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Income disparities and convergence across regions of Central Europe

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Abstract. This paper deals with the analysis of regional income disparities of the net disposable income of households (in Euro per inhabitant) across the regions of Central Europe (Austria, Czech Republic, Slovakia, Poland, Hungary and Germany) during the period 2000-2013. The analysis deals with the 82 NUTS 2 (Nomenclature of Territorial Units for Statistics) regions and is based on the concept of sigma-convergence, beta-convergence and growth-volatility relationship. Preliminary analysis concentrating on mapping of the analysed indicators is followed by consideration of the region's location supported by the results of spatial autocorrelation testing. The sigma-convergence analysis reveals the persistence of disparities in the net disposable income of households in the period 2000-2013 both at the national and subnational level. Although the results of spatial analysis have proved the existence of spatial dependence, following the classical approach, the beta-convergence concept is tested with the use of both non-spatial and spatial models. The potentially different convergence characteristics of Visegrad 4 countries' (Czech Republic, Slovakia, Poland, Hungary) regions and regions of Austria and Germany as well as the examination of the possible relationship between the regional growth and volatility are also taken into account in the econometric convergence modelling.

Keywords: net disposable income of households, sigma-convergence, beta-convergence, volatility, spatial econometrics

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1. Introduction

Nowadays, the issue of regional disparities is the subject of many research papers and policy creators. The reduction of regional disparities has also been declared in the European Union's (EU's) strategy "Europe 2020" [7] as one of the main EU priorities. Concerning the empirical testing of regional disparities, the concepts of sigma and beta-convergences are usually used. In the analysis of the regional

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income disparities across the EU regions, the NUTS 2 (Nomenclature of Territorial Units for Statistics) regions represent the most commonly employed territorial specification [5, 8]. Regional income disparities can be investigated based on various measures. Besides the convergence of GDP per inhabitant as an output indicator, it is also possible to assess the convergence of the net disposable income of households per inhabitant [5]. The book of Barro and Sala-i-Martin [4] represents one of the most famous works dealing with the convergence analysis based on cross-sectional data. However, during in recent years some authors have pointed out the interconnections between regions that should be taken into account by modelling. Studies dealing with regional growth mention the spatial aspect in convergence analysis e.g. [6,10,11,13,17,18]. To assess the connections among analysed regions, the spatial matrix $\mathbf{W}$ is used. In addition, there exist various approaches how to specify it, but to find its "proper" specification is quite complicated and many authors assert that it is the most controversial issue of spatial analysis (for different types of weight matrices see e.g. [12]). Although mapping of the corresponding variable(s) could help in deciding if there exist some clusters of similar values, to receive the information about its statistical significance requires providing the spatial autocorrelation analysis both on the global and local level. Since the global indicators (e.g. global Moran's I) give us information as to the strength of the spatial association across neighbouring regions (a single value for the whole data set), the LISA (Local Indicators of Spatial Association) [1] enables determining the existence of local spatial clusters. An issue in analyzing regional income disparities and convergence is the interesting role of examining the possible relationship between the regional growth and volatility, given the various arguments underlying the hypothesis that economic growth and volatility are positively or negatively related (for more information see e.g. [8]). Some studies e.g. [8,9,15] analyze this relationship for the EU regions Though studies [8,9] have shown the existence of a positive statistically significant relationship between regional growth and volatility, nonetheless, Martin and Rogers [15] detected a negative relationship. However, as mentioned by Ezcurra and Rios [8], further empirical research is required in order to investigate whether the volatility has a positive or negative impact on regional growth.

The main aim of the paper is to analyse regional disparities of net disposable income of households (in Euro per inhabitant) – based on the concept of sigma-convergence, beta- convergence and growth-volatility relationship – across 82 NUTS 2 regions of Austria, Czech Republic, Slovakia, Poland, Hungary and Germany during the period 2000-2013.

