Spatial Econometric Modelling of Regional Club Convergence in the European Union[1]

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Abstract

This paper focuses on the testing of income convergence of the EU regions using both non-spatial and spatial approaches. The main motivation for this analysis was the fact that the classical income convergence models suffer from a misspecification due to omitted spatial dependence among regions. Our empirical results provide support for the absolute beta-convergence modelling from spatial econometric perspective in our sample of 252 NUTS 2 regions over the period 2000 – 2011. Another serious finding is that the assumption of a single steady-state for all regions often mismatches with the reality. The club spatial beta-convergence models we found to be more appropriate for analysed data.

Keywords: *beta-convergence, club convergence, spatial econometric models, NUTS 2 regions*

JEL Clasification: C21, R11

Introduction

During the last decades the issue of the regional income convergence in the European Union (EU) has become an important research area, since it is commonly known that deepening and widening of the integration process is accompanied by the problem of regional disparities and convergence. "The economic and social development of the Union as a whole and the balanced development of its regions" (EC, 2012, p. 133), "reducing of disparities between the levels of

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development of the various regions and the backwardness of the least favoured regions" (EC, 2012, p. 127), "achieving balanced economic growth" (EC, 2012, p. 349) are some of the main goals of the EU.

Concerning the issue of regional income convergence in the EU, which deals with the question whether poor economies catch-up to wealthier economies, wide range of empirical research on international, national, state, county and urban level has been conducted based on different approaches (for an extensive survey see e.g. Rey and Janikas, 2005). Although, it is generally accepted that regions with high economic growth are geographically faraway from those with a slow growth performance, majority of earlier regional income convergence studies does not consider the spatial aspect. The problem of possibly biased results and hence misleading conclusions with using of non-spatial empirical analyses that have ignored the influence of spatial location on the process of growth is pointed out by e.g. Carrington (2003), Fingleton and López-Bazo (2006) and Paas et al. (2007).

In general the treatment of space in the growth analysis can be considered based on the distinction between the absolute and relative location. As mentioned by Abreu et al. (2005b), absolute location expresses the impact of being located at a particular point in space and relative location reflects the impact of being located closer or further away from another region, i.e. important is the position of a region relative to another region(s).[2] From the studies dealing with the European regional convergence, income disparities and spillovers taking into account spatial pattern we can mention e.g. Baumont et al. (2001), Paas et al. (2007), Fischer and Stirböck (2004), Debarsy and Ertur (2006), Paas and Schlitte (2009), Feldkircher (2006), Battisti and DiVaio (2009), Ramajo et al. (2005), Chocholatá and Furková (2015).

The aim of this paper is to verify the hypotheses of absolute and club income convergence of the EU regions for the period 2000 – 2011 using both non-spatial and spatial approaches. GDP per capita in Euro of NUTS 2 (Nomenclature of Units for Territorial Statistics) EU regions is used as a proxy for the income level of individual regions. The empirical evidence for the absolute and also the club convergence modelling with respect to geographical proximity of the regions is out of the mainstream of regional income convergence modelling. Due to this reason and 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.

[2] The rest of the paper will concentrate on the relative location.

The rest of the paper is organized as follows: section 1 deals with general specification of regional income convergence, section 2 is devoted to spatial aspects of analysis, section 3 provides a description of the data, estimation results are presented and interpreted in section 4 and the last section concludes.

1. General Specification of Regional Income Convergence

In the literature we can distinguish three hypotheses concerning the regional income convergence: the absolute (unconditional) convergence hypothesis, the conditional convergence hypothesis and the club convergence hypothesis (see e.g. Galor, 1996; Paas et al., 2007; Hančlová et al., 2010). The absolute (unconditional) convergence hypothesis is based on neoclassical growth theory and assumes the convergence of all regions to the same unique and globally stable steady state equilibrium independently of their initial conditions. Concerning the hypothesis of conditional convergence it is supposed that the equilibrium differs by region and each region can approach its own but unique equilibrium. Models of conditional convergence include the explanatory variables that enable to capture different initial conditions. In case of club convergence hypothesis the regions converge to steady state club equilibriums (regions with similar structural characteristics and initial factors create "clubs"). This hypothesis allows multiplicity of equilibriums and coexistence of several steady states (Paas et al., 2007; Debarsy and Ertur, 2006).

The empirical analysis is mostly concentrated on testing the validity of income convergence hypotheses based on the so-called β-convergence (catching up in per capita income levels). Also other measures of convergence can be used, e.g. σ-convergence answering the question whether the cross-sectional dispersion of per capita incomes is becoming more equitable or γ-convergence dealing with changes in the rankings of relative per capita income (Ramajo et al., 2005). Since these measures are less appropriate to the questions assessed in this paper, we will furthermore deal only with the β-convergence framework (Arbia, 2006).

The analysis of β-convergence is usually based on the cross-country/region growth regression model suggested by Mankiw et al. (1992) and Barro and Sala--i-Martin (1995):

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)=\mu_{i,\ 0,\ T}\ +\ \varepsilon_i \qquad \varepsilon_i \sim i.i.d\left(0,\ \sigma_\varepsilon^2\right) \tag{1}$$

where $y_{i,0}$ and $y_{i,T}$ are the per capita incomes of the region i ($i=1,\ 2,\ ...,\ N$) in the base year 0 and in the final year T, respectively.

