discern k European technologies, which correspond to analogous but distinct country productive frontiers that envelop the corresponding $i-th$ region production entities. In the framework of k frontiers, a specific region of each country employs a vector of inputs $x \in R_+^n$ to produce a vector of outputs $y \in R_+^m$. The production possibility set is given as $S = \{(x, y):\ x \text{ can produce } y\} \subseteq R_+^{n+m}$ with the input set defined as $L(y) = \{x \in R_+^n : (x, y) \in S\}$. The input-oriented efficiency associated with S can be measured with respect to the input set through the direct *input distance function* $D_I(x, y) = \sup\{\theta > 0 : x|\theta \in L(y)\}$. Thus, the productive efficiency for the $i-th$ region (x, y) in each of the examined European countries is given as Eq. (1):

$$\hat{Eff}_{i|k}(x, y) = \min\{\theta \,|\, \theta > 0, y_i \le \sum_{i=1}^{n} \gamma_i y_i ; \theta_x \ge \sum_{i=1}^{n} \gamma_i x_i \text{ for } \gamma_i \text{ such that } \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \ge 0, i = 1,2,\ldots,n\} \quad (1)$$

Data envelopment analysis is one of the most well-known approaches that uses mathematical programming to compute the frontier and the technical efficiency scores corresponding to all production entities under analysis. However, previous research by Simar and Wilson (1999; 2008), hereafter SW procedure, referred to the nature of DEA estimators of efficiency as biased by construction and introduced the concept of bootstrap DEA efficiency scores. Following SW procedure, we are able to estimate the bias for the original DEA estimator for the $i-th$ production entity as:

$$bias\left(\theta_i\left(x,y\right)\right) \approx \frac{1}{\mathrm{B}}\sum_{b=1}^{B}\theta^{*}_{i,B}\left(x,y\right)-\theta_i\left(x,y\right) \qquad (2)$$

which is a bias corrected estimator of $\theta^{*}_{iB}\left(x,y\right)$, given as follows:

$$\overset{*}{\theta}_{i,B}\left(x,y\right)=\overset{*}{\theta}_{i,B}\left(x,y\right)-bias_i\overset{*}{\theta}_{i,B}\left(x,y\right)=2\theta_{i,B}\left(x,y\right)-\frac{1}{B}\sum_{i=1}^{B}\overset{*}{\theta}_{i,B}\left(x,y\right) \quad (3).$$

In the case where multiple technologies are possible and every region has access to information of other regions in different countries, each region is considered as operating under exactly type of technology one of those. Hence, the assumption of technological isolation (Tsekouras et al., 2015) is violated for each of the k country frontiers, and each of the i regions acquires knowledge from a common meta-technology. Thus, given p multiple technologies $S^1, S^2, ..., S^p$, the meta-technology set, denoted as S^M, is defined as the convex hull of the jointure of all technology sets represented as $S^M = \{(x, y : x \geq 0, y \geq 0,\ \ x$ can produce y in at least one of $S^1, S^2, ..., S^p\}$ (Rao et al. 2003; Battese et al., 2004). The input set $L^M\left(x\right)$ associated with the meta-technology is defined in the same way as the input set for a single technology. The input-oriented meta-technical efficiency score $MTEff_{i|k}$ for each region is easily obtained by solving an analogous LP problem as in Eq. (1).

Meta-frontier analysis is an approach that allows the comparison of different technologies (Battese et al. 2004). The characteristic of the meta-frontier as an envelope of all the respective frontiers offers the opportunity to account for all the possible heterogeneity existing among the regions participating in a sample (Rao et al. 2003; Matawie and Assaf 2008). In the framework of productive efficiency analysis under technology heterogeneity, many studies have attributed such heterogeneity to environmental factors (i.e., size, ownership scheme, classification, regulation, and staff education) that affect the efficiency of the units under examination (i.e., Matawie and Assaf 2008, Assaf et. al., 2012). Furthermore, in a series of papers based on the definition of the meta-frontier, such heterogeneity may exist because of differences in available resource endowments; economic infrastructure (O'Donnell et al., 2006); other characteristics of the physical, social and economic environment in which production occurs (O'Donnell et al., 2006; Kontolaimou et al., 2012; Kounetas, 2015); structure of national markets, national regulations, institutional frameworks and cultural profiles (Halkos and Tzeremes, 2011; Kontolaimou and Tsekouras, 2010); or managerial schemes (Wang et al., 2013). Finally, technological heterogeneity may also be dependent on characteristics related to the capacity to absorb knowledge, core competences and development of dynamic capabilities (Cohen and Levinthal, 1989; Kontolaimou and Tsekouras, 2010).

O'Donnell et al. (2008) employed conventional Shepard distance functions to estimate technical efficiency with respect to meta-technology and individual technology sets. Each efficiency score obtained from the estimation with respect to the common technology can be used to define the so-called meta-technology ratio (MTR), which is considered as a measure of the proximity of the *k*-th group individual frontier to the meta-frontier and for a given point (x, y) can be defined as:

$$MTR_{i|k}(x,y)=\frac{MTEff_{i|k}(x,y)}{Eff_{i|k}(x,y)} \qquad (4)$$

Conceptually, the technology gap ratio, defined as the distance from the group frontier to the meta-frontier and weighted with the minimum inputs attainable employing the group-specific technology, is given by $Tg_{i|k}(x,y)=1-MTR_{i|k}(x,y)$ (5)

3.2. Econometric strategy: Panel VAR analysis

In the last two decades, the development of a detailed database has allowed the development of panel econometric techniques suitable to explore the relationship between economic variables (at micro level, considering the behavior of firms, banks, and individuals, and at macro level, considering aggregates of regions, countries, etc.) and has attracted economists' interest in the results of empirical research based on panel methodologies. Canova and Ciccarelli (2013) assert that the world economy as a whole has recently undergone a process of "globalization" whose effects have included an increase of economic interdependence at different levels.

In this context, the European economic area has not only escaped this process but, through the process of economic and monetary integration, it has even amplified it. This interdependence has however, de facto, reduced heterogeneity that, still remain between the various European regions. Asymmetries in the propagation of shocks, the North–South divide and the resilience of some regions make the study of convergence among the European regions interesting and important in terms of policy implications.

The presence of dynamic heterogeneities among the European countries/regions offers economists the opportunity to study how shocks are transmitted across regions and how cross-sectional differences can emerge, helping to understand the potential sources of heterogeneities and provide policymakers with facts useful for building alternative scenarios and formulating policy decisions.

In this paper, we use a Panel VAR methodology (henceforth PVAR; Holtz-Eakin et al, 1988) because it seems particularly suited to address the research questions presented in Section 1. In particular, it allows us to examine both static and dynamic interdependencies;

like most of the VAR models for time series, it allows us to treat the relations across regions in an unrestricted way, account for cross-sectional dynamic heterogeneities (Arellano and Bover, 1995) and identify short-run dynamic relationships (Lütkepoh, 2005).

Hence, PVAR models have been increasingly used in applied research because they combine the traditional VAR approach treating all variables of the system as endogenous with estimation techniques for panel data. Therefore, while the use of VAR models in time series analysis is a common standard, the use of VAR in a panel data context is less common.

In what follows, we define the data generating process and the econometric estimation and identification of the structural dynamics of the panel. The important aspect of our estimation is the assumption that a model representation exists and depends on structural shocks that can be decomposed into common and idiosyncratic structural shocks, which are mutually orthogonal[1]. Below, we provide a brief outline of the panel VAR model, estimation and inference in a generalized method of moments (GMM) framework.

We consider a k-variate panel VAR of order g with panel-specific fixed effects represented by the following system of linear equations that allows for unobserved individual heterogeneity (Love and Zicchino, 2006):

$$\begin{aligned} &Z_{i,t} = \Phi_1 \mathrm{Z}_{\mathrm{i.t}-1} + \Phi_2 \mathrm{Z}_{\mathrm{i.t}-2} + \ldots + \Phi_{p-1} \mathrm{Z}_{\mathrm{p}-1,\mathrm{t}-p+1} + \Phi_p \mathrm{Z}_{\mathrm{i,t}-p} + BX_{i,t} + \mu_{i,t} + \varepsilon_{i,t}, \\ &\mathrm{i} = 1, 2, \ldots, \mathrm{N}, \mathrm{t} = 1, 2, \ldots \mathrm{T} \end{aligned} \tag{6}$$

where $Z_{i,t}$ t is a $(1 \times K)$ vector of dependent variables; $X_{i,t}$ is a $(1 \times L)$ vector of exogenous covariates; $\mu_{i,t}$ and $\varepsilon_{i,t}$ are $(1 \times K)$ vectors of dependent variable-specific fixed effects and idiosyncratic errors. The $\Phi_1, \Phi_2, \ldots, \Phi_{p-1}, \Phi_p$ $(K \times K)$ matrices and the

[1] Regarding estimation and inference, we use a system-based GMM estimator for each equation (Arellano and Bover, 1995).

$\left(1\times K\right)$ matrix B are parameters to be estimated. The model postulates that the innovations have the following characteristics: $E\left(\varepsilon_{i,t}\right)=0, E\left(\varepsilon_{i,t+s},\varepsilon_{i,t}\right)=0$ for all t > s.

The parameters of the above model can be estimated jointly with the fixed effects or, alternatively, using equation-by-equation ordinary least squares (OLS). "With the presence of lagged dependent variables in the right-hand side of the system of equations, however, estimates would be biased even with large N (Nickell, 1981). Although the bias approaches zero as T gets larger, simulations by Judson and Owen (1999) find significant bias even when T = 30" (Abrigo and Love, 2015, p. 3).

Various estimators based on GMM have been proposed to calculate consistent estimates of the above model. One can improve efficiency by including an extended set of lags as instruments. This, however, has the unpleasant property of reducing the number of observations, especially with unbalanced panels. As a remedy, Holtz-Eakin et al. (1988) proposed creating instruments using "observed realizations". In particular, they suggest substituting missing observations with zero based on the standard assumption that the instrument list is uncorrelated with the errors.

While equation-by-equation GMM estimation yields consistent estimates of panel VAR, estimating the model as a system of equations may result in efficiency gains (Holtz-Eakin, Newey and Rosen, 1988). Joint estimation of the system of equations makes cross-equation hypothesis testing straightforward. Wald tests about the parameters may be implemented based on the GMM estimate.

Finally, in applied work, it is of great interest to know the response of one variable to an impulse in another variable in a system that also includes additional variables. One would like to examine the impulse response relationship between two variables in a higher dimensional system. Hence, within a panel VAR framework, we will also study this type of causality by noting the effect of an exogenous shock in one of the variables on some or all of the other variables in the model.

4. Data and Variables

To examine our research hypothesis, we used a database taken from the Cambridge Econometrics Regional Database that covers the period 2003-2011 for 232 NUTS-2 regions, creating a panel of 2088 observations[2]. Table 1 presents the countries that constitute our dataset and the number of corresponding regions.

