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Convergence in GDP per capita across the EU regions—spatial effects[1]

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Abstract: The aim of this paper is to offer an empirical insight into the spatial effects of growth of regional income and disparities across EU regions (NUTS 2). Since regions are spatial units and there are interrelated standard linear regression is not sufficient to evidence the convergence process. Two models (Spatial Lag Model – SLM and Spatial Error model – SEM), derived from spatial econometrics, have been used to identify and explain spatial effects in convergence clubs—all EU countries (EU-28), countries that entered the EU in 2004 (EU-13) and countries that were in EU prior to 2004 (EU-15). Unconditional and conditional β-convergence has been examined in the period 2000-2015 thus covering two financial perspectives (including n + 2 rule[3]). Dummy variables have been also applied to catch the country-specific effects, such as national policies, legislation, technology progress, etc.

Keywords: convergence, growth, cohesion policy, regional development.

JEL codes: O47, O43, P25.

Introduction

The European Union is striving for economic, social and territorial cohesion as well as upward convergence and balanced economic growth while using different measures and policy tools. Inequalities in member states of the European Union are not acceptable for several reasons. First of all because they are not in accordance with the foundation of the European Union based on the deep faith and to some extent expectation that European integration must lead to growing cohesion at all levels and finally contributing to the improvement of

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[3] According to the rules member states shall send claims for reimbursement to the EU Agencies for the amount allocated to year "n" at the latest at the end of the second consecutive year "n + 2".

the quality of life in all countries and across all societies.[4] Secondly, because it can spread a feeling of social and economic injustice which can lead to social unrest, fuelling the currently strong anti-European sentiment in many countries and even undermine the idea of the European project (Eurofound, 2018). Thirdly, they disable further and deeper integration reflected in the adoption of a common currency in all member states. Inequalities are finally a reason for implementing cohesion policy measures which are politically sensitive since they require a large proportion of the EU budget thus capturing social and political attention. Taking into account national contributions and private funds the allocation of the Cohesion Policy in the 2014-2020 Framework is estimated to be approximately 450 billion euros, which includes cohesion policy funding of around 350 billion euros. For 7 out of the 28 European Union countries (including Poland) in the years 2015-2017, the cohesion policy accounted for over 50% of public investment (European Commission, 2017), which reflects the real impact and the added value of the cohesion policy to the development and structural adjustments of regions and nations.

The convergence process has been restored in Europe for most parts of the economy in 2013 (Eurofound, 2018), but since many regions of the new member states stuck in the "middle income trap" (European Commission, 2017), divergence is still a concern. Especially within its spatial context.

The paper is structured as follows. The first section is devoted to the literature review on the convergence processes on national and regional levels. Sections 2 presents the methodology and data used in the model analysed. Section 3 presents results of the analysis of the spatial effects of the convergence process. A conclusion closes the paper.

1. Review of the literature

Research into convergence has a long history going back to the 1980s (Baumol, 1986). The classic and neoclassical models of growth, especially Solow-Swan (Solow, 1956; Swan, 1956) model and the framework developed by Mankiw, Romer and Weil (1992) as well as Barro and Sala-i-Martin (1992, 2003) suggested that that rich and poor countries will converge mainly because they experience diminishing returns on capital. Opponents, who are mostly advocates of the new economic geography (Krugman, 1991), argue that the contemporary economic processes (especially the creation of the Single Market and the opening of national economies) rather support divergence resulting in the core-periphery structure with strong spatial concentration, thus spatial effects will be

[4] "The notion of the convergence is at the heart of Economic Union: convergence between member states towards the highest levels of prosperity; and convergence within European societies, to nurture our unique European model" (European Commission, 2015, p. 7).

considered and reflected in any analysis of the regional economic convergence dynamics. It can be observed that the spatial structure of the income level is marked by an east-west gradient with higher regional growth rates in the east, confirming the catching-up process (Paas & Schlitte, 2009). Prior to the 2008 economic crisis EU countries indeed experienced both economic and social convergence (Eurofound, 2018). The financial crisis and double deep recession in 2008 and 2011 affected almost all member states in the EU and stopped or even reversed the process of a long-term reduction in disparities in basic variables of the real economy like GDP per head or labour productivity (European Commission, 2017). The process of divergence in regions has been even stronger than on the national level, since space experiences a natural process of polarization which runs in two dimensions: metropolitan – non-metropolitan areas, as well as high and less developed regions (Smętkowski & Wójcik, 2008; Broll, Kemnitz, & Murkherjee, 2019). Monfort (2009) noticed the convergence of regions but also indicated the creation of growth poles as the effect of the urban agglomerations and the drainage of production factors from peripheries. The spatial agglomeration of economic activities and growth correlate positively which has been evidenced in literature many times (Hohenberg & Lees, 1985; Baldwin & Forslid, 2000; Martin & Ottaviano, 2001; Guevera, 2016). The role of large cities in boosting economic development has been also emphasised by many researchers (Williamson, 1998; Henderson, 2003; Prasad, Singh, & Swami, 2016; Nguyen & Nguyen, 2018). It is because large cities and highly developed areas attract a more skilled labour force, suppliers, specialised services, better infrastructure, education and training availability, as well as the proximity of firms and NGOs, existing clusters produce more innovation and knowledge spill-overs which boost local economy, leading to divergence. As regions tend to diverge, and at the same time national convergence can be noted, leads to the conclusion that national macroeconomic factors may have had larger impact than the spatial interactions and spill-overs. There can be also a trade-off between national and regional convergence (Paas & Schlitte, 2009), which is of great importance for the cohesion policy. Although Esposti and Busoletti (2008) argued that the cohesion policy has a great impact on regional convergence later research does not confirm that correlation (Gorzelak et al., 2017).

