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EAST CENTRAL EUROPEAN REGIONAL CLUB CONVERGENCE IN THE NEW MILLENNIUM

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Abstract

The study analyses economic convergence in the NUTS3 regions of eight East Central European (ECE) countries (Poland, Czechia, Slovakia, Hungary, Slovenia, Croatia, Romania and Bulgaria) that joined the European Union in 2004. In our analysis, we reject the hypothesis of global income convergence for the period 2001–2019, arguing for the presence of geographical convergence clubs with different steady states. We also attempt to describe the factors that influence the formation of these clubs.
In our analysis, we first used the log t-test to classify the 201 regions of ECE into seven convergence clubs with own steady states. The results indicate a 'multi-speed' East Central Europe in terms of income, which shows and predicts strong spatial polarisation and persistence across the region. Our further results suggest that the initial and structural factors impacting club formation are mainly influenced by initial development, changes in the active population, agglomeration characteristics and spatial interactions and, finally, economic structure. The paper demonstrates the validity of the East Central European club convergence hypothesis for the first two decades of the new millennium.

Keywords: convergence, East Central Europe, club convergence, log t-test

INTRODUCTION

The issue of regional convergence and territorial equalisation is one of the European Union's main political and socio-political objectives, which have already been enshrined in the Treaty of Rome (1957), the Single European Act (1987) and the Treaty of the European Union (2012). In the European Union, deepening integration has led to significant convergence, with regional growth accompanied by more favourable inequality trends (Ridao-Cano & Bodewing, 2018). In recent decades, the EU as a 'convergence machine' no longer supports everyone, and it has become clear that convergence within integration is not an automatic phenomenon (Iammarino et al., 2020; Diemer et al., 2022). Development traps seen at various levels of development represent a self-reinforcing process that makes catching-up and progress difficult (Diemer et al., 2022).

In the era of globalisation, regional divergence poses a serious threat to the social, economic and political development of the EU (Iammarino et al., 2017). The topic is particularly exciting for the so-called 'new member states' that joined in 2004 and have faced lots of challenges and new and novel phenomena during the post-socialist transformation (Bourdeau & Lepage, 2007; Capello & Fratesi, 2013; Capello & Pericca, 2013; Smetkowski, 2015; Gorzelak, 2020). The self-reinforcing processes of globalisation, the interdependence of economies, the presence of foreign direct investment, the technological and structural changes in the economy, the deepening of economic integration and the processes of deregulation-liberalisation-privatisation have essentially caused a widening of spatial disparities (Iammarino et al., 2017; Smetkowski, 2018; Ezcurra & Del Villar, 2021).,

The enormous economic growth that the region saw since the EU accession has not yet brought the 'new members' fully up to the average economic development of either the EU27 or the EU15. Regional differences also remained significant. In 2021, 15 out of the 25 lowest performing development regions in terms of GDP per capita were in East Central Europe (Yuzhen tsentralen, Severozapaden, etc.), while 5 out of the 25 regions with the highest GDP/capita were also in East Central Europe (Praha, Bucuresti-Ilfov, etc.). All these performances are realised by the fact that the ECE countries that joined in 2004 received 56.0 per cent of the EU budget's 'Economic, social and territorial cohesion' spending for development in 2014–2020. That is why territorial growth, catching-up and convergence are also important issues for the region.

Within the European Union and East Central Europe, the issue of economic convergence has been the subject of numerous studies (Crespo Cuaresma et al. 2014; Iammarino et al. 2020; Cutrini & Mendez 2024), but its local geographical implications (especially below NUTS2 level) and its evolution still represent a significant research potential.

Basically, the purpose of our study is to highlight the complex geographical and socio-economic transformation of the East Central European region in the new millennium. Our study rejects the phenomenon of global and unique economic convergence for ECE regions (i.e. that all regions reach a unique level of development in the future), aims at detecting geographically differentiated local convergence clubs and explains their multifaceted emergence.

