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Interregional R&D spillovers and regional convergence: a spatial econometric evidence from the EU regions

JEL Classification: *O47; C21*

Keywords: *beta convergence modelling; spatial econometrics; R&D indicators; R&D spillovers effects*

Abstract
Research background: Many contemporary empirical studies and also most of economic growth theories recognize the importance of innovation and knowledge for achieving an economic growth. A large part of empirical literature has treated the issue of beta convergence without the spatial aspect, i.e. the possible spatial dependence among regions or states in growth process was neglected.
Purpose of the article: In this paper, we investigate the link between selected R&D (Research and Development) indicators as proxies for the regional innovation and knowledge and economic performance of the region. We also assume a significant role of regional R&D spillovers in the regional growth process determination.
Methods: The main methodological basis for our analysis is beta convergence approach and the dataset under the consideration consists of 245 NUTS 2 (Nomenclature of Units for Territorial Statistics) EU (European Union) regions during the 2003–2014 period. Our analysis is made with respect to spatial interactions across the EU regions.
Findings & Value added: The influence of R&D indicators on the economic growth has been confirmed, and spatial interconnection across the EU regions have been proven. Poten-

tial existence of geographical R&D spillovers across the EU regions was examined by formulation of additional beta convergence model with spatial lag variables. We have identified that the influence of R&D spillovers is not strictly restricted to the neighbouring regions, but they spread across a larger area. For the construction of spatial lags of R&D indicators different spatial weight matrices were considered.

Introduction

In the last decades, various theoretical and empirical studies have highlighted the role of technology as a key factor in the growth process of countries and regions. Most of growth theories considered the knowledge and technological progress as the main engines of economic dynamics (Solow, 1956; Romer, 1990; Lucas, 1988; Barro, 1990; Rebelo, 1991). Many contributions concerning the importance of R&D in the growth process have been pursued within the framework of the New Growth Theory, built upon the research of prominent economists in the late 1980s and early 1990s (Fernández *et al*., 2012). Nowadays, there is a general consensus that R&D plays a crucial role as a determinant of the competitiveness of firms, and of progress for countries and regions. These ideas are also the basis for the strategic EU document Europe 2020 (European Commission, 2010). Generally, the aim of R&D activities is to generate new ideas and innovations, which can be lately transformed into commercial innovations with wide usage.

Nowadays, there is a notable interest in studying whether countries/regions showing high or low values of productivity are randomly distributed across space or, on the contrary, are clearly concentrated in particular territories. In the spatial context, the local growth depends on the amount of technological activity which is carried out locally, and possibly on the ability to take advantage of external technological achievements (Coe & Helpman, 1995; Martin & Ottaviano, 2001). There are some papers which have already stressed the connection between R&D indicators and growth e.g. Fernández *et al*. (2012), van Stel & Nieuwenhuijsen (2004), Forni & Paba (2003), Pohulak-Żołędowska, (2016) or Sokolov-Mladenović *et al*. (2016). However, papers dealing with innovation and knowledge spillovers and using spatial econometric techniques at the same time are very rare.

It is clear that one of the aims of R&D policy is increasing the innovation outputs. The economists (e.g. Griliches, 1990) have been debating about the issue of measuring innovative activity and technological progress, but the answer for the question of what can be considered as innovation output is not so straightforward, and it can be represented in various ways.

Based on the concept of Knowledge Production Function (Pakes & Griliches, 1980; Furková, 2016), two types of indicators are usually identified: technology input measures (such as R&D expenditure and employees) and technology output measures (such scientific publications and citations, patents or new products and processes announcements).

Our study is aimed at the investigation of the link between the R&D indicators and economic growth of the EU regions. *Beta*-convergence model was the basis for analysis of 245 NUTS 2 EU regions during the 2003–2014 period. Since neither traditional income convergence models nor many empirical models usually do not account for spatial interactions across regions, serious misspecification problems of these models may arise. Due to those facts, we decided to consider the geographical dimension of data in the estimation of the regional income convergence and to emphasize geographic spillovers in regional economic growth process. Thus, in order to verify the hypothesis that there is a link between the R&D indicators and economic growth of the EU regions, spatial extension of *beta*-convergence model was used. Spatial version of *beta*-convergence model was also exploited to verify our next hypothesis that the spillovers of R&D indicators among regions do matter, i.e. there is a link not only between R&D indicators and economic growth within the region, but that innovation and knowledge spill over to neighbouring regions and influence the economic performance of these regions. Sensitivity of different spatial schemes will be taken into account. As proxies for R&D indicators human resources in science and technology and patent applications were chosen. GDP per capita in Euro of NUTS 2 regions was used as a proxy for the income level of individual regions. Hence our convergence analysis is the case of *between*-country convergence, absolute *beta*-convergence appears quite unrealistic since regions belonging to different countries may not show a common steady-state. Consequently, we decided to test the hypothesis of the conditional *beta*-convergence.