2. Methodology and data

In the research absolute and conditional β-convergence of the real income GDP per capita in the European Union economies at the NUTS2 level has been examined and extended for a spatial effect. Knowing the deficits of standard linear regression models analysis has been extended for other techniques derived from the spatial econometrics. The real convergence term refers to the tendency of the countries, regions or other areas involved towards higher equality of real variables like GDP per capita or labour productivity. The theoretical background for this is derived from neoclassical models (Solow, 1956; Mankiw et al., 1992), popularised by Baumol, Barro and Sala-i-Martin (Baumol, 1986; Barro, & Sala-i-Martin, 1992, 2003; Barro, 2000; Sala-i-Martin, 1996a, 1996b, 2002). A basic assumption in those models—decreasing marginal productivity of capital has to lead to the faster growth of underdeveloped countries. As the examined areas converge they become more and more similar. This approach is called σ-convergence and refers to a reduction in the dispersion (usually standard deviation) of the feature examined (e.g. GDP per capita) in a considered group of economies over time. The second measure of convergence, the so called β-convergence, relates to the relationship between the average rate of growth of an index determining a certain level of development and its initial value which refers to the 'catching up' effect and the diminishing or closing gap between lesser and highly developed countries. Statistical verification of this relationship may be a model where the dependent variable is the growth rate, e.g. GDP per capita, and its initial value as an explanatory variable. If there is just one explanatory variable the hypothesis about the occurrence of absolute or unconditional convergence will be tested and if there are more additional exogenous variables having a potential impact on the dependent variable in the model, the hypothesis on conditional convergence shall be tested. To verify whether β-convergence occurs the following regression equitation has to be estimated [Kusideł, 2013]:

$$\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) = a_i - (1-e^{-\beta})\left[\ln(y_{i,t-1}) - x_{i,t-1}\right] + u_{it}, \tag{1}$$

where:

$a_i = x_i + (1 - e^{-\beta})\ln(y_i^*)$
y_{it} – value of the variable of the area i at the given time t,
x_{it} – value of structural exogenous variables influencing the economy
y_i^* – value of the variable in the equilibrium, so called steady-state,
β – pace of convergence towards equilibrium,
u_{it} – stochastic error.

Skipping the existence and influence of other structural variables x_{it} the equation (1) can be transformed to the following:

$$\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) = a_i - (1-e^{-\beta})\ln(y_{i,t-1}) + u_{it}, \tag{2}$$

and then to the linear form:

$$\ln\left(\frac{y_{it}}{y_{i,t-1}}\right) = a_i + b\ln(y_{i,t-1}) + u_{it}, \tag{3}$$

where:

$b = -(1 - e^{-\beta})$ thus $\beta = -\ln(1 + b)$.

While cross-sectional data is used and the real GDP per capita as the variable the quotation (3) has to be changed to the following form (Kusideł, 2013):

$$\ln\left(\frac{y_{it_0+T}}{y_{i,t_0}}\right) = a + b\ln(y_{i,t_0}) + u_{it_0+T}, \tag{4}$$

where negative estimator $b = -(1 - e^{-\beta T})$ means convergence (positive—divergence). An estimator b is mostly used to calculate the convergence coefficient calculated as:

$$\beta = -\ln(1 + b)/T, \tag{5}$$

where T is an interval between first and last observation.

The existence of β-convergence is a necessary condition for the occurrence of σ-convergence, not necessarily the opposite. It means that convergence in the GDP per capita between certain areas can be shown, while having a discrepancy of its value at the same time (this can be explained by γ convergence and leapfrogging phenomenon).