THEORETICAL BACKGROUND

Bourdin (2007) argues that the demonstration of convergence is moving from a global to a local approach. This not only means that subnational contexts are modelled, but also that geographical proximity and linkages, and regional affiliation, are prominent determinants of growth and inequality (Quah, 1996; Le Gallo, 2004; Le Gallo & Fingleton, 2021).

The most common analytical framework for convergence analysis is the so-called β- and σ-convergence. Absolute (or unconditional) β-convergence is based on Robert Solow's (1956) neoclassical model and assumes that poor countries or regions will eventually catch up with rich ones. According to this theory, regions converge towards a single steady state, the so-called global convergence (Barro & Sala-i-Martin, 2004). However, absolute convergence is not always guaranteed, as besides the initial income level many other factors (conditions) can influence convergence, such as investments, technological progress, institutions, policies, etc. In the case of conditional convergence, the steady state may vary from region to region, depending on the conditions (Mankiw et al., 1992; Rodríguez-Pose & Ketterer, 2020).

The trade-off between absolute and conditional convergence is provided by the club convergence theory, stating that clubs are regions with similar initial and structural conditions that converge to a common steady state (Baumol, 1986; Baumol & Wolff, 1988; Galor, 1996; Friedrich-Eckey & Türck, 2007). In a space with multiple steady states, heterogeneous convergence clubs have been/can be delineated using a variety of complex methods and samples (Durlauf & Johnson, 1995; Quah, 1996; Phillips & Sul, 2007; Friedrich-Eckey & Türck, 2007; Rey, 2019; Karahasan, 2020).

Experiences from the European Union and East Central Europe

Alexiadis (2013) delineated regional convergence clubs in the EU27, pointing to significant geographical differences in convergence. The results of the convergence analysis of the gross value added per worker based on NUTS2 level (1995–2006) clearly illustrate the spatial heterogeneity of growth and initial development in the EU. Calculations based on multiple regressions (with the addition of geography and technology) define the almost contiguous ECE region as a 'diverging' club, which is clearly different from the uniform convergence club of the regions of old EU states.

Spatial interactions (trade, labour flows, knowledge spillovers) are also clearly contributing to the formation of convergence clubs (Rodríguez-Pose & Tselios, 2015). The spatial distribution of clubs is characterised by polarisation, clusterisation and the spatial concentration of poverty traps (Le Gallo, 2001; Annoni et al., 2019; Ayouba & Le Gallo, 2020). Geographical heterogeneity based on spatial autocorrelation of GDP/capita is the basis for the European convergence and club convergence analyses of Le Gallo and Ertur (2003), Fischer and Strirböck (2006), Ayouba and Le Gallo (2020) and Annoni et al. (2019). Based on the results of spatial autocorrelation analysis, the low own and low neighbouring income regions form a coherent convergence club of NUTS2 regions in East Central Europe, which in some cases is also characterised by club convergence (Fischer & Strirböck, 2006; Annoni et al., 2019).

The new generation of convergence club analysis methodology is an innovative solution by Phillips and Sul (2007, 2009) based on regression analysis and a clustering algorithm that allows the analysis of the temporal and spatial heterogeneity of regions in the direction of convergence or divergence. Using this method, Bartkowska and Riedl (2012) identified 6 income convergence clubs (based on Gross Value Added per worker for the period 1990–2002) for NUTS2 regions in the old Member States. The delineated clubs show a clear geographical distribution in Europe (North-South). The authors use ordinal logistic regression to verify the role of initial conditions (human capital, income level) and structural characteristics as well as spatiality in club formation, as used in conditional convergence analyses. Cutrini (2019) already performed the club convergence analysis (based on GDP per capita) for the EU27 with the addition of the ECE region using the Phillips–Sul methodology. Between 2003 and 2016, the NUTS2 regions of East Central Europe are far from uniform across the EU28, and they are spread across the five emerging clubs. For example, some capital city regions (Mazowieckie, Bucurest-Ilfov, Praha, Bratislavský kraj) were placed in the best performing ‘Metropolitan and capital regions’ club, while several Hungarian and Bulgarian regions, for example, were placed in the lowest income club ‘South-East falling behind’. The authors demonstrate the role of economic structural change, in particular manufacturing and high-productivity service activities, in explaining different income equilibrium paths. Szakálné Kanó and Lengyel (2021) show the income convergence paths of a part of the ECE region (Visegrad Group) using the Phillips–Sul method for the period 2000–2016. With the exception of Warsaw, Wroclaw, Prague and Bratislava (Club 1), none of the NUTS3 regions approach the average income path (GDP per capita) of the EU15 and the results show significant spatial heterogeneity. The authors characterise each convergence club on the basis of sectoral differences in gross value added (agriculture, industry, etc.), urban-rural classification and simple club averages of endogenous factors.

