Bednář, P., & Halásková, M. (2018). Innovation performance and R&D expenditures in Western European regions: Divergence or convergence? *Journal of International Studies, 11*(1), 210-224. doi:10.14254/2071-8330.2018/11-1/16

Journal of International Studies

Scientific Papers

Innovation performance and R&D expenditures in Western European regions: Divergence or convergence?

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Received: May, 2017
1st Revision: August, 2017
Accepted: November, 2017

DOI: 10.14254/2071-8330.2018/11-1/16

Abstract. Although Western Europe is a global leader in innovation activities among the OECD countries, these activities are not distributed evenly across NUTS 2 regions. Thus, the analysis of convergence or divergence related to innovation performance and R&D expenditures among Western European NUTS 2 regions is posed as the aim of this paper. Applying differential local version of spatial autocorrelation (LISA), difference-in-difference estimation the paper reveals the local variation of convergence and divergence and general spatial regime divergence in innovation performance and R&D expenditures within Western European NUTS 2 regions. Moreover, spatial lag cross-sectional regression provides support to the consideration of R&D expenditures as determinant for innovation performance along with the continuing divergence between most of Western and Southern European NUTS 2 regions and the others. Thus, the results confirm the stability in innovation performance and R&D expenditures in Western European NUTS 2 regions which could be the source of lagging behind not only other OECD countries but BRICS countries as well. On the regional level several NUTS 2 regions demonstrated the convergence dynamics, however, the general spatial divergence regime should lead to more actions regarding R&D polices under the EU programming period of 2014-2020.

Keywords: European regions, expenditures, innovation, performance, research and development, spatial econometrics, Western Europe.

JEL Classification: C21, C22, O30, O52, R12

1. INTRODUCTION

Research and development plays the key role in creation of new knowledge, products and technologies that are essential for a stable and sustainable economic development. The EU as a whole, as well as individual countries, have been increasingly focused on the creation and improvement of conditions for research, development and innovation in recent decades. A comprehensive system of innovation is considered the precondition for a sustainable growth and competitiveness within knowledge economy, and not just research and development alone, but also the production of market-oriented knowledge along with managerial application. This paper follows the same approach as implemented by Varga et al. (2012) calling this type of research Edison which is predominantly linked with tacit knowledge as well as agglomeration effects in relation to spatial distribution (ibid).

Hence, R&D productivity is expressed as innovation performance and is considered to be the indicator of knowledge production of the Edison type of research (ibid.), measured here (as well as in several other studies) by the number of patent applications to the European Patent Organization (EPO).

Investigation into innovation performance together with R&D expenditures is derived from its relevance, where R&D expenditures as percentage of GDP are considered to be the driver for knowledge production and hence the enhancement of regional competitiveness. Furthermore, the EU encourages both the public and the private sector to increase these expenditures as part of the Europe 2020 strategy. However, due to lack of absorption capacity in regions lagging behind in innovation, subsidies do not always result in growing innovation performance, the same applies to market-oriented outputs as compared to patent numbers. This leads us to the so-called regional innovation paradox (Oughton et al., 2002).

Nevertheless, both indicators could be considered crucial for evaluation of the Edison-type market-oriented research and, in addition, they are related to regional competitiveness which may result in the growth of regional GDP as well as export activities of firms. Moreover, this set of selected indicators may increase the innovation absorption capacity of regions in terms of growth in the number of firms and employment in R&D, high-tech sectors and knowledge intensive business services (KIBS).

The NUTS 2 size problem leads to the selection of Western European countries for the paper solely, thus excluding Nordic countries and namely Finland since their NUTS regions size may affect the results in terms of spatial autocorrelation and spatial regression analysis, as it is clearly observed in Dominicis et al. (2011). Moreover, Western European countries are comparable not only in terms of panel data availability but also because none of these economies has experienced systemic spontaneous transformations after 1989 as opposed to the postsocialist countries of Eastern, Central and Southeastern Europe. This experience of the latter group of countries has resulted in their different innovation development trajectories during the 1990s and in the early 2000s as well. Thus, our approach to countries' selection for this study ensures continuity in economic and political settings and also makes sure we are not dealing with structural brakes here.

Hence, the main contribution of this paper is to present the indication of convergence and divergence in innovation performance and R&D expenditures by means of employing Explanatory Spatial Data Analysis (ESDA) and spatial regression techniques using dummy variables for time and spatial regimes, i.e., combining the measurement of both static and dynamic components of divergence and convergence in the Edison type of knowledge process production. Furthermore, the additional contribution here is the recorded attempt to exploit both ESDA local indicators of spatial association techniques, static and dynamic, in case of the Edison type of research following the approaches presented in Feng et al. (2016).

Thus, the two main aims of the paper have been formulated as follows: 1) to detect and explain the static component of convergence and divergence in innovation performance and R&D expenditures within Western European NUTS 2 regions utilizing the cross-sectional data, and 2) to determine the dynamic component of convergence and divergence in innovation performance and R&D expenditures within Western European NUTS 2 regions utilizing the panel data.