Since regions are interrelated due to their proximity in space and a wide network of links of different nature there is a need to include spatial effect in the socio-economic analysis. Accommodating spatial effect in the regression context it has to be divided into two components: spatial dependencies or its weaker expression of spatial autocorrelation and spatial heterogeneity (Anselin, 2003, Anselin, LeGallo, & Jayet, 2008). Spatial heterogeneity is a result of a structural instability and can be tackled by most of the standard econometric tools. Spatial dependencies have to be captured by spatial stochastic process. According to the well-known first law of geography published by Tobler (1970) we know, that "everything is related to everything else, but near things are more related than distant things". Since regions have their closer and further neighbourhoods, it is intuitionally assumed that it must have an impact on different features and regional characteristics, such as production or income. Evidence can also be found in the literature that ignoring spatial effects can lead to biased results and hence misleading conclusions (Fingleton & López-Bazo, 2006; Kuc, 2017). Accommodation of spatial heterogeneity and interdependence in regional growth specification was also underlined by many other researchers (e.g. Rey & Montouri, 1999; López-Bazo, Vayá, Mora, & Suriñach, 1999; Paas & Schlitte, 2009; Suchecki, 2010; Olejnik, 2014; Kuc, 2017). Spatial autocorrelation enables us to understand the degree to which one object is similar to nearby objects. Consideration of specific relationships between observation units resulting from their location is made possible by the design and use of the spatial weight matrix 'W'. A spatial weights matrix W is a $n \times n$ matrix in which the rows and columns correspond to the cross-sectional observations and it typically reflects the "spatial impact" of unit *j* on unit *i*. The mutual neighbourhood has a stimulating effect on spatial relationships and the distance is dissimulative, hence the most commonly used types of matrix are those based on boundaries or distance. In the simplest case of the weights based on boundaries, the matrix is binary, with $w_{ij} = 1$ when i and j are neighbours and $w_{ij} = 0$ when they are not. In the weights based on the distance the specification of elements is based on the measurement of the distance d_{ij} between the units *i* and *j*, and the individual weights are calculated most commonly using negative power or exponential functions in accordance with the formulas (Kisiała, 2016):

$$w_{ij} = d_{ij}^{-\alpha},\ w_{ij} = e^{-\alpha\, d_{ij}} \tag{6}$$

The researcher has to choose a way towards measuring the distance (Euclidean distance, km, miles), the analytical form of the function used and the value of the α parameter determining the strength of the decrease in spatial dependency. In this research a critical distance cut-off has been used. It is assumed that above this distance the spatial interaction is 0 and the formula takes the following form (Paas & Schlitte, 2009):

$$W = \begin{cases} w_{ij} = 0 & \text{if } i = j \\ w_{ij} = \dfrac{1}{d_{ij}^2} & \text{if } d_{ij} \le D \\ w_{ij} = 0 & \text{if } d_{ij} > D \end{cases} \tag{7}$$

where:

w_{ij} – a spatial weight for interaction between regions *i* and *j*,
d – distance between geographical centres of regions *i* and *j*,
D – critical distance cut-off. To enhance the interpretation, elements of the weight's matrix are usually row standardised, such that for each *i*, $\sum_i w_{ij} = 1$.

The most common technique used to test the strength of the spatial dependencies is the Global Moran's I. This tool measures spatial autocorrelation based on both feature locations and feature values simultaneously. It calculates index value as well as *z*-score and *p*-value being proxy for its significance. Global Moran's I can be computed while using the following formula (Suchecki, 2010; Kisiała, 2016):

$$I = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} = \frac{n}{S_0}\frac{z^T W z}{z^T z} \tag{8}$$

where:

z_i – the deviation of an attribute for feature i from its mean $(x_i - \bar{X})$,

w_{ij} – is the spatial weight between feature i and j,

n – equal to the total number of features,

S_0 – the aggregate of all the spatial weights: $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$.

The Z_1-score for the statistic is computed as:

$$Z_1 = \frac{I - E(I)}{\sqrt{\mathrm{Var}(I)}} \sim N(0,1), \tag{9}$$

where

$$E(I) = -\frac{1}{n-1}, \tag{10}$$

and

$$\mathrm{Var}(I) =$$

$$= \frac{n\left[(n^2 - 3n + 3)S_1 - nS_2 + 3S_0^2\right] - k\left[(n^2 - n)S_1 - 2nS_2 + 6S_0^2\right]}{(n-1)(n-2)(n-3)S_0^2} - \frac{1}{(n-1)^2}, \tag{11}$$

where:

k – the empirical measure of kurtosis, i.e. the quotient of the fourth moment by the square of the second moment:

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^2}, \tag{12}$$

and

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}, \tag{13}$$

$$S_1 = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(w_{ij} + w_{ji})^2, \tag{14}$$

$$S_2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\right)^2. \tag{15}$$

When Moran's I is positive and significant there is a tendency towards a spatial clustering of similar parameter values in the sample (local Moran and cluster mapping tools). As the spatial autocorrelation occurs the estimation of the ordinary regression methods, such as Ordinary Least Squares (OLS) are not accurate (Kisiała et al., 2017) and there is a need to use alternative methods delivered by the spatial econometrics. Considering the linear regression context spatial dependence can be incorporated in the two following distinct ways (Anselin, 2003): as an additional regressor – a spatially lagged dependent variable (W_y), or in the error structure ($E[\varepsilon_i \varepsilon_j] \neq 0$). The first one refers to Spatial Lag Model (SLM), or a mixed regressive, the Spatial Autoregressive Model (SAR), which is used when spatial dependencies are expected. It is formally expressed as:

$$y_i = \alpha + \rho \sum_{j-1}^{n} w_{ij} y_j + \varepsilon_i, \quad i = 1, \ldots, n, \tag{16}$$

where:

w_{ij} – the element of W,

$\sum_{j-1}^{n} w_{ij} y_j$ – the weighted average of the dependent variable,

ρ – a spatial autoregressive coefficient which measures the intensity of spatial interdependency,

ε – a vector of error terms ($\varepsilon \sim N(0, \sigma^2 I)$).