Monfort (2020) describes the income evolution of the EU28 before and after the economic crisis using the Markov chain method. The local results based on NUTS2 regions show that the ECE region becomes much more heterogeneous in the latter period, in particular due to the strong growth of the Western Polish and the Czech and Romanian regions. At the same time, the analyses of the European Commission (2017) and Iammarino et al. (2017) indicate a low level of stagnation and stability in the majority of NUTS2 regions in ECE, with the multidimensional (but essentially GDP/capita) ‘development club’ regions differing along demography, labour market and knowledge base. Rodríguez-Pose and Ketterer (2020) explain the growth of the EU 'low income' (convergence) club of regions (actually only ECE regions) by traditional growth factors (accessibility, human capital, agglomeration) between 2000 and 2013. Iammarino et al. (2020) classify EU regions into different types of development traps at different income levels, with the majority of ECE regions belonging to the 'regions trapped at low levels of income' club. Structural and demographic factors influence the trap at low income levels, while institutional quality, high skills and R&D reduce the trap at high income levels.

Smetkowski (2018) describes the development of core (metropolitan) and non-core (non-metropolitan) post-socialist regions ('clubs') between 2002 and 2010 and the factors that influence development. The preliminary region classification appears to be significant in terms of factors affecting development, in particular human capital, migration and small and medium-sized enterprises.

On the one hand, analyses suggest a 'multi-speed' and club-like EU and East-Central Europe, the geographical pattern of the latter having certainly become more sophisticated since the beginning of the post-socialist transition.

On the other hand, the more detailed context of club convergence (especially below NUTS2 level), i.e. the determinants of the conditions (initial and structural factors, geographical proximity) influencing convergence clubs, is not known yet for the wider East Central European region.

Therefore, these two hypotheses are the motivation for our investigations. Since the wider East Central Europe local convergence (club) processes are not well understood, we use the Phillips-Sul (2007, 2009) log t-test and the von Lyncker-Thoennessen merging procedure to delimit NUTS3-level regions in Central and Eastern Europe with similar income trajectories, and create convergence clubs. We hypothesise that the wider ECE region will be characterised by significant income inequalities in the new millennium, and thus the presence of convergence clubs can be detected.

On the other hand, the factors influencing the formation of local convergence clubs are described using ordinal logistic regression (i.e. the club convergence hypothesis is tested), and these processes are not known in detail in the ECE region under study. Both subanalyses can be considered as novel for the region under study, as the phenomenon under study has not been analysed using these methods (in particular the von Lyncker-Thoennessen procedure and ordinal logistic regression). Our second hypothesis is that the emergence of convergence clusters is fundamentally explained by initial, structural and spatial characteristics, in addition to socio-economic and territorial transformations.

DATA AND METHODS

The analysis of income convergence in the East Central European regions is carried out in three steps. First, the Phillips and Sul log t-test method (2007, 2009) and the von Lyncker and Thoennessen (2017) cluster merging algorithm are used to detect convergence clubs, followed by ordinal logistic regression to identify the factors that influence club formation. Since we can assume that spatial proximity also plays a significant role in the formation of income clubs (Bartkowska & Riedl, 2012; Li et al., 2018; Cutrini & Mendez, 2023), we also perform Global Moran's I and Local Moran's I calculations for the indicators affecting convergence.