Hence, particular aims within the first main aim are put forward as follows A) to confirm the continuation of regional disparities in spatially-lagged innovation performance and R&D expenditures as in (Dominicis et al., 2011) and (Varga et al., 2012) within Western European NUTS 2 regions; B) to investigate the spillover effect as the proxy for convergence and divergence in innovation performance and R&D expenditures; C) to reveal the spatial heterogeneity of convergence or divergence in spatially lagged innovation performance and R&D expenditures and thus investigate also weather their spatial dispersion tends to decrease, considering this approach as a proxy for the σ convergence concept; D) to model the stability of R&D expenditures and the eligible EU convergence regions as determinants for innovation performance.

Furthermore, particular aims within the second main aim are put forward as follows A) to reveal the spatial heterogeneity of convergence or divergence in differences over time in spatially lagging behind innovation performance and R&D expenditures and thus to test whether the lagging behind regions are growing significantly faster than more advanced regions considering this approach as a proxy for the β-convergence concept; B) to investigate the influence of time and spatial regime by the eligible lagging EU convergence regions as well as their interaction in terms of innovation performance and R&D expenditures and thereby to provide evidence to support the regional innovation paradox.

2. LITERATURE REVIEW

2.1. R&D expenditures and innovations in the EU context

Research policies can be considered part of integrated system of national policies regarding major society aspects in advanced countries. More importantly, it is a combination of policies for research and development, with policies for education, innovation, employment, information, industry, and trade. As Halásková & Halasková (2015b) discuss, innovation policies represent a rather new concept, compared to other policies implemented at national or regional levels. Innovation policies are affected by dynamic development as innovation is a result of successful research and development. However, it is essential to keep track of individual elements within national innovation policies, in conjunction with interdependence and efficiency of their links. Freeman (1995) or Ludvall (2007) argue that several features of national innovation systems are essential such as the level of educational systems, labour market characteristics, social system settings, and financial systems with access to financial resources for research and development, level of demand for innovation in private and public sectors, motivation of scientists towards innovation, and macroeconomic development. Furthermore, Pazour & Kučera (2009) claim that innovation policy merges with research and development policy with the aim to support research and development. R&D is one of the main sources for new knowledge creation through human capital and it can be seen as one of the most important sources of competitiveness. Lelek (2014) discusses the issue of precondition for the number of researchers as an important input factor for R&D. In this research an analysis was carried out on higher education graduates, who can be considered a base of a group of researchers, and the number of inhabitants. An assessment of quantitative indicators related to the number of inhabitants and the number of higher education graduates was performed by regression analysis.

The emphasis is put on improvement of R&D, and innovation funding, which happens to be one of the objectives in Europe 2020 Strategy for improving competitiveness of the EU (Martinez & Potluka, 2015). The ambition is to ensure public and private investment in order to achieve 3% of GDP (EC, 2010). Horizon 2020 programme (H2020) was introduced regarding research funding in 2014-2020 programming period at the EU level. The H2020 is considered a financial instrument implementing the Innovation Union and Europe 2020 flagship initiatives aimed at securing Europe's global competitiveness. Simultaneously, it is an indicator to evaluate objectives based on improving competitiveness, creating new job opportunities, and increasing employment. In addition, it is dedicated to social problems and focused on eliminating insufficient connection between research and market (EC, 2017). The major indicator applied to compare the performance of innovation at the level of European countries is the Summary Innovation Index (SII). Innovation performance in EU countries with focus on the individual categories of innovators (Innovation Leaders, Strong Innovators, Moderate Innovators, Modest Innovators) is dealt with by Prokop & Stejskal (2017). Then, in the analysis of innovation activities in terms of the regional dimension, the Regional Innovation Index is applied (Bramanti & Tarantola, 2012).

Statistical methodology of OECD is the standard in the evaluation of R&D and innovation outcomes, with over one hundred defined indicators (OECD, 2015). Halásková & Halásková (2015b) stated that NABS methodology (Methodology for Analysis and Comparison of Scientific Programmes and Budgets) is used in order to manage R&D policies of EU members. NABS methodology is an extension of OECD and it classifies R&D outcomes respecting socioeconomic objectives (predominately programmes that include these outcomes). Total R&D expenditures on GDP (GERD) is known as the intensity of R&D and often used for an international comparison of competitiveness in this regard. Similarly, share of tax revenue to GDP was used by Šimková (2015). Total R&D expenditures on GDP (GERD) is a ration indicator that belongs to the structural indicators group, which development is assessed in objectives of Europe 2020 (EC, 2010, 2017). In terms of Frascati (OECD, 2015), total expenditures on R&D (GERD) are defined as total internal expenditures (common and capital) on the R&D realized in the nation and certain period. These are total expenditures of public and private sectors leading to the R&D related to the GDP of certain economy. Policy documents (OECD, 2015) demonstrate that GERD enables the view on innovation capacity of countries and evaluates the efforts towards knowledge creation and the use of research outcomes with verifiable positive externalities. Total expenditures on R&D (GERD) include expenditures in four sectors of R&D, i.e. business enterprise, government, higher education, and private non-profit sector (OECD, 2015).