As spatial lags are used to reflect dependencies in the disturbances process the Spatial Error Model (SEM) can be used which in fact is not a theoretical model reflecting spatial dependencies, but a special case of non-spherical error covariance matrix. The general standard model of spatial autocorrelation is used in the following form (Kisiała, 2016):

$$y_\gamma = \sum_{i=1}^{k} \beta_i x_{i\gamma} + \varepsilon_\gamma, \tag{17}$$

$$\varepsilon_\gamma = \lambda \left(\sum_{s=1}^{n} w_{rs} \varepsilon_s \right) + u_\gamma, \tag{18}$$

where:

ε_γ – spatially correlated residual being a function of an error lag $\sum_{s=1}^{n} w_{rs} \varepsilon_s$,

λ – the autoregressive parameter for the error lag $\sum_{s=1}^{n} w_{rs} \varepsilon_s$ and reflects the strength of the residual's interdependencies, which in fact enable the conclusion that there is the existence of other factors having an impact on the dependent variable and not included in the regression model. Both models—SLM (SAR) and SEM can be estimated while using the maximum likelihood (ML) method. Testing Lagrange Multiplier (LM) results or their robust modification can be a basis of the choice as to which model fits better with the modelled reality.

GDP per capita data have been derived from the Eurostat database. Period 2000-2015 has been considered which covers two financial frameworks (2000-2006 and 2007-2013, extended to 2015 to include $n + 2$ rule which is applied in cohesion policy). While including these two additional years the effects of all projects which have been started before the end of the given Financial Perspective but not reimbursed up to this time can be captured. Regressions have been calculated for the whole area of the European Union (276 Regions of the European Union (NUTS2 level according the Nomenclature of Territorial Units for Statistics 2013), but also separately for 218 Regions of EU-15 (Countries in the European Union prior to 2004) and finally 58 Regions of new member states that joined the EU in 2004 (the so called club convergence). Additionally dummy variables have been included to estimate the influence country-specific effects (economic policy, legislation, tax system, technological diffusion, etc.), which impact growth heavily, in particular in the long-run. In this kind of estimation the high importance of the stochastic error can be expected.

Referring to the exchange rate: the parameters for nominal GDP per capita were estimated which were then converted to real values using the GDP deflator at the level of prices for the year 2000; and in the second case, GDP per capita based on purchasing power standards (PPS) was used. Analysing purchasing power parity better reflects the nature of real economic processes as it takes into account the purchasing power of the population of a given country. What is also important is that PPS is used to calculate the level of the income, which enables the qualification of a region for the structural assistance under Objective 1. In effect several models and variants have been estimated to tackle and cover a variety of issues.

3. Results

The analysis started with the investigation of the range of spatial dependencies between all 276 Regions of the European Union. Moran I coefficient has been calculated to capture it. The numbers in Table 1 demonstrate the strong positive spatial dependence among all 276 regions in EU. The Moran's I index is highest with a cut-off distance of a 190 km and then decreases thereafter approaching 0 by 1250 km. All measures are statistically significant. Therefore a critical cut-off distance of 190 km has been used in the analysis for all 276 Regions of EU (Table 1). In case of the 218 regions of "Old Member States" and 58 regions of "New Members States" analysed, the highest Moran's I index has been noticed for a cut-off distance of 195 km and this weight threshold matrix has been used for the analysis of this group of regions.[5]

[5] 0.4841 and 0.4740 respectively, calculated but not presented in the separate Table.

Table 1. Moran's I-test for Spatial Autocorrelation NUTS2 level (276 Regions of EU), 2000-2015

Critical distance cut-off (km)	Real GDP per capita (PPS)			Real GDP per capita (current prices)		
	$\ln\left(\frac{y_{i2015}}{y_{i2000}}\right)$	$\ln(y_{i2015})$	$\ln(y_{i2000})$	$\ln\left(\frac{y_{i2015}}{y_{i2000}}\right)$	$\ln(y_{i2015})$	$\ln(y_{i2000})$
150	0.508698	0.425562	0.537414	0.55263	0.651447	0.670499
175	0.63811	0.481284	0.660118	0.646333	0.767707	0.797953
185	0.714291	0.481739	0.695497	0.700607	0.790416	0.832616
190	**0.71388**	**0.496071**	**0.695813**	**0.701249**	**0.790003**	**0.827989**
195	0.720146	0.492962	0.689828	0.701632	0.78116	0.819852
200	0.70596	0.483775	0.674483	0.684472	0.769267	0.806254
225	0.700481	0.466541	0.661074	0.671378	0.755366	0.79343
250	0.699786	0.467064	0.660529	0.680034	0.75557	0.792881
300	0.69595	0.440417	0.63164	0.666879	0.732572	0.768253
500	0.520937	0.407175	0.518662	0.503647	0.637334	0.637705
750	0.291764	0.301677	0.344426	0.290697	0.473257	0.442412
1000	0.121429	0.192922	0.192373	0.135417	0.320593	0.273448
1250	0.036255	0.0917306	0.0743245	0.0478158	0.179428	0.13809

Source: Based on (Geoda).