The growth rate of the *i*-th region per capita income in the period $(0, T)$ is given by $\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)$, where *T* denotes also the number of periods for which we have data and *N* is the number of regions in the data set. Symbol $\mu_{i,\,0,\,T}$ represents the systematic component of the model given by the following formula (Arbia, 2006):

$$\mu_{i,\,0,\,T} = \alpha' - \frac{\left(1 - e^{-bT}\right)}{T}\ln\left(y_{i,0}\right) \tag{2}$$

where

b – the speed of convergence,

ε_i – a random disturbance term reflecting e.g. unexpected changes in production conditions.

Concerning the formula (2), the model (1) can be rewritten as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha' - \frac{\left(1 - e^{-bT}\right)}{T}\ln\left(y_{i,0}\right) + \varepsilon_i \qquad \varepsilon_i \sim i.i.d\left(0,\ \sigma_\varepsilon^2\right) \tag{3}$$

Model (3) can be estimated either by nonlinear least squares or alternatively after reparameterizing $\beta = -\left(1 - e^{-bT}\right)$, i.e. $b = -\frac{\ln\left(1+\beta\right)}{T}$ and $\alpha = T\alpha'$ with ordinary least squares (OLS). In this context Abreu et al. (2005a) pointed out that there are no appreciable statistical discrepancies between these methods. The reparameterized version of model (3) is as follows:

$$\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln\left(y_{i,0}\right) + \varepsilon_i \qquad \varepsilon_i \sim i.i.d\left(0,\ \sigma_\varepsilon^2\right) \tag{4}$$

where α and β are unknown parameters.

The absolute convergence hypothesis can be accepted if the estimated β parameter is statistically significant and negative which indicates not only that poor regions grow faster than the rich ones, but also that they all converge to the same level of per capita income (Arbia, 2006).

Besides the speed of convergence *b*, also the second indicator for judging the convergence of economy, the so called half-life time $t_{half-life} = \frac{\ln(2)}{b}$ can be calculated. The half-life time represents the time that it takes for half of the initial gap in the per capita income to be eliminated (Arbia, 2006).

The conditional β-convergence hypothesis incorporates the variables $x_{1\,i,0},\ x_{2\,i,0},\ ...,\ x_{k\,i,0}$ which enable the differentiation of the regions and also to capture different initial conditions, e.g. population growth rates, development of foreign trade, degree of political instability, stock of the human capital, technologies, etc.:

$$\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln\left(y_{i,0}\right) + \gamma_1 x_{1\,i,0} + \gamma_2 x_{2\,i,0} + ... + \gamma_k x_{k\,i,0} + \varsigma_i$$

$$\varsigma_i \sim i.i.d\left(0,\ \sigma_\varsigma^2\right) \qquad (5)$$

where α, β and γ_j $(j = 1,\ 2,\ ...,\ k)$ are parameters assumed to be constant across regions and ς_i is a random disturbance term.

Concerning the club convergence hypothesis, Debarsy and Ertur (2006) distinguish between exogenous and endogenous way of determination of convergence clubs. Firstly, they mention various criteria used to create clubs exogenously, e.g. the belonging to a geographical zone or choosing of threshold levels of per capita GDP. On the other hand they also present a survey of several methods which can be used to endogenize the determination of clubs. In this paper the clubs will be created in exogenous way based on the initial income levels.

Models presented above are based on the fact that each region is treated as a geographically independent entity without any spatial interactions. Since it is clear that each region is likely to interact with its neighbouring regions, during the last years these models have been modified in order to capture the spatial effects. Although literature distinguishes two spatial effects, namely spatial autocorrelation and spatial heterogeneity, it is not easy to determine whether the spatial effects are in the form of spatial autocorrelation or spatial heterogeneity.

Since our main aim is to test the club convergence hypothesis is convenient to mention some studies dealing with the evidence of multiple convergence regimes. From the studies taking into account the spatial context can be mentioned e.g. Baumont et al. (2002) who focused on European regional convergence process considering convergence clubs among regions during 1980 – 1995 period. The estimation of the appropriate spatial regimes shows that the convergence process is different across regimes. Fischer and Stirböck (2004) analysed and confirmed the club-convergence hypothesis for 256 regions of the European countries during the period 1995 – 2000. Ramajo et al. (2005) estimated the speed of convergence for a sample of 163 regions of the EU over the period 1981 – 1996. They identified two regimes (Cohesion and non-Cohesion countries) and proved a faster convergence in relative income levels of the regions belonging to Cohesion countries (5.3%) than in the rest of the regions of the EU

(3.3%). Debarsy and Ertur (2006) investigated convergence processes in the context of the enlargement of the EU to new member states over the period 1993 – 2002 concerning the two spatial convergence clubs. They identified convergence process in the group of "West" regions whereas they did not find any convergence process in the "East" spatial regime.

2. Spatial Aspects of Analysis

One of the crucial spatial effects is the spatial autocorrelation. Although, there exist many definitions of spatial autocorrelation, commonly known in this context is the Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things" (see Tobler, 1970, p. 234). The term "*spatial autocorrelation*" was first developed in a statistical framework by Cliff and Ord (1969) and can be in general characterized as the correlation of a variable with itself through space, i.e. the data from one region may influence the data from some other region through spatial spillover effects. The spatial interactions among regions are specified by the spatial weight matrix $\mathbf{W}$ of dimension ($N \times N$), where N is the number of regions in the data set. The simplest and most commonly used is the contiguity matrix $\mathbf{W}$. Besides this specification we can meet with the distance-based weights, combination of contiguity and distance, ranked distances, k nearest neighbours, etc. (for some other schemes see e.g. Getis, 2010).

Spatial heterogeneity, on the other hand, can be controlled for e.g. by allowing cross-region parameter variation in the form of various spatial regimes (clubs). In such a case the convergence process, if it exists, could differ across the considered clubs (Ramajo et al., 2005). Another possibility to capture the region heterogeneity is to use the region dummies.

In order to examine the spatial structure of the underlying data and to check whether spatial patterns exist, the Exploratory Spatial Data Analysis (ESDA) can be used. Besides mapping of observed values, quantile maps etc. also various tests of spatial autocorrelation can be used. These tests can be differentiated by the scope of analysis into global and local categories. Global statistics provide a measurement of the global spatial autocorrelation – a single value which applies to the entire data set, but they fail to capture the local spatial pattern. Local statistics usually assess the spatial autocorrelation for individual spatial units (regions). The Local Indicators of Spatial Association (LISA) were published by Anselin (1995) and are especially useful for identifying of spatial clusters. The most well-known and commonly used statistics are the global and local Moran's I statistic (see e.g. Fischer and Getis, 2010).

Concerning the econometric models, it is also necessary to deal with the problem of spatial autocorrelation in order to avoid possibly biased results and hence misleading conclusions. After estimation of the model (4) or (5) using the OLS, the spatial diagnostic statistics (e.g. the Moran's *I*), which indicate whether there is spatial autocorrelation in the residuals, should be calculated. In case that the spatial autocorrelation is present, the Lagrange Multiplier (LM) tests can be used in order to decide whether a spatial autoregressive (SAR) or a spatial error (SEM) model of spatial dependence is the most appropriate. If both statistics are significant, robust modifications of these statistics should be used (see Arbia, 2006; Paas et al., 2007). Regarding the specification of the SAR and SEM models, it is not adequate to use the OLS method but both these models can be estimated by the maximum likelihood (ML) method (for more details of ML procedure for spatial models see e.g. Viton, 2010).

2.1. Spatial Autoregressive Model and Spatial Error Model

Model SAR, known also as spatial lag model, is appropriate if spatial autocorrelation among neighbouring regions exists, i.e. if the growth rate in a region is related to those of its surrounding regions conditioning on the initial level of per capita income. In this case the β-convergence model (4) can be modified as follows:

$$\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln\left(y_{i,0}\right) + \rho\sum_j w_{ij}\left(\ln\left(\frac{y_{j,T}}{y_{j,0}}\right)\right) + \zeta_i, \quad \zeta_i \sim i.i.d\left(0,\ \sigma_\zeta^2\right) \quad (6)$$

where

ρ – the scalar spatial autoregressive parameter,

w_{ij} – the elements of matrix **W** describing the structure and intensity of spatial effects,

ζ_i – a random disturbance term and all other terms were previously defined.

The model SEM is appropriate when it is supposed that the spatial autocorrelation exists in the error term. In such a case the non-spatial model (4) can be modified as follows:

$$\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln\left(y_{i,0}\right) + \vartheta_i, \quad \vartheta_i = \lambda\sum_j w_{ij}\vartheta_j + \xi_i, \quad \xi_i \sim i.i.d\left(0,\ \sigma_\xi^2\right) \quad (7)$$

where

λ – a scalar spatial error coefficient expressing the intensity of spatial autocorrelation between regression residuals,

ϑ_i – a random disturbance term.

3. Data

The data used in this study were retrieved from the Eurostat database (General and Regional Statistics). The explanatory variable is initial GDP per capita (defined at current market prices in Euro) in 2000; the dependent variable is the growth rate from 2000 to 2011, both variables are expressed in logarithms. Our data set covers 252 NUTS 2 EU regions in 26 countries over the 2000 – 2011 period: Austria (9), Belgium (11), Bulgaria (6), Czech Republic (8), Germany (38), Denmark (5), Estonia (1), Greece (9), Spain (15), Finland (4), France (21), Croatia (2), Hungary (7), Ireland (2), Italy (19), Latvia (1), Lithuania (1), Luxembourg (1), Netherland (12), Poland (16), Portugal (5), Romania (8), Sweden (8), Slovenia (2), Slovakia (4), United Kingdom (37). We considered NUTS 2 regions of EU corresponding to actual state in 2011. However, it is necessary to mention that the original data set contained 272 regions of 28 EU countries, but due to the possible problems with isolated regions we had to exclude 20 island regions of Cyprus, Malta, France, Finland, Spain, Greece, Portugal and Italy. These isolated regions were identified following the connectivity histogram based on the binary contiguity weight matrix of queen case definition of neighbours in which two units are considered as neighbours if they share any part of a common border. This form of the spatial weight matrix was used in whole analysis in order to capture spatial structure of analysed regions.

The time span 2000 – 2011 was chosen because there were no reliable data available for all analysed regions before 2000 and the year 2011 was the last year of published statistics by Eurostat. The whole analysis was carried out in the software GeoDa (Geographic Data Analysis). The corresponding shapefile (.shp) for Europe was downloaded from the web page of Eurostat and thereafter 252 NUTS 2 regions were selected in GeoDa.

4. Empirical Results

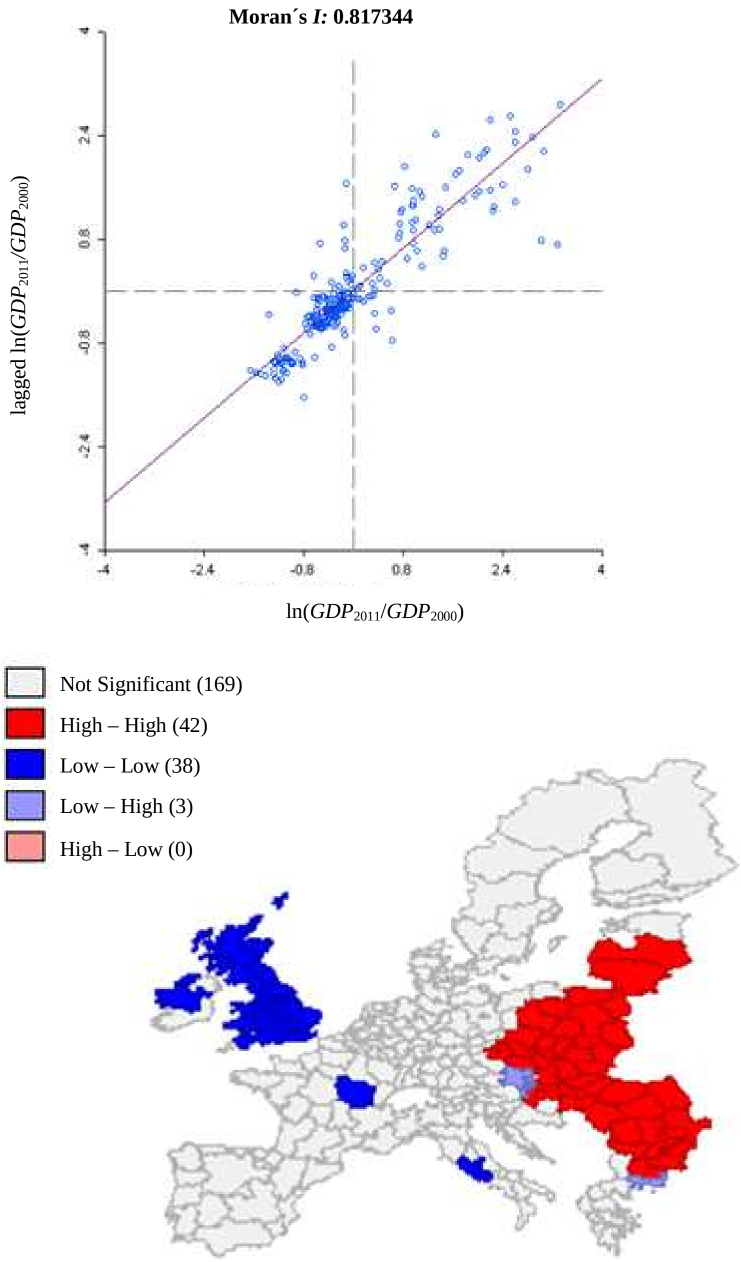
In this section we used Exploratory Spatial Data Analysis, cross-sectional non-spatial and spatial convergence econometric models briefly described in previous parts in order to test absolute and club convergence of per capita GDP hypotheses. The examination of the existence of per capita GDP convergence clubs is considered to be the main goal of our study.

As the recent growth theories and empirical results suggest that the distribution of income per capita of countries (regions) may display convergence clubs; the main aim of this paper is to test the club convergence hypothesis using both non-spatial and spatial approaches. Our empirical part begins with the spatial dependence analysis of the per capita GDP growth rate, i.e. we try to evaluate the fact that the per capita GDP growth rate in one region may be associated with the growth rate in neighbouring regions and to confirm the existence of spatial clustering. The main tool for this analysis were global Moran's *I* statistic (for formula see e.g. Viton, 2010) and local Moran's *I* statistic (for formula see e.g. Feldkircher, 2006) based on a spatial weight matrix **W** which was specified as a binary contiguity weight matrix of queen case definition of neighbours. The calculated value of global Moran's *I* statistic was 0.8173 and it shows the existence of a strong positive spatial autocorrelation process, confirming the visual impression of spatial clustering given by the LISA cluster map based on local Moran statistic (see Figure 1). The LISA cluster map enables us to assess the sign of spatial association of per capita GDP growth rates in different regions. This map shows that there is a clear association of *high – high* values in most of regions of post-communist countries. On the other hand, *low – low* values are significant mainly in regions of United Kingdom. The *high – high* and *low – low* locations (positive local spatial autocorrelation) are typically referred to as spatial clusters. Our analysis indicates positive spatial association of 80 regions (42 regions with *high – high* association and 38 regions with *low – low* 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. LISA map also provide us information about so-called spatial outliers, i.e. the *high – low* and *low – high* locations (negative local spatial autocorrelation). We can observe that regions with *low – high* values are significant only for 3 regions and there are no regions with *high – low* association (see Figure 1).

Next, we proceed with the estimation of the income convergence models. The models defined by equations (6) and (7) account for spatial dependence and as our previous empirical part confirmed that the per capita GDP growth rate is spatially correlated, we regard spatial lagged variable as inevitable part of the income convergence model. By means of spatial econometrics techniques, we do no start with the estimation of the spatial model directly, but we started with the estimation of the traditional absolute β-convergence model (4) in which the effects of spatial dependence are not considered. It is important to emphasise that first we consider whole data set, i.e. 252 NUTS 2 EU regions which are involved into the estimation of the model. The estimation of this model was done by OLS and thereafter the tests aiming at detecting the presence of spatial dependence were carried out using a spatial contiguity weight matrix of queen case definition of neighbours. The estimation results are summarized in Table 1 (Linear model).

F i g u r e 1

Moran´s *I* Statistic and LISA Cluster Maps for the for the GDP Growth Rate in 2011 (in %, initial level 2000)



Source: Own calculations.

The parameter β of the model (Linear model – Table 1) associated with the initial per capita GDP is significant and negative, which confirms the hypothesis of absolute convergence for the EU regions. This means that the regions with lower per capita GDP grew at a higher speed during the period 2000 – 2011. The Moran's I test adapted to the OLS regression residuals confirms a presence of spatial dependence but does not allow testing the presence of the two possible forms of spatial dependence. For this reason we use two LM tests as well as their robust counterparts. Robust LM tests show that the absolute β-convergence model is misspecified due to spatial autocorrelation and more appropriate model is model SAR because the robust LM (lag) statistic is statistically significant while the robust LM (error) statistic is not. Therefore the linear model of absolute β-convergence should be modified to integrate this form of spatial dependence explicitly and we follow SAR model defined by equation (6). The estimation results by ML for SAR model are given in Table 1. The parameters are all strongly statistically significant; β coefficient is again negative confirming absolute β-convergence hypothesis. The statistical significance of spatial autoregressive parameter ρ confirms the existence of spatial effects among neighbouring regions. The statistical adequacy of the spatial lag model also confirms low value of Moran's I statistic applied on spatial residuals (see Table 1).

T a b l e 1

Estimation Results of *β*-convergence Models – 252 NUTS 2 Regions

Estimation	Linear model OLS	SAR model ML
α	3.240***	1.459***
β	–0.300***	–0.136***
ρ	–	0.584***
λ	–	–
R^2	0.692	0.814
Convergence characteristics		
Speed of convergence	0.0324 (3.24%)	0.0133 (1.33%)
Half-life	21.417	52.148
Tests		
Moran's *I* (error)	9.265***	–
LM (lag)	103.470***	–
Robust LM (lag)	23.295***	–
LM (error)	80.783***	–
Robust LM (error)	0.607	–
Moran's *I* (spatial residual)	–	–0.062

Note: Symbol *** indicates statistical significance at 1% level of significance.

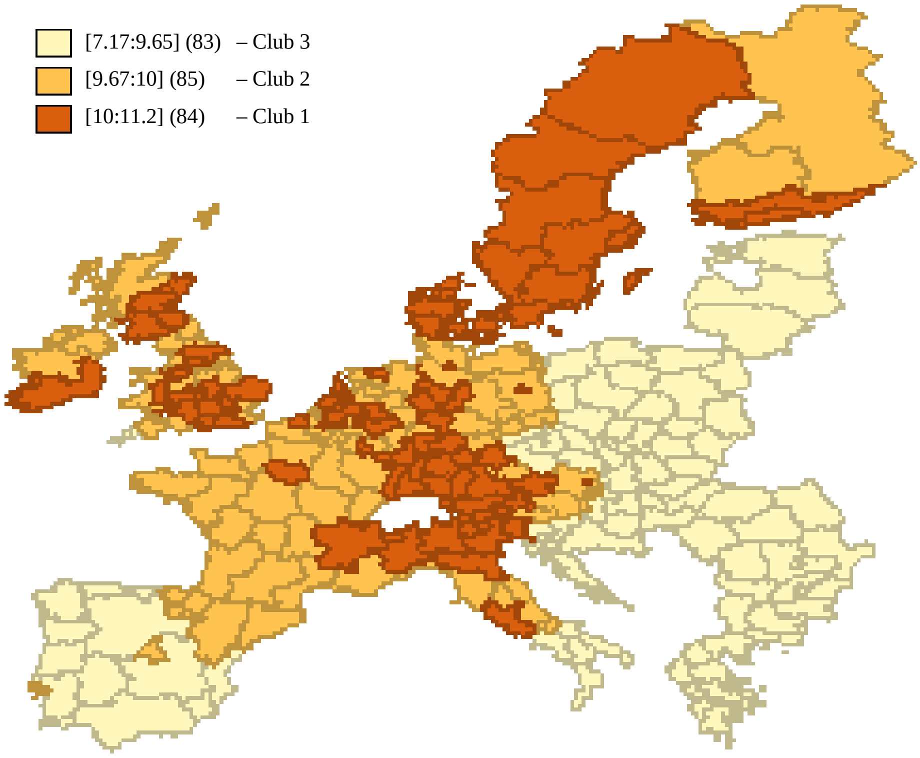
Source: Own calculations.

From the estimation of the β parameter can be derived the characteristics of the β-convergence process: the speed of convergence $b = -\frac{\ln(1+\beta)}{T}$, where T denotes the number of periods and the half-life indicator $t_{half-life} = \frac{\ln(2)}{b}$. The speed of convergence associated with this estimation of the linear model is 3.24% per year and half-life is 21 years. In spatial autoregressive model, we can notice that the convergence process appears to be weaker if spatial effects are taken into account, i.e. speed of convergence is 1.33% per year and half-life increased to 52 years. Similar results were received e.g. in study of Carrington (2003) who pointed out that income convergence was reduced in the spatial specification in the analysis of 110 EU regions during the period 1989 – 1998. Arbia and Pirras (2005) on the sample of 92 Italian provinces in the period 1951 – 2000 detected lower speed of convergence estimated using the spatial lag model. Also Rey and Montouri (1999) found a slower rate of convergence in incomes for the US states over the 20^{th} century in case of spatial models.

In order to control for possible convergence clubs inside the EU, we decided to estimate income convergence models not only for 252 EU regions as a whole but also for the three possible convergence clubs. If regional economies differ in e.g. growth parameters or knowledge spillovers across regions are weak, regional economies may not converge to a common per capita income, but to different economic-specific equilibrium levels of per capita income (spatial heterogeneity). Thus, there might be convergence among similar groups of economies, i.e. club convergence. Economic theory does not provide unique rule neither for the number of clubs nor variable which determines clubs. However, as was mentioned before, some authors distinguish between exogenous and endogenous way of determination of convergence clubs. Our decision for possible three convergence clubs was based on the exogenous way of the club determination, i.e. we set threshold levels of per capita GDP in 2000 supported by GDP quantile map (see Figure 2) in order to divide the regions into highly, middle and weak developed ones. Consequently, the convergence characteristics of the models will be the main tool for verification of the club convergence hypothesis. If the speed of convergence is significantly higher for those three groups compared to the EU regions as a whole, we can conclude that different convergence clubs exist. The maps of club 1, club 2 and club 3 are depicted on the Figure 2. For the econometric analysis the isolated regions of the particular clubs were excluded from the consideration and after this modification the final numbers of regions in individual clubs were as follows: club 1 – 76 regions, club 2 – 80 regions and the club 3 – 82 regions.

Figure 2

Quantile Map for GDP in 2000 (at current market prices by NUTS 2, in Euro per inhabitants)



Source: Own calculations.

The estimation results of β-convergence models with corresponding spatial convergence models for the particular clubs are provided in Table 2. As for club 1 results, we can notice that the parameter β of the model is not statistically significant, hence the hypothesis of absolute convergence during the period 2000 – 2011 was not confirmed within this group of regions, although there was an overall regional income convergence in the EU regions as a whole. This means that each region does not move towards club specific steady state equilibrium, which depends on the initial position of the regions. On the other hand, as for the results indicating spatial dependences, we can see that the spatial dependences extension of the absolute β-convergence model is inevitable modification. Consequently, we proceed with the estimation of the model SEM defined by equation (7). The estimation results now yield significant but still positive parameter for the starting income level such that the hypothesis of absolute β-convergence was not confirmed within this club of regions. The statistical significance of spatial autoregressive parameter λ confirms the existence of spatial effects among neighbouring regions within the club 1 and this conclusion is also supported by low value of Moran's *I* statistic applied on spatial residuals (see Table 2).

In contrast to estimation results of club 1, the outcomes of the regressions of the two remaining clubs (club 2 and club 3) confirm the hypothesis of absolute β-convergence within these two clubs (see results in Table 2). Also the appropriateness of the spatial β-convergence models was detected based on the diagnostics for the presence of spatial effects. Thereafter, SAR models for both clubs were estimated. The principal finding resulting from the club convergence point of view is that spatial interactions and spillovers among regions do matter and we found out that the convergence process appears to be weaker if spatial effects are taken into account (the club 1 is excluded from the consideration due to the detected process of divergence). The convergence characteristics for the club 2 and the club 3 are only slightly different; the results imply the annual convergence rate of 3.32% for regions within the club 2 and the rate of 3.77% per year for those in club 3. As we have already mentioned above, spatial income convergence models for the club 2 and the club 3 estimate weaker convergence characteristics (speed of convergence: club 2 – 2.16%; club 3 – 1.96%).

Overall, the estimation of the spatial income convergence models showed that the spatial dependence among regions does matter. Accordingly, our club convergence hypothesis of three possible convergence clubs was confirmed in our sample of NUTS 2 regions. This conclusion is based on the convergence characteristics of the particular models (see Table 2) and the model as a whole (see Table 1). As far as the club 1, there was confirmed divergence process instead of convergence process observed in β-convergence model of the EU regions as a whole. With reference to the conventional definition of the club convergence (see Fischer and Stirböck, 2004), i.e. each region belonging to a club moves from a disequilibrium position to its club specific steady-state positon, our club 1 is not a club. Although, in this sense club 1 does not fulfil this definition because of detected process of divergence, we see this group of countries as separate club. This conclusion supports significant difference between the convergence parameters in club 1 (divergence) and the parameters of the model as whole. Also, we consider the hypothesis of three groups as possible convergence clubs confirmed as the rates of convergence for the club 2 and the club 3 are higher that for the EU 252 as a whole. It is necessary to remind that we made this decision according to the convergence characteristics of spatial models because of the approved appropriateness of the spatial lag variables in the income convergence models.

T a b l e 2

Estimation Results of β-convergence Models for Individual Clubs

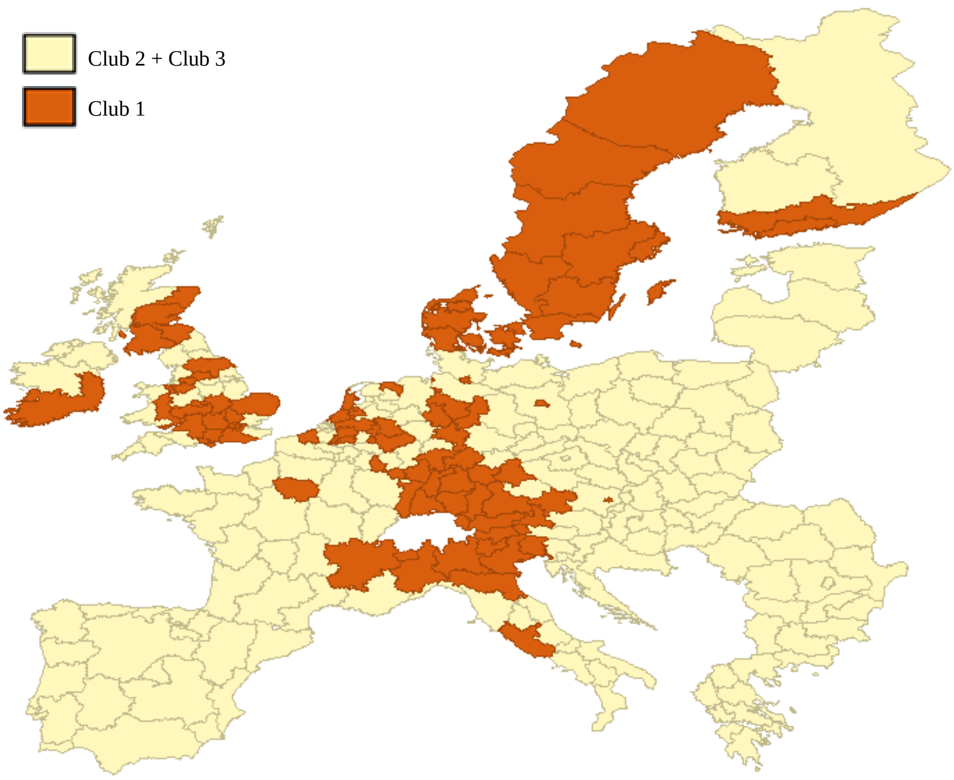
Estimation	**Club 1 (Linear model)** OLS	**Club 1 (SEM model)** ML	**Club 2 (Linear model)** OLS	**Club 2 (SAR model)** ML	**Club 3 (Linear model)** OLS	**Club 3 (SAR model)** ML	**Club 2+Club 3 (Linear model)** OLS	**Club 2+Club 3 (SAR model)** ML
α	–0.203	–0.372	3.258***	2.162***	3.593***	2.018***	3.574***	2.199***
β	0.0397	0.058*	–0.306**	–0.211***	–0.340***	–0.194***	–0.337***	–0.209***
ρ	–	–	–	0.696***	–	0.482***	–	0.422***
λ	–	0.731***	–	–	–	–	–	–
R^2	0.004	0.724	0.0751	0.699	0.583	0.696	0.737	0.802
Convergence characteristics								
Speed of convergence	–	–	0.0332 (3.32%)	0.0216 (2.16%)	0.0377 (3.77%)	0.0196 (1.96%)	0.0374 (3.74%)	0.0214 (2.14%)
Half-life	–	–	20.9043	32.1390	18.369	35.320	18.521	32.428
Tests								
Moran's *I* (error)	7.8863***	–	7.7783***	–	3.568***	–	5.8907***	–
LM (lag)	57.9865***	–	58.3780***	–	19.6360***	–	38.2895***	–
Robust LM (lag)	0.0541	–	2.6424	–	10.9597***	–	7.4857***	–
LM (error)	58.1893***	–	55.7379***	–	10.0274***	–	31.6233***	–
Robust LM (error)	0.2569	–	0.0023	–	1.3511	–	0.8195	–
Moran's *I* (spatial residual)	–	–0.100	–	–0.195	–	–0.040	–	0.005

Notes: Symbols ***, **, * indicate statistical significance at 1%, 5% and 10% level of significance, respectively.
Concerning the adequacy of spatial models, further diagnostics based on Breusch-Pagan test and Likelihood Ratio (LR) test were checked and the tests results indicate that the heteroscedasticity is not present and the spatial autocorrelation has disappeared in case of club 1, club 2 and club 3. However in case of joint club 2 + club 3 appeared the heteroscedasticity which could be solved by inclusion of appropriate additional variables to capture the heterogeneity of analysed regions.

Source: Own calculations.

Recall, three different convergence regimes have been identified, however if we look more closely over the estimation results of the club 2 and the club 3 (club 2 – SAR model and club 3 – SAR model), we can notice that there is no apparent difference between the convergence parameters in each of the two clubs. Subsequently, we dealt with the question of a possible merger of these two clubs. Map of joint club is depicted in Figure 3. The estimation results (given in Table 2) imply proper structure of the joint club, seeing that all the estimated parameters of all models are strongly statistically significant, parameter β has expected negative sign and once again LM tests on our OLS specifications indicated a clear spatial dependence.

Figure 3
Maps of Club 1 and Club 2 + Club 3*



Note: * Isolated regions were excluded after the connection of the club 2 and club 3.

Source: Own calculations.

Conclusion

In this paper we considered the problem of regional income convergence among EU regions for the period 2000 – 2011. GDP per capita in Euro of NUTS 2 was used as a proxy for the income level of individual regions and β-convergence approach was applied. At the beginning of the empirical part the whole data set, i.e. 252 NUTS 2 EU regions were considered for the model estimation. The results showed the negative correlation between per capita GDP levels and subsequent growth rates for regions what is perceived as an evidence of absolute convergence among EU regions for the period 2000 – 2011. This allow us to conclude that on average, regions with low initial per capita GDP are growing faster than those with higher initial per capita GDP and they all converge to the same level of per capita GDP. This finding is in line with many other studies dealing with the absolute income β-convergence of the European regions. Unlike most of these studies, we have adopted a spatial econometric perspective to allow for spatial interactions and spillovers among regions as mechanisms that may lead to convergence. Our decision to incorporate spatial factor into income convergence models was supported by global and local versions of Moran's I statistic. The results of SAR model also confirmed the absolute β-convergence hypothesis, appropriateness of the spatial effects and weaker convergence process when spatial effects are taken into account. These results are in accordance with the findings of several other studies e.g. Arbia and Pirras (2005), Carrington (2003) or Baumont et al. (2002).

Another factor which differs this paper from the mainstream in this field is the relaxation of the implicit assumption of a growth single stable steady-state, i.e. we supposed multiple convergence regimes – clubs. Our club convergence hypothesis was verified following the convergence characteristics and our findings have implied the existence of two final clubs. Club 1 consists of the regions with the best performance (based on the per capita GDP in 2000) and the remaining middle and weak developed regions (based on the per capita GDP in 2000) have created the joint club (club 2 + club 3). As for the structure of the joint club in more details, we can notice that this club mainly consists of the regions of post-communist countries which had similar economic development. In almost all post-communist countries in the early 90´s started economic reforms to change the planned economy to the market oriented economy. The second substantial group of the regions which have been involved to the joint club are all regions of Spain, Portugal, Greece and south regions of Italy. These regions are in the EU economic context considered as "poorer" regions. Also these countries are associated with the term "PIGS" which refers to the economies of these EU member states that were unable to refinance their government debt during the debt crisis. Surprisingly, joint club contained most of French regions. As regards the structure of the club 1, it consists mainly of the regions of Austria, Germany, Sweden, United Kingdom and north Italy. These regions from the long term point of view exhibit best economic performance among the EU regions.

Empirical procedure had identified the treating of spatial effects in income club convergence models as appropriate, thus it is convenient to deal only with results from the spatial econometric perspective. Surprisingly, we observed that the sample of regions belonging to club 1 exhibit the process of divergence. On the other hand, income β-convergence process has been confirmed for the joint club. The estimated speed of convergence of this joint club was 2.14% per year what implies that it will take more than 42 years for half of the distance between the initial level of income and the steady-state of this club to be vanished. Although, these characteristics are in accordance with the previous studies (e.g. Fischer and Stirböck, 2004), the speed of convergence about 2% per year is considered to be very weak. In addition, if we ignore club convergence considering only the whole data set, i.e. 252 NUTS 2 EU regions, corresponding speed of convergence is even lower. The speed of convergence associated with the estimation of the spatial absolute β-convergence model as a whole was 1.33% per year and the corresponding half-life was 52 years. But it is necessary to keep in mind that different groups of regions are compared and the different steady states are considered.

The empirical evidence for the club convergence hypothesis is rather scarce and in addition, the studies dealing with the spatial club convergence hypothesis are even less common. From this point of view this paper can be an asset in the field of β-convergence modelling.

The two major contributions of this paper could be summarized as follows. If the spatial dependence among the spatial units is taken into account, we are able to improve the reliability of the estimates of the speed of convergence among the European regions. This highlights that the classical convergence models suffer from a misspecification due to omitted spatial dependence. We also found that taking spatial effects into account reduces convergence (e.g. Rey and Montouri, 1999; Lim, 2003; Arbia et al., 2005). The second serious finding is that the assumption of a single steady-state for all regions often mismatches with the reality. Thus, we refer to a differentiation of convergence regimes.

The results of spatial econometric analysis could be used as a support tool in decision making of the EU authorities in order to distribute its limited resources more effectively to encourage the “proper” regions, i.e. such regions the higher prosperity of which can contribute in case of positive spatial autocorrelation to the higher prosperity of their neighbouring regions.

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