Total expenditures on the R&D (GERD) as a one of the objectives within Europe 2020 Strategy, are associated with assessment of R&D development efficiency among the EU countries. In addition, itis observed at both national and regional level, i.e. NUTS 2 regions. Analysis of total expenditures (GERD), key R&D indicators and indicators of financial performance in EU countries solves to the name of few Corea (2014); Szarowska & Žurkova (2017); Tkač et al. (2017). These authors dealt with relation between GERD and economic growth, and between GDP and R&D expenditure by sector performance in the European context, through the application of regression analysis. Mutual dependence between total expenditures on the R&D and other key indicators (number of publications, number of patents in European Patent Office – EPO, and number of researchers) in the EU countries is followed up by Halásková & Halásková (2015a). In connection with the allocated total R&D expenditure (GERD), as one of the Europe 2020 targets, the aspect in focus is mainly the evaluation of R&D efficiency, as proved by research, e. g. Conte et al. (2009) or Aristovnik (2012). Aristovnik (2012) measures relative efficiency in utilizing R&D expenditures in the new EU member states in comparison to the selected EU (plus Croatia) and OECD countries. A number of questions on R&D expenditures and efficiency are addressed in terms of the regional dimension at the level of European regions (Aristovnik, 2014; Roman, 2010). Aristovnik (2014) to assess the relative technical efficiency of R&D activities across selected EU (NUTS-2) regions. The empirical results show regions with a high intensity of R&D activities the most efficient performers. The empirical analysis integrates available inputs (R&D expenditures, researchers and employment in high-tech sectors) and outputs (patent and high-tech patent applications) over the period 2005–2010. Roman (2010) analyses research efficiency at the regional level for NUTS 2 regions from Romania and Bulgaria between 2003 and 2005. Others the authors examined research and development expenditure, spillovers effect and innovation activity in European regions (Moreno et al., 2005; Rodríguez-Pose & Crescenzi, 2008). This study solves regional economic performance in Europe: (1) the analysis of the link between investment in research and development (R&D), patents, and economic growth; (2) existence and efficiency of regional innovation systems; and (3) the examination of the geographical diffusion of regional knowledge spillovers.

2.2. NUTS 2 regions and spatial analysis of innovation performance

Two primary problems arise from focusing on NUTS 2 regions for innovation production analysis in relation to their selection, where the first is connected to economic and political settings given by the former division of Europe into centrally planned economies and market economies, and the second one is linked to spatial weights matrix influencing results, both spatial autocorrelation and spatial cross-section regression. As previously stated, the Edison type of research is predominantly related to agglomeration economies, however, used panel data are available for NUTS 2 regions only. Thus, as Meliciani & Savona (2014) stated, the different magnitude of the effects of agglomeration economies, depending on the spatial unit of analysis should be considered. The NUTS 2 spatial level of aggregation is relatively large compared to standard measure of agglomerations economies in spatial analysis as NUTS 2 regions vary in their size (i.e. area) and the location of the centroids from which distances in spatial weights are measured. However, due to lack of availability of comparable innovation spatial data at the lower hierarchical administrative level, this allows us to consider the given spatial unit selection free from the Modifiable Areal Unit Problem (MAUP).

Furthermore, spatial weights matrix setting is a crucial issue for spatial econometric analysis as a proxy for spatial interaction among the regions. Anselin & Rey (2014) discuss two standard approaches to evaluation of this spatial interaction, i.e. contiguity matrix and distance matrix. As the Western European NUTS 2 regions consist of islands, the contiguity matrix prerequisites are not fulfilled as some of these islands such as Corse or Sardinia do not share borders with any other region. In this case a distance matrix is assumed for several reasons. The first is to ensure that all regions will have at least one connected observation to meet the requirements of standard spatial econometric measures in accordance with Anselin & Rey (2014), and Anselin (2016). The second is that the defining distance matrix follows natural features of spatial innovation interaction relating to intensity of interregional dependence. Bottazzi & Peri (2003) observed in their investigation for knowledge spillovers resulting from R&D investments and patent applications, a significant positive impact on innovative activities in neighbouring regions appears to exist for a distance up to 300 km (Dominicis et al., 2011, p.10) using the inverse distance band of the squared distance (k^2) with 300 km as the spatial weight matrix with row-standardization for easier interpretation.

3. METHODOLOGY

The paper follows Dominicis, et al. (2011) methodology for the Western European NUTS 2 regions delimitations which resulted in a total of 178 NUTS 2 regions which have been selected for the analysis covering eleven countries. Two variables were selected from the Eurostat database to deal with innovation performance and R&D expenditure. The first variable called patent applications to the EPO and the second variable, the intramural R&D expenditure as percentage of GDP for consecutive years from 2007 to 2012 were extracted as panel data due to both their availability and respecting the EU programming period 2007-2013. However, an adjustment had to be applied to this data selection as Germany and Austria provides their datasets relating R&D expenditures in odd years solely. In this case, the data for 2007, 2009, 2011 and 2013 were used. Data imputation for R&D expenditures in two German NUTS 2 regions, namely Niederbayern and Oberpfalz, was applied as a strategy for missing data management by subtracting the sum for Bavarian NUTS 2 regions with known R&D expenditures from the sum of R&D expenditures for Bavaria NUTS 1 region and dividing this interim result proportionally by number of patent application in the given year assuming linear relationships between these variables.

To reflect the time lag between R&D expenditure and innovation performance measured by patent applications to the EPO in this case the two years' lag was employed for the dependent variable. This temporally lagged variable (MPAT) was expressed as a three-year average for the period from 2007 to 2009 and from 2010 to 2012. This approach was opted based on Marrocu et al. (2013) and Varga et al. (2014) experimentation as there is no agreement as well as proof for optimal time lag relating to patent application. The same computation was used for smoothing of R&D expenditure as percentage of GDP 2012, creating variable MEXP as data may vary year by year and, moreover, the temporally lagged variable lessening the potential for endogeneity problem (Varga et al., 2014). Due to the availability of data for odd years only for variable R&D expenditure as percentage of GDP in German and Austrian case, the average for 2007 and 2009 for $MEXP_{2009}$ as well as average for 2011 and 2013 for $MEXP_{2012}$ was calculated.

The natural logarithm transformation was applied to reduce positive skew to make distribution of both variables more normal, which is a common feature of spatially aggregated economic data. Moreover, it is recommended to model percentage change of independent variable in relation to dependent variable, and vice versa using natural log of one or both variables. Hence, two transformed variables were created for further investigation of convergence and divergence in relation to innovation performance and R&D expenditures, i.e. LNMPAT and LNMEXP. The first variable (LNMPAT) is considered as a proxy for innovation performance in Western European NUTS regions respecting Varga et al. (2014) although being aware that not all innovation outputs can be patented per se. However, the patent application to the EPO is only one relevant source of data for comparison innovation outputs across time and space providing base for panel data regression. The second variable (LNMEXP) represents the proxy for R&D intensity relating to the objectives of the EUROPE 2020 strategy.

The presented spatial econometric analysis strategy consists of three stages, where the first employed Explanatory Spatial Data Analysis (ESDA) techniques, such as global spatial autocorrelation, local spatial autocorrelation (LISA) and differential local spatial autocorrelation (Differential LISA). The second stage used the difference-in-difference regression model, and the third stage utilized OLS regression, and the mixed autoregressive spatial model (SAR or spatial lag model) is exploited after examination of OLS models by set of test on diagnostics for spatial autocorrelation.

The first stage applying ESDA techniques was performed for A, revealing convergence or divergence for LNMPAT and LNMEXP comparing patterns of spatial association and B, suggesting spatial regimes for consequent investigation using spatial modelling and, moreover, spatial autocorrelation on change over time within these variables. The Moran I was applied as a standard measure for detection of global spatial autocorrelation where null hypothesis is set as absence of spatial autocorrelation and values of Moran I larger than the expected value E(I) = −1 (n−1) indicate positive spatial autocorrelation (Dominicis et al., 2011, p.10).

Moran I is defined as

$$I = \frac{\mathrm{N}}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{1}$$

where N is the sum of observations, w_{ij} is the element in the spatial weight matrix corresponding to the observation pair i, j (with i≠j), x_i and x_j are observations for the locations i and j (with mean x), and the first term is a scaling factor (ibid).

Local indicator of spatial association (LISA) or local spatial autocorrelation provides decomposition of global spatial autocorrelation such as Moran I into the contribution of each individual observation (Anselin

& Rey, 2014) as this global indicator is not able to distinguish between situations where the index is determined by close-by positive values or by close-by negative values (Dominicis et al., 2011, p.12). Hence, Local Moran I tests whether the distribution of values around that specific location deviates from spatial randomness (ibid, p. 13) and thereby can indicate both spatial clusters as detection of spatial regimes and spatial outliers as identification of spatial instability. Spatial cluster is an expression of positive spatial association, where one where a location with an above-average value is surrounded by neighbours whose values are also above average (high-high – HH), or where a location with a below-average value is surrounded by neighbours whose values are also below average (low-low – LL) (Dominicis et al., 2011, p.11). Spatial instability represents negative spatial association, where a location with an above-average value is surrounded by neighbours with below-average values (high-low – HL), or where a location with a below-average value is surrounded by neighbours with above average values (low-high – LH) (ibid). The local Moran I is computed in accordance to Anselin (2016) as:

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j} \left(x_j - \bar{x}\right) \quad (2)$$

where x_i is an attribute for feature i, $\bar{x}$ is the mean of the corresponding attribute, w_{ij} is the spatial weight between feature i and j, and

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} (x_j - \bar{x})^2}{n-1} \quad (3)$$

with n equating to the total number of features.

Differential local indicator of spatial association (differential LISA) is spatial autocorrelation on change over time, i.e. on $y_t - y_{t-1}$ (Anselin, 2016), where for example high-high spatial cluster suggested a positive spatial association of a NUTS 2 region with an above-average difference which is, in addition, surrounded with NUTS 2 regions of above-average difference (Lau et al., 2015) of LNMPAT or LNMEXP respectively.

Examining positive spatial association on LNMPAT using LISA (Figure 1) a spatial regime which was detected both in $LNMPAT_{2009}$ and $LNPAT_{2012}$ in southern Italian, western Spanish and all Portugal NUTS 2 regions. This spatial regime almost fit the delimitation of regions eligible for funding from the Structural Funds under the Convergence objective for the period 2007-2013 in these countries. Hence, respecting Commission Decision of 4th August 2006 (Commission of the European Communities, 2006), all these eligible NUTS 2 regions, including Área Metropolitana de Lisboa due to values of $LNMPAT_{2009}$ and $LNMPAT_{2012}$ as well as applied spatial weight matrix to avoid unconnected NUTS 2 regions, were assigned with value 1 in a dummy variable CONVERGSE, having been treated as a control variable, consequently applied spatial regression models in the second and third stage of the analysis.

The second stage of the analysis used difference-in-difference regression model (dummy variable regression) to compare full factorial model, i.e. main effect for time (y_{2012}– y_{2009}), main effect for spatial regime (CONVERGSE) and their interaction effect for variables $LNMPAT_{2009-2012}$ and $LNMEXP_{2009-2012}$ to test convergence or divergence relating to spatial regime utilizing CONVERGSE. Following approach in Anselin (2016) the regression model was defined as

$$y = \alpha + \gamma CONVERGSE_s + \lambda d_t + \delta(CONVERGSE_s * d_t) + \varepsilon \quad (4)$$

where,

- CONVERGSE is a dummy variable which is equal to 1 if the observation is from convergence NUTS 2 region in southern part of Western Europe in accordance with delimitation by the Commission of the European Communities (2006).
- d is a dummy variable which is equal to 1 if the observation is from 2012.

The third stage of the analysis commenced with OLS cross-sectoral regression to test $LNMEXP_{2009}$ and $LNMEXP_{2012}$, i.e. R&D intensity, controlling for CONVERGSE as determinants for innovation performance measured by $LNMPAT_{2009}$ and $LNMPAT_{2012}$ to check whether these explanatory variables significantly influenced the level of dependent variables over time. Theoretical assumption for OLS model relating to regression diagnostic such as multicollinearity (the multicollinearity condition number), normality (Jarque-Bera test), and heteroskedascity (Breusch-Pagan, Koenker-Bassett, and White test) were fulfilled in both cases, i.e. y_{2009} and y_{2012}). The White heteroskedasticity-consistent standard errors were utilized for both regression diagnostics. Diagnostic of spatial autocorrelation based on Lagrange Multiplier test statistics and their robust versions respectively was applied to decide which alternative of spatial model specification should be used, i.e. whether spatial autoregressive model (SAR or spatial lag model) or spatial error model (SEM). As the robust Lagrange Multiplier (lag) test were significant ($p<0.05$) in both cases, spatial autoregressive models were estimated in accordance with Anselin & Rey (2014) where values of the dependent variable in neighbouring locations (Wy) are included as an extra explanatory variable. Thus, the SAR model controls spatial autocorrelation in the dependent variable, i.e. dependent variable is influenced by its values in neighbours.

Hence, a mixed spatial autoregressive model (SAR), i.e. spatial lag model with other additional explanatory variables, was applied according to Anselin & Rey (2014, p. 159) as follows:

$$y = \rho Wy + X\beta + u \tag{5}$$

where,

W is a n × n spatial lag operator, Wy is the spatial lag term with spatial autoregressive parameter ρ, X is an n × k matrix of observation on explanatory variables with k × 1 coefficient β, and a n × 1 vector of errors u.

Thus, for cross-sectional data on LNMPAT for the given year the SAR model was extended and estimated as:

$$y = \rho WLNMPAT_t + \beta LNMEXP_t + \beta CONVERGSE + u \tag{6}$$

Respecting meeting with all OLS assumptions, the maximum likelihood estimation was used for SAR models, which allows mutual comparison of both OLS and SAR regression for the best fitted model identification based on log likelihood, and information criterion, i.e. Akaike (AIC) and Bayesian-Schwarz (BIC) ones, where the rule 'lower value' for better quality model was implemented.

4. EMPIRICAL RESULTS AND DISCUSSION

As the original aggregated data for MPAT and MEXP present skew, therefore, in addition, results of median computations are included in the descriptive statistics. The total sum of patent applications to the EPO decreased from 51,703.5 in 2009 to 47,568.4 in 2012. The MPAT shows mean 298.5, st. dev. 446.5 and median 136.8 for 2009, and mean 267.2, st. dev. 401.8 and median 128.6 for 2012. The MEXP exhibits mean 1.7%, st. dev. 1.2% and median 1.3% for 2009 and mean 1.8%, st. dev. 1.2% and median 1.5% for 2012.

Table 1

Moran's I measure of spatial autocorrelation for selected variables*

Variable	Moran's I	St. Dev.	Z-Value	P-Value
$LNMPAT_{2009}$	0.345	0.034	10.293	**0.000*** **
$LNMPAT_{2012}$	0.347	0.034	10.251	**0.000*** **
$LNMPAT_{2012-2009}$	0.078	0.034	2.143	**0.012***
$LNMEXP_{2009}$	0.115	0.034	3.511	**0.001*** **
$LNMEXP_{2012}$	0.185	0.034	5.531	**0.000*** **
$LNMEXP_{2012-2009}$	0.107	0.039	3.321	**0.002****

Source: Authors' results based on Eurostat (2016)
*based on 10^4 permutations, * indicates significance level at 0.05 level ** indicates significance level at 0.01 level, *** indicates significance level at 0.001 level.

Table 1 compares global Moran's I measure for LNMPAT and LNMEXP as well as their time lagged counterparts. Positive values of this indicator demonstrate positive spatial autocorrelation within all variables and therefore significant spatial clustering. The higher Moran's I values for LNMPAT exhibit more spatial concentration than LNMEXP values, i.e. these are spatially more dispersed vice versa.

Figure 1 depicts spatial clustering of high-high LNMPAT values in German NUTS 2 regions in both observed years, where Sachsen region converged to this category.

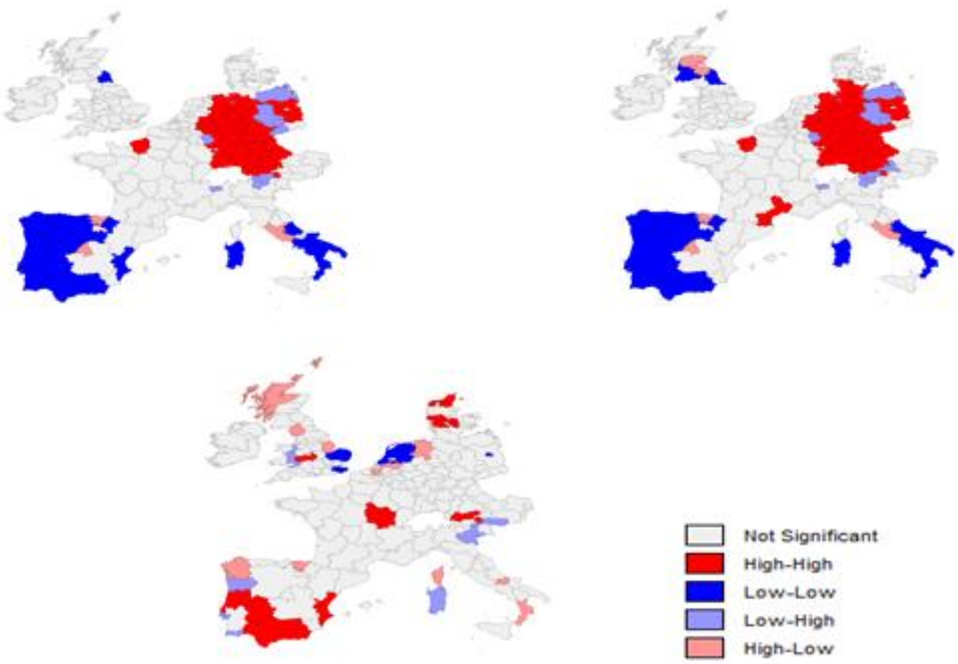

Figure 1. Local Moran's I scatterplot map* for patent applications to the EPO 2009 (top-left), patent applications to the EPO 2012 (top-right), and patent applications to the EPO 2012-2009 (bottom)
Source: Authors' elaboration based on Eurostat (2016). *based on 10^4 permutations.

On the contrary, low-low values reveal spatial concentration primarily in Portuguese, western Spanish and southern Italian NUTS 2 regions. Spatial heterogeneity was indicated in differences over time where β - divergence was inspected in NUTS 2 regions in the Netherlands and β - convergence in southern Spanish regions vice versa. In addition, spatial instability was found in Scotland (high-low values). The similar spatial pattern showed by LNMEXP in Figure 2 is pronounced as the positive spatial autocorrelation was founded in Germany but with indication of more spatial instability (negative autocorrelation) with low-high values in 2009 and, on the contrary, high-high values for eastern German NUTS 2 regions. Thus, the convergence was revealed between western and eastern German region but the divergence was detected in northern Portuguese and western Spanish regions which resulted in opposite process to σ convergence.

The inspection of differences over time reveals spatial instability as well as spatially clustered divergence in England NUTS 2 regions.

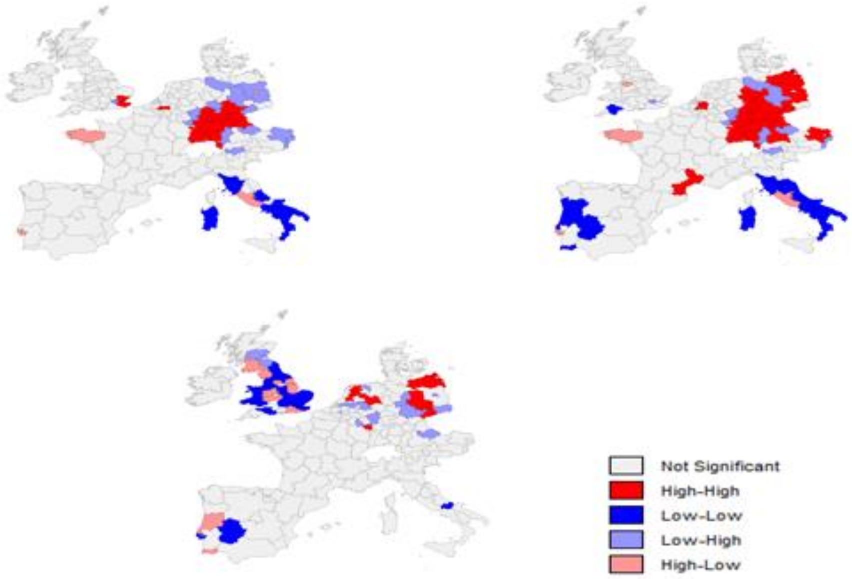

Figure 2. Local Moran's I scatterplot maps for total intramural R&D expenditure as percentage of GDP2009 (top-left), R&D expenditure as percentage of GDP 2012 (top-right), and R&D expenditure as percentage of GDP 2012-2009 (bottom)

Source: Authors' elaboration based on Eurostat (2016). *based on 10^4 permutations.

Table 2

Difference-in-difference regression results comparing time and spatial regime for patent applications to the EPO 2009-2012

Variable	**Coefficient**	**Std. Error**	**T-Statistic**	**P-Value**
CONSTANT	5.062	0.100	50.449	**0.000*** **
SPACE (CONVERGSE)	-2.006	0.307	-6.533	**0.000*** **
$TIME_{2009-2012}$	-0.072	0.142	-0.504	**0.614**
INTERACT	0.012	0.434	0.027	**0.979**
Adj. R^2	0.188			
F-statistic	28.384			**0.000*** **
Log likelihood	-586.853			
AIC	1181.71			
BIC	1197.21			

Source: Authors' elaboration based on Eurostat (2016). ***indicates significance level at 0.001 level.

Table 3

Difference-in-difference regression results comparing time and spatial regime for R&D expenditure as percentage of GDP 2012

Variable	Coefficient	Std. Error	T-Statistic	P-Value
CONSTANT	0.368	0.049	7.592	**0.000*** **
SPACE (CONVERGSE)	-0.527	0.149	3.547	**0.000*** **
$TIME_{2009-2012}$	0.087	0.069	1.267	**0.206**
INTERACT	-0.086	0.210	-0.407	**0.684**
Adj. R^2	0.073			
F-statistic	10.341			**0.000*** **
Log likelihood	-328.117			
AIC	664.234			
BIC	679.734			

Source: Authors' elaboration based on Eurostat (2016). *** indicates significance level at 0.001 level.

Table 2 and Table 3 indicate the same results for determinants in difference-in-difference regression of both LNMPAT and LNMEXP, where the selected eligible lagged regions for the EU Convergence objective (CONVERGSE) were detected as significant supporting continuation of regional innovation paradox as well as spatial regime, and suggesting that no changes were proved over time. However, the model for LNMEXP provided better fit model than the LNMPAT one show in lower values of log likelihood AIC and BIC.

The first and second model applying OLS regression in Table 4 and Table 5 estimated as significant determinants $LNMEXP_{2009}$ and $LNMEXP_{2012}$ for both dependent variables, i.e. $LNMPAT_{2009}$ and $LNMPAT_{2012}$ respectively, as well as dummy variable CONVERGSE. The positive sign of both LNMEXP indicators means that increasing R&D expenditures suggest higher innovative performance while negative sign of CONVERGSE indicates that the selected eligible lagged regions for the EU Convergence objective in programming period 2007-2013 performed lower that the other regions, which is similar to the results in Table 1. As both robust Lagrange Multiplier spatial lag tests suggested, the spatially lagged dependent variable (W_LNMPAT) was significant employing SAR model detecting influence of LNMPAT in neighbouring regions to the given region, i.e. spatial autocorrelation. Moreover, both SAR models performed better fit than OLS models referring to log likelihood, AIC and BIC values.

Our research confirmed spatial clusters in innovation performance in accordance with Dominicis et al. (2011), who used the cross-sectional aggregated data from 2000 to 2002, i.e. spatial concentration of high-high regions in western Germany and low-low regions in western Spanish, Portuguese as well as in southern Italian NUTS 2 regions. In addition, our paper verified that R&D expenditures as the significant determinant along with the spatial regime of the abovementioned lagged regions for innovation performance in accordance with findings in Varga et al. (2012) and Lau et al. (2015) respectively. Finally, the results of the paper support Oughton et al (2002) recommendations for lagged regions suffering from regional innovation paradox as well as synthesis of objectives and means for regional innovation policies by Autant-Bernard et al (2013); Borrás & Edquist (2013). Nonetheless, all these lagged regions are considered to be precise when they apply regional innovation policies related to their specifics in both regional innovation systems and regional smart specializations, conditions and barriers in accordance to type of regions to avoid the 'one size fits all' approach (Tödtling & Trippl, 2005) under their implementation.

Table 4

Regression results for OLS and spatial-lag model for patent applications to the EPO 2009

Variable	Model 1	Model 2
	OLS	**SAR (ML)**
CONSTANT	4.595***	3.214***
$LNMEXP_{2009}$	1.268***	1.243***
CONVERGSE	-1.338***	-0.691*
W_LNMPAT_{2009}		0.272*
Adj. R^2/R^2	0.493	0.521
F-statistic	86.879***	
Log likelihood	-252.459	-249.144
AIC	510.918	506.287
BIC	520.463	519.014
LM (lag)	12.185***	
Robust LM (lag)	7.871**	
LM (error)	5.442*	
Robust LM (error)	1.128	
SARMA	13.313**	
Likelihood Ratio Test		6.631**

Source: Authors' elaboration based on Eurostat (2016). * indicates significance level at 0.05 level, ** indicates significance level at 0.01 level, *** indicates significance level at 0.001 level

Table 5

Regression results for OLS and spatial-lag model for patent applications to the EPO 2012

Variable	Model 1	Model 2
	OLS	**SAR (ML)**
CONSTANT	4.401***	3.060***
$LNMEXP_{2012}$	1.293***	1.254***
CONVERGSE	-1.203***	-0.607*
W_LNMPAT_{2012}		0.270*
Adj. R^2/R^2	0.503	0.529
F-statistic	90.387***	
Log likelihood	-248.310	-245.088
AIC	502.620	498.176
BIC	512.165	510.903
LM (lag)	10.159**	
Robust LM (lag)	6.134*	
LM (error)	4.646*	
Robust LM (error)	0.621	
SARMA	10.780**	
Likelihood Ratio Test		6.444*

Source: Authors' elaboration based on Eurostat (2016). * indicates significance level at 0.05 level, ** indicates significance level at 0.01 level, *** indicates significance level at 0.001 level

5. CONCLUSION

The aim of the paper was to determine both static and dynamic components of convergence and divergence in innovation performance and R&D expenditures for aggregated data within Western European NUTS 2 regions in the years 2009-2012.Consequently, our research proved the continuation of regional disparities of innovation performance in Western European NUTS 2 region, i.e. lower performance in lagged regions was revealed in the period from 2009 to 2012. The positive spillover effect was exhibited in the case of Brandenburg and Berlin NUTS 2 regions in eastern Germany and showed their presence in high-high regions as an example of convergence. Contrariwise, southern Spanish NUTS 2 regions showed β-convergence in the period 2009-2012. Nevertheless, σ-convergence was not confirmed. Moreover, R&D expenditures reflected convergence in eastern German NUTS 2 regions which can be considered and divergence in southern Italian ones vice versa. Thus, although these southern Italian regions were eligible for subsidies under the EU Convergence objective for programming period 2007-2013, these subsidies not encouraged them as lagged regions to show β - convergence between period 2009-2012 but, on the contrary, they exhibited divergence. Furthermore, the lagged regions, i.e. Portuguese, western Spanish and southern Italian, having been under the EU Convergence objective, exhibited spatial regime and thereby verified regional innovation paradox where the time lag is not proved as determinant for the change. Thus, the detected spatial regime leads to the confirmation of continuation of regional disparities in innovation performance as well as in R&D expenditures although the presence of β-convergence in lagged NUTS 2 regions was revealed. However, σ convergence was not confirmed as time did not prove significant contribution to the estimation in our difference-in-difference regression models. Thereby, confirmed innovation paradox suggests a research question whether increasing R&D expenditures lead to higher innovation performance in the Edison type of research in lagged NUTS 2 regions again. Despite the results, it is proposed to develop the given dataset exploiting spatial panel data regression to control for the years 2009-2012, and other determinants suggested in Varga et al. (2012); Lau et al. (2015). This proposal is specifically projected to confirm significance of these determinants for regional innovation performance.

ACKNOWLEDGEMENT

The authors are thankful to the Operational Programme Education for Competitiveness (Project No. CZ. 1.07/2.3.00/20.0296) and Tomas Bata University in Zlín (Project No. VaV-IP-RO/2016/08).

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