The potentially different convergence characteristics of V4 (Visegrad) regions[‡] and regions of Austria and Germany as well as the relative location should also be taken into account in convergence modelling.
The structure of the paper is as follows. After the introductory section, the second section introduces the methodological issues relating to the sigma and beta-convergence in the context of spatial econometrics as well as consideration of the growth-volatility relationship. The third section contains the data description and preliminary evidence, the empirical results of sigma and beta-convergence testing are given in the fourth section. The fifth section concludes with some challenges for future research.

2. Methodology

Concerning the issues of convergence, as was already mentioned above, generally two concepts of convergence are presented in the literature, the sigma-convergence and the beta-convergence. The concept of sigma-convergence refers to the dynamics of income disparities over time. Sigma-convergence occurs if the dispersion measured, e.g., using the standard deviation of the logarithm of per capita income across a group of regions, declines over time [4]. Beta-convergence, on the other hand, implies that the poor regions have a tendency to grow faster than the rich ones. The classical linear regression model of beta-convergence using the cross-sectional data has the following form [4,14]:

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

where $y_{i,0}$ and $y_{i,T}$ are the i-th region ($i = 1,2,..., n$) initial and final level of per capita incomes, respectively. The average growth rate of the i-th region per capita income in the period $(0, T)$ is expressed as $\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)$, α and β are unknown parameters and ε_i is an error term. The beta-convergence hypothesis can be accepted if the estimated β parameter is statistically significant and negative. Convergence characteristics – speed of convergence and half-life (i.e. the time span which is necessary for current disparities to be halved) can also be computed

[‡] The Visegrad group was created in 1991 in Visegrad by the Czech and Slovak Federative Republic (CSFR), Hungary and Poland. Since the dissolution of the CSFR in 1993, the group has consisted of four countries – the Czech Republic, Slovakia, Poland and Hungary, which are often denoted as V4 countries. The group was originally created in order to achieve common objectives, especially the transformation of economics and integration into the European Union.

(for formulas see e.g. [3,17]). To investigate the different convergence characteristics for a subgroup of analysed regions, the dummy variable D_i in a multiplicative form should be included [6]. This variable indicates whether the region i belongs to a tested subgroup of regions ($D_i = 1$) or not ($D_i = 0$), the corresponding unknown parameter is denoted as γ. To assess the impact of volatility on average growth, model (1) can be further extended by inclusion of the volatility variable σ_i (measured as the standard deviation of the growth over the analysed period) with the corresponding unknown parameter φ . Model (1) can be therefore modified as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln(y_{i,0}) + \gamma D_i \ln(y_{i,0}) + \varphi\sigma_i + \varepsilon_i ,\ \varepsilon_i \sim i.i.d(0,\sigma_\varepsilon^2) \tag{2}$$

In order to consider the spatial interdependencies of individual regions (based on values of Moran's I for residuals, Lagrange Multiplier tests – LM(lag), LM(err) and their robust versions), the classical linear regression model (1) or its modification (2) should be extended by inclusion of the spatial component. The spatial autoregressive model of beta-convergence, known also as SAR model, contains the spatially lagged dependent variable, i.e. spatially lagged average growth rate. Based on the model (2) the SAR model takes the following form:

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln(y_{i,0}) + \gamma D_i \ln(y_{i,0}) + \varphi\sigma_i + \rho\sum_{j\neq i} w_{ij}\left(\frac{1}{T}\ln\left(\frac{y_{j,T}}{y_{j,0}}\right)\right) + \varepsilon_i ,$$

$$\varepsilon_i \sim i.i.d(0,\sigma_\varepsilon^2) \tag{3}$$

where ρ is the scalar spatial autoregressive parameter, w_{ij} are the elements of the row-standardized matrix of spatial weights **W** describing the structure and intensity of spatial effects and all other terms were previously defined above. The specification of the spatial error model (SEM) with spatially autocorrelated error terms is based on the model (2) as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta\ln(y_{i,0}) + \gamma D_i \ln(y_{i,0}) + \varphi\sigma_i + \vartheta_i ,$$

$$\vartheta_i = \lambda\sum_{j\neq i} w_{ij}\vartheta_j + \varepsilon_i , \quad \varepsilon_i \sim i.i.d(0,\sigma_\varepsilon^2) \tag{4}$$

where λ is a scalar spatial error coefficient expressing the intensity of spatial autocorrelation between regression residuals.