Log t-test

We use a regression based on the convergence test to examine the behaviour of local incomes in ECE region between 2001 and 2019. The panel variable of income (X_{it}) is as follows: $X_{it} = g_{it} + a_{it}$, where g_{it} is the systematic factor (which includes the permanent common component) and a_{it} is the transitory component. To consider temporal transitional heterogeneity, the equation can be modified as follows: $X_{it} = \left(\frac{g_{it} + a_{it}}{\mu_{it}} \mu_t\right) = b_{it}\mu_t$, where b_{it} is the time varying idiosyncratic element and μt is a single common component.

To test whether different regions converge, the estimation of b_{it} has a key function, which is defined by the following relative transition path:

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{b_{it}}{N^{-1}\sum_{i=1}^{N} b_{it}}.$$

The relative transition path expresses relative individual behaviour and reveals the relative deviations of the i-th region from the μ_t common growth path. In the case of convergence, the relative transition paths of h_{it} converge to 1, or the cross-sectional variance of h_{it} converges to zero in the long run.

$$H_t = N^{-1}\sum_{i=1}^{N} (h_{it} - 1)^2 \to 0 \; as \; t \to \infty$$

The cross-sectional variance of h_{it} and H_{it} might decrease even if no overall convergence occurs and only local convergence exists within certain subgroups. For this reason, the PS method proposes to consider the following semi-parametric specification of coefficient b_{it}:

$$b_{it} = b_i + \frac{\sigma_i \xi_{it}}{L(t)t^{\alpha}},$$

where b_i is constant (time invariant), ξ_{it} represents i.i.d. N(0,1) random variables across i, but is weakly dependent over t, $L(t)$ is a slowly varying increasing function (with $L(t) \to \infty \; as \; t \to \infty$) and α is the decay rate, or in this case, the convergence rate. The null hypothesis of convergence can be written as H_0: $b_i = b$ and $\alpha \geq 0$ versus the alternative H_1: $b_i \neq b$ for all i or $\alpha < 0$. Different transitional paths are possible under H_0, including temporary divergence.

Based on the results, Phillips and Sul (2007, 2009) recommended the log t convergence test, which involves estimating the following ordinary least squares regression with a robust covariance matrix:

$$log\left(\frac{H_1}{H_t}\right) - 2logL(t) = a + \beta logt + u_t, for\ t = [rT], [rT] + 1, \ldots, T,$$

where $H_t = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2$, H_1/H_t is the cross-sectional variance ratio, β represents the speed of convergence for b_{it}, $-2logL(t)$ (where $L(t) = log(t+1)$) is the role of a penalty function and improves test performance particularly under the alternative, r assumes a positive value in the interval (0, 1) to discard the first block of observation from the estimation and $[rT]$ is the integer part of rT. The PS method proposes using $r = 0.3$ for a low number of samples (T < 50). β equals 2α, where the value of α other than 0 is studied using a robust one-sided t-test for heteroscedasticity and autocorrelation. The null hypothesis of convergence is rejected if $t_b < -1.65$ at 5% significance level. Moreover, the size of parameter β is also relevant as $0 \leq \beta \leq 2$ indicates relative convergence, implying convergence in growth rates, while $\beta \geq 2$ means absolute convergence. If convergence for the entire sample is rejected, the testing procedure is applied to convergence clubs, following the clustering mechanism (Phillips & Sul 2007, 2009).