We approximate the output variable (Y) by the gross value added of each industry, while the inputs include the capital stock (K) in million Euros and the labor input (L), which is captured by the total hours worked by employees. Very often, the most severe obstruction in the assessment of productive efficiency for a group of Decision Making Units (DMUs) is the lack of a consistent variable reflecting capital stock. To overcome this, we draw on the Perpetual Inventory Method (PIM; see Tsekouras et al. 2016) to create a consistent measure of capital stock. The initial condition for the capital stock is given by $K_{1999} = \frac{I_{1999}}{\delta + g}$, where g is estimated as the average growth rate in capital investments for the preceding 5 years for each of the examined industries and countries. Given this initial value, the capital stock for each subsequent year is constructed using the formula in Eq. (6):

$$K_{i,t|k} = (1-\delta)K_{i,t-1|k} + I_{i,t|k}$$

[2] Countries that do not report consistent data for the examined period have been omitted.

where $K_{i,t|k}$ and $I_{i,t|k}$ represent the capital stock and investment of the *i-th* country on the *k-th* industry for the year t, respectively, and where δ is the depreciation rate, which is assumed to be equal to 10% yearly.[3]

The second step in the estimation of productive performance measures and more specifically for technology gaps requires data on the explanatory variables. In particular, data are needed for human capital and patents. As a proxy for human capital, we calculated the average number of years of university attendance in the region. We used the ratio of patents to regional GDP to proxy regional innovative activities. Patents have the advantage of being a direct outcome of R&D processes. The patent data are numbers of corporate patent applications. Corporate patents cover inventions of new and useful processes, machines, manufactured goods, and compositions of matter. To this extent, patents document inventions; hence, an aggregation of patents is arguably more closely related to a stock of knowledge than is an aggregation of R&D expenditures. However, a well-known problem of using patent data is that not all technological inventions are patented. This could be because applying for a patent is a strategic decision, and thus, not all patentable inventions are actually patented. Even if this is not an issue, as long as a considerable part of knowledge is tacit, patent statistics will necessarily miss that part because codification is necessary for patenting to occur. We assume that part of the knowledge generated with the idea leading to a patent is embodied in persons, imperfectly codified, and linked to the experience of the inventor(s).

5. Econometric strategy, empirical results and discussion

[3] In fact, the estimated capital series did not change in a significant manner when different levels of depreciation rates were considered.

The presentation and discussion of our empirical results follow the two-stage structure of the analysis. In the first stage, the region-specific efficiency scores and meta-technology ratios (which arise in the context of the European meta-frontier) are presented and discussed. Subsequently, we present and discuss the estimation result of the panel VAR model focusing on the underlying relationships between technological gaps, patents and human capital without applying any a priori restrictions.

5.1 Efficiency, meta-technology ratios and technology gap estimates

The estimations of technical efficiency $Eff_{i|t}^{j}$ and $MTR_{i|t}^{j}$ have been carried out using the bootstrap DEA[4] approach to fulfill the statistical properties for our measures and overcome weaknesses of traditional DEA (Simar and Wilson, 2007). An analytical presentation of this approach can be found in Simar and Wilson (1999; 2000; 2007) and Tsekouras et al. (2010). However, is crucial to note that both the $Eff_{i|t}^{j}$ and $MTR_{i|t}^{j}$ estimations are grounded on a cross-sectional basis and estimated separately for each year in the sample, indicating each year as a unique technology production function. Therefore, the successive values of the estimated technical efficiency and technology gap for each region encompasses two factors, the change of the distance of each region from the European frontier and the movement of it (Tsekouras et al. 2015).

Table 2 summarizes the main results with respect to the country-specific frontiers and the meta-frontier, respectively. For all regions in our sample, the basic efficiency measures $\left(Eff_{i|t}^{j}, MTR_{i|t}^{j}\right)$ in the period 2003-2011 have been computed and reported at country level[5]. On the whole, average technical efficiency scores for the examined period indicate that European regions are highly efficient when compared to their counterparts at a national level

[4] FEAR package (Wilson, 2008) has been used to carry out our estimations.
[5] To save space and avoid making our analysis more complex, we choose to report our results at country level.

since, with the exception of the year 2005[6], their average varies between 0.814 and 0.842. In particular, the regional systems of the Scandinavian countries including Norway, Sweden and Denmark appear to be among the most technically efficient, constructing the champions group, attaining average TE scores close to 90%, together with low dispersions for the period 2003-2011. In contrast, countries such as Romania and Greece (the laggards group), compared with the other European countries, achieve lower technical efficiency scores, suggesting that significant knowledge spillover effects are not in operation within country-specific technologies. Moreover, the regional market structure and the non-existence of appropriate filters may play a significant role.

Turning now our attention to $MTR_{i|t}^{j}$, we estimate regional efficiency scores under the condition that they have access to a common technology, that is, the European meta-technology. Again, Scandinavian countries (Denmark, Sweden, Finland and Norway) as well as Germany and Austria are the leading countries in European technology, representing the meta-frontier. Thus, we could assume that they are able to effectively absorb the existing stock of knowledge (Cefis and Orsenigo, 2001), exploit their technological opportunities (Brechi et al., 2000) and efficiently use the external sources of opportunities (Reichstein and Slater, 2006); they are therefore the most prominent candidates for the creation of new technological trajectories in the European regional system (Dosi, 1982). On the other hand, the opposite describes countries such as Greece and Romania, which display no significant incoming spillover effects (Tsekouras et al., 2015). Our results reveal the idiosyncratic behavior of France and the UK, which are characterized as “falling behind” rather than “leaping forward” with respect to the meta-technology.

The time evolution of the bootstrapped productive efficiency scores, depicted in Figure 2a, in general indicates that no significant changes in the TE scores achieved by

[6] The average value of technical efficiency for this year is 0.768.

European regions can be traced between the examined periods. Moreover, it reflects a process of continuous behavior with small and significant fluctuations. On the other hand, focusing on the yearly performance of individual countries, it can be noticed that no significant dispersions of their diachronically performance has been occurred (see Table 2). Furthermore, the corresponding time evolution for the meta-technology ratios (Figure 2b) depicts that the overall picture is quite similar for all the periods examined, and the whole distribution remains almost steady with no apparent divergence or convergence processes in operation.

Apart from the findings concerning technical efficiency and meta-technology ratios, it is interesting to consider the results concerning the best regional performers with respect to their national frontier and the European meta-frontier. Table 3 presents a rather complex picture of the national champions among all participating countries. A further examination of it give us the diachronic national champions for each country. As such, we can mention regions such as Burgenland and Vienna for Austria; Brussels; Yugozapaden for Bulgaria; Hamburg and Oberbayern for Germany; Attiki for Greece; Basque for Spain; Etelä-Suomi and Åland for Finland; Île de France; Közép-Magyarország and Dél-Dunántúl for Hungary; Piemonde and Lombardia for Italy; Noord-Holland; Oslo og Akershus, Hedmark og Oppland and Agder og Rogaland for Norway; Świętokrzyskie and Opolskie for Poland; Lisboa, Alentejo, Região Autónoma dos Acores and Região Autónoma da Madeira for Portugal; Nord-Vest and Bucureşti for Romania; Stockholm and Övre Norrland for Sweden; and finally Inner London for the UK.

Shifting our attention to the regional champions with respect to the meta-technology, we note the persistence of regions such as Inner London, Oslo og Akershus Thüringen, Attiki, and Île de France in defining the meta-technology. Furthermore, according to our results, we can observe that a minority of the regions participating in our sample seems to define the meta-frontier of the European meta-technology since the corresponding percentage varies between 2.2% and 5.3%.

Finally, a Gaussian kernel functions (Figure 3) were used in our density estimation to reflect the supplemental measure of meta-technology ratios, the so-called technology gap due to country-specific environments that is usually used to identify technological differentials with respect to the European meta-technology due to country specific environments (Battese et al., 2004, O' Donnell et al., 2006, Tsekouras et al., 2010; 2015). It is interesting to note the bimodal pattern of the technology gaps over time. Two clubs of regional TGs have been created with different idiosyncratic performances with respect to their distances from the European meta-technology. The first club has a very low performance over time (approximately 0.16), with the great majority of regions having a very low technology gap and being very close to the European meta-technology. The second club has a mean of approximately 0.78 and a performance much more distant from the meta-frontier; these regions do not exploit the technology available to all of the regions.

5.2 Empirical results from panel VAR estimations.

The notion of the technology gap, employed in our first stage of analysis, allows us to examine productive performance differentials between European regions. Of course, these gaps are not simply a function of market failure, and definitely most can be viewed as more than an endowment as well as more than the consequences of technological choices. On the other hand, the notion of incoming knowledge spillovers from the meta-frontier and outgoing knowledge spillovers from individual frontiers can be used to explain these differences (Tsekouras et al., 2016). Thus, it is crucial to investigate factors related with incoming and outgoing spillover effects that significantly alter a region's technology performance and the resulting technology gap.

We focus on two variables, human capital and patent activity[7], for two main reasons. The first reason concerns the extensive literature that presents human capital and patent activity as the most influential factors capable of boosting productivity (Romer, 1990; Lucas, 1998, among others). The second reason refers to the well-known idea that factors such as institutional framework, inter-firm relationships, learning capabilities, R&D intensity and patents and innovation activities significantly differ across European regions. In addition, we use these two specific variables because of the link between them and the technology gaps that reflects the level of knowledge that is essential for increasing competitiveness and consequently for fostering economic growth (Kitson et al., 2004). More specifically, departing from neoclassical growth theory, GDP growth per capita can be induced by growth in the stock of knowledge (Rosenberg, 1963; Arrow, 1985; Barro and Sala-i-Martin, 1995; Aghion and Howitt, 1998).

In light of what has been said so far, we start this section by analyzing separately the relationship between technological knowledge, patents and human capital (HC). The basic idea is that technological knowledge, such as that shown in patent realization, can accelerate regional economies, enhance the production and diffusion of innovations and promote economic growth. In an attempt to decompose cause and effect, we estimate panel vector autoregressions (PVAR) that describe the above dynamic relation, and subsequently, we test the hypothesis that patents as well as human capital may reduce technology gaps (TGs) and vice versa.

[7] We use patents instead of R&D relying on previous results from empirical studies that indicated patents as a more representative and reliable measure of innovations (Acs et al., 2002) or an "upstream indicator" (Faber and Hensen, 2004) that can better generate productivity gains (Duguet, 1999).

We take the same sample used in the previous analysis that consists of 1638 observations covering 234 European regions. Based on the three model selection criteria proposed by Andrews and Lu (2001) and because the smallest MBIC, MAIC and MQIC are achieved with lag = 1, the first-order panel VAR is preferred in both models. Moreover, we perform the Granger causality test, whose results are presented in Table 5.