3. Data description and preliminary evidence

The analysis requires employing data on net disposable income of households (in Euro per inhabitant) from the Eurostat database REGIO available at [19]. The data were retrieved for the 82 NUTS 2 Central European regions (9 Austrian, 8 Czech, 38 German, 7 Hungarian, 16 Polish and 4 Slovak) for the entire available period 2000-2013 in order to analyse the regional disparities based on the concept of sigma-convergence, beta-convergence and growth-volatility relationship. The growth rates are expressed as the average annual growth rates of the net disposable income per inhabitant from 2000 to 2013 (calculated as the logarithmic difference divided by the number of years). To analyse the sigma-convergence, the standard deviation of net disposable household income per inhabitant (expressed in natural logarithms) over the period 2000-2013 is investigated. In the analysis of growth-volatility relationship, the volatility is specified as the standard deviation of the growth. The main part of analysis was performed using the software GeoDa [21]. From the shape file (.shp) of the European regions [20], the 82 NUTS 2 Central European regions were selected in GeoDa.
Analysis of the regional income disparities and convergence issues in Central European regions as well as an assessment of the similarities between regions starts with the mapping of corresponding indicators. As some results will also be discussed on a national level, Figure 1 depicts regions of the analysed countries.

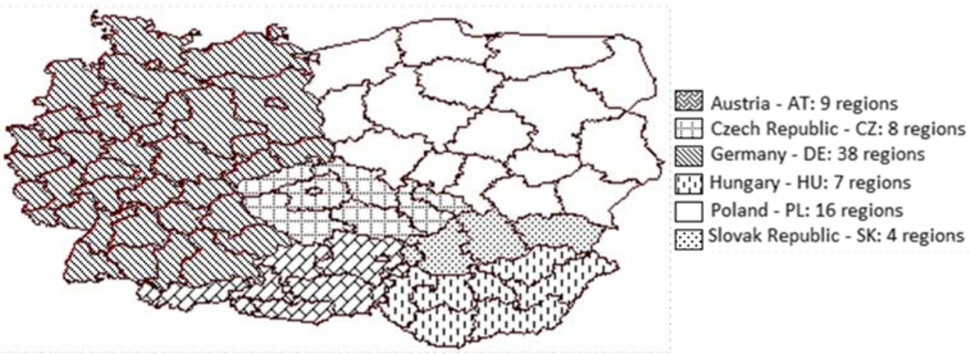
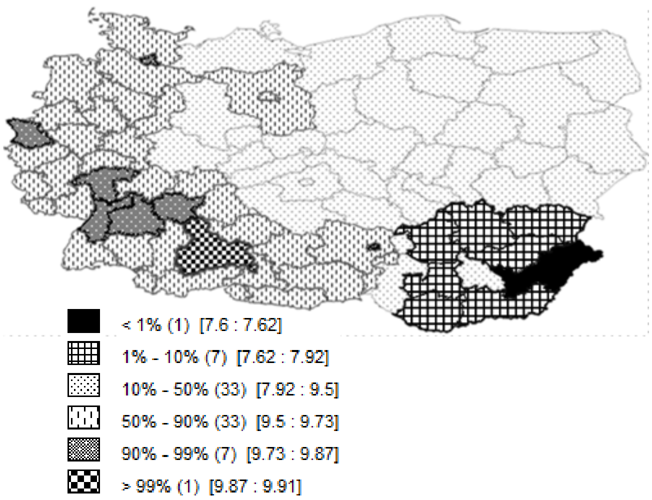