- Step 1 (*cross-section last observation ordering*): order the regions according to the last panel observation of the period.
- Step 2 (*formation of the core group of k^* regions*): the log t-test is run for the first $k = 2$ regions. If $t_k > -1.65$, both regions form the core group (G_k). Following this, the log t-test is run for G_k plus the next region. In case of t_k $(k = 3) > t_k$ $(k = 2)$, the region belongs to G_k. This mechanism is conducted as long as t_k $(k) > t_k$ $(k-1)$ for all $N > k \geq 2$. If t_k $(N) > t_k$ $(N-1)$, the remaining panel converges. If the condition $t_k > -1.65$ does not hold for the first two units, we drop the first unit and repeat the process. If $t_k > -1.65$ does not hold for any units chosen, the whole panel is divergent.
- Step 3 (*filter the data for new club members*): we add one remaining region at a time to the core primary group with k members (G_k) and run the log t-test again. All districts that have a t_k higher than the critical value c^* are added to the core group. If $t_k > -1.65$ is met for this group of districts, it is the first convergence club. If not, we raise the critical value and repeat the procedure until $t_k > -1.65$.
- Step 4 (*recursion and stopping rule*): we create a second group including all regions we could not filter in step 3 and run the log t-test on this subgroup again. If $t_k > -1.65$, the remaining units form their own convergence club. If $t_k < -1.65$, we repeat steps 1–3 to

find another convergence club for all remaining units. If no further club is found, the remaining regions diverge.

Phillips and Sul (2007) suggest $t_k > -1.65$ for clubs. If this is not the case, the procedure must be repeated by increasing parameter c^* until the condition $t_k > -1.65$ is met. In our analysis we apply the innovative club merging procedure proposed by von Lyncker and Thoennessen (2017). Its steps are described below (Sichera & Pizzuto, 2019).

Take all the P groups detected in the basic clustering mechanism and run the t-test for adjacent groups, obtaining a $(M \times 1)$ vector of convergence test statistics t (where $M = P-1$ and $m = 1,.., M$). Then merge for adjacent groups starting from the first, under the conditions $t(m) > -1.65$ and $t(m) > t(m+1)$. In particular, if both conditions hold, the two clubs determining $t(m)$ are merged and the algorithm starts again from previous step, otherwise it continues for all following pairs. For the last element of vector M (the value of the last two clubs) the only condition required for merging is $t(m = M) > -1.65$.

If the basic clustering procedure produces non-converging (diverging) clubs, the following steps are justified on the basis of the algorithm of von Lyncker and Thoennessen (2017).

Run a log t-test for all diverging regions, if $t_k > -1.65$, all these regions form a convergence club. Then run a log t-test for each diverging regions and each club, creating a matrix of t-statistic values with dimension $(d \times p)$, where each row d represents a divergent region and each column p represents a convergence club. Take the highest t-value greater than a critical parameter e∗ and add the respective region to the corresponding club, then start again from step 1. von Lyncker and Thoennessen (2017) suggest to use $e* = t = -1.65$. The algorithm stops when no t-value > e∗ is found in step 3, and as a consequence all remaining regions are considered divergent.

Ordinal logistic regression

However, according to von Lyncker and Thoennessen (2017), the PS method is not sufficient to prove club convergence, thus the two-step procedure of Bartkowska and Riedl (2012) is proposed. It is suggested to perform clustering algorithm as a first step and then to identify the factors leading to the formation of each cluster using the ordinal logistic regression. In this case, the dependent variable is c, which indicates the regions belonging to a given convergence club. The clubs can be ranked according to steady-state income, thus obtaining an ordinal-level outcome variable. Based on the club convergence hypothesis, we assume that initial and structural conditions matter in the evolution of steady-state income (Galor, 1996; Bartkowska & Riedl, 2012), i.e. in the formation of convergence clubs. Therefore, the regression equation is as follows:

$$y_i^* = X_i\beta_i + \varepsilon_i,$$

where club membership is related to a latent variable y_i^*, which represents the steady-state income of individual regions, X_i means the initial explanatory factors, ε is the residual with logistic distribution, while *i* (*1…201*) refers to the number of regions. The estimation of y_i^* and β_i is based on the maximum likelihood technique. In order to assess the importance of each explanatory variable in determining club membership, we calculate the (marginal) effects of the estimated probabilities. The marginal effects estimate how a unit change in an explanatory variable changes the probability that an average region belongs to a given club, while holding all other variables at the sample average.