Table 5 shows that technology gaps do not Granger-cause patents, while patents do Granger-cause technology gaps. This means that past values of patents should contain information that helps predict the technology gap and not vice versa. However, applying the same test to human capital, we note that technology gaps Granger-cause human capital, while human capital does not Granger-cause technology gaps.

Based on the selection criteria and using GMM estimation[8], we fit a first-order panel VAR with the same instrument specifications as above. For a typical VAR model, Panel VAR estimates are hardly ever interpreted individually. In practice, economists are more often interested in the impact of exogenous changes in each endogenous variable on other variables presented in the panel VAR system. Prior to estimating impulse-response functions (IRF) and forecast-error variance decompositions (FEVD), however, we first check the stability of the estimated panel VAR. Since all the eigenvalues lie inside the unit circle, the resulting figure (4 a and b) confirms that the estimate PVARs are stable.

As we are more interested in the long-run effects of patents and of human capital on the technology gap, we consider that a dynamic model such as a PVAR is most suitable for estimation. Figures 5 and 6 depict the impulse-response functions derived from the estimated PVAR (Equation 6). Figure 5 shows the impact on patents (left column) and TGs (right column) for a period of ten years after a positive shock to either patent (top row) or

[8] The estimation tables of Panel vector autoregression models and forecast-error variance decompositions are available upon request from the authors.

technology gap (bottom row). From the diagonal panels (top left and bottom right), it seems that shocks to patents and technology gap are temporary. In fact, the effects of a shock die out within approximately five years, with shocks to patents (top left) being clearly more persistent than shocks to TGs (bottom right).

The off-diagonal panels show the impact on patents after a shock to TGs (bottom left) and the reverse impact on TGs after a shock to patents (top right), which is our main interest. The top-right impulse response shows no evidence for a significant effect of patents on TGs. A positive shock to the technology gap does, however, have a significant negative effect on patents (bottom left), which persists for approximately three years, after which the effect dies out. According to these figures, it seems that the negative correlation between patents and TGs results from the negative impact of TGs on patents rather than the negative impact of patents on TGs. Slightly different results apply when we look at the long-run effects of the technology gap on human capital. Figure 6 depicts the cumulative impulse response functions from the VAR.

Figure 6 shows the impact on human capital (left column) and TGs (right column) for a period of ten years after a positive shock to either HC (top row) or technology gap (bottom row). For the previous analysis, from the diagonal panels (top left and bottom right), it seems that shocks to HC and technology gap are temporary. However, in this case, the effects of a shock die out more slowly, within approximately 10 years, with shocks to HC (top left) undoubtedly more persistent than shocks to TGs (bottom right), which die out within four years.

The off-diagonal panels show the impact on human capital after a shock to TGs (bottom left) and the reverse impact on TGs after a shock to HC (top right), which is our main interest. The top-right impulse response shows a negative and significant effect of HC on TGs. A positive shock to HC does, however, have a significant negative effect on the technology gap that persists for approximately three years, after which the effect slowly dies out. The bottom-left impulse response shows no evidence for a significant effect of TGs on HC. Considering these figures, it seems that the negative correlation between HC and TGs results from the negative impact of human capital on TGs rather than from the negative impact of technology gaps on HC.

The overall picture from Figures (5-6) is clear in that we find no significant long-run effect of patent on TGs for the 232 European regions, while a significant negative effect of TGs on patents is presented. How can we explain this specific result? We believe that the non-significant sign of patents on TGs describes the regional innovation paradox. That is, the existence of strong complementarities between businesses', universities', organizations', regions', and governments' R&D spending in fact leads the regional innovation policies to work in opposite directions. Oughotn et al. (2002) assert that this paradox reflects the lagging regional difficulty in absorbing funds for R&D activities. On the other hand, this innovation paradox indicates the role of knowledge and the structure of regional innovation systems and institutional information.

A significant effect on the technology gap comes from a positive human capital shock. The results of PVAR make clear that when estimating the long-run effect of patents on TGs, it is important to control for the reverse effect of TGs on patents. In contrast, when estimating the long-run effect of human capital on TGs, it is important to control for the reverse effect of HC on TGs. Therefore, this long-run analysis reveals that TGs must be reduced, as they have negative impact on patents and human capital has negative and persistent effects on TGs. The policy implication is that if the reduction of TGs through HC is achieved, greater economic growth and efficiency among the European regions may be possible.

6. Conclusions

European regional performance has drawn increasing attention in recent years since several studies have found divergent patterns. Its growing popularity owes significant share to factors related to human capital, innovation behavior and wage growth. In this paper, we have explored and highlighted the distorting role of technological heterogeneity in the benchmarking process using a European dataset of 232 regions from 19 countries over the period 2003-2011. A non-parametric frontier approach in combination with bootstrapping techniques has been used to explore productive performance scores with respect to national and European technology. Moreover, by relaxing the technological isolation assumption, we have introduced the concept of a meta-frontier to compare alternative technological structures and disentangle technological heterogeneity captured by the technology gap values indicating the crucial role of knowledge spillovers.

The empirical results indicated that with respect to the hierarchy dominated by the country frontiers, regions that belong to economies with incomplete market mechanisms and low technological opportunities fail to perform well, and most of them are located in southern Europe. Concerning the European meta-technology, Scandinavian countries dominate, while the idiosyncratic performance of France and the UK is striking. In addition, it has been found that the economic hierarchy of the examined regions over time has remained stable, while two clubs of technology gap can be identified: leaders and laggards.

In the second stage of the analysis, we employed a dynamic panel VAR model. We explored the relationships between the regional technology gap and two of the most important regional development determinants, that is, human capital and patents. This investigation was of a great importance since, within governmental and European circles, interest has grown not only in investigating productivity and efficiency measures but also in identifying possible determinants to devise policies and foster productivity and efficiency growth.

The estimated PVAR models have provided robust evidence for the role played by human capital and innovation activity through patents realization on the regional technology gaps in Europe. Our findings suggest that a higher regional level of patent realization and consequently innovation activity decrease the technology gap. At the same time, a reverse process was not confirmed by the data. The existence of significant technology gaps between regions did not seem to affect the technological knowledge created and accumulated in R&D. Concerning the human capital variable, our estimates showed that regional economies benefited from the presence of well-educated people and the consequent implementation and/or creation of new technologies, and localization of innovative firms significantly reduces the distance from the European meta-technology.

Our empirical results have some interesting policy implications for social cohesion. They emphasize the importance of policy strategies aimed at accelerating technology gap convergence through innovation activities. Due to the heavy deindustrialization and regulations, regional economies with incomplete market mechanisms and fragmented industries cannot be assimilated to the performance of the most efficient regions. In addition, policy makers have to set carefully designed goals to accelerate, in terms of productive performance, the convergence of European regions that lag behind. This paper has shown that inter-regional disparities still exist among European regions. Cohesion policy does not seem to be successful in altering the pathway of development. The reasons for this are complex and are beyond the scope of this work, but it is clear that the procedures for the implementation of convergence policies or the absence of a realistic view of regions' economic growth potential have played a major role. In addition, the finding that human capital and knowledge creation through patent activities matter differently indicates that policies aiming to improve productive performance should be planned considering different technological regimes and not only assuming homogeneous technologies across European regions.

Our analysis calls for further research in terms of the identification of possible intra- and inter-regional dynamics. Moreover, the extension of the analysis including production entities from different countries (i.e., the USA, China) raises the issue of the meta-frontier framework. Finally, the inclusion of more explanatory variables such as public infrastructure could add new insight regarding regional technology gap differences.

REFERENCES

Abrigo, M. R. M., Love, I. 2015. Estimation of panel vector autoregression in stata: A package of programs. http://paneldataconference2015.ceu.hu/Program/Michael-Abrigo.pdf

Acs, Z. J., Anselin, L., Varga, A. 2002. Patents and innovation counts as measures of regional production of new knowledge. Research policy 31(7), 1069-1085.

Aghion, Philippe, and Peter Howitt. Endogenous Growth Theory. Cambridge, MA: MIT Press, 1998.

Andrews D., Lu B. 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models Journal of Econometrics 101 (1), 123-164.

Arellano,M., O. Bover Another look at the instrumental-variable estimation of error-components models Journal of Econometrics 68 1995, 29-52.

Arrow, A Economic welfare and the allocation of resources for invention. Collected papers of Kenneth J. Arrow, Vol. 5: Production and capital, Harvard University Press, Cambridge, MA (1962, 1985), 104-119.

Barro, Robert J., and Xavier Sala-i-Martin. 1995. Economic Growth. New York: McGraw-Hill.

Battese, G. E., Rao, D. S. P. O'Donnell, C. J. 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. Journal of Productivity Analysis 21, 91-103.

Boldrin, M., Canova, F. 2001. Inequality and convergence in Europe’s regions: reconsidering European regional policies. Economic policy 16(32), 206-253.

Bronzini, R, Piselli P 2009. Determinants of long-run regional productivity: The role of RD, human capital and public infrastructure. Regional Science and Urban Economics 39, 187–199.

Canova, F., Ciccarelli, M. 2013. Panel Vector Autoregressive Models: A Survey☆ The views expressed in this article are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem. In VAR Models in Macroeconomics – New Developments and Applications: Essays in Honor of Christopher A. Sims (205-246). Emerald Group Publishing Limited.

Cefis, E., L. Orsenigo 2001. The persistence of innovative activities: a cross-countries and cross-sectors comparative analysis Research Policy 30, 1139-1158.

Cohen WM, Levinthal DA. 1989. Innovation and learning: the two faces of RD. Economic Journal 99, 569–596.

Destefanis S., Sena V. 2005. Public capital and total factor productivity: new evidence from the Italian regions 1970–98 Regional Studies 39, 603-617

Dettori, B., Marrocu, E., Paci, R. 2012. Total factor productivity, intangible assets and spatial dependence in the European regions. Regional Studies 46, 1401–1416.

Dosi, G., 1982. Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. Research Policy 11, 147-162.

Dyson, R.G., R. Allen, A.S. Camanho, V.V. Podinovski, C.S. Sarrico, E.A. Shale. 2001. Pitfalls and protocols in DEA. European Journal of Operational Research 132, 245-259

Duguet, E. 2003. Are RD subsidies a substitute or a complement to privately funded RD? Evidence from France using propensity score methods for non-experimental data.

Enflo, K. Hjertstrand, P., 2009. Relative sources of European regional productivity convergence: a bootstrap frontier approach. Regional Studies 43, 643–659.

Faber, J., Hesen, A. B. 2004. Innovation capabilities of European nations: Cross-national analyses of patents and sales of product innovations. Research Policy, 33(2), 193-207.

Fagerberg, J., Verspagen, B. Caniëls, M., 1997. Technology, growth and unemployment across European Regions. Regional Studies 31, 457–466.

Fagerberg, J B. Verspagen, B., 1996. Heading for divergence? Regional growth in Europe reconsidered Journal of Common Market Studies 34, 431-448.

Wilson, P. W., 2008. FEAR: A software package for frontier efficiency analysis with R. Socio-economic planning sciences, 42(4), 247-254.

Foddi, M., Usai, S., 2013. Regional knowledge performance in Europe. Growth and Change 44 (2), 258–286.

Haas, A.D., Murphy, F.H., 2003. Compensating for non-homogeneity in decision-making units in data envelopment analysis European Journal of Operational Research, 144-154 .

Halkos, G.E., Tzeremes, G.N., 2012. Modelling the effects of national culture on multinational banks' performance: A conditional robust nonparametric frontier analysis Economic modelling 28 (1–2) , 515-525.

Holtz-Eakin, D., Newey, W., Rosen, H., 1988. Estimating vector autoregressions with panel data. Econometrica, 56, 1371-1395.

Judson, R. A., Owen, A. L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. Economics letters 65(1), 9-15.

Kitson, M., Martin, R., Tyler, P. 2004. Regional competitiveness: an elusive yet key concept?. Regional Studies 38: 991–999.

Kontolaimou, A., Tsekouras, K. 2010, Are the Cooperatives the weakest link in European Banking? A Non-parametric Metafrontier Approach, Journal of Banking and Finance 34(8), 1946-1957.

Kontolaimou A., Kounetas K., Mourtos I., Tsekouras K., 2012 Technology gaps in European banking: Put the blame on inputs or outputs? Economic Modelling 29, 1798-1808.

Kounetas, K., 2015. Heterogeneous technologies, strategic groups and environmental efficiency technology gaps for European countries Energy Policy 83, 277-287.

Lin, W.T. and Chiang, C.Y., 2011. The Impacts of country characteristics upon the value of information technology as measured by productive efficiency. International Journal of Production Economics 132 (1), 13-33.

Love, I., Zicchino, L., 2006. Financial development and dynamic investment behavior: Evidence from panel VAR. The Quarterly Review of Economics and Finance 46(2), 190-210.

Lütkepohl, H. 2005. New introduction to multiple time series analysis. Springer Science Business Media.

Lucas, R. E. 1998. On the mechanics of economic development. Econometric Society Monographs 29, 61-70.

Matawie, K. M., Assaf, A., 2010. Bayesian and DEA efficiency modelling : an application to hospital food service operations. Applied Statistics 37(6), 945-953.

Matawie K. M., Assaf A 2008. A metafrontier model to assess regional efficiency differences. Journal of Modelling in Management 3(3), 268-276

Mas, M., Maudos, J., Pérez, F., Uriel, E. 1996. Infrastructures and productivity in the Spanish regions. Regional Studies 30(7), 641-649.

Nickell, S., 1981 Biases in Dynamic models with fixed effects. Econometrica 49, 1417–1426.

O'Donnell, C.J., Rao, D.S.P., Battese, G.E. 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empirical Economics 34, 231–255.

O'Donnell, O., E. van Doorslaer, and A. Wagstaff. 2006. "Decomposition of Inequalities in Health and Health Care." In The Elgar Companion to Health Economics, ed. A. M. Jones. Cheltenham, United Kingdom: Edward Elgar.

Oughton, C., Landabaso, M., Morgan, K. 2002. The regional innovation paradox: innovation policy and industrial policy. The Journal of Technology Transfer 27(1), 97-110.

Percoco M 2004 Infrastructure and economic efficiency in Italian regions. Network Spatial Economics 4, 361–378.

Rao, P., O'Donnell, C., Battese, G., 2003. Metafrontier Functions for the Study of Inter-group Productivity Differences. CEPA Working Paper Series No. 01/2003, School of Economics, University of New England, Armidale.

Romer, P.,1990. Endogenous technological change Journal of Political Economy, 98 S71-S102.

Rosenberg, N., 1963. Technological change in the machine tool industry, 1840–1910. The Journal of Economic History 23, 414–443.

Samoilenko, S., Osei-Bryson , K. 2010. Determining source of relative inefficiency in heterogenous samples: Methodology using Cluster Analysis, DEA and Neural Networks. European Journal of Operation Research 206 (10), 479-487.

Simar, L., Wilson, P. W. 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of econometrics 136(1), 31-64.

Simar, L., P. Wilson 2000. Statistical inference in nonparametric frontier models: the state of the art Journal of Productivity Analysis, 13, 49-78.

Simar, L., and P. W. Wilson. 1999b. "Of Course We Can Bootstrap DEA Scores! But Does It Mean Anything? Logic Trumps Wishful Thinking." Journal of Productivity Analysis 11, 93-97.

Simar, L. and P.W. Wilson 2008, Statistical Inference in Nonparametric Frontier Models: recent Developments and Perspectives, in The Measurement of Productive Efficiency, 2nd Edition, Harold Fried, C.A.Knox Lovell and Shelton Schmidt, editors, Oxford University Press, 2008.

Tzeremes NG 2014. The effect of human capital on countries' economic efficiency. Economics Letters, 124(1), 127-131.

Tsekouras, K., Chatzistamoulou, N., Kounetas, K., Broadstock, D. C. 2016. Spillovers, path dependence and the productive performance of European transportation sectors in the presence of technology heterogeneity. Technological Forecasting and Social Change 102, 261-274.

Tsekouras, K., Chatzistamoulou, N., Kounetas, K. 2017. Productive performance, technology heterogeneity and hierarchies: Who to compare with whom. International Journal of Production Economics 193, 465-478.

Tsekouras, K., Papathanassopoulos, F., Kounetas, K., Pappous, G. 2010. Does the adoption of new technology boost productive efficiency in the public sector? The case of ICUs system. International Journal of Production Economics 128(1), 427-433.

Wang, Q., Zhao, Z., Zhou, P., Zhou, D. 2013. Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. Economic Modelling 35, 283-289.

Zabala-Iturriagagoitia, J.M., P. Voigt, A. Gutierrez-Gracia, F. Jimenez-Saez 2007. Regional innovation systems: how to assess performance Regional Studies 41 (5), 661-672.

APPENDIX

Table 1. Number of Regions per Country.

Austria	9	Denmark	5	Greece	12	Norway	7	Spain	19
Belgium	11	Finland	5	Hungary	7	Poland	16	Sweden	8
Bulgary	6	France	26	Italy	21	Portugal	7	UK	37
Czech R	8	Germany	39	Netherlands	12	Romania	8		

Table 2. Productive Efficiency and metatechnical ratio scores for European countries for 2003-2011 (Bootstrap DEA)

	TE	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**TE**	**MTR**	**Mean TE**	**Mean MTR**
	2003		2004		2005		2006		2007		2008		2009		2010		2011			
Austria	0.894 (0.059)	0.762 (0.044)	0.903 (0.051)	0.819 (0.091)	0.904 (0.051)	0.820 (0.092)	0.905 (0.057)	0.822 (0.092)	0.906 (0.051)	0.823 (0.092)	0.865 (0.192)	0.814 (0.099)	0.899 (0.056)	0.811 (0.101)	0.894 (0.050)	0.803 (0.104)	0.812 (0.101)	0.803 (0.104)	0.841 (0.186)	0.814 (0.091
Belgium	0.863 (0.080)	0.787 (0.133)	0.879 (0.071)	0.778 (0.123)	0.868 (0.079)	0.76 (0.131)	0.881 (0.075)	0.782 (0.130)	0.892 (0.071)	0.800 (0.125)	0.765 (0.129)	0.528 (0.177)	0.860 (0.078)	0.746 (0.133)	0.865 (0.080)	0.755 (0.138)	0.863 (0.080)	0.751 (0.138)	0.833 (0.14)	0.765 (0.127)
Bulgary	0.85 (0.088)	0.729 (0.14)	0.826 (0.087)	0.689 (0.141)	0.843 (0.078)	0.715 (0.128)	0.850 (0.072)	0.727 (0.121)	0.853 (0.079)	0.738 (0.128)	0.747 (0.159)	0.726 (0.132)	0.851 (0.088)	0.731 (0.141)	0.853 (0.092)	0.735 (0.145)	0.858 (0.095)	0.744 (0.151)	0.837 (0.095)	0.726 (0.127)
Czech R	0.878 (0.068)	0.776 (0.118)	0.889 (0.074)	0.794 (0.128)	0.874 (0.074)	0.768 (0.125)	0.879 (0.070)	0.778 (0.119)	0.868 (0.072)	0.757 (0.122)	0.815 (0.105)	0.714 (0.125)	0.878 (0.068)	0.776 (0.118)	0.877 (0.068)	0.774 (0.117)	0.877 (0.066)	0.773 (0.114)	0.809 (0.212)	0.774 (0.113)
Denmark	0.888 (0.064)	0.941 (0.034)	0.878 (0.128)	0.785 (0.202)	0.897 (0.052)	0.808 (0.094)	0.917 (0.034)	0.842 (0.064)	0.925 (0.032)	0.856 (0.060)	0.917 (0.014)	0.814 (0.105)	0.843 (0.119)	0.723 (0.178)	0.914 (0.066)	0.841 (0.116)	0.934 (0.040)	0.874 (0.075)	0.862 (0.163)	0.827 (0.115)
Finland	0.896 (0.054)	0.806 (0.096)	0.915 (0.046)	0.84 (0.83)	0.920 (0.043)	0.849 (0.078)	0.911 (0.049)	0.831 (0.088)	0.915 (0.045)	0.840 (0.081)	0.898 (0.098)	0.805 (0.128)	0.897 (0.054)	0.808 (0.096)	0.898 (0.054)	0.808 (0.096)	0.864 (0.092)	0.750 (0.090)	0.851 (0.182)	0.824 (0.082)
France	0.771 (0.099)	0.602 (0.149)	0.733 (0.073)	0.543 (0.110)	0.733 (0.073)	0.543 (0.110)	0.749 (0.085)	0.569 (0.131)	0.756 (0.088)	0.579 (0.138)	0.789 (0.114)	0.614 (0.158)	0.771 (0.094)	0.604 (0.151)	0.778 (0.095)	0.611 (0.151)	0.775 (0.090)	0.609 (0.141)	0.746 (0.109)	0.582 (0.135)
Germany	0.837 (0.076)	0.707 (0.126)	0.82 (0.077)	0.678 (0.124)	0.822 (0.076)	0.682 (0.123)	0.829 (0.074)	0.693 (0.119)	0.837 (0.071)	0.706 (0.116)	0.714 (0.140)	0.811 (0.114)	0.837 (0.076)	0.707 (0.123)	0.836 (0.072)	0.705 (0.119)	0.835 (0.066)	0.702 (0.110)	0.782 (0.172)	0.798 (0.115)

Greece	0.737 (0.137)	0.56 (0.203)	0.705 (0.097)	0.657 (0.155)	0.754 (0.125)	0.584 (0.188)	0.736 (0.127)	0.557 (0.188)	0.743 (0.134)	0.569 (0.201)	0.724 (0.105)	0.598 (0.147)	0.735 (0.136)	0.557 (0.21)	0.733 (0.143)	0.557 (0.212)	0.733 (0.143)	0.557 (0.212)	0.722 (0.157)	0.575 (0.191)
Hungary	0.867 (0.069)	0.757 (0.117)	0.891 (0.072)	0.798 (0.123)	0.891 (0.069)	0.799 (0.121)	0.882 (0.073)	0.783 (0.124)	0.880 (0.074)	0.78 (0.125)	0.812 (0.105)	0.81 (0.125)	0.868 (0.069)	0.757 (0.117)	0.864 (0.071)	0.751 (0.121)	0.86 (0.073)	0.744 (0.122)	0.861 (0.084)	0.771 (0.114)
Italy	0.863 (0.064)	0.749 (0.109)	0.86 (0.068)	0.745 (0.116)	0.866 (0.064)	0.754 (0.109)	0.871 (0.061)	0.762 (0.106)	0.873 (0.062)	0.768 (0.108)	0.869 (0.068)	0.755 (0.098)	0.863 (0.064)	0.749 (0.109)	0.865 (0.064)	0.752 (0.110)	0.867 (0.063)	0.755 (0.109)	0.809 (0.183)	0.754 (0.107)
Netherlands	0.874 (0.074)	0.77 (0.123)	0.879 (0.074)	0.778 (0.124)	0.873 (0.077)	0.768 (0.127)	0.854 (0.083)	0.736 (0.134)	0.870 (0.079)	0.762 (0.131)	0.888 (0.087)	0.784 (0.104)	0.874 (0.074)	0.769 (0.123)	0.877 (0.076)	0.774 (0.125)	0.879 (0.076)	0.779 (0.126)	0.822 (0.174)	0.767 (0.122)
Norway	0.917 (0.045)	0.844 (0.081)	0.943 (0.028)	0.89 (0.052)	0.932 (0.035)	0.871 (0.064)	0.924 (0.040)	0.855 (0.073)	0.924 (0.040)	0.855 (0.072)	0.898 (0.089)	0.814 (0.087)	0.917 (0.045)	0.844 (0.081)	0.915 (0.047)	0.839 (0.083	0.92 (0.043)	0.849 (0.086)	0.918 (0.046)	0.856 (0.071)
Poland	0.867 (0.092)	0.761 (0.147)	0.792 (0.109)	0.639 (0.167)	0.794 (0.106)	0.642 (0.163)	0.825 (0.104)	0.659 (0.160)	0.826 (0.099)	0.692 (0.156)	0.874 (0.098)	0.705 (0.108)	0.867 (0.092)	0.761 (0.147)	0.858 (0.091)	0.745 (0.145)	0.851 (0.091)	0.732 (0.145)	0.818 (0.115)	0.704 (0.156)
Portugal	0.828 (0.021)	0.858 (0.041)	0.88 (0.018)	0.862 (0.036)	0.879 (0.020)	0.859 (0.038)	0.876 (0.023)	0.854 (0.044)	0.875 (0.024)	0.852 (0.046)	0.859 (0.104)	0.847 (0.058)	0.879 (0.021)	0.859 (0.041)	0.881 (0.020)	0.861 (0.039)	0.874 (0.014)	0.814 (0.024)	0.854 (0.087)	0.781 (0.038)
Romania	0.721 (0.132)	0.535 (0.176)	0.713 (0.135)	0.524 (0.178)	0.704 (0.136)	0.512 (0.178)	0.722 (0.129)	0.536 (0.174)	0.725 (0.136)	0.542 (0.183)	0.748 (0.112)	0.625 (0.124)	0.741 (0.091)	0.535 (0.177)	0.735 (0.095)	0.528 (0.181)	0.711 (0.143)	0.523 (0.185)	0.712 (0.129)	0.531 (0.169)
Spain	0.859 (0.053)	0.741 (0.092)	0.85 (0.059)	0.725 (0.100)	0.845 (0.058)	0.718 (0.098)	0.838 (0.061)	0.706 (0.102)	0.833 (0.061)	0.698 (0.103)	0.789 (0.11)	0.709 (0.129)	0.86 (0.054)	0.742 (0.093)	0.862 (0.052)	0.746 (0.091)	0.864 (0.052)	0.75 (0.09)	0.786 (0.204)	0.728 (0.095)
Sweden	0.862 (0.071)	0.748 (0.118)	0.882 (0.060)	0.781 (0.103)	0.884 (0.060)	0.785 (0.103)	0.897 (0.056)	0.808 (0.098)	0.909 (0.062)	0.831 (0.108)	0.899 (0.058)	0.846 (0.068)	0.863 (0.071)	0.749 (0.117)	0.862 (0.076)	0.748 (0.126)	0.861 (0.081)	0.747 (0.134)	0.871 (0.076)	0.775 (0.109)
UK	0.751 (0.071)	0.684 (0.144)	0.762 (0.099)	0.591 (0.151)	0.748 (0.100)	0.566 (0.153)	0.748 (0.104)	0.663 (0.158)	0.740 (0.109)	0.559 (0.161)	0.764 (0.129)	0.574 (0.146)	0.814 (0.104)	0.654 (0.124)	0.759 (0.113)	0.587 (0.174)	0.752 (0.103)	0.568 (0.176)	0.786 (0.189)	0.673 (0.157)
Mean	0.814	0.704	0.828	0.695	0.768	0.823	0.826	0.692	0.829	0.699	0.841	0.698	0.831	0.701	0.834	0.705	0.832	0.702		
St.Dev	0.121	0.161	0.101	0.162	0.164	0.103	0.103	0.164	0.105	0.166	0.165	0.157	0.101	0.163	0.101	0.163	0.102	0.165		
Min	(ROM)	(ROM)	(GRC)	(ROM)	(ROM)	(ROM)	(ROM)	(ROM)	(ROM)	(ROM)	(ROM)	(BEL)	(GRC)	(ROM)	(GRC)	(ROM)	(ROM)	(ROM)		
Max	(NOR)	(DNK)	(NOR)	(NOR)	(NOR)	(NOR)	(NOR)	(SWE)	(DNK)	(NOR)	(DNK)	(SWE)	(NOR)	(PRT)	(NOR)	(PRT)	(DNK)	(DNK)		

Table 3. Regions that are national champions by year (using DEA)

A.A	2003		2004		2005		2006		2007		2008		2009		2010		2011	
1	Austria	at11	Austria	at11	Austria	at11	Austria	at11	Austria	at11	Austria	at11	Austria	at11	Austria	at11	Austria	at11
2	Austria	at13	Austria	at13	Austria	at13	Austria	at13	Austria	at13	Austria	at13	Austria	at13	Austria	at13	Austria	at13
3	Austria	at22	Austria	at22	Austria	at22	Austria	at22	Austria	at22	-	-	Austria	at22	Austria	at22	Austria	at22
4	-	-	-	-	Austria	at31	Austria	at31	Austria	at31	-	-	Austria	at31	Austria	at31	Austria	at31
5	Austria	at34	Austria	at34	Austria	at34	Austria	at34	Austria	at34	-	-	Austria	at34	Austria	at34	Austria	at34
6	Belgium	be1	Belgium	be1	Belgium	be1	Belgium	be1	Belgium	be1	Belgium	be1	Belgium	be1	Belgium	be1	Belgium	be1
7	Belgium	be33	Belgium	be32	Belgium	be31	Belgium	be21	Belgium	be31	Belgium	be21	Belgium	be31	Belgium	be24	Belgium	be24
8	Belgium	be34	Belgium	be33	Belgium	be33	Belgium	be31	Belgium	be34	Belgium	be31	Belgium	be33	Belgium	be31	Belgium	be31
9	-	-	Belgium	be34	Belgium	be34	Belgium	be33	Belgium	-	Belgium	be35	Belgium	be34	Belgium	be33	Belgium	be33
10	-	-	-	-	-	-	Belgium	be34	Belgium	be33	-	-	-	-	Belgium	be34	Belgium	be34
11	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31	Bulgary	bg41	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31
12	Bulgary	bg33	Bulgary	bg33	Bulgary	bg33	Bulgary	bg33	Bulgary	bg33	Bulgary	bg42	Bulgary	bg33	Bulgary	bg33	Bulgary	bg33
13	Bulgary	bg41	Bulgary	bg41	Bulgary	bg41	Bulgary	bg41	Bulgary	bg41	-	-	Bulgary	bg41	Bulgary	bg41	Bulgary	bg41
14	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31	Bulgary	bg31	-	-	-	-	-	-	-	-
15	Czech R	cz01	Czech R	cz01	Czech R	cz01	Czech R	cz01	Czech R	cz01	Czech R	cz01	Czech R	cz01	Czech R	cz01	Czech R	cz01
16	Czech R	cz02	Czech R	cz02	Czech R	cz02	Czech R	cz02	Czech R	cz02	-	-	Czech R	cz02	Czech R	cz02	Czech R	cz02
17	Czech R	cz04	Czech R	cz04	Czech R	cz04	Czech R	cz04	Czech R	cz04		-	Czech R	cz04	Czech R	cz04	Czech R	cz04
18	Czech R	cz08	-	-	-	-	-	-	-	-	-	-	Czech R	cz08	Czech R	cz08	Czech R	cz08
19	Germany	de21	Germany	de21	Germany	de21	Germany	de21	Germany	de21	Germany	De21	Germany	de21	Germany	de21	Germany	de21
20	Germany	de23	Germany	de23	Germany	de23	Germany	de23	Germany	de23	Germany	de13	Germany	de23	Germany	de41	Germany	de41
21	Germany	de41	Germany	de25	Germany	de25	Germany	de41	Germany	de41	Germany	de6	Germany	de41	Germany	de5	Germany	de5
22	Germany	de5	Germany	de41	Germany	de41	Germany	de5	Germany	de5	Germany	dea4	Germany	de5	Germany	de6	Germany	de6
23	Germany	de6	Germany	de5	Germany	de5	Germany	de6	Germany	de6	Germany	dea5	Germany	de6	Germany	de71	Germany	de71

24	Germany	de71	Germany	de6	Germany	de6	Germany	de71	Germany	de71	Germany	deb3	Germany	de71	Germany	de92	Germany	dea1
25	Germany	dea1	Germany	de71	Germany	de71	Germany	dea1	Germany	dea1	Germany	ded1	Germany	dea1	Germany	de94	Germany	deb2
26	Germany	deb2	Germany	dea1	Germany	de91	Germany	deb2	Germany	deb2	Germany	dee	Germany	deb2	Germany	dea1	-	-
27	-	-	Germany	deb2	Germany	dea1	-	-	-	-	-	-	Germany	deb3	Germany	dea4	-	-
28	-	-	-	-	Germany	deb2	-	-	-	-	-	-	-	-	Germany	deb2	-	-
29	-	-	-	-	-	-	-		-	-	-	-	-	-	Germany	deb3	-	-
30	-	-	-	-	-	-	-		-	-	-	-	-	-	Germany	dee	-	-
31	Denmark	deg	Denmark	dk01	Denmark	deg	Denmark	deg	Denmark	dk01	Denmark	deg	Denmark	deg	Denmark	dk01	Denmark	dk01
32	Denmark	dk04	Denmark	dk05	Denmark	dk01	Denmark	dk01	Denmark	dk05	Denmark	dk01	Denmark	dk02	Denmark	dk05	Denmark	dk02
33	Denmark	dk05	-	-	Denmark	dk05	Denmark	dk05	-	-	Denmark	dk02	Denmark	dk03	-	-	Denmark	dk05
34	Spain	es21	Spain	es21	Spain	es21	Spain	es21	Spain	es21	Spain	es11	Spain	es21	Spain	es21	Spain	es11
35	Spain	es3	Spain	es3	Spain	es3	Spain	es3	Spain	es3	Spain	es21	Spain	es3	Spain	es3	Spain	es21
36	Spain	es51	Spain	es51	Spain	es51	Spain	es51	Spain	es51	Spain	es41	Spain	es51	Spain	es51	Spain	es3
37	Spain	es63	Spain	es63	Spain	es63	Spain	es63	Spain	es63	Spain	es52	Spain	es63	Spain	es63	Spain	es51
38	Spain	es64	Spain	es64	Spain	es64	Spain	es64	Spain	es64	-	-	Spain	es64	Spain	es64	Spain	es63
39	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	Spain	es64
40	Finland	fi13	Finland	fi13	Finland	fi13	Finland	fi13	Finland	fi13	Finland	fi18	Finland	fi13	Finland	fi13	Finland	fi13
41	Finland	fi18	Finland	fi18	Finland	fi18	Finland	fi18	Finland	fi18	Finland	fi2	Finland	fi18	Finland	fi18	Finland	fi18
42	Finland	fi2	Finland	fi2	Finland	fi2	Finland	fi2	Finland	fi2	-	-	Finland	fi2	Finland	fi2	Finland	fi2
43	France	fr1	France	fr1	France	fr1	France	fr1	France	fr1	France	fr21	France	fr1	France	fr1	France	fr1
44	France	fr72	France	fr71	France	fr71	France	fr71	France	fr72	France	fr24	France	fr53	France	fr24	France	fr93
45	France	fr93	France	fr72	France	fr72	France	fr72	France	fr93	France	fr3	France	fr72	France	fr26	-	-
46	France	fr94	France	fr93	France	fr93	France	fr93	France	fr94	France	fr53	France	fr93	France	fr93	-	-
47	-	-	France	fr94	France	fr94	France	fr94	-	-	France	fr61	France	fr94	-	-	-	
48	-	-	-	-	-	-	-	-	-	-	France	fr83	-	-	-	-	-	-
49	-	-	-	-	-	-	-	-	-	-	France	fr91	-	-	-	-	-	-
50	Greece	gr21	Greece	gr3	Greece	gr3	Greece	gr3	Greece	gr3	Greece	gr13	Greece	gr21	Greece	gr21	Greece	gr21
51	Greece	gr3	Greece	gr41	Greece	gr41	Greece	gr41	Greece	gr41	Greece	gr14	Greece	gr3	Greece	gr3	Greece	gr3

52	Greece	gr41	Greece	gr42	Greece	gr42	Greece	gr42	Greece	gr42	Greece	gr21	Greece	gr41	Greece	gr41	Greece	gr41
53	Greece	gr42	-	-	-	-	-	-	-	-	Greece	gr3	Greece	gr42	Greece	gr42	Greece	gr42
54	-	-	-	-	-	-	-	-	-	-	Greece	gr43	-	-	-	-	-	-
55	Hungary	hu1	Hungary	hu1	Hungary	hu1	Hungary	hu1	Hungary	hu1	Hungary	hu1	Hungary	hu1	Hungary	hu1	Hungary	hu1
56	Hungary	hu23	Hungary	hu22	Hungary	hu22	Hungary	hu22	Hungary	hu23	Hungary	hu21	Hungary	hu23	Hungary	hu23	Hungary	hu23
57	Hungary	hu31	Hungary	hu23	Hungary	hu23	Hungary	hu23	Hungary	hu31	Hungary	hu22	Hungary	hu31	Hungary	hu31	Hungary	hu31
41	-	-	Hungary	hu31	Hungary	hu31	Hungary	hu31	-	-	Hungary	hu23	-	-	-	-	-	
42	Italy	itc1	Italy	itc1	Italy	itc1	Italy	itc1	Italy	itc1	Italy	itc1	Italy	itc1	Italy	itc1	Italy	itc1
43	Italy	itc4	Italy	itc4	Italy	itc4	Italy	itc4	Italy	itc4	Italy	itf2	Italy	itc4	Italy	itc4	Italy	itc4
44	Italy	itd1	Italy	itd1	Italy	itd1	Italy	itd1	Italy	itd1	Italy	itf3	Italy	itd1	Italy	itd1	Italy	itd1
45	Italy	itd5	Italy	itd5	Italy	itd5	Italy	itd5	Italy	itd5	Italy	itf5	Italy	itd5	Italy	itd5	Italy	itd5
46	Italy	ite3	Italy	ite4	Italy	ite4	Italy	ite4	Italy	ite3	Italy	itg1	Italy	ite3	Italy	ite3	Italy	ite3
47	Italy	ite4	Italy	itf5	Italy	itf5	Italy	itf5	Italy	ite4	-	nl12	Italy	ite4	Italy	ite4	Italy	ite4
48	Italy	itf5	-	-	-	-	-	-	Italy	itf5	-	nl22	Italy	itf5	Italy	itf5	Italy	itf5
49	Netherlands	nl11	Netherlands	nl11	Netherlands	nl11	Netherlands	nl11	Netherlands	nl11	Netherlands	nl32	Netherlands	nl11	Netherlands	nl11	Netherlands	nl11
50	Netherlands	nl21	Netherlands	nl21	Netherlands	nl21	Netherlands	nl21	Netherlands	nl21	Netherlands	nl41	Netherlands	nl21	Netherlands	nl21	Netherlands	nl21
51	Netherlands	nl23	Netherlands	nl23	Netherlands	nl23	Netherlands	nl22	Netherlands	nl23	Netherlands	no01	Netherlands	nl22	Netherlands	nl23	Netherlands	nl23
52	Netherlands	nl32	Netherlands	nl32	Netherlands	nl32	Netherlands	nl23	Netherlands	nl32	Netherlands	no02	Netherlands	nl23	Netherlands	nl32	Netherlands	nl32
53	Netherlands	nl33	Netherlands	nl33	Netherlands	nl33	Netherlands	nl32	Netherlands	nl33	-	-	Netherlands	nl32	Netherlands	nl33	Netherlands	nl33
54	Netherlands	nl34	-	-	-	-	Netherlands	nl33	-	-	-	-	Netherlands	nl33	Netherlands	nl34	Netherlands	nl34
55	-	-	-	-	-	-	-	-	-	-	-	-	Netherlands	nl34	-	-	-	-
56	Norway	no01	Norway	no01	Norway	no01	Norway	no01	Norway	no01	Norway	no04	Norway	no01	Norway	no01	Norway	no01
57	Norway	no02	Norway	no02	Norway	no02	Norway	no02	Norway	no02	Norway	pl11	Norway	no02	Norway	no02	Norway	no02
58	Norway	no04	Norway	no04	Norway	no04	Norway	no04	Norway	no04	Norway	pl32	Norway	no04	Norway	no04	Norway	no04
59	Poland	pl12	Poland	pl12	Poland	pl12	Poland	pl12	Poland	pl12	Poland	pl33	Poland	pl12	Poland	pl12	Poland	pl12
60	Poland	pl33	Poland	pl33	Poland	pl33	Poland	pl33	Poland	pl33	Poland	pl41	Poland	pl31	Poland	pl33	Poland	pl33
61	Poland	pl52	Poland	pl52	Poland	pl34	Poland	pl34	Poland	pl34	Poland	pl51	Poland	pl33	Poland	pl52	Poland	pl42
62	Poland	pl63	Poland	pl63	Poland	pl52	Poland	pl42	Poland	pl52	Poland	pl52	Poland	pl52	Poland	pl63	Poland	pl52

63	-	-	-	-	Poland	pl62	Poland	pl52	Poland	pl63	Poland	pl62	Poland	pl63	-	-	Poland	pl63
64	-	-	-	-	Poland	pl63	Poland	pl63	-	-	Poland	pt17	-	-	-	-	-	-
65	Portugal	pt11	Portugal	pt11	Portugal	pt11	Portugal	pt11	Portugal	pt11	Portugal	pt2	Portugal	pt11	Portugal	pt11	Portugal	pt11
66	Portugal	pt15	Portugal	pt15	Portugal	pt15	Portugal	pt15	Portugal	pt15	Portugal	pt3	Portugal	pt15	Portugal	pt15	Portugal	pt15
67	Portugal	pt17	Portugal	pt17	Portugal	pt17	Portugal	pt17	Portugal	pt17	Portugal	ro11	Portugal	pt17	Portugal	pt17	Portugal	pt17
68	Portugal	pt18	Portugal	pt18	Portugal	pt18	Portugal	pt18	Portugal	pt18	Portugal	ro12	Portugal	pt18	Portugal	pt18	Portugal	pt18
69	Portugal	pt2	Portugal	pt2	Portugal	pt2	Portugal	pt2	Portugal	pt2	-	-	Portugal	pt2	Portugal	pt2	Portugal	pt2
70	Portugal	pt3	Portugal	pt3	Portugal	pt3	Portugal	pt3	Portugal	pt3	-	-	Portugal	pt3	Portugal	pt3	Portugal	pt3
71	Romania	ro11	Romania	ro11	Romania	ro11	Romania	ro11	Romania	ro11	Romania	ro21	Romania	ro11	Romania	ro11	Romania	ro11
72	Romania	ro32	Romania	ro32	Romania	ro32	Romania	ro12	Romania	ro32	Romania	ro32	Romania	ro12	Romania	ro21	Romania	ro32
73	Romania	ro42	Romania	ro42	Romania	ro41	Romania	ro22	Romania	ro42	Romania	ro41	Romania	ro21	Romania	ro32	Romania	ro42
74	-	-	-	-	Romania	ro42	Romania	ro31	-	-	Romania	se11	Romania	ro32	Romania	ro42	-	-
75	-	-	-	-	-	-	Romania	ro32	-	-	Romania	se21	Romania	ro41	-	-	-	-
76	-	-	-	-	-	-	Romania	ro42	-	-	-	-	Romania	ro42	-	-	-	-
77	Sweden	se11	Sweden	se11	Sweden	se11	Sweden	se11	Sweden	se11	Sweden	se23	Sweden	se11	Sweden	se11	Sweden	se11
78	Sweden	se32	Sweden	se23	Sweden	se23	Sweden	se23	Sweden	se32	Sweden	se32	Sweden	se32	Sweden	se12	Sweden	se23
79	Sweden	se33	Sweden	se32	Sweden	se32	Sweden	se32	Sweden	se33	Sweden	se33	Sweden	se33	Sweden	se33	Sweden	se32
80	-	-	Sweden	se33	Sweden	se33	Sweden	se33	-	-	-	-	-	-	-	-	Sweden	se33
81	UK	uke4	UK	ukd2	UK	ukd1	UK	uke1	UK	ukd1	UK	uke4	UK	uki1	UK	ukc1	UK	ukd1
82	UK	uki1	UK	uke1	UK	uke4	UK	uki1	UK	uki1	UK	ukj1	UK	ukk3	UK	ukd1	UK	ukd4
83	UK	ukj1	UK	uki1	UK	uki1	-	-	UK	ukk3	UK	ukj2	UK	ukk4	UK	uki1	UK	uki1
84	UK	ukj2	UK	uki2	-	-	-	-	UK	ukk4	UK	ukk1	-	-	-	-	UK	ukk3
85	UK	ukk1	UK	ukk3	-	-	-	-	UK	ukm5	UK	ukk3	-	-	-	-	UK	ukk4
86	UK	ukk3	UK	ukk4	-	-	-	-	-	-	UK	uki1	-	-	-	-	UK	ukm5
87	UK	ukm2	UK	ukm5	-	-	-	-	-	-	UK	ukm3	-	-	-	-	-	-
88	UK	ukm3	-	-	-	-	-	-	-	-	UK	ukm6	-	-	-	-	-	-

Table 4. European Champions w.r.t to Metafrontier (using DEA)

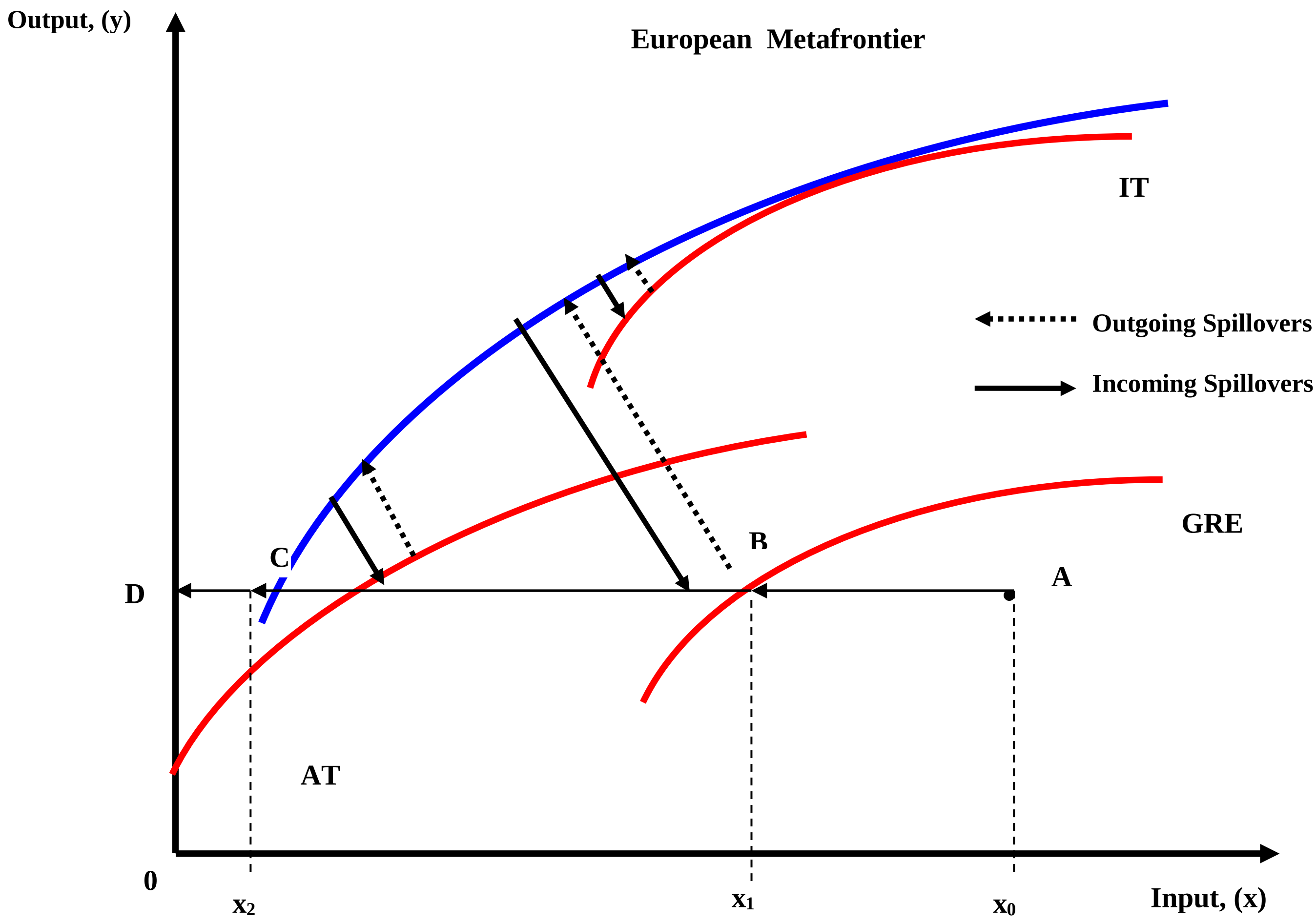
Country	Region	Number of Appearance	Country	Region	Number of Appearance
Belgium	Brussels (be1)	2	The Netherlands	Gelderland (nl22)	3
	Walloon Brabant (be31)	1		Noord-Holland (nl32)	2
Bulgary	Yugozapaden (bg41)	1		Oslo og Akershus (no01)	4
Czech Republic	Střední Čechy (Central Bohemia) (cz02)- Severozápad (Northwest) (cz04)	1	Poland	Lubelskie (pl31)-	1
Denmark	Hovedstaden (dk01)	1		Zachodniopomorskie (pl42)	2
Finland	Etelä-Suomi (fi18)	1	Romania	Nord-Est (ro21)	2
	Åland (fi2)	4	Sweden	Stockholm (se11)	2
France	Centre (fr24)- Burgundy (fr26)	1		Västsverige (se23)- Mellersta Norrland (se32)	1
	Île de France (fr53)	3	Spain	Galicia (es11)	1
Germany	Stuttgart (de11)- Freiburg (de13)- Braunschweig (de91)- Hannover (de92)- Weser-Ems (de94)- Detmold (dea4)- Arnsberg (dea5)- Sachsen-Anhalt (dee)	1		Basque Community (es21)	2
	Hamburg (de6)- Rheinhessen-Pfalz (deb3)	2		Melilla (es64)	3
	Thüringen (deg)	4	UK	Inner London	5
Greece	Attiki (gr3)	3		West Yorkshire (uke4)- Berkshire, Buckinghamshire and Oxfordshire (ukj)	2
Hungary	Dél-Dunántúl (hu23)	1		South Western Scotland (ukm3)	3
				Surrey, East and West Sussex (ukj2)- Cornwall and Isles of Scilly (ukk3)	1

Table 5. Panel VAR-Granger causality Wald test

Equation \ Excluded	**chi2**	**df**	**Prob > chi2**
TGs			
PATGDP	0.026	1	0.871
ALL	0.026	1	0.871
PATGDP			
TGs	9.028	1	0.003
ALL	9.028	1	0.003
TGs			
Human Capital	3.427	1	0.064
ALl	3.427	1	0.064
Human Capital			
TGs	0.227	1	0.634
ALL	0.227	1	0.634
Ho: Excluded variable does not Granger-cause Equation variable Ha: Excluded variable Granger-causes Equation variable			

Appendix B

Figure 1 Meta-frontier, individual frontiers, Incoming and Outgoing Spillovers for the single output-single input case.



$$Eff_{i|k}(x,y)=\frac{BD}{AD},\ MTEff_{i|k}(x,y)=\frac{CD}{AD},\ Tg_{i|k}(x,y)=BC$$

Figure 2a. Bootstrapped efficiency scores for all regions during the 2003-2011 period.

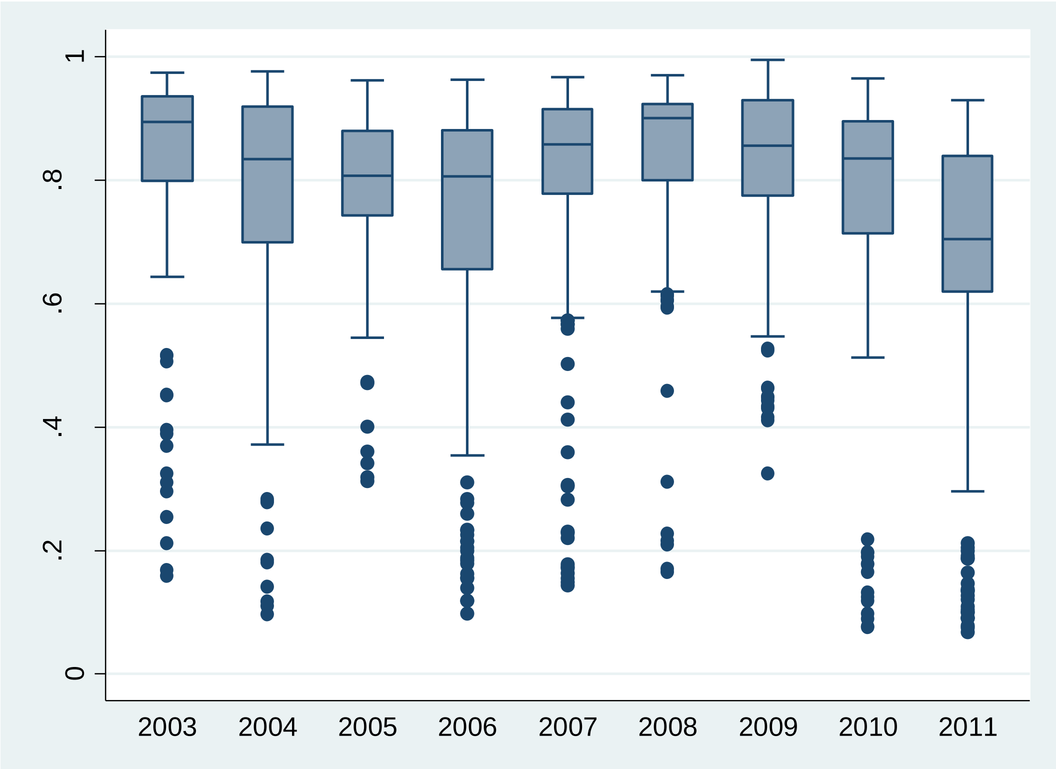


Figure 2b. Bootstrapped Metatechnology ratios for all regions during the 2003-2011 period.

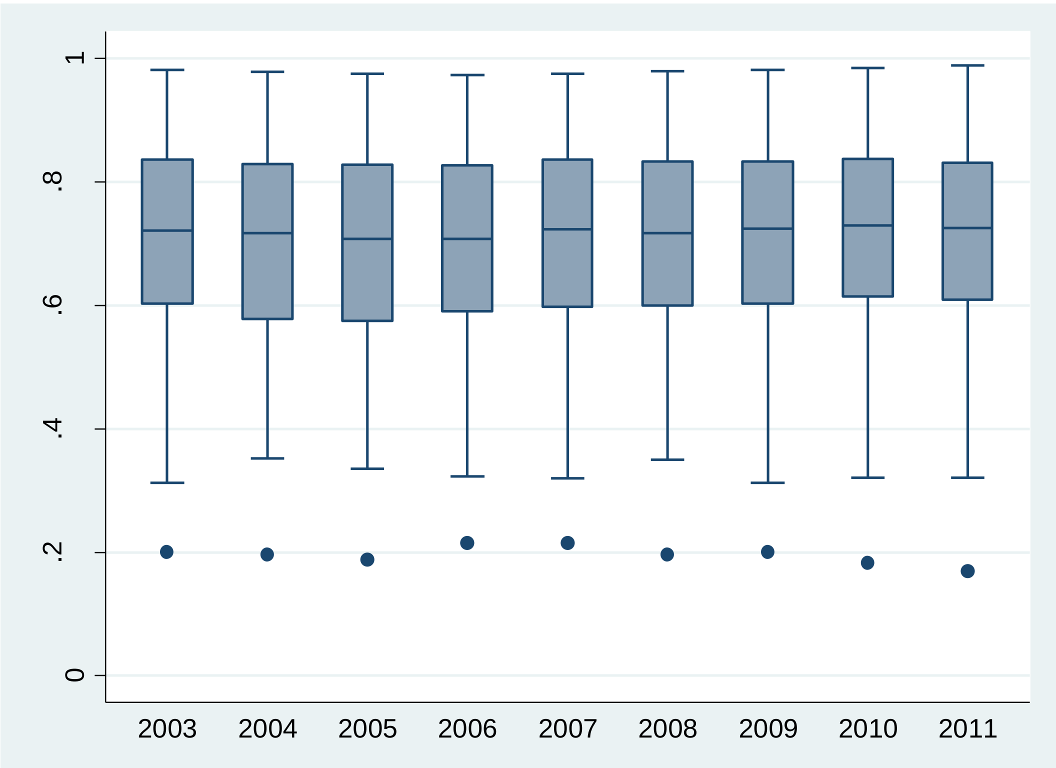


Figure 3: Technology gaps for regions over the 2003-2011 period.

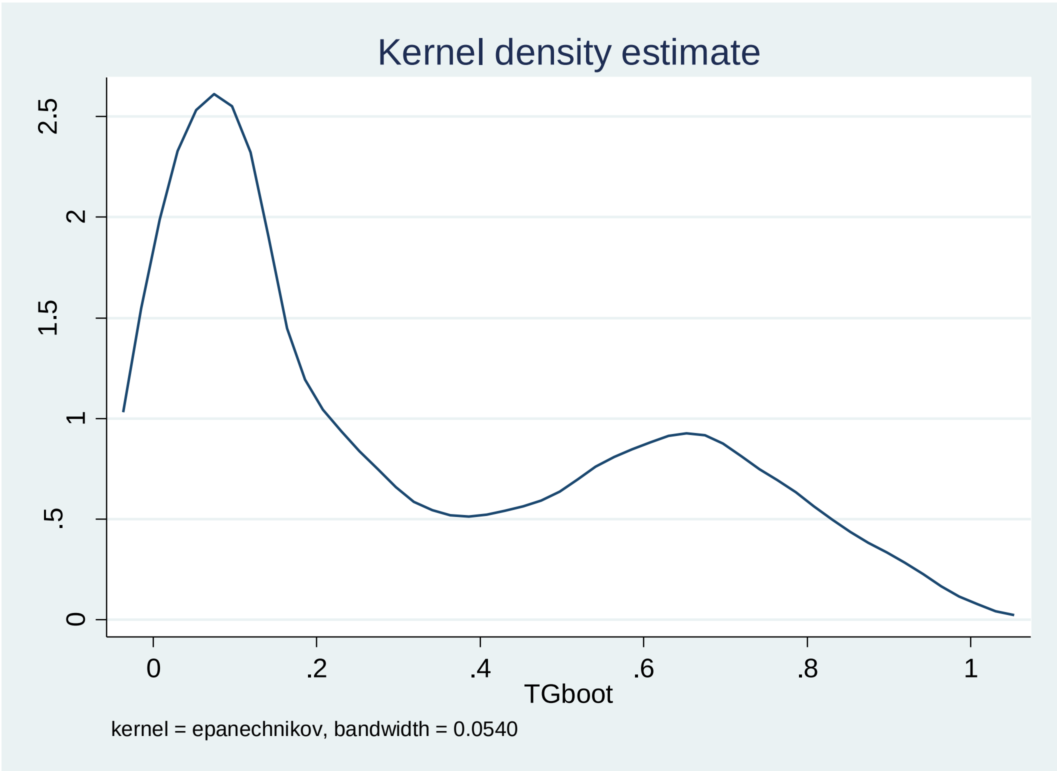


Figure 4 PVAR stability condition (Patents - Technological gap – Human capital)

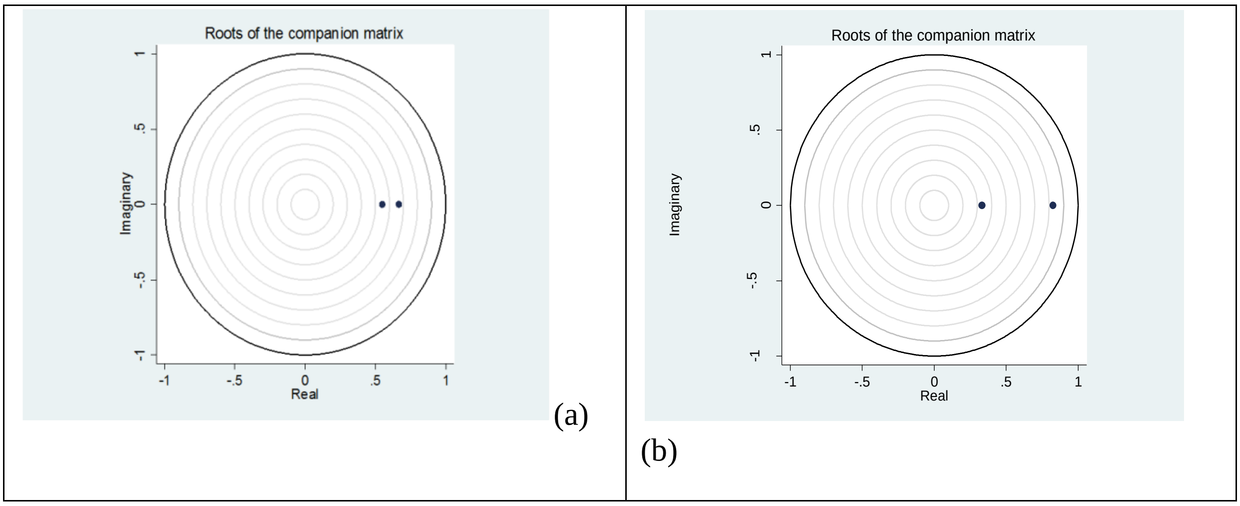


Figure 5. PVAR Patents and TGs

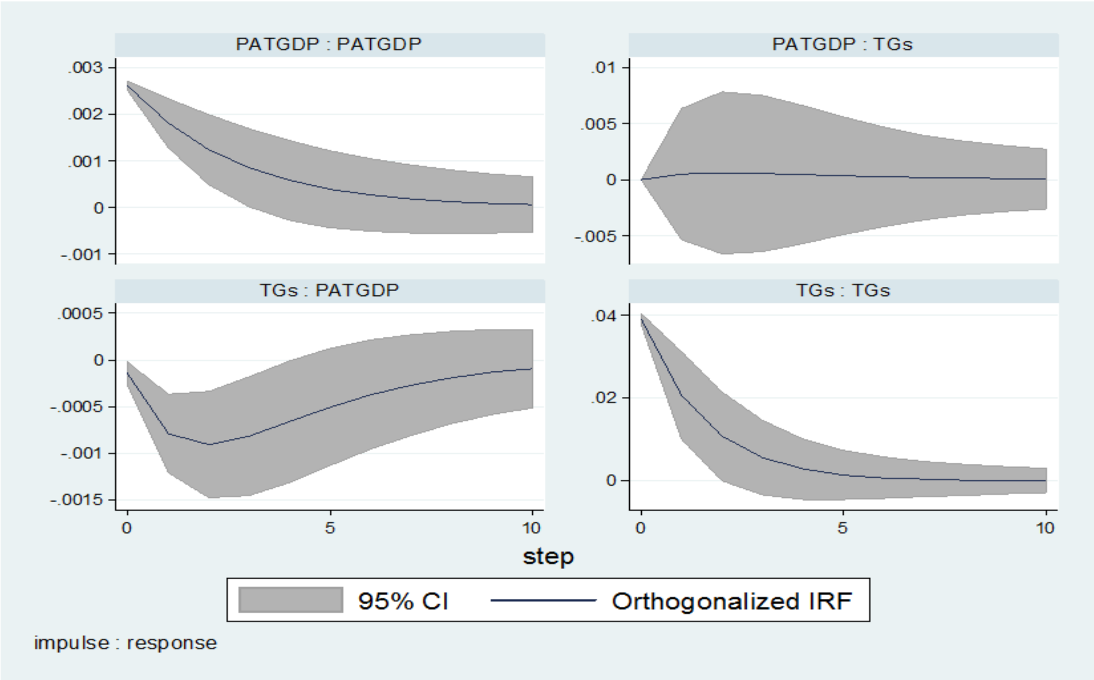


Figure 6. PVAR Human capital and TGs