Figure 1: *NUTS2 regions of analysed countries*

Figure 2 shows the percentile maps and the mean values of (a) the net disposable income of households in 2000 (expressed in natural logarithms), (b) its average annual growth 2000-2013 and (c) standard deviation of the growth 2000-2013 for regions of individual countries. Percentile maps specify six categories for the classification of the ranked observations: 0%-1%, 1%-10%, 10%-50%, 50%-90%, 90%-99% and 99%-100%. Concerning all the three indicators, it is clearly visible that there are quite large differences at the national level and also some disparities at the subnational level. The net disposable income of households in 2000 (expressed in natural logarithms) was the lowest in the Hungarian and the Slovak regions followed by the Polish, Czech and some eastern German regions. The net disposable income of households during the period 2000-2013 on the other hand had the tendency to rise more quickly in regions of the V4 countries than in the majority of Austrian and German regions. The highest average annual growth rate of 9.04 % was detected for the Slovak regions, followed by 6.06% growth in the Czech regions, 5.54% in Hungarian regions and 4.50% in Polish regions. The average annual growth rates of Austrian and German regions were only 2.58% and 2.13%, respectively. Percentile maps (a) and (b) are clearly in line with the concept of beta-convergence, since the poorer regions rose during the period 2000-2013 more quickly than the richer ones. The third map (c) depicts the standard deviation of the growth in 2000-2013 for individual regions. Regarding the individual countries, the highest average value was recorded for Poland (9.84%), followed by Hungary (8.42%), the Czech Republic (6.90%) and Slovakia (6.48%). The volatilities in Austria and Germany reaching the values of 1.96% and 1.57%, respectively, were also substantially lower than in the V4 countries. It seems also to be clear that in general the standard deviation of the growth tends to be higher for quickly growing regions than for regions with lower growth rates.

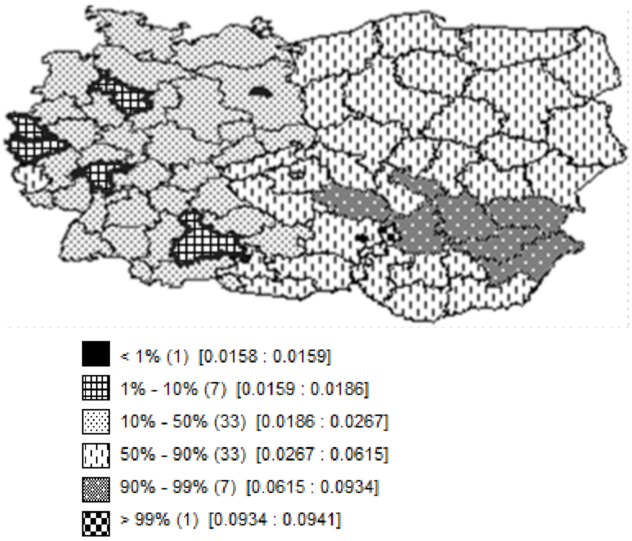
Although the percentile maps enable identification of both the spatial clusters and the extreme values (defined as observations in the bottom and top one percent of the distribution), they do not give any information about statistical significance of the clustering and of the ordering presented, respectively [16].

(a) ln (net disposable income of households 2000)



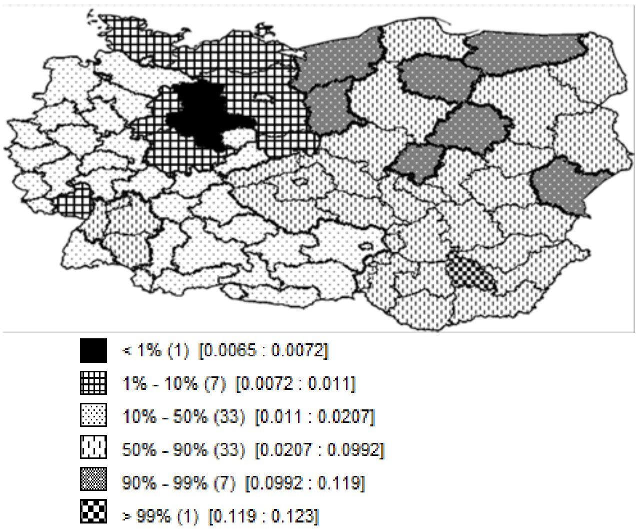
Country	Mean
AT(9)	9.6593
CZ(8)	8.1466
DE(38)	9.6514
HU(7)	7.8224
PL(16)	8.0706
SK(4)	7.8345
All(82)	8.9522