Spatial patterns of regional convergence

For testing the neighbourhood effect and spatial dependence, we use a global autocorrelation test to reveal average patterns in the income performance of the regions under study. We capture this correlation using the Global Moran's I (Moran, 1948):

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where *n* means the number of regions, $\bar{y}$ is the arithmetic mean of the indicator under study and $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$. The value of w_{ij} is 1 if *i* and *j* are neighbouring regions, otherwise the value is 0. The expected value of Moran's I is *–1/(N–1)*. I values above *–1/(N–1)* indicate positive spatial autocorrelation, in which similar values, whether high or low, show spatial clusters. I values below *–1/(N–1)* indicate negative spatial autocorrelation, in which neighbouring values are different. To describe the spatial patterns, we used a local test function of spatial autocorrelation i.e. the Local Moran's I statistic suggested by Anselin (1995). The Local Moran statistic can be used to detect regions that are similar to or different from their neighbours. The Local Moran's I formula is as follows:

$$I_i = z_i \sum_j w_{ij}\, z_j$$

where z_i, *t* and z_j, *t*, are the standardised values of the observation units at time *t*. For the univariate Local Moran, z_i, *t* and z_j, *t* refer to the same database. w_{ij} is the spatial weight matrix (Anselin, 1995). The Moran scatter plot generated by the test classifies the regions into four categories according to their location in the four quadrants of the plot: (1) High-high (HH): high value locations where the neighbourhood also has a high value. (2) High-low (HL): high value locations where the neighbourhood has a low value. (3) Low-low (LL): low value locations where the neighbourhood also has a low value. (4) Low-high (LH): low value locations where the neighbourhood has a high value.

Data

The data sources are the OECD[1] Regional Database, the ESPON[2] Database, and the Eurostat Regional Database. The basic indicator of income inequality is Gross Value Added (GVA) per capita. The income indicator is expressed in US dollars and calculated at constant prices and purchasing power parity, with 2015 taken as the base year.

In our analyses, the wider East Central European (ECE) region consists of Bulgaria, Czechia, Croatia, Hungary, Poland, Romania, Slovenia and Slovakia. The NUTS3 region is the basic territorial unit of analysis. In order to approximate the functional regional organisation, we have created so-called 'metropolitan' regions (Eurostat, n.d./a, Smetkowski, 2018), i.e. we have merged urban and agglomeration NUTS3 regions. The merging affected the following cities and regions (agglomerations are shown in brackets): Bucharest (Ilfov), Budapest (Pest), Gdansk (Trojmiejski), Katowice (Bytomski, Gliwicki, Sosnowiecki, Tyski), Krakow (Krakowski), Lódz (Lódzki), Poznan (Poznanski), Warszawa (Warszawski wschodni, Warszawski zachodni), Prague (Stredoceský kraj), Sofia (Sofia, Pernik) and Zagreb (Krapinsko-zagorska zupanija, Zagrebacka zupanija).

The panel database contains income data for 201 regions from 2001 to 2019 (T=19), with a total of 3,819 observations analysed. The main characteristics of the income panel database are presented in Table 1.

Table 1 Main features of the income database (2001–2019)

	obs.	**nr of regions**	**mean (2001, USD)**	**mean (2019, USD)**	**SD2001 (USD)**	**SD2019 (USD)**
Bulgaria	494	26	7,629	12,957	1,854	5,394
Czechia	247	13	19,588	29,725	4,113	7,740
Croatia	361	19	13,359	18,779	3,391	4,933
Hungary	361	19	13,759	21,221	3,936	6,572
Poland	1,197	63	12,323	24,108	3,690	8,519
Romania	779	41	9,253	19,487	2,779	7,497
Slovenia	228	12	19,508	27,676	4,115	6,846
Slovakia	152	8	15,650	30,284	7,904	16,156
ECE8	3,819	201	12,355	21,768	4,982	9,035

Note: obs. is observation (number of regions x T), mean is the average GVA per capita, SD is the standard deviation.
Source: authors' calculations

[1] The Organization for Economic Cooperation and Development.
[2] European Observation Network for Territorial Development and Cohesion.

Based on the literature (Mankiw et al., 1992; Bartkowski & Riedl, 2012; von Lyncker & Thoennessen, 2017), we attribute the emergence of regional convergence clubs to the following initial and structural factors used in conditional convergence analyses (explanatory factors refer to the year 2001, Appendix 1.). The initial period conditions are GVA per capita, employment rate and growth of the active population (15–64 years old). Gross fixed capital formation data, which appear in regional conditional convergence analyses, are only available at NUTS2 level (Bartkowski & Riedl, 2012; Cutrini, 2019), so this indicator is omitted and therefore our models are limited. The regional knowledge dimension is expressed as the value of high-tech patents per million capita due to the limited availability of education data. This indicator also reflects the modernisation of regional economies and can therefore be understood as a structural characteristic.

Structural characteristics basically describe the structural economic features of regions (Bartkowska & Riedl, 2012; Cutrini & Mendez, 2023). The explanatory structural variables for the ordinal regression are the shares of manufacturing, market services, and public services and other services (out of total gross value added), based on the East Central European and EU transformation experiences (Smetkowski, 2018; Gorzelak, 2020; Szakálné Kanó & Lengyel, 2021, Capello & Cerisola, 2023). Since the determinants of regional development and convergence are not only linked to the characteristics of a given region, we included a country dummy variable (Visegrad countries) to address heterogeneity as a geographical and institutional (and integration development) control in our analysis, following Bartkowska and Riedl (2012) and Pintera (2024). On the other hand, to express agglomeration trends and spatial interactions based on the new economic geography theory (Krugman, 1991; Crespo Cuaresma et al., 2014; von Lyncker & Thoennessen, 2017, Cutrini, 2019), we used as explanatory factors the dummy variables 'predominantly urban areas' and 'remote', which expresses transport geography accessibility.

Convergence clubs were defined using the R programme 'ConvergenceClubs' package (Sichera & Pizzuto, 2019), ordinal logistic regression was carried out using Stata 16, and local autocorrelation analyses were performed using GeoDa and ArcGIS.

RESULTS

Having run the log t-test on the gross value added per capita data for the East Central European regions, the hypothesis of overall convergence can be clearly rejected at 5% significance level. The beta is significantly different from 0 and the t-value is –63.381 (standard error: 0.013, beta:

-0.847). In other words, the 201 ECE regions do not converge to a single common steady state, inferring the presence of geographical convergence clubs.

Based on the Phillips and Sul algorithm, the 201 regions are primarily classified into eight clubs, with a t-value greater than –1.65 for all clubs. Based on the von Lyncker and Thoennessen clustering algorithm (2017), the fourth and fifth clubs are merged, with the resulting new club showing a t-value greater than –1.65. Overall, the seven clusters are in a steady state (i.e. multiple equilibrium for the ECE region) with clearly different growth paths in the space under study. There are also non-converging, i.e. diverging, regional clubs in ECE (Tab.2). There are 5, 15, 58, 52, 34, 25 and 9 regions in the first, second, third, fourth, fifth, sixth and seventh club, respectively. Overall, the final results show a 'multi – seven – speed' East Central European region with clear differentiation as to start and end dates (last two columns of Tab. 2). As far as income is concerned, the panel data highlight one outstanding, one high, one average and four low/lagging spatial clubs. Differences between regions in GVA per capita are clearly visible. Simple income averages indicate the problems of income inequality in the ECE region, with constant and widening centre-periphery relations. The most prosperