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Spatial spillovers and European Union regional innovation activities

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Abstract

This paper explores the role of spatial spillovers in the innovation processes across 245 NUTS 2 European Union (EU) regions for the 2008–2012 period. The patent applications at the European Patent Office were chosen as a proxy for innovative activity. In the first step of the empirical analysis, the spatial pattern examination of the innovative activity based on the selected global and local indicators for spatial association confirmed the presence of a spatial dependence process in the distribution of innovative activity. Next, we attempted to model the behaviour of innovative activity at the EU regional level on the basis of extended regional knowledge production model. Spatial econometric analysis indicated the relevance of internal innovation inputs (R&D expenditure and human resources in science and technology) and we also found out that, the production of knowledge by EU regions seems to be also affected by spatial spillovers due to innovative activity performed in other regions.

Keywords EU regions · Research and development · Innovation activities · Spatial spillover impacts · General Nesting Spatial econometric model

1 Introduction

In recent decades, many theoretical as well as empirical studies have highlighted the role of technology as a key factor in the process of country and regional growth. Also, most theories of economic growth regard knowledge and technological progress as the main drivers of economic dynamics (Solow 1956; Romer 1986, 1990; Lucas 1988; Barro 1990; Rebelo 1991). Innovation and technological progress have played

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an important role not only in research but also in the agenda of economic policy makers. There is now a general consensus that innovation and knowledge play a crucial role in the competitiveness of companies and the process of economic development of regions and countries. These ideas also form the basis of the European Union (EU) strategic document "Europe 2020" (European Commission 2010) where research and development are essential components of the so-called "Smart Growth". "Smart Growth: Developing an economy based on knowledge and innovation" is one of the EU's three priorities for the period 2010–2020.

Conte et al. (2009) states two main economic reasons why the EU governments should actively stimulate investment in research and development (R&D). In the first place, research and development are generally considered to be the main driver of long-term economic development. The goal of R&D activities is to create new ideas and innovations that can be transformed into commercially exploited innovations. The second reason is that the private R&D investment is risky, with unclear results and outcomes. The government's role in R&D investing is therefore very important, especially during economic crises.

Although knowledge diffusion has geographic components, the spatial aspect was not explicitly taken into account in economic growth theory, and the role of spatial effects was ignored (see e.g., Grossman and Helpman 1991; Lucas 1988; Romer 1986; Romer 1990). In recent years, however, we have noted a great interest in analysing whether states, countries (regions) with high (low) productivity levels are randomly spread in space or concentrated in specific areas. In the spatial context, local economic performance depends not only on the level of local inputs or potentially also on inputs in neighbouring locations (Coe and Helpman 1995; Martin and Ottaviano 2001). Taking into account spatial dependencies, asymmetries in relations and the interaction of objects and data that are the subject of econometric modelling, spatial econometrics is concerned. Also gravity approach can be applied for modelling spatial interaction between spatial units. This approach is based on the gravity theory which can be considered as a relational theory which describes the degree of spatial interaction between two or more points in a manner analogous to physical phenomena (for more details see e.g., Nijkamp and Reggiani 1992; Paas 2000; Bogataj and Drobne 2005; Drobne and Bogataj 2005).

The main area of interest of spatial econometrics are spatial effects, namely spatial autocorrelation and spatial heterogeneity. The term spatial dependence refers to spatial autocorrelation, and the term spatial structure is related to spatial heterogeneity. Nowadays, spatial econometrics is adapted in theoretical econometrics and its popularity is also growing in the area of empirical works. The main reason for this growing interest is the shift in consideration from individual entities that take decisions in isolation to take into account the mutual interaction of objects. Another important reason for increased interest in spatial econometric tools is the better accessibility of geocoded data that contain information about the location of spatial units (observations), e.g., address or latitude and longitude.

The lack of specialized technologies, geographic systems and software support were among the reasons for the slow development of spatial econometrics. Over the last two decades, there has been a significant expansion of specialized technologies, Geographic Information Systems (GIS) as well as software products for application of spatial econometrics.

An important milestone in the history of spatial econometrics was the presentation of a "New Economic Geography" (NEG) theory. This approach is linked to the works of Krugman (1991), Fujita et al. (1999), Ottaviano and Puga (1997) or Venables and Puga (1999). NEG models provide a framework for spatial analysis of economic data when examining issues such as regional convergence, regional concentration of economic activities and adjustment dynamics. Also, the number of empirical studies on geographic aspects of knowledge and innovation activities has increased (Jaffe et al. 1993; Feldman 1994; Feldman and Florida 1994; Audretsch and Feldman 1996; Anselin and Varga 1997; Anselin et al. 2000a, b; Acs et al. 2002). The innovation process, the accumulation of knowledge as well as its dissemination are often heavily localized into clusters of innovative companies, sometimes in close cooperation with public institutions such as research centres and universities. Geographic concentration of companies allows companies to exploit technological development, share experiences with similar technologies, knowledge, etc. Most new technological opportunities depend on the scientific knowledge that results from the research of universities or research centres. The geographic proximity of companies and research institutions makes it possible for scientific information to be translated into practice. It is therefore clear that the localization of knowledge and the ability to absorb external knowledge (absorption capacity) are two phenomena that are considered as key factors in analysing the determinants of local technological progress and consequently local economic growth.

Griliches (1979; Pake and Griliches 1980) proposed to analyse the determinants of innovation activities through the Knowledge Production Function (KPF), finding that the KPF model is better suited to describe the functional relationship between technological progress and innovation inputs at the country/region economic sector level than at company or firm level.

Regional analysis based on Regional Knowledge Production Function (RKPF) has been widely used to assess the role of regional inputs in the process of innovation activities. According to the authors such as Audretsch and Feldman (2004), the knowledge can not only have a local character, but knowledge can also be generated beyond the boundaries of the analysed region, because there is no reason why the diffusion of knowledge should be stopped, because of the borders of the region or the borders of the state. Knowledge that is the output of one region can spread to other regions, affecting their innovation activities, and geographic proximity allows for faster knowledge diffusion. Such spatial interconnections motivate for the modified RKPF model specification to capture the regional innovation activities that may potentially influence the innovation process in neighbouring regions. The study of Jaffe (1989) was the first work in which the RKPF model took into account the spatial context. From other studies dealing with the so-called knowledge spillover effects can be mentioned the studies of e.g., Audretsch and Feldman (1996), Moreno et al. (2005a, b), Kumar (2008), Khan (2012) and Charlot et al. (2015).

It is clear that one of the main objectives of R&D policy is to increase innovation outcomes. However, the problem is how to measure the level of innovation activities and technological progress, and to answer this question, what can be considered as innovative output, is not easy and can be represented in different ways. Based on the RKPF concept, two types of indicators are usually considered: technological innovation inputs (e.g., R&D expenditure and human capital) and technological innovation outputs (e.g., scientific publications and citations, patents or new products).

The complexity of the innovation process is a relevant challenge for empirical research, especially when quantitative approaches are applied. The aim of this paper will be the verification of localized knowledge and absorption capacity roles in the process of increasing innovation outputs of the EU regions. Empirical part of the paper will include verification of two hypotheses:

Hypothesis 1 We hypothesize that the regional innovation process (represented by patent applications) is influenced by innovation activities in neighbouring regions.

Testing the hypothesis 1 In order to test hypothesis 1, global and local spatial autocorrelation statistics, namely global Moran's I and local Getis–Ord statistics will be used. These spatial autocorrelation statistics tools will allow us to detect potential spatial dependencies at global and local levels and quantify the intensity and the type of spatial dependencies as well.

Hypothesis 2 Does the location of the region matter in the regional innovation process modelling? We hypothesize that there is global level of spillover innovation effects among the EU regions, i.e., the changes in innovation inputs (R&D expenditure and human resources in science and technology) in the ith region will affect the number of patent applications not only the region itself but these changes will also have significant impacts on neighbouring regions with higher degree of neighbourhood.

Testing the hypothesis 2 Spatial econometric model (two versions) will be applied as the hypothesis validation tool. The models will be used to quantify and to test statistical significance of the direct, indirect and total impacts of the selected innovative inputs. Following spatial partitioning of these impacts and their statistical significance we will try to answer the question what level of neighbourhood degree still matter in the regional innovation process modelling.

2 Theoretical backrounds

The greatest attention within the spatial econometrics is focused on the estimation of models with spatially autoregressive process, i.e., models that explicitly allow for spatial dependence through spatially lagged variables. This group of models includes the well-known SAR (Spatial Autoregressive) model, which in the simplest version only assumes spatial spillover effects within the dependent variable. A generalized version of this model is called General Nesting Spatial (GNS) model, which includes all types of spatial interaction effects. The GNS model for cross-sectional data in matrix form takes the following form:

$$\begin{aligned} \mathbf{y} &= \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \mathbf{u} \\ \mathbf{u} &= \lambda \mathbf{W}\mathbf{u} + \mathbf{v}, \quad \mathbf{v} \sim N\left(\mathbf{0}, \sigma_v^2 \mathbf{I}_N\right) \end{aligned} \tag{1}$$

where $\mathbf{y}$ denotes $N \times 1$ vector of the observed dependent variable for all N locations, $\mathbf{X}$ denotes a $N \times k$ matrix of exogenous explanatory variables (k represents the number of explanatory variables), $\boldsymbol{\beta}$ is associated $k \times 1$ vector of unknown parameters to be estimated, $\mathbf{v} \sim N\left(\mathbf{0}, \sigma_v^2 \mathbf{I}_N\right)$ is $N \times 1$ vector of random errors, σ_v^2 is random error variance, $\mathbf{I}_N$ is N dimensional unit matrix and $\mathbf{W}$ is N dimensional spatial weighting matrix (for details concerning construction and different approaches see e.g., Chocholatá 2017). Model (1) includes all types of interaction effects, namely endogenous interaction effects among the dependent variable ($\mathbf{Wy}$), the exogenous interaction effects among the independent variables ($\mathbf{WX}$) and the interaction effects among the disturbance term of the different units ($\mathbf{Wu}$). Hence $k \times 1$ vector $\boldsymbol{\gamma}$, parameters ρ and λ represent spatial autoregressive parameters and their statistical significance, value and mathematical character indicate the direction and the strength of spatial dependence. Other spatial econometrics models can be obtained from the GNS model by imposing restrictions on one or more of its parameters e.g., SEM—Spatial Error Model (Anselin 1988; LeSage and Pace 2009), SARAR also called SAC or Cliff—Ord model (Kelejian and Prucha 1998), SDM—Spatial Durbin Model (Anselin 1988), SDEM—Spatial Durbin Error Model (LeSage and Pace 2009) or SLX model (Spatial Lag v X) (Gibbons and Overman 2012).

Estimation of spatial autoregressive models requires special estimation methods. The problem is caused for example by the presence of spatially lagged variable $\mathbf{Wy}$ on the right hand side of the regression equation (in GNS, SDM, SAR, SARAR models), which causes problems with endogeneity (see the assumptions of the classical linear model e.g., Ivaničová et al. 2012) and therefore the least squares method (OLS) is not a suitable estimation method. The estimation of spatial econometric models is based on familiar estimation econometric methods but they must be modified with respect to spatial aspects: Maximum Likelihood (ML), two-stage least squares (2SLS), and generalized moment method (GMM). The latest approaches use Bayesian's MCMC (Markov Chain Monte Carlo) estimation method (LeSage and Pace 2009). Review of estimation methods can be found in Anselin and Rey (2014).

2.1 Direct, indirect and total impacts in spatial econometric models

Spatial econometric models are characterized by a complicated structure of spatial dependencies between spatial units (such as districts, regions or states). Due to the spatial dependence, the estimated parameters of the spatial econometric model contain more information about relations between spatial units compared to the classical linear regression model. Let us consider the classical linear regression model: $y = \sum_{r=1}^{k} x_r \beta_r + u$, where r denotes the rth explanatory variable. In this case, linear regression parameters have a straightforward interpretation as the partial derivative of the dependent variable with respect to the explanatory variable. This stems from the linearity and independence assumptions of observations in the model. Partial derivatives of y_i with respect to x_{ir} correspond to parameter of given variables, i.e., $\frac{\partial y_i}{\partial x_{ir}} = \beta_r$ for $\forall i, r$ and this derivatives equal $\frac{\partial y_i}{\partial x_{jr}} = 0$ for $j \neq i$ and $\forall r$. These conclusions are not valid in spatial models that contain spatial lags of explanatory variables and/or dependent variables. The expected value of the dependent variable in the ith location is no longer influenced only by exogenous location characteristics, but also by the exogenous characteristics of all other locations through a spatial multiplier $(\mathbf{I}_N - \rho\mathbf{W})^{-1}$ (for more details see LeSage and Pace 2009). To demonstrate this effect, let us consider SDM model in the following form:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \mathbf{u} \tag{2}$$

After simple formula modification and adding a constant term into the model (2), we get the following formula:

$$(\mathbf{I}_N - \rho\mathbf{W})\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \mathbf{l}_N\alpha + \mathbf{u} \tag{3}$$

where $\mathbf{l}_N$ represents $N \times 1$ vector of ones associated with the constant term α. Let us consider next model adaptation:

$$\mathbf{y} = \sum_{r=1}^{k} \mathbf{S}_r(\mathbf{W})\mathbf{x}_r + \mathbf{V}(\mathbf{W})\mathbf{l}_N\alpha + \mathbf{V}(\mathbf{W})\mathbf{u} \tag{4}$$

where

$$\begin{aligned} \mathbf{S}_r(\mathbf{W}) &= \mathbf{V}(\mathbf{W})(\mathbf{I}_N\beta_r + \mathbf{W}\gamma_r) \\ \mathbf{V}(\mathbf{W}) &= (\mathbf{I}_N - \rho\mathbf{W})^{-1} = \mathbf{I}_N + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \rho^3\mathbf{W}^3 + \cdots \end{aligned}$$

The relation in (4) indicates that the partial derivatives $\frac{\partial y_i}{\partial x_{jr}}$ for $j \neq i$ and $\forall r$ is not necessarily zero but equals:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \tag{5}$$

The relation (4) indicates that own derivative for the ith location does not equal to the parameter estimate but results in:

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii} \neq \beta_r \tag{6}$$

The relationship (5) implies that changing the explanatory variable in a given spatial unit can affect the dependent variable in other spatial units, as a consequence of the simultaneous spatial structure in the SDM model (as well as in the GNS, SAR, SARAR models). Changes in neighbouring location characteristics may cause changes in the value of the dependent variable in particular region that will affect the value of the dependent variable in neighbouring units. These impacts are dispersed within the system of locations under the consideration. Formula (5) quantifies the indirect impact and direct impact is quantified by the formula (6). Direct impact captures feedback loops where observation i affects observation j and observation j also affects observation i as well as longer parts which might go from observation i to j to k and back to i. The derivatives in (6) equals the scalar $S_r(W)_{ii}$ what

Table 1 Summary measures of direct, indirect and total impacts

Average total impacts (*ATI*)	$ATI = N^{-1}\mathbf{l}_N^{\mathrm{T}}\mathbf{S}_r(\mathbf{W})\mathbf{l}_N$
Average direct impacts (*ADI*)	$ADI = N^{-1}\mathrm{tr}(\mathbf{S}_r(\mathbf{W}))$
Average indirect impacts (*AII*)	$AII = ATI - ADI$

Source: own elaboration

Table 2 Overview of *ADI*, *ATI* and *AII* impact measures

SDM model (**Wy**, **WX**)/GNS model (**Wy**, **WX**, **Wu**)	
Average total impacts (*ATI*)	$N^{-1}\mathbf{l}_N^{\mathrm{T}}(\mathbf{I}_N - \hat{\rho}\mathbf{W})^{-1}\left(\mathbf{I}_N\hat{\beta}_r + \mathbf{W}\hat{\gamma}_r\right)\mathbf{l}_N$
Average direct impacts (*ADI*)	$N^{-1}\mathrm{tr}\left((\mathbf{I}_N - \hat{\rho}\mathbf{W})^{-1}\left(\mathbf{I}_N\hat{\beta}_r + \mathbf{W}\hat{\gamma}_r\right)\right)$
Average indirect impacts (*AII*)	$AII = ATI - ADI$
SAR model (**Wy**)/SARAR model (**Wy**, **Wu**)	
Average total impacts (*ATI*)	$(1 - \hat{\rho})^{-1}\hat{\beta}_r$
Average direct impacts (*ADI*)	$N^{-1}\mathrm{tr}\left((\mathbf{I}_N - \hat{\rho}\mathbf{W})^{-1}\left(\mathbf{I}_N\hat{\beta}_r\right)\right)$
Average indirect impacts (*AII*)	$AII = ATI - ADI$
SLX model (**WX**)/SDEM model (**WX**, **Wu**)	
Average total impacts (*ATI*)	$\left(\hat{\beta}_r + \hat{\gamma}_r\right)$
Average direct impacts (*ADI*)	$\hat{\beta}_r$
Average indirect impacts (*AII*)	$\hat{\gamma}_r$
OLS model/SEM model (**Wu**)	
Average total impacts (*ATI*)	$\hat{\beta}_r$
Average direct impacts (*ADI*)	$\hat{\beta}_r$
Average indirect impacts (*AII*)	0

Source: own elaboration

is the diagonal element of the matrix $\mathbf{S}_r(\mathbf{W}) = (\mathbf{I}_N - \rho\mathbf{W})^{-1}(\mathbf{I}_N\beta_r + \mathbf{W}\gamma_r)$. Following a series expansion of the inverse term, this matrix can also be written as $\mathbf{S}_r(\mathbf{W}) = \left(\mathbf{I}_N + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \rho^3\mathbf{W}^3 + \cdots\right)(\mathbf{I}_N\beta_r + \mathbf{W}\gamma_r)$. From this matrix obvious feedback effects can be seen since this matrix contains e.g., matrix $\mathbf{W}^2$ which reflects second order neighbours and contains non-zero elements on the diagonal. The magnitude of these feedbacks depends on a number of factors such as the position of the locations in space, the spatial interconnection of the regions as well as the regression parameter values. The diagonal elements of the matrix $\mathbf{S}_r(\mathbf{W})$ provide information about direct impacts, and non-diagonal elements of this matrix represent indirect impacts. Since the matrix $\mathbf{S}_r(\mathbf{W})$ has the $N \times N$ dimension and we are considering k explanatory variables, the total number of partial derivatives is $k \times N^2$. LeSage and Pace (2009) suggested a summary measures of these impacts (see Table 1). An overview of the *ATI, ADI*, and *AII* impacts for spatial and non-spatial models is shown in Table 2.

In the context of indirect impacts, it is questionable whether these impacts have local or global nature or in other words, whether it is local or global spatial spillover effects (Anselin 2003). A key aspect in distinguishing these effects is the existence of feedbacks in the spatial model. The local spatial spillover effects are characterized by the absence of endogenous interactions and feedbacks. Endogenous interactions means that changes in the ith spatial unit activate a series of reactions in others, potentially in all spatial units. The local spillover effect does not cause such a series of reactions and concerns only neighbouring spatial units where this effect is extinguished. Models with local spillover specifications include SLX and SDEM models where local spatial spillover effects are taken into consideration through the $\mathbf{WX}$ term. The GNS, SAR, SARAR, and SDM models are models with global spatial spillover effects because they contain spatial lag variable $\mathbf{Wy}$.

In order to draw inferences regarding the statistical significance of individual impacts associated with changing the explanatory variables, the distribution of scalar summary impact measures is required. For this purpose, simulation approaches are applied which allow for the empirical distribution of model parameters, which is constructed based on the use of a large number of simulated parameters from the multivariate normal distribution of the parameters implied by ML estimates (LeSage and Pace 2009).

3 Data and empirical results

The spatial spillover analysis of the EU regional innovation activities was performed based on the cross-sectional data set obtained from the regional Eurostat statistics database (http://ec.europa.eu/eurostat/). The dataset includes 245 NUTS 2 (Nomenclature of Units for Territorial Statistics) EU regions from the 26 countries surveyed for 2008–2012[1] period. Based on the RKPF concept, we have chosen patent applications from the European Patent Office (number per million inhabitants) as a proxy for innovative output. Despite certain limitations associated with patent applications as an indicator of innovation output, patent applications are considered to be an adequate "representative" of innovation activities because the patent process is a demanding procedure, and only innovations that are potentially of high value are considered. At the beginning of the empirical analysis, we had to exclude 20 island regions of Cyprus, Malta, France, Finland, Spain, Greece, Portugal and Italy from our sample of data in order to avoid possible problems with isolated regions. Another data file reduction had to be done due to missing data. We excluded 7 regions of Bulgaria, Germany and Greece. Following other empirical analyses of the innovation activities of the EU regions (e.g., Moreno et al. 2005a, b; Khan 2012; Kumar 2008), the more appropriate spatial units are the EU regions at NUTS 2 level than at higher territorial level e.g., at national level. In our analysis, therefore, the spatial units are the EU regions at NUTS 2 level. The geographic characteristics of these spatial units, in this case of the spatial units—polygons, contain the .shp file obtained from the Eurostat webpage,

[1] The year 2012 was the last published year of used statistics at the time of the analysis and the chosen time span was determined mainly by the availability of data.

which was subsequently corrected in the GeoDa[2] software. The regions included in our analysis are shown in Figs. 1 and 2 in form of quantile, natural breaks[3] and box[4] maps. Figure 1 shows the innovation activities of the regions in 2008 and 2012. Based on the 2008 quantile map, the most intensive innovation activities are evident for the initial period under review, especially in the regions of "western" Germany, Austria, the Netherlands, Denmark and Luxembourg. Several regions with the most intensive innovation activity can be found in northern Italy, France, Sweden, Finland and the UK. On the contrary, the low level of innovation activity is associated with regions of southern Europe such as the regions of Spain, Portugal, Greece and southern Italy. The same, low intensity of innovation activities is also reported by most of the former socialist countries. Compared to the year 2012, based on the Fig. 1 similar pattern of regional innovation activities is evident as in 2008. However, with regard to the level of innovation activities in 2008 and 2012, we see (Fig. 1) that in 2012 there was a significant decrease in patent applications compared to 2008. While in 2008, the average regional innovation output was 214.47 patents per million of inhabitants; in 2012, it was surprisingly only 85.91 patents per million of inhabitants. Since 2008, a continuous decrease in the average value of patent applications is recorded (in brackets): 2008 (214.47), 2009 (212.07), 2010 (211.93), 2011 (175.83) in 2012 (85.91). This negative trend can be attributed to the financial crisis beginning in 2008.

Figure 1 also provides natural breaks maps for 2008 and 2012, which provides a more adequate insight into the region's innovative activities compared to the quantile maps. In the quantile maps, there are many "dark" fields, i.e., many regions are perceived as "top" regions in the field of innovative activities. In natural breaks maps, the distribution of regions into four categories is uneven, which means that, for example, the number of regions with the highest values is only 14 in 2008 and only 9 in 2012. The regions with the highest innovation activity are mainly the regions of Germany, Austria, Luxembourg, Sweden and Finland, the difference between 2008 and 2012 again being minimal. These "top" regions identified on the basis of natural breaks maps are almost in accordance with the so-called outliers in the fourth quartile in the box maps (Fig. 2). With regard to outliers in the first quartile, no extreme values of this character were identified on the basis of the box map in 2008 and even in 2012.

The application of spatial econometrics tools is based on the construction of the spatial weight matrix W and therefore the first step of the empirical analysis was its construction. We have chosen several different approaches to constructing this matrix but based on the preliminary analysis,[5] just the following k—nearest neighbours approach was applied. Based upon the arc distance (for more details see e.g., Anselin and Rey 2014) the centroid distances from each unit i to all other units $j \neq i$ were ranked as follows: $d_{ij(1)} \leq d_{ij(2)} \leq \cdots \leq d_{ij(244)}$. Then for each $k = 1, \ldots, 244$, set $B_k(i) = \{j(1), j(2), \ldots j(k)\}$ contains k nearest neighbours to the unit i. For each

[2] The empirical part of the paper was carried out in the GeoDa, GeoDa Space and R software packages.

[3] Natural Breaks Maps are constructed on the basis of the Jenks Natural Breaks algorithm (see e.g., De Smith et al. 2009).

[4] The Box Map is an extended version of the Quartile Map, in which observations with extreme values in the first and fourth quartile are displayed separately.

[5] With respect to the goal of the paper this analysis is not presented here.

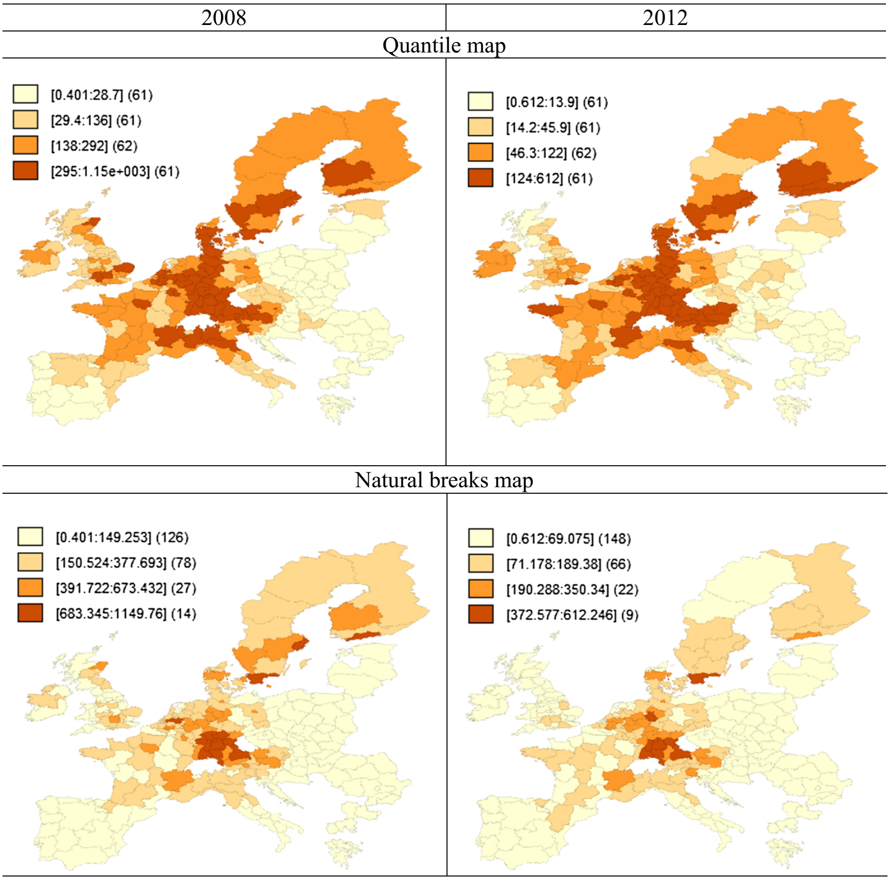

Fig. 1 Natural breaks maps (four categories) for patent application in 2008 and 2012. *Source*: own calculations

given k, the elements of the matrix of weights to the nearest neighbours have the following form:

$$w_{ij} = \begin{cases} 1, & j \in B_k(i) \\ 0, & \text{inak} \end{cases} \tag{7}$$

The result of this approach is asymmetric matrix of spatial weights. We set $K = 8$ what ensured that each region has just eight neighbours and this associated spatial weight matrix ($\mathbf{W}_{8\mathbf{KNN}}$) was used in all parts of our analysis.

As a second part of our preliminary spatial dependence analysis of the innovative activities of the EU regions selected ESDA (Exploratory Spatial Data Analysis) tools were used. We assume that the regional innovation process (represented by patent applications) is influenced by innovation activities in neighbouring regions. To verify this hypothesis, we used global and local spatial autocorrelation statistics, namely global Moran's I and local Getis–Ord statistics calculated for the 2008 and 2012 years.

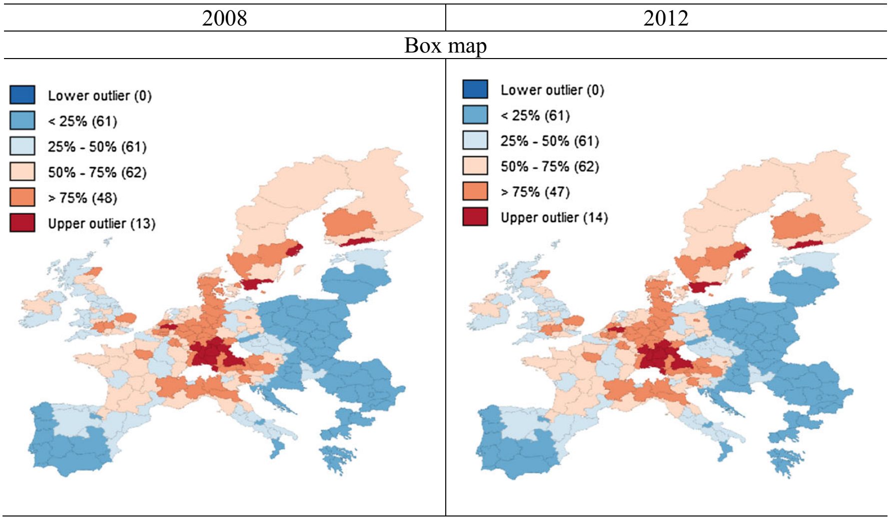

Fig. 2 Box maps (four categories) for patent application in 2008 and 2012. *Source*: own calculations

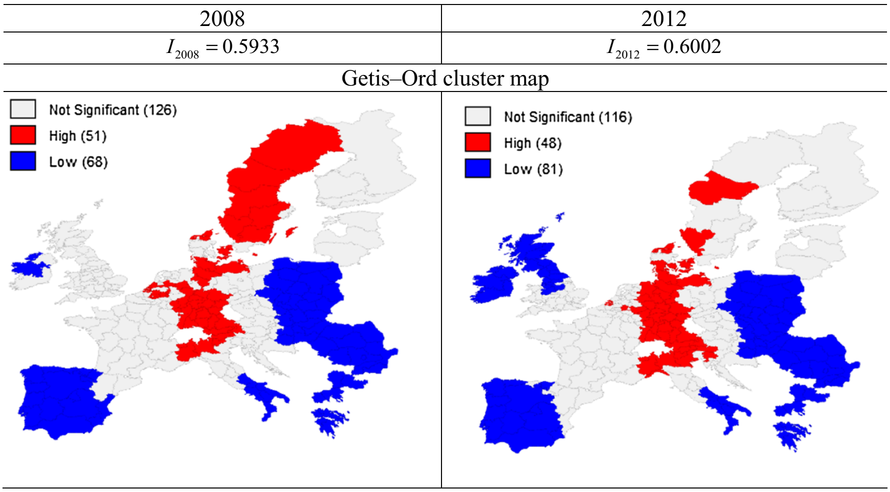

Fig. 3 Moran's I statistics and Getis–Ord cluster maps for patent application in 2008 and 2012. *Source*: own calculations

The high values and statistical significance of both Moran's I statistics (see Fig. 3) confirmed the existence of positive spatial autocorrelation. Thus, similar patent application values tend to be clustered across the space, i.e., regions with high (i.e., "high–high" association) or low (i.e., "low–low") values are clustered together.

In the next step of ESDA, we have identified clusters based on the local version of Getis–Ord statistics that identified clusters based on concentration of patent applications values in neighbouring regions. These statistic were calculated for all 245 regions, and based on graphical visualization, we can see statistically significant[6] clusters, so called hotspot and coldspot locations (see Fig. 3). A comparison of 2008 and 2012 Getis–Ord cluster maps imply very similar spatial process.

Taking into account spatial aspects of the EU innovation process involves a series of logical steps. Selected ESDA tools applied in the previous section were the initial step of the analysis that typically precedes the spatial effects specification tests in the context of spatial regression models. Our ESDA results indicate the spatial interconnection of the regional innovation process. Another logical step is to specify the spatial econometric model that would take into account the indicated spatial effects. The basis of our analysis was an extended RKPF model (see e.g., Moreno et al. 2005a; Furková 2016). While the basic RKPF model assumes that the innovation output in the ith region is determined only by the innovation inputs of the region, the extended version of this model contains additional economic and institutional factors as well as variables taking into account the spillover effects of knowledge among regions. As an innovative outcome, we will consider the *PATAV* variable representing the averaged value of patent applications for 2011 and 2012 and the first innovative input is represented by the *RDE* variable, expressed as total R&D expenditure in 2011 (in % of *GDP*) and the second one is the *HRST* variable representing human resources (university graduates) in science and technology in 2011 (% of active population). The *HRST* variable captures the ability to generate new knowledge as well as the ability to absorb external knowledge in the form of knowledge spillover effects. All data comes from Eurostat regional statistics. The specification of spatial econometric model followed the "from general to specific" strategy when the model selection process starts with the model construction and estimation without spatial lagged variables and OLS estimation. Thus, we start to estimate the following RKPF model in the form:

$$\mathbf{y} = \mathbf{l}_N\alpha + \mathbf{X}\boldsymbol{\delta} + \mathbf{u} \quad \mathbf{u} \sim N\left(\mathbf{0}, \sigma_u^2\mathbf{I}_N\right) \tag{8}$$

where $\mathbf{y}$ denotes $N \times 1$ vector of the observed dependent variable (*PATAV* in logarithmic form), $\boldsymbol{\delta}$ denotes (2×1) vector of parameters containing parameter β_1 associated with explanatory *RDE* variable (in logarithmic form) and parameter β_2 associated with explanatory *HRST* variable (in logarithmic form), $\mathbf{X}$ is $N \times 2$ matrix of explanatory variables, $N \times 1$ dimensional vector $\mathbf{u}$ represents random errors vector and remaining terms of model (8) were defined before. The model (8) does not take into account any spatial aspects, the model can be estimated on the basis of OLS method. Consequently, we will decide on the form of a suitable spatial econometric model based on spatial autocorrelation statistics. The estimation results of model estimation (8) are given in Table 3.

The statistical significance of the Moran's I applied on the OLS residuals as well as the LM test specification statistics (LM_ρ, LM_λ and their robust versions—see Table 3) confirmed the presence of spatial dependencies of the regional innovation process and therefore the OLS estimation results can be misleading and we will not pay them attention. However, the LM specification tests did not lead to the clear spatial version of model (8), so we have decided to estimate multiple spatial versions, the estimation

[6] Statistical inference was based on a random permutation procedure (for details see e.g., Getis 2010).

Table 3 Estimation results—OLS, SAR and SDM models

	OLS model OLS	SAR model SML	SDM model SML
α	– 3.8969***	– 2.3767***	– 0.3846
β_1 (ln **RDE**)	0.9362***	0.5167***	0.4885***
β_2 (ln **HRST**)	2.1411***	0.9698***	1.3195***
γ_1 (**W** ln **RDE**)	–	–	0.0418
γ_2 (**W** ln **HRST**)	–	–	0.9572**
ρ (**W** ln **PATAV**)	–	0.6840***	0.7397***
Goodness of fit statistics			
R^2	0.6008	–	–
AIC	656.326	458.22	455.86
SC	666.830	–	–
ln*L*	– 325.163	– 224.110	– 220.929
Jarque–Bera	3.092	–	–
Breusch–Pagan	4.256	–	–
Koenker–Basset	4.841*	–	–
Spatial autocorrelation statistics			
Moran's *I* (residuals)	15.741***	–	–
LM_ρ	229.541***	–	–
Robust LM_ρ	64.454***	–	–
LM_λ	222.691***	–	–
Robust LM_λ	57.605***	–	–
LM test	–	2.8857*	0.0630
LR test	–	202.11***	111.82***

Symbols ***, **, * in all tables of the paper indicate the rejection of H_0 hypotheses at 1, 5 and 10% level of significance, respectively

AIC Akaike information criterion; *SC* Schwarz criterion; ln*L* logarithm of log likelihood function, *A–K* Anselin–Kelejian, *LR* Likelihood Ratio, *LM* Lagrange Multiplier

results of the SAR and the SDM[7] specifications are shown in Table 3. The choice of SAR and SDM specifications has also been supported by our assumption of the existence of global spillover effects in relation to modelling of regional innovation activities. The SAR and SDM models allow spillover effects at the global level, which means that changes in the *i*th region activate a series of responses in others, potentially in all regions. The estimations of the SAR and the SDM model were based upon the specification (9) and (10), respectively:

$$\text{SAR specification:} \quad \mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{l}_N\alpha + \mathbf{X}\boldsymbol{\delta} + \mathbf{u} \tag{9}$$

$$\text{SDM specification:} \quad \mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{l}_N\alpha + \mathbf{X}\boldsymbol{\delta} + \mathbf{W}\mathbf{X}\boldsymbol{\omega} + \mathbf{u} \tag{10}$$

[7] We do not report the results of other spatial versions of the model (8) due to insufficient space.

where ρ is the spatial autoregressive process parameter, $\mathbf{W}$ is a spatial weight matrix $\mathbf{W}_{8\mathbf{KNN}}$ defined before, $\boldsymbol{\omega}$ denotes (2×1) vector of parameters containing the parameter γ_1 corresponding to the spatial lag of *RDE* variable and the parameter γ_2 corresponding to the spatial lag of *HRST* variable, the remaining model terms were defined before. SAR model estimation was performed by SML (spatial ML) estimator. The results are presented in Table 3. SML estimation of the model (9) produced statistically significant estimates of the parameters of the selected innovation inputs with the expected signs. The estimation of the spatial autoregressive parameter ρ is statistically significant as well, and it confirms the adequacy of the explicit incorporation of the spatial lags of dependent variables into the model. In addition, this is also confirmed by *LR* test. The *LM* test indicates estimate the problem with "residual" spatial autocorrelation.

In the last column of Table 3 the estimation of the SDM model (10) results are presented. This model contains not only a spatial lag of dependent variable but spatial lags of explanatory variables $\mathbf{WX}$ are also considered. Again, the SML method was used to estimate the model (10), apart from the estimations of γ_1 (associated with *RDE* variable) and α, all parameters were statistically significant and the *LM* test did not indicate the problem of remaining spatial autocorrelation.

As we have already mentioned, the parameter γ_1 corresponding to the spatial lag of *RDE* variable is not statistically significant and we could say that spatial *RDE* spillover effects do not exist. However, this conclusion may not be correct because the statistical inference of the individual impacts associated with the changes in the explanatory variables should be based on the summary measures of impacts of the SDM model as well as the SAR model (see Table 2). Table 4 summarizes the cumulative impacts of *RDE* calculated on the basis of the SAR and SDM estimates. Testing the statistical significance of these cumulative impacts was based on a simulation approach (see LeSage and Pace 2009).

Next, we will focus on illustrating the impacts associated with R&D expenditure, i.e., with the *RDE* variable (see Tables 4 and 5). We can notice that, based on the SAR model estimation, the average direct impacts does not match the estimate of the parameter β_1. The difference between the average direct impacts (0.5635) and the value of the parameter estimate (0.5167) is 0.0468, which is the amount of feedback that arises from the effects passing through the neighbouring regions, and is reversed by the region itself. We also found positive feedback effects based on the SDM model estimate. However, compared to the SAR model, these feedbacks are greater than or equal to 0.0647 (0.5532–0.4885). This difference is caused by the spatial lag of *RDE* variable in the SDM model, and then the quantification of the average direct impact is affected by the value of parameter β_1 and the parameter γ_1 as well (see Table 2).

Even greater differences are evident between the average indirect impacts of *RDE* and the SDM estimate of parameter γ_1, this difference (1.4841–0.0418) is up to 1.4423. It is also important to note that all of the *RDE*'s summary impacts (Tables 4 or 5) are statistically significant, but the parameter γ_1 is not statistically significant, and therefore, if we perceive estimate of parameter γ_1 as an indirect impact, our conclusions regarding the *RDE* spillover effects would be wrong.

Also, to consider the sum of SDM model parameter estimate corresponding to the *RDE* variable and its spatial lag variable as the average total impact can lead

Table 4 Spatial partitioning of direct, indirect and total impacts of RDE—SAR and SDM models

Cumulative impacts of *RDE*						
			SAR model			SDM model
Direct impact			0.5635***			0.5532***
Indirect impact			1.0717***			1.4841***
Total impact			1.6352***			2.0372***
Spatial partitioning of *RDE* impacts						
W-order	Direct	Indirect	Total	Direct	Indirect	Total
$\mathbf{W}^0$	0.5167***	0	0.5167***	0.4885***	0.0418	0.5303
$\mathbf{W}^1$	0	0.3534***	0.3534***	0.0031	0.3892***	0.3923***
$\mathbf{W}^2$	0.0239***	0.2179***	0.2417***	0.0276***	0.2626***	0.2902***
$\mathbf{W}^3$	0.0089***	0.1564***	0.1654***	0.0115***	0.2031***	0.2147***
$\mathbf{W}^4$	0.0056***	0.1076***	0.1131***	0.0077***	0.1511***	0.1588***
$\mathbf{W}^5$	0.0032***	0.0742***	0.0774***	0.0048***	0.1127***	0.1175***
$\mathbf{W}^6$	0.0019***	0.0510***	0.0529***	0.0032***	0.0837***	0.0869***
$\mathbf{W}^7$	0.0012**	0.0350**	0.0362**	0.0021**	0.0622**	0.0643**
$\mathbf{W}^8$	0.0008**	0.0240**	0.0248**	0.0014**	0.0461**	0.0475**
$\mathbf{W}^9$	0.0005**	0.0165**	0.0169**	0.0010*	0.0342*	0.0352*
Σ	0.5626	1.0359	1.5985	0.5508	1.3867	1.9375

Source: own calculation in R

Table 5 Summary of direct, indirect and total impacts of RDE–SAR and SDM models

	SAR model	SDM model
$\hat{\beta}_1$	0.5167***	0.4885***
Average direct impact (*ADI*)	0.5635***	0.5532***
Difference *ADI* and $\hat{\beta}_1$	0.0468	0.0647
$\hat{\gamma}_1$	–	0.0418
Average indirect impact (*AII*)	1.0717***	1.4841***
Difference *AII* and $\hat{\gamma}_1$	–	1.4423
Average total impact (*ATI*)	1.6352***	2.0372***
$\hat{\beta}_1 + \hat{\gamma}_1$	–	0.5303
AII/ATI	0.66	0.73
ADI/ATI	0.34	3.27

Source: own calculation

to misleading conclusions. While the average total impacts is 2.0372, this impact if we sum up the corresponding parameter values ($\beta_1 + \gamma_1$) would be equal to 0.5303, i.e., almost four times smaller. This great difference depends on the extent of indirect impacts which can not be directly identified based on SDM parameter estimates. In the case of the SAR estimation, there are no such great differences, because this model does not contain spatial lag of independent variables.

Average total impacts can be interpreted as elasticity since the variables in both models were expressed in logarithmic form. For example, as for the SAR model estimation and based on its average total *RDE* impact we can conclude that a 1% increase in total R&D expenditure will cause an average of 1.6352% increase in patent applications, while approximately 34% of this impact is attributed to direct impact and 66% to indirect impact. These percentage shares, i.e., the ratios of direct and indirect impacts to total impact is always the same in the SAR model for all explanatory variables. The SDM also contains spatial lags of explanatory variables, and that is why these ratios are not constant for all explanatory variables. From this perspective, SDM model can be considered more realistic.

It is clear that changes in explanatory variables will have a greater impact on regions with a lower degree of neighbourhood than on regions with higher degrees of neighbourhood. Table 4 provides the spatial partitioning of the direct, indirect and total *RDE* impact on the basis of the SAR and SDM models. Spatially partitioned (marginal) direct, indirect, and total impacts are calculated for neighbourhood degrees 0 through 9. Based on the definition $\mathbf{S}_r(\mathbf{W})$ matrix for SAR and SDM models (see Sect. 2 and LeSage and Pace 2009), it is possible to quantify the effect corresponding to each degree of neighbourhood. For instance, the direct impact corresponding to the neighbourhood $\mathbf{W}^0$ degree equals to the parameter β_1 estimate according to the SAR and SDM model as well. The indirect impact corresponding to this neighbourhood degree is zero according to the SAR model but according to the SDM model, this impact is no longer zero but equal to the estimate of parameter γ_1. This difference is due to the presence of the spatial lag of *RDE* variable in the SDM model, or in other words due to the different definition of the matrix $\mathbf{S}_r(\mathbf{W})$. The total marginal impact according to both models is equal to the sum of the direct and indirect marginal impacts. From the spatial partitioning of the direct impact we can further notice that, in the SAR model, until we reach the ninth degree of neighbourhood, we will "explain" a substantial part of the cumulative effect and that is 0.5626 of 0.5635 (see Table 4). We can also see that the direct marginal impacts according to both models quickly disappear with the growing degree of neighbourhood, while the indirect marginal impacts decrease much more slowly. The statistical significance[8] of marginal impacts corresponding to all degree of neighbourhood in both models suggests the need to investigate the decomposition of the impacts of *RDE* even for several higher degrees of neighbourhood.

As for the second innovation input, *HRST* variable (human resources in science and technology) has been chosen. The calculations of summary impact measures and spatial partitioning of all impacts based on the SAR and SDM models have been done (see Table 6), however with respect to the scope of the paper we will not interpret these results.

[8] Testing the statistical significance of marginal impacts corresponding to different levels of neighbourhood was based on a simulation approach (see LeSage and Pace 2009).

Table 6 Spatial partitioning of direct, indirect and total impacts of HRST–SAR and SDM models

Cumulative impacts of *HRST*	SAR model	SDM model
Direct impact	1.0576***	1.3225***
Indirect impact	2.0116***	0.0693
Total impact	3.0693***	1.3917

Spatial partitioning of *HRST* impacts

W-order	Direct	Indirect	Total	Direct	Indirect	Total
$\mathbf{W}^0$	0.9698***	0	0.9698***	1.3195***	− 0.9572**	0.3623
$\mathbf{W}^1$	0	0.6634***	0.6634***	− 0.0699**	0.3379	0.2680
$\mathbf{W}^2$	0.0448***	0.4090***	0.4538***	0.0430***	0.1553	0.1982
$\mathbf{W}^3$	0.0168***	0.2936***	0.3104***	0.0098	0.1368	0.1466
$\mathbf{W}^4$	0.0104***	0.2019***	0.2123***	0.0076	0.1009	0.1085
$\mathbf{W}^5$	0.0060***	0.1393***	0.1452***	0.0042	0.0760	0.0802
$\mathbf{W}^6$	0.0036***	0.0957***	0.0993***	0.0027	0.0566	0.0594
$\mathbf{W}^7$	0.0022***	0.0657***	0.0679***	0.0018	0.0421	0.0439
$\mathbf{W}^8$	0.0014**	0.0451**	0.0465**	0.0012	0.0313	0.0325
$\mathbf{W}^9$	0.0009**	0.0309**	0.0318**	0.0008	0.0232	0.0240
Σ	1.0560	1.9445	3.0005	1.3207	0.0029	1.3236

Source: own calculation in R

4 Conclusion

This paper was focused on spatial econometric analysis of the innovation activities of the EU regions, emphasizing the importance of spatial regional interactions in the innovation process modelling. Even the initial ESDA analysis based on the local as well as global spatial autocorrelation statistics confirmed the assumption that the regional innovation process (represented by patent applications) is not a spatially isolated process but is also influenced by innovative activities in neighbouring regions. Consequently, we constructed the RKPF model following SAR and SDM specifications. These models differ in the type of spatial autoregressive process, but both models allow for global spillover effects, which we considered to be a more realistic assumption for modelling innovative activities than to predict only the local level of spillover effects. Based on the SML estimates of both models, it was possible to quantify the summary measures of the direct, indirect and total impacts of the innovative inputs under consideration (R&D expenditure and human resources in science and technology). We also realized spatial partitioning of these impacts and quantified the impacts corresponding to each degree of neighbourhood. Based on tests of statistical significance of summary impact measures as well as marginal impacts, we can, for example, in connection with the R&D expenditure to draw the conclusion that R&D expenditure changes in the *i*th region will affect the number of patent applications not only the region itself but these changes will also have significant impacts on neighbouring regions. We have found that marginal impacts are statistically significant even at the level of the ninth degree of neighbourhood according to both models. We also found that direct marginal impacts quickly disappear with the growing degree of neighbourhood, while indirect marginal impacts are decreasing much more slowly. The proportion of the average indirect impact on the average total impact compared to the average direct impact proportion is significantly higher, based on both models. These results clearly confirmed the importance of the geographic location of the regions, i.e., the significant role of spatial spillover effects in the process of modelling innovative activities in the EU regions.

As we have already mentioned, ESDA analysis have confirmed our spatial autocorrelation assumption of the regional innovation activities. But identified clusters based on the local Getis–Ord statistics also invoke a question concerning another important spatial aspect of the analysis. It would be appropriate to estimate the SAR and the SDM specification of the RKPF model separately for spatial innovation regimes in order to capture spatial heterogeneity of the EU regional innovation process. The problem of the spatial heterogeneity can be perceived as a certain limitation of our study and we suppose this topic will be the subject of our further research.

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