(b) average annual growth 2000-2013



Country	Mean
AT(9)	0.0258
CZ(8)	0.0606
DE(38)	0.0213
HU(7)	0.0554
PL(16)	0.0450
SK(4)	0.0904
All(82)	0.0365

(c) standard deviation of the growth 2000-2013



Country	Mean
AT(9)	0.0196
CZ(8)	0.0690
DE(38)	0.0157
HU(7)	0.0842
PL(16)	0.0984
SK(4)	0.0648
All(82)	0.0457

Figure 2: *Percentile maps and mean values for (a) net disposable income of households in 2000 (expressed in natural logarithms), (b) its average annual growth 2000-2013 and (c) standard deviation of the growth 2000-2013 for regions of individual countries*[§]

[§] Number of regions is in parentheses.

The next step follows the analysis of spatial autocorrelation both on the global (test for clustering) and local level (test for clusters) based on global Moran's *I* statistic and local Moran's *I* statistic. The global test is visualized by means of a Moran scatterplot and local analysis is based on the local Moran statistic visualized as a cluster map [2]. Figure 3 illustrates the Moran scatterplot and LISA cluster map for the average annual growth of the net disposable income of households 2000-2013**. The Moran scatterplot depicts the value at a region versus the average value of its neighbouring regions (based on the first order queen case definition of spatial weight matrix) and enables furthermore to identify regions with positive ("High-High" - upper right quadrant, "Low-Low"- lower left quadrant) and negative ("Low-High" - upper left quadrant, "High-Low" - lower right quadrant) spatial autocorrelation. A high value of Moran´s *I* statistic (0.6936) indicates the existence of a strong positive spatial association. The LISA cluster map shows the locations with significant local Moran's *I* statistics. In all, 45 regions were identified with statistically significant positive spatial autocorrelation and 2 regions with statistically significant negative spatial autocorrelation. Since the statistically significant positive autocorrelation of "High-High" type was detected for the 18 regions of V4 countries, the "Low-Low" type was proved to be significant for 27 German and Austrian regions. Regions of V4 also display similarly high average annual growth as their neighbours and the German and Austrian regions display similarly low average annual growth as their neighbours. Two regions (Niederösterreich and Közép-Magyarország) with low average annual growth rates significantly differ from their neighbouring regions with high average annual growth rates.

** Moran scatterplots as well as LISA cluster maps for net disposable income of households in 2000 and for standard deviation of the growth 2000-2013 are not presented in the paper, but can be provided by authors upon request.