It can be observed (Figure 1) that countries that entered EU in 2004 demonstrate a very fast pace of β-convergence, while in Italy, Greece, partially in France and in the majority of the UK, the process is very low. While using the 190 km cut-off weight matrix, 128 regions (46,4%) from all together 276, have been marked as significant.

As weights based on the boundaries are used—spatial contiguity weights (so called queen contiguity), results are similar, but it can be observed that a shift of the low pace of convergence area from the UK to continental Europe, now covers larger parts of France. New member states remain in the fast unconditional β-convergence area (Figure 2). Significant then are 101 regions (36,6% of whole population).

Next step in the analysis was the regional β-convergence in its unconditional and conditional form. A common cross-sectional OLS approach has been used with per capita growth as the dependent variable and its initial income level as the explanatory variable. Dummy variables have also been applied to catch country-specific effects. Next tables (2,3 and 4) present different models—Table 2 shows a β-convergence estimation using standard OLS while ignoring spatial dependencies in 276 Regions of Europe, 218 Regions of EU coun-

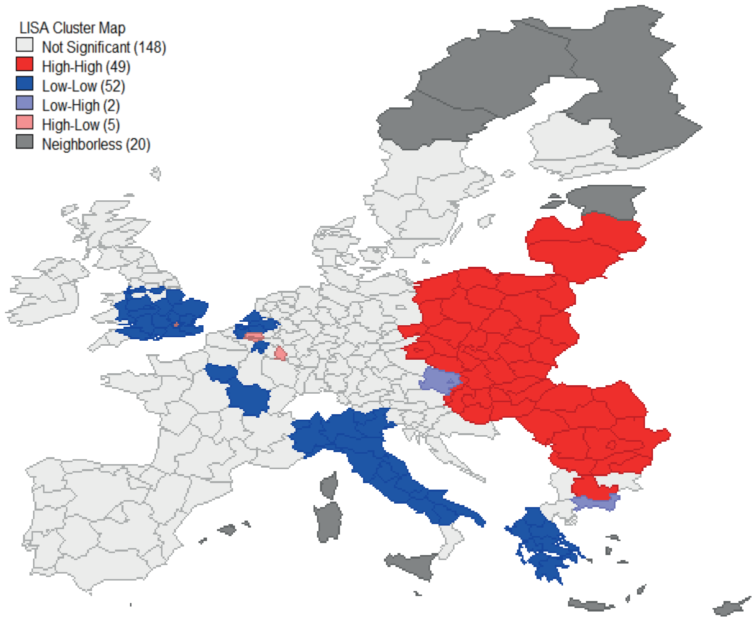

Figure 1. LISA Cluster Map (unconditional β-convergence, PPS) for 276 EU Regions (cut-off 190 km matrix), 2000-2015

Source: Based on (Geoda).

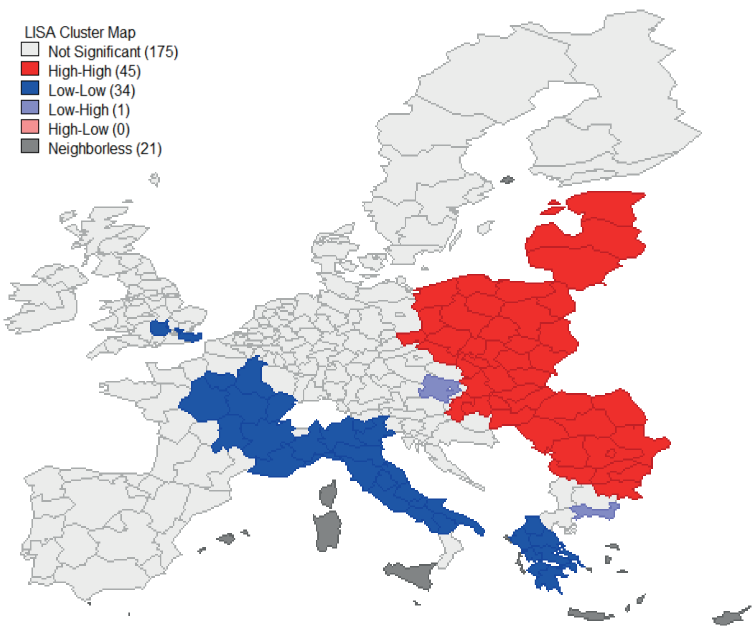

Figure 2. LISA Cluster Map (unconditional β-convergence, PPS) for 276 EU Regions (queen contiguity matrix), 2000-2015

Source: Based on (Geoda).

tries belonging prior to 2004 and finally the 58 regions of countries that joined the EU in 2004. Table 3 presents estimations of the Spatial Lag Model (SLM) and Table 4 demonstrates calculations for the Spatial Error Model (SEM). The Purchasing Power Standard has been applied to calculate the level of the GDP growth. Dummy variables have been also used with the reference base "Old Member States", Germany and Poland respectively. Using dummy variables increased strongly the model adjustment in case of EU-28 (not in the remaining cases), indicating that the pace of convergence in countries that joined EU in 2004 is about 35% higher than in the remaining countries. In case of the countries being a member of the EU before 2004 the pace of convergence is higher in Germany than in the remaining countries (in total). Poland and other new member states (in total) have a very similar pace of β-convergence. This confirms, to some extent, the conclusions from the analysis of the local Moran's statistic (Figure 2). Considering national effects, the results demonstrate high spatial error dependencies in the EU-15, while it is not so evident for the EU-13. In all cases the coefficient α_1 is negative which reflects β-convergence over the 2000-2015 period.

Tests indicate a very high level of spatial dependencies (Moran I value)—the statistics are not significant which means that the null hypothesis cannot be rejected and the assumption that spatial distribution of the β-convergence process can be a result of various and also random spatial process. The spatial dependency is highest in the case of the EU-15, lowest (still positive) in the case of EU-13. Tests of the Lagrange Multiplier (LM-), both in a normal and robust form have been applied to identify the form of spatial autocorrelation. In the case of EU-28, all LM-statistics, both in normal and robust form are statistically significant, which means that it is not possible to indicate which model is better. Probably the best solution would be to use models including both effects, such as SAC (Spatial Autocorrelation with Corrections of Errors) or SARAR (Spatial Autoregressive with Autoregressive disturbances of order). However the Likelihood ratio tests seem to indicate SLM in the version without dummy variables and SEM in the version with dummy variables to be the better (both values are statistically significant). In case of the EU-15 LM-tests indicate SLM as a better model to reflect spatial dependencies in both variants, which is opposite to the EU-13 case, where tests demonstrate a better fitting SEM.

It is worth mentioning that using SLM or SEM in all calculated variants, increases the adjustment of the model.

Rho ρ demonstrates existing very high spatial dependencies, highest in EU-28 case (Table 3).

Also in the case of the SEM analysis the very strong intensity of spatial autocorrelation between regression residuals (high level of λ) can be seen. While using dummy variable λ the level decreases which means that by introducing this variable some noise from the model can be eliminated.

Table 2. OLS Estimation Results for 2000-2015 Period (Purchasing Power Standard)

	EU-28				EU-15				EU-13			
No of regions (NUTS2)	**276**				**218**				**58**			
Dummy variable	**no**		**yes OMS—reference**		**no**		**yes Germany—reference**		**no**		**yes Poland—reference**	
	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value
Intercept	3.40	0.00	1.28	0.00	0.38	0.14	0.67	0.00	3.14	0.00	3.12	0.00
α1	−0.31	0.00	−0.10	0.00	−0.01	0.76	−0.03	0.26	−0.26	0.00	−0.27	0.00
Dummy variable	–	–	0.35	0.00	–	–	−0.13	0.00	–	–	0.02	0.67
R^2 adjusted	0.45	–	0.63	–	0.00	–	0.17	–	0.27	–	0.26	–
AIC	−195.74	–	−304.16	–	−322.82	−0.76	−363.59	–	−28.76	–	−26.95	–
Schwarz	−188.50	–	−293.30		−316.05	–	−353.44	–	−24.63	–	−20.77	–
Convergence speed	0.02	–	0.01	–	0.00	–	0.00	–	0.02	–	0.02	–
Half-life	28.17	–	99.92	–	1345.76	–	387.13	–	33.78	–	33.71	–
Jarque-Bera test	73.82	0.00	17.09	–	18.76	0.00	59.61	0.00	7.37	–	6.01	0.05
White-test	21.27	0.00	–	–	96.46	0.00	n/a	–	2.12	–	n/a	–
Breusch-Pagan test	1.95	0.16	39.70	0.00	31.67	0.00	33.59	0.00	0.59	0.44	6.95	0.03
Koenker-Basset test	0.92	0.34	25.63	0.00	18.44	0.00	14.85	0.00	0.46	0.50	5.50	0.06
Moran's I (error)	10.26	0.00	9.05	0.00	11.12	0.00	9.10	0.00	2.30	0.02	2.47	0.01
Lagrange Multiplier error	96.44	0.00	73.83	0.00	113.96	0.00	73.61	0.00	3.52	0.06	3.35	0.07
Robust LM error	12.25	0.00	21.71	0.00	47.76	0.00	33.62	0.00	0.08	0.77	0.05	0.82
Lagrange Multiplier lag	117.98	0.00	64.03	0.00	67.04	0.00	40.88	0.00	6.59	0.01	6.63	0.01
Robust LM lag	33.80	0.00	11.92	0.00	0.84	0.36	0.54	0.46	3.16	0.08	3.33	0.07

Source: Based on GeoData software.

Table 3. SLM Estimation Results 2000-2015 (Purchasing Power Standard)

	EU-28				EU-15				EU-13			
No of regions (NUTS2)	**276**				**218**				**58**			
Dummy variable	**no**		**yes OMS—reference**		**no**		**yes Germany—reference**		**no**		**yes Poland—reference**	
	value	p-value	value	p-value	value	p-value	value	p-value	value	p-value	value	p-value
Intercept	1.872	0.000	0.931	0.000	0.730	0.001	0.849	0.000	1.910	0.001	1.888	0.000
α1	−0.171	0.000	−0.074	0.001	−0.056	0.009	−0.059	0.005	−0.156	0.005	−0.156	0.005
Dummy variable	–	–	0.222	0.000	–	–	−0.080	0.000	–	–	0.027	0.581
Rho ρ	0.522	–	0.381	–	0.466	–	0.378	–	0.339	–	0.341	–
R-squared	0.670	–	0.718	–	0.290	–	0.335	–	0.400	–	0.404	–
AIC	−316.197	–	−366.538	–	−384.009	–	−400.743	–	−35.172	–	−33.475	–
Schwarz	−305.335		−352.057		−373.899	–	−387.205	–	−28.991	–	−25.233	–
Convergence speed	1.25%	–	0.51%	–	0.38%	–	0.41%	–	1.13%	–	1.13%	–
Half-life	55.326	–	134.668	–	180.128	–	170.819	–	61.408	–	61.436	–
Likelihood Ratio test	122.456	0.000	64.376	0.000	63.187	0.000	39.150	0.000	8.417	0.004	8.527	0.004

Source: Based on GeoData software.

Table 4. SEM Estimation Results 2000-2015 (Purchasing Power Standard)

	EU-28				EU-15				EU-13			
No of regions (NUTS2)	**276**				**218**				**58**			
Dummy variable	**no**		**yes OMS—reference**		**no**		**yes Germany—reference**		**no**		**yes Poland—reference**	
	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value
Intercept	1.669	0.000	0.979	0.000	0.688	0.002	0.819	0.000	1.648	0.005	1.471	0.014
α1	–0.135	0.000	–0.069	0.006	–0.040	0.075	–0.044	0.045	–0.103	0.113	–0.079	0.227
Dummy variable	–	–	0.319	0.000	–	–	–0.100	0.000	–	–	–0.050	–0.568
Rho ρ	0.740	0.000	0.606	0.000	0.671	0.000	0.601	0.000	0.568	0.000	0.615	0.000
R-squared	0.690	–	0.742	–	0.423	–	0.439	–	0.422	–	0.436	–
AIC	–308.855	–	–376.412	–	–415.856	0.000	–426.385	–	–35.614	–	–33.860	–
Schwarz	–301.614		–365.550	–	–409.087	–	–416.232	–	–31.493	–	–27.679	–
Convergence speed	0.97%	–	0.47%	–	0.27%	–	0.30%	–	0.72%	–	0.55%	–
Half-life	71.485	–	146.114	–	254.009	–	230.397	–	96.133	–	125.641	–
Likelihood Ratio test	113.114	0.000	72.249	0.000	93.034	0.000	62.793	0.000	6.859	0.009	6.912	0.009

Source: Based on GeoData software.

Analysis of the β-convergence while using GDP per capita converted according to current princes (Table 5, 6 and 7 in the Annex) brings similar results, with the following exception:

1. There is lower pace of β-convergence in all cases.
2. There is divergence of GDP per capita in the area of EU-15.
3. There is evidence of a normal distribution of data (Jarque-Bera test significance exceeds 0.05 almost in all cases).

Conclusions

Examination of the pace of β-convergence in the regions of the European Union reveals a discrepancy between particular club countries (EU-28, EU-15 and EU-13). Countries that entered the EU in 2004 experience a much higher pace than the old member states while the Purchasing Power Standard is used to calculate the variable—real GDP per capita, however when estimating variable in current prices a process of divergence can be observed. Model adjustment is relatively high but a large portion of the model remains unexplained. In the entire β-convergence process strong spatial effects can be evidenced, as indicated by the high Moran I statistics. While identifying spatial clusters of a high or low pace of β-convergence again the strong discrepancy between growth in "Old" and "New" member states can be observed. All countries that entered the EU in 2004 demonstrate a much higher pace of real GDP per capita growth, which confirms the standard analysis without spatial effects. Since the results indicate high spatial dependencies between regions, models from spatial econometry have been applied. Using the Spatial Lag Model and Spatial Error Model increased the fit of the model, which indicates that the national development factor matters. There is no one clear solution in the dilemma as to which model is better in explaining the remaining part of the model. Applying dummy variables enabled some country-specific effects to be identified although the adjustment of the model has not increased considerably. It can be assumed that national development factors are of great importance for the ongoing convergence. The less-infrastructural areas such as social inclusion, healthcare, energy and climate issues, employment or R&D need to be sought. In these areas a higher EU-value-added can be achieved which will enhance convergence processes, both the on national and regional level. The analysis should also be extended to the long-term to avoid shocks which interfere with the core processes. It would be worthwhile to search for other models that evidence both: spatial dependencies and dependencies in the disturbances process such as SAC or SARAR. It could also be useful to investigate different periods in cross-sectional observations. What is perfectly clear is that regional convergence is spatially dependent and omitting spatial effects in the analysis will certainly bias the results. Standard linear regression in this case is certainly insufficient.

Annex

Table 5. OLS Estimation Results for 2000-2015 Period (current prices)

	EU-28				EU-15				EU-13			
No of regions (NUTS2)	**276**				**218**				**58**			
Dummy variable	**no**		**yes OMS—reference**		**no**		**yes Germany—reference**		**no**		**yes Poland—reference**	
	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value
Intercept	1.754	0.000	0.184	0.306	–0.544	0.007	1.472	0.000	1.754	0.000	0.184	0.306
α1	–0.164	0.000	–0.009	0.613	0.064	0.002	–0.120	0.001	–0.164	0.000	–0.009	0.613
Dummy variable	–	–	0.367	0.000	–	–	–	–	–	–	0.367	0.000
R^2 adjusted	0.441	–	0.593	–	0.040	–	0.160	–	0.441	–	0.593	–
AIC	–257.175	–	–344.115	–	–332.789	–	–47.302	–	–257.175	–	–344.115	–
Schwarz	1.19%	–	0.06%	–	–0.41%	–	0.85%	–	1.19%	–	0.06%	–
Convergence speed	58.021	–	1141.224	–	–168.083	–	81.160	–	58.021	–	1141.224	–
Half-life	3.574	0.168	5.790	0.055	113.242	0.000	1.074	0.584	3.574	0.168	5.790	0.055
Jarque-Bera test	4.976	0.083	n/a	n/a	68.668	0.000	1.789	0.409	4.976	0.083	n/a	n/a
White-test	1.754	0.000	0.184	0.306	–0.544	0.007	1.472	0.000	1.754	0.000	0.184	0.306
Moran's I (error)	12.757	0.000	9.695	0.000	9.852	0.000	4.098	0.000	12.757	0.000	9.695	0.000
Lagrange Multiplier error	149.537	0.000	84.394	0.000	88.309	0.000	12.485	0.000	149.537	0.000	84.394	0.000
Robust LM error	17.372	0.000	9.634	0.002	1.244	0.265	1.269	0.260	17.372	0.000	9.634	0.002
Lagrange Multiplier lag	143.330	0.000	87.688	0.000	90.228	0.000	13.204	0.000	143.330	0.000	87.688	0.000
Robust LM lag	11.165	0.000	12.928	0.000	3.163	0.075	1.988	0.159	11.165	0.000	12.928	0.000

Source: Based on GeoData software.

Table 6. SLM Estimation Results 2000-2015 (current prices)

	EU-28				**EU-15**				**EU-13**			
No of regions (NUTS2)	**276**				**218**				**58**			
Dummy variable	**no**		**yes OMS—reference**		**no**		**yes Germany—reference**		**no**		**yes Poland—reference**	
	value	p-value	value	p-value	value	p-value	value	p-value	value	p-value	value	p-value
Intercept	0.799	0.000	0.069	0.651	0.005	0.974	0.708	0.000	0.799	0.000	0.069	0.651
α1	–0.075	0.000	–0.002	0.880	0.003	0.835	–0.054	0.097	–0.075	0.000	–0.002	0.880
Dummy variable	–		0.214	0.000	–	–	–	–	–		0.214	0.000
Rho ρ	0.611	–	0.494		0.643	–	0.467	–	0.611	–	0.494	
R-squared	0.685	–	0.716	–	0.410	–	0.392	–	0.685	–	0.716	–
AIC	–385.536	–	–423.116	–	–411.909	–	–59.587	–	–385.536	–	–423.116	–
Convergence speed	0.005	–	0.000	–	0.000	–	0.004	–	0.005	–	0.000	–
Half-life	132.504	–	4568.921	–	–3174.013	–	187.943	–	132.504	–	4568.921	–
Likelihood Ratio test	130.361	0.000	81.002	0.000	81.120	0.000	14.285	0.000	130.361	0.000	81.002	0.000

Source: Based on GeoData software.

Table 7. SEM Estimation Results 2000-2015 (current prices)

	EU-28				EU-15				EU-13			
No of regions (NUTS2)	**276**				**218**				**58**			
Dummy variable	**no**		**yes OMS—reference**		**no**		**yes Germany—reference**		**no**		**yes Poland—reference**	
	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value	value	*p*-value
Intercept	1.369	0.000	0.440	0.025	0.061	0.766	1.185	0.000	1.369	0.000	0.440	0.025
α1	−0.128	0.000	−0.035	0.075	0.003	0.902	−0.087	0.036	−0.128	0.000	−0.035	0.075
Dummy variable	–	–	0.278	0.000	–	–	–	–	–	–	0.278	0.000
Rho ρ	0.694	0.000	0.619	0.000	0.668	0.000	0.530	0.000	0.694	0.000	0.619	0.000
R-squared	0.691	–	0.729	–	0.422	–	0.379	–	0.691	–	0.729	–
AIC	−381.892	–	−425.716	–	−415.699	–	−59.170	–	−381.892	–	−425.716	–
Convergence speed	0.009	–	0.002	–	0.000	–	0.006	–	0.009	–	0.002	–
Half-life	75.978	–	288.194	–	−4038.264	–	113.629	–	75.978	–	288.194	–
Likelihood Ratio test	124.717	0.000	81.601	0.000	82.910	0.000	11.868	0.000	124.717	0.000	81.601	0.000

Source: Based on GeoData software.

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