The rest of the paper is structured as follows: section 2 presents methodological backgrounds of the study. Data and empirical results are presented and interpreted in section 3. The paper closes with concluding remarks in section 4.

Methodological framework

This part will provide the methodological framework upon which our empirical analysis is based. This paper will present a multi-region model in which regional innovation and knowledge and also inter-regional innovation and knowledge spillovers determine the growth of regions. Our econometric analysis follows traditional *beta*-convergence model which will be extended by spatial aspect. The issues related to the traditional *beta*-convergence can be found in many theoretical and also empirical studies (see e.g. Barro & Sala-i-Martin, 1992; Paas *et al*., 2007; Bal-Domańska, 2016). Due to this fact, next, we will briefly summarize only the problems concerning the *beta*-convergence models with spatial aspects.

Many authors dealing with the income convergence issues have argued that, due to geographical spillovers, the distribution of regional per capita income across EU tends to be influenced by geographical location of the regions. If this spatial dependence is not properly modelled, it can lead to the misspecification problems in traditional *beta*-convergence models. In order to avoid these problems, a spatial component is usually explicitly incorporated into the regression in the form of a spatial lag or spatial error. If the geographical location of regions matter, we speak of spatial autocorrelation, i.e. in general, one observation in region i depends on other observations at regions j $(j \neq i)$. A simple check of spatial autocorrelation can be performed by means of Global and Local indicators of spatial association. In empirical part of this paper we employed global and local Moran´s I statistics. The spatial pattern can be also visualised by the Moran scatterplot, which provides the information about the type of spatial association between particular regions (Anselin, 2010; Bivand, 2010).

The construction of spatial weight matrix **W** of dimension $N \times N$ is a starting point for any spatial analysis. N is the number of regions in the data set and w_{ij} are the elements of spatial weight matrix **W**. There are various possibilities how to specify the spatial weight matrix **W**. The most commonly used spatial weights in practice can be divided into two main groups: weights based on distance and weights based on boundaries (for more details see e.g. Smith, 2014; Getis, 2010).

Indicators of spatial association indicate if spatial autocorrelation matters. If spatial autocorrelation is detected, we can proceed with the estimation of the income convergence models based on the standard Ordinary Least Squares (OLS) and next to test the existence of the spatial autocorrelation among the regression residuals. In the case that the spatial autocorrelation is present, the set of Lagrange Multiplier (LM) tests can be used in order to decide whether a spatial autoregressive (SAR) model or a spatial error (SEM) model is the most suitable (see Arbia, 2006; Paas *et al*., 2007). Both SAR and SEM models can be estimated by e.g. the maximum likelihood method (ML) for formulas see e.g. Viton (2010). Next, we present only the theoretical aspects of the SAR model because only this version of spatial model was applied in the empirical part of the paper.

Spatial Autoregressive Model is also known as spatial lag model. The main feature of this spatial model is that the levels of the dependent variable *y* depend on the levels of *y* in neighbouring units. In the case of income convergence, it means that the growth rate in a region is related to those of its neighbouring regions. The extension of the conditional convergence model[1] to spatial autoregressive model can be written as follows:

$$\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)=\alpha+\beta\ln\left(y_{i,0}\right)+\gamma_1 x_{1\,i,0}+\gamma_2 x_{2\,i,0}+\ldots+\gamma_k x_{k\,i,0}+\rho\sum_j w_{ij}\left(\ln\left(\frac{y_{j,T}}{y_{j,0}}\right)\right)+u_i \quad (1)$$

where $y_{i,0}$ and $y_{i,T}$ are the per capita GDP's of the region *i* ($i=1,2,\ldots,n$) in the base year 0 and in the final year *T*, respectively. $\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)$ is the growth rate of the *i*-th region per capita GDP in the period $(0,T)$, $x_{1\,i,0}, x_{2\,i,0},\ldots, x_{k\,i,0}$ is a set of control variables, *T* denotes the number of periods , *n* is the number of regions, α, β, γ_j ($j=1, 2,\ldots, k$), ρ are unknown parameters and $u_i \sim i.i.d\left(0,\sigma_u^2\right)$ is an error term. ρ is called spatial autoregressive parameter.

Data and empirical results

The data used in this paper were extracted from the Eurostat database (http://ec.europa.eu/eurostat/). Our data set covers 245 NUTS 2 EU regions from 26 countries observed over the 2003–2014 period. 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, in order to avoid the possible problems with isolated regions. Another reduction of data set had to be done due to missing data; we excluded 7 regions of Bulgaria, Germany and Greece. The whole analysis was carried out in the GeoDa software and corresponding shp file for the EU was downloaded from the Eurostat web page.

[1] Since our analysis is aimed at the conditional convergence modelling (for more detail see e.g. Battisti & Di Vaio, 2009) we present only the extension of the conditional convergence model.

The paper is aimed at verifying of two hypotheses. The first hypothesis deals with the impact of regional innovation and knowledge on regional economic performance in the EU regions. The second hypothesis is related to the regional innovation and knowledge spillovers, i.e. we examine whether the regional innovation and knowledge spills over to neighbouring regions and influence the economic performance of these regions. In order to verify these hypotheses, spatial extension of conditional *beta*-convergence approach is used. As the dependent variable per capita GDP growth rate from 2003 to 2014 (defined at current market prices in Euro) was used. Following the traditional concept of *beta*-convergence model as the explanatory variable the initial GDP per capita (defined as the current market prices in Euro) in 2003 was used. All variables are expressed in natural logarithms. In our analysis, innovation and knowledge is substituted by R&D input and output indicators following the Knowledge Production Function concept (Pakes & Griliches, 1980; Moreno *et al*., 2005) where R&D expenditure and human recourses are proposed as R&D input measures and patent applications as R&D output measures. In our analysis, *PAT* represents patents applications in 2011 (per million of inhabitants) as a proxy for innovative output, *RDE* represents total intramural R&D expenditure in 2011 (% of GDP) and *HRST* represents human resources (persons with tertiary education) in science and technology in 2011 (% of active population). As we are assuming time lags between R&D indicators and regional economic growth, the year 2011 was chosen for R&D indicators. In general, it is necessary to emphasize a significant lack of the regional science and technology data for all regions in the NUTS 2 structure.

As a preliminary part of our econometric analysis, calculation of global Moran´s *I* statistics was done in order to indicate the spatial pattern of variables used in our analysis. We started with the calculation of Moran´s *I* statistic for the GDP growth rate in 2014 which is visualised by the form of LISA Cluster Map (see Figure 1). This calculation and all following calculations have been done based on the contiguity weight matrix of queen's case definition of neighbours ($\mathbf{W_{Q1}}$). High value of Moran´s *I* statistic (0.83796) indicates a strong positive spatial autocorrelation. The type of spatial association (*high* — *high* (H–H) values, *high* — *low* (H–L) values, *low* — *high* (L–H) values, *low* — *low* (L–L) values) is depicted on LISA cluster map. Our analysis indicates positive spatial association of 89 regions, (40 regions with H–H association and 49 regions with L–L association), which means that similar values of per capita GDP growth rates tend to cluster in space and the per capita GDP growth rate in one region is associated with the growth rate in neighbouring regions. There were L–H values only for 3 regions and there was no region with H–L association.

Next, we proceed with the examination of the spatial dependence process of innovation and knowledge in the EU regions, i.e. we try to evaluate the fact that innovative activity (represented by *PAT*, *HRST* and *RDE*) performed in one region may be affected by the innovative activity performed in neighbouring regions. The values of global Moran's *I* statistics (*PAT* 0.60785; *HRST* 0.54436; *RDE* 0.27518) show the existence of a strong positive spatial autocorrelation process, especially for *PAT* and *HRST*.

Following the results of our preliminary spatial analysis, we would expect that spatial dependence matters for the study of *beta*-convergence in the EU regions and consequently the spatial aspect should not be neglected at *beta*-convergence modelling. In the whole econometric analysis, all ML estimations and all calculations of spatial statistics were done using spatial weight matrix of the first order queen case definition ($\mathbf{W_{Q1}}$).

The estimation results (see Table 1) of Model 1 and its spatial version Model 2 (chosen based on the LM tests) have yielded strongly statistically significant estimations of all parameters with expected signs. Negative sign of β parameter has confirmed our *beta* conditional convergence hypothesis. The R&D indicators listed in the Table 1 are the final R&D indicators in our models. At the beginning of our analysis we also checked the influence of R&D expenditure on the economic growth. The parameter associated with this variable was statistically significant in non-spatial version of *beta* convergence model, but its statistical non significance in spatial version of this model led to its exclusion from the further analysis.

The appropriateness of spatial version of model was proved by Moran´s *I* statistic applied on the regressions residuals and the statistical significance of spatial autoregressive parameter ρ also confirms the existence of spatial effects among neighbouring regions. Statistical significance of the parameters associated with R&D indicators suggests that regional innovation and knowledge factor plays an important role in regional economic performance in the EU regions. Thus, our first defined hypothesis can be perceived as confirmed.

The convergence characteristics (see: e.g. Arbia, 2006; Chocholatá & Furková, 2016; Furková & Chocholatá, 2016) of the models offer the possibility to evaluate regional convergence process for the 2003–2014 period. Convergence rate corresponding to the Model 1 equals about 5.14 % leading to a half-life of about 13 years. This means that the poorest regions are thus supposed to fill half of the gap to the richest ones as quickly as in 13 years. However, those positive convergence characteristics are misleading due to the omitted spatial component. The Model 2 has provided the weaker convergence characteristics, i.e., the speed of convergence is 2.06 % per year and half-life increased to about 34 years.

In order to investigate spatial spillovers among regions generated by the R&D indicators, we considered their spatial lags. Identifying the existence and the magnitude of those spillovers, we used two different types of spatial weight matrices, namely contiguity weight matrix and distance weight matrix. Our innovation and knowledge spillover analysis started with the first and the second order queen case contiguity spatial weight matrices under the consideration, $\mathbf{W_{Q1}}$ and $\mathbf{W_{Q2}}$ respectively. In Model 3 — Model 6 we considered first order and second order spatial lags for the *PAT* and *HRST* and these models allowed to answer the question if the innovation and knowledge carried out in one region spills over only to the physical neighbouring regions, or also to the second order regions (regions sharing a border with the first order regions). It is necessary to mention that spatial matrix $\mathbf{W_{Q2}}$ was constructed without inclusion of lower orders, which means that using spatial lag of variable created based on this spatial matrix allows answer the question if only spillovers with second order neighbours do matter. Analogous analysis of spillovers effects was made based on the distance weight matrix (Model 7 — Model 12). We considered spatial lags for the *PAT* and *HRST* variables within a radius of 420 km, 480 km and finally 650 km. Corresponding distance weight matrices are denoted as $\mathbf{W_{0\text{-}420}}$, $\mathbf{W_{0\text{-}480}}$ and $\mathbf{W_{0\text{-}650}}$. The model defined by equation (2) also contains spatial lag of the initial GDP per capita, which appears to be a suitable part of this model.

Subsequent equation was the basis for the estimation of all following models:

$$\ln\left(\frac{GDP_{i,2014}}{GDP_{i,2003}}\right)=\alpha+\beta\ln\left(GDP_{i,2003}\right)+\delta_1\sum_j w_{ij}\ln GDP_{i,2003}+\delta_2\sum_j w_{ij}\ln HRST_i+ \\ +\delta_3\sum_j w_{ij}\ln PAT_i+u_i \qquad u_i\sim i.i.d\left(0,\sigma_u^2\right) \tag{2}$$

where w_{ij} are the elements of spatial weight matrix either $\mathbf{W_{Q1}}$, $\mathbf{W_{Q2}}$, $\mathbf{W_{0\text{-}420}}$, $\mathbf{W_{0\text{-}480}}$ or $\mathbf{W_{0\text{-}650}}$.

The estimation results are given in Table 2 and Table 3. Our attention will be paid to the interpretation of spatial models, because neglected spatial aspect in the models provides biased and misleading results.

Table 2 summarized our innovation and knowledge spillover analysis supposing spatial weight matrices W_{Q1} and W_{Q2}. Almost all estimated parameters of Model 3 — Model 6 are statistically significant and have expected signs. Only the parameters associated with spatial lag of *HRST* are not statistically significant in spatial models. This means that *HRST* linked with particular region do not spill over neither to the physical neighbouring regions (expressed as spatial lag of *HRST* based on W_{Q1}) nor to second order neighbouring regions (expressed as spatial lag of *HRST* based on W_{Q2}). On the other hand, *PAT* carried out in one region spills over to the physical neighbouring regions and also to the regions sharing a border with these first-order regions, although with a lower impact.

Analogous analysis of innovation and knowledge spillovers effects was made based on the distance weight matrix with threshold distances 420 km, 480 km and 650 km (see Table 3). All estimated parameters of Model 7 — Model 12 are strongly statistically significant and have expected signs. The statistical significance of the parameters concerning to spatial lags for the *PAT* and *HRST* within the first radius value (420 km) imply that the innovative activity in a region is positively related to the level of innovative activity in regions located within 420 km. We found out that the radius values 480 km and 650 km still matter, although with a lower impact of patent applications within the 650 km. The outcomes of the spatial models led us to conclude that the economic growth performance in a region depends not only on its own R&D factors, but also on the innovation and knowledge available in other regions and our second defined hypothesis can be also perceived as confirmed.

Conclusions

In this paper we focused on the role of regional innovation and knowledge in the regional economic growth process. We were motivated by the fact that many theoretical and empirical studies have highlighted the role of technology as a key factor in the growth process of countries and regions, but very rarely can one find the studies dealing with this topic which consider spatial interactions across regions. The relevance of geographical dimension was indicated by our preliminary spatial analysis. Spatial versions of conditional *beta*-convergence models served as a basis for the verification of two defined hypotheses. Following the empirical evidence of our paper, both defined hypotheses can be perceived as confirmed.

First, the conditional income convergence among regions was confirmed, and statistical significance of parameters associated with opted R&D indicators have suggested that regional innovation and knowledge factor plays an important role in regional economic performance in the EU regions. From spatial point of view, the results implied that convergence process is not determined only by a region's initial income and other specific factors, but also essentially by its neighbourhood region's growth performance. When spatial effects were taken into account, we detected weaker convergence process, and those results are in accordance with the findings of several other empirical studies.

The potential existence of geographical R&D spillovers among regions was analysed by formulation of an additional *beta*-convergence model. The model contained the spatial lags of *PAT*, *HRST* and the initial GDP per capita. These spatial lag variables were constructed based on the two types of spatial weight matrices. We found out that patent applications linked with particular region spills over to the physical neighbouring regions (expressed as spatial lag of patent application based on $\mathbf{W}_{\mathbf{Q1}}$) and to the second order neighbouring regions (expressed as spatial lag of patent application based on $\mathbf{W}_{\mathbf{Q2}}$). Also, the statistical significance of the parameters concerning the spatial lags for the patent application within all radius values have implied that the innovative activity in a region is positively related to the level of innovative activity in regions located within 420 km, 480 km and also 650 km. As for human resources spillovers, positive relations were also detected if distance matrices of all radiuses were used. However, the parameters associated with spatial lag of human resources based on $\mathbf{W}_{\mathbf{Q1}}$ and $\mathbf{W}_{\mathbf{Q2}}$ were not statistically significant in spatial versions of model. Overall, the results of our analysis imply that convergence process is not determined only by a region's initial income but also essentially by its neighbourhood region's growth performance. R&D indicators play an important role in regional economic growth determination. And finally, the last important finding of our analysis was the confirmation of the hypothesis that innovation and knowledge spillovers among regions do matter, and this fact should not be omitted in regional economic growth modelling.

The contribution of this paper could be summarized as follows. In empirical literature many studies dealing with *beta* convergence approach can be found, however the empirical evidence for the income convergence modelling with respect to geographical proximity of the regions is out of the mainstream of regional income convergence modelling. Due to the scarce empirical evidence of the spatial convergence modelling, we regard our empirical evidence as a contribution to the discussion and to the empirical literature of the spatial convergence modelling at the regional level. Also, we consider identifying the magnitude of innovation and knowledge spillovers among regions as a useful contribution to the debate on innovation policy, because the impacts of any policy may depend greatly not just on, for instance, a given inventor's behaviour, but on a ‘multiplier effect’ at the individual level that affects the broader innovation process.

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Annex

Table 1. Estimation results of Model 1 and Model 2

	Model 1 (Linear model)	**Model 2** (SAR model)
Estimation	OLS	ML
α	2.869***	1.126 ***
β	-0.432***	-0.203***
γ_1 (ln*HRST*)	0.391***	0.247***
γ_2(ln*PAT*)	0.052***	0.020***
ρ	-	0.572**
R^2	0.738569	0.836
Moran's *I* (error)	7.914***	-
LM (lag)	87.224***	-
Robust LM (lag)	30.722***	-
LM (error)	56.503***	-
Robust LM (error)	0.001	-
Moran's *I* (spatial residuals)	-	-0.042

Note: Symbols ***, ** indicate statistical significance at 1% and 5% level of significance, respectively.

Table 2. Estimation results of Model 3 – Model 6

	Model 3 ($\mathbf{W_{Q1}}$)	**Model 4** ($\mathbf{W_{Q1}}$)	**Model 5** ($\mathbf{W_{Q2}}$)	**Model 6** ($\mathbf{W_{Q2}}$)
Estimation	OLS	ML-SAR	OLS	ML-SAR[1]
α	4.030***	1.929***	3.086***	1.281***
β	-0.052*	-0.046*	-0.275***	-0.119***
δ_1(**W**lnGDP_{2003})	-0.448***	-0.182***	-0.162***	-0.028
δ_2 (**W**ln*HRST*)	0.201***	0.070	0.330***	0.036
δ_3(**W**ln*PAT*)	0.097**	0.043***	0.062***	0.029***
ρ	-	0.528***	-	0.654***
R^2	0.755	0.818	0.674	0.820
Moran's *I* (error)	5.927***	-	6.172 ***	-
LM (lag)	44.716 ***	-	90.811***	-
Robust LM (lag)	15.874***	-	78.163***	-
LM (error)	30.363***	-	32.169***	-
Robust LM (error)	1.521	-	19.520***	-
Moran's *I* (spatial residuals)	-	-0.065	-	0.135

Note: Symbols ***, ** indicate statistical significance at 1%, 5% and 10% level of significance, respectively.

[1] According to the LM tests of Model5, we were not able to choose proper spatial version of this model. The decision for SAR model - Model6 was supported by the values of Akaike information criterion of SAR and SEM models.

Table 3. Estimation results of Model 7 – Model 12

	Model 7 ($\mathbf{W}_{0\text{-}420}$)	**Model 8** ($\mathbf{W}_{0\text{-}420}$)	**Model 9** ($\mathbf{W}_{0\text{-}480}$)	**Model 10** ($\mathbf{W}_{0\text{-}480}$)	**Model 11** ($\mathbf{W}_{0\text{-}650}$)	**Model 12** ($\mathbf{W}_{0\text{-}650}$)
Estimation	OLS	ML-SAR	OLS	ML-SAR	OLS	ML-SAR
A	4.318***	2.432***	4.259***	2.334***	4.152***	2.032***
B	-0.109***	-0.071***	-0.142***	-0.088***	-0.172***	-0.103***
$\delta_1(\mathbf{W}\ln GDP_{2003})$	-0.510***	-0.278***	-0.504***	-0.271***	-0.574***	-0.262***
$\delta_2(\mathbf{W}\ln HRST)$	0.401***	0.228***	0.481***	0.275***	0.764***	0.369***
$\delta_3(\mathbf{W}\ln PAT)$	0.129***	0.072***	0.136***	0.075***	0.147***	0.074***
ρ	-	0.438***	-	0.451***	-	0.505***
R^2	0.789	0.827	0.786	0.828	0.766	0.825
Moran's *I* (error)	5.4088***	-	5.789***	-	6.077***	-
LM (lag)	33.8172***	-	38.710***	-	50.160***	-
Robust LM (lag)	10.3572***	-	11.138***	-	23.141***	-
LM (error)	24.4326	-	28.1767	-	30.998**	-
Robust LM (error)	0.9727***	-	0.604***	-	3.979***	-
Moran's *I* (spatial residuals)	-	-0.029	-	-0.030	-	-0.058

Note: Symbols ***, ** indicate statistical significance at 1% level of significance.

Figure 1. Moran´s *I* statistic for the GDP growth rate in 2014 (in %, initial level 2003)