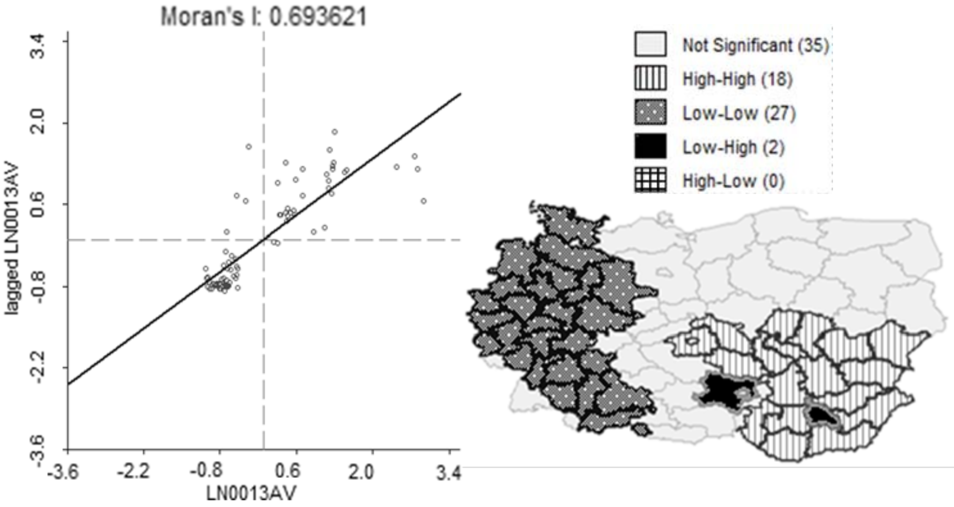


Figure 3: *Moran scatterplot and LISA cluster map for the average annual growth of the net disposable income of households 2000-2013*[††]

4. Results of sigma-convergence and beta-convergence analyses

The preliminary analysis is followed by the investigation of the sigma-convergence in order to assess the dynamics of the income disparities over the analysed period 2000-2013 both across all 82 regions as well as separately for regions of each analysed country. Figure 4 presents the movement of the standard deviation of natural logarithm of the net disposable income of households for the whole set of 82 regions as well as for regions within each country over the period 2000-2013. Income dispersion across all regions did not have the clearly downward trend, strongly confirming the evidence for the sigma-convergence. During the first three analysed years, the dispersion declined from 0.83 to 0.75, but then rose to 0.78 in 2003. In the subsequent analysed years, it went down – the decline stopped in 2008 upon reaching a low point of 0.59. In 2009, it rose to 0.63 followed by a slow decline in 2010, remaining relatively flat over the next three analysed years. Concerning the regional income disparities within each country, the highest regional inequality is observed across Slovak regions, followed by Hungarian, Czech and Polish regions. Only slightly better (in comparison to Polish regions) was inequality across German regions. Considerably the lowest were the regional

[††]Abbreviations “LN0013AV” and “lagged LN0013AV” denote average annual growth of the net disposable income of households 2000-2013 and its spatially lagged values, respectively.

income disparities within Austrian regions. With the exception of Hungary, the regional inequalities remained quite stable during the analysed period with no clearly declining trend. The regional income disparities in Hungary went slowly up during the first analysed years (2000-2005), and it was followed by a decline which ceased in 2010. Thereafter, the standard deviation across Hungarian regions rose to a peak in 2011, with a declining trend till the end of the analysed period. The analysis of sigma-convergence also revealed the persistence of disparities in the net disposable income of households 2000-2013 both at the national and subnational level.

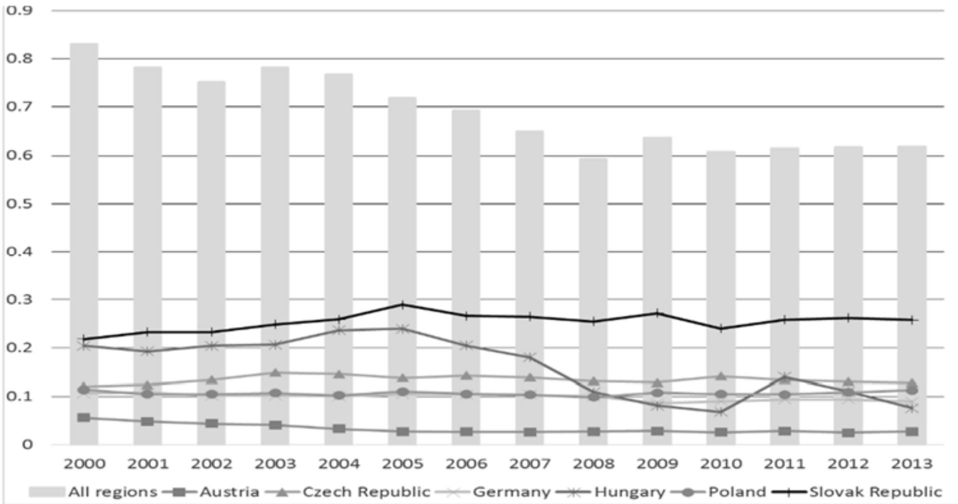


Figure 4: *Sigma convergence across regions of individual countries*

Following the above presented results of the spatial analysis, we would expect that spatial dependence does matter and therefore the spatial aspect should not be neglected for beta-convergence modelling. Based on a classical approach, we do not start with the estimation of the spatial model directly, but begin with the OLS (Ordinary Least Squares) estimation of the model (1) – Model1 (estimation results see Table 1). The diagnostic check is followed by an ML (Maximum Likelihood) estimation of SEM model (see (4) without both the dummy variable and volatility variable) – Model2 (Table 1). The estimation results of both Model1 and Model2 yield statistically significant estimations of all parameters. The negative sign of β parameter speaks for the validity of the beta-convergence hypothesis across analysed regions during the 2000-2013 period. In both cases the convergence characteristics were calculated. However, for the case of Model1, these positive convergence characteristics are misleading due to the omitted spatial component. Model2 implies a convergence speed of 2.91% leading to a half-life of almost 24 years, i.e. the poorest regions are supposed to fill half the gap with the wealthiest ones in about 24 years.

Based on preliminary results of exploratory spatial data analysis indicating substantial differences between V4 regions and regions of Germany and Austria, we decided to enrich the econometric models by the inclusion of a dummy variable indicating whether the region belongs to a V4 country ($D_i = 1$) or not ($D_i = 0$). The incorporation of this variable in a multiplicative form allows assessing of the convergence process separately for two groups of regions, i.e. regions of V4 countries and regions of Germany and Austria. The estimation of results from the corresponding models are summarized in Table 1 – Model3 (without the spatial component) and Model4 (SEM model). To eliminate the misleading conclusions based on Model3 (no spatial component included) we will focus on interpretation of the regression results based on Model4 (with consideration of spatial dimension). The negative sign of the statistically significant β parameter strongly confirms the beta-convergence hypothesis. Furthermore, the negative sign of the γ parameter indicates the higher speed of convergence as well as shorter half-life of V4 regions (5.83% and 11.894 years, respectively) in comparison to German and Austrian regions (5.26% and 13.183 years, respectively).

	Model1 (Linear model)	Model2 (SEM model)	Model3 (Linear model with dummy variable)	Model4 (SEM model with dummy variable)
Estimation	OLS	ML	OLS	ML
α	0.222**	0.252**	0.294**	0.386*
β	-0.021**	-0.024**	-0.028**	-0.038**
γ	-	-	-0.002	-0.003*
λ	-	0.714**	-	0.771**
R^2	0.771	0.855	0.775	0.869
Convergence characteristics				
Speed of convergence (%)	2.42%	2.91%	3.51% (AT+DE) 3.76% (V4)	5.26% (AT+DE) 5.83% (V4)
Half-life (years)	28.654	23.841	19.775 (AT+DE) 18.449 (V4)	13.186 (AT+DE) 11.894 (V4)
Tests				
Moran's *I* (err)	5.597**	-	5.886**	-
LM (lag)	6.194*	-	6.420*	-

Robust LM (lag)	4.168*	-	4.396*	-
LM (err)	25.199**	-	26.859**	-
Robust LM (err)	23.173**	-	24.835 **	-
Moran's I (spatial residual)	-	0.031	-	0.037

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

Table 1: *Estimation of results for beta-convergence models (Model1-Model4)*

The last step of the analysis deals with the growth-volatility relationship based on beta-convergence concept with additional inclusion of a volatility variable represented by standard deviation of the growth during 2000-2013. The corresponding estimation results are presented in Table 2. The OLS estimation of a linear model (Model5) was followed by the estimation of SEM model (Model6) indicated by the results of LM tests and their robust versions. The results confirmed the beta-convergence hypothesis and proved a negative relationship between growth and its standard deviation. The convergence characteristics indicate a speed of convergence of 5.36 % and a half-life of almost 13 years. The inclusion of a dummy variable - Model7 (no spatial component included) and Model8 (with consideration of spatial dimension) led to worsening of convergence characteristics. As it has been already explained above, we will concentrate on interpretation of the SEM model (Model8). It can be again concluded, that the beta-convergence hypothesis was confirmed, and similarly as in Model6 there is a negative relationship between growth and its standard deviation. Unlike the Model4, the sign of the γ parameter is positive and therefore the convergence characteristics of V4 regions implied by Model8 are slightly worse than in case of German and Austrian regions.

	Model5 (Linear model +SD)	Model6 (SEM model +SD)	Model7 (Linear model + SD with dummy variable)	Model8 (SEM model + SD with dummy variable)
Estimation	OLS	ML	OLS	ML
α	0.387**	0.400**	0.252**	0.310**
β	-0.037**	-0.039**	-0.023**	-0.029**
γ	-	-	0.004**	0.003*
φ	-0.408**	-0.400**	-0.553**	-0.498**
λ	-	0.739**	-	0.672**
R^2	0.858	0.915	0.878	0.917
Convergence characteristics				
Speed of convergence (%)	5.06%	5.36%	2.72% (AT+DE) 2.14% (V4)	3.65% (AT+DE) 3.23% (V4)
Half-life (years)	13.709	12.939	25.483 (AT+DE) 32.393 (V4)	18.993 (AT+DE) 21.460 (V4)
Tests				
Moran's *I* (err)	5.977**	-	5.493**	-
LM (lag)	5.797*	-	4.927*	-
Robust LM (lag)	1.116	-	0.342	-
LM (err)	27.903**	-	22.096**	-
Robust LM (err)	23.222**	-	17.511**	-
Moran's *I* (spatial residual)	-	0.063	-	0.053

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

Table 2: *Estimation results of beta-convergence models (Model5-Model8)*

5. Conclusion

This paper has proved the existence of regional income disparities of the net disposable income of households (in Euro per inhabitant) across 82 NUTS 2 regions of Central Europe during 2000-2013. The concept of sigma-convergence has revealed the persistence of disparities in the net disposable income of households in the analysed period both at the national and subnational level. The highest regional inequality at the subnational level was identified for the Slovak regions, followed by regions of the remaining V4 countries (Hungary, Czech Republic and Poland). On the other hand, considerably the lowest were the regional income disparities within Austrian regions. Following the classical approach, the testing of beta-convergence was based both on non-spatial and spatial models. Based on diagnostic checking, it has been proven that the spatial autoregressive error component should be taken into account for modelling in order to avoid the problem of possibly biased results and hence misleading conclusions. The received results supported the validity of beta-convergence, i.e. that poor regions catch-up to wealthier regions. The observed differences between a group of V4 regions and regions of Germany and Austria were taken into account by inclusion of the corresponding dummy variable (in multiplicative form) into estimated models which also enabled capturing the differences in the speed of convergence for analysed groups of regions. The speed of convergence of the V4 regions during the analysed period was higher than for regions of Austria and Germany. Additionally, the negative impact of volatility on the growth of the net disposable income of households was proved based on inclusion of growth standard deviation into the beta-convergence model (both non-spatial and spatial).

The main contributions of the paper can be summarized as follows. Firstly, studies dealing with the convergence of disposable income of households are rather scarce. Secondly, there is some complexity to the paper, since different approaches were employed to analyse the regional income disparities (sigma-convergence, beta-convergence and inclusion of volatility variable into the beta-convergence model). Besides traditional non-spatial analysis, consideration of the region location, i.e. spatial econometric analysis, is a significant contributions of the paper. Moreover, the analysis has proved the process of different convergence speeds in the group of V4 regions and the group of Austrian and German regions. Further investigation of the impact of additional explanatory variables on regional income growth as well as subsequent analysis of spillover effects across regions are challenges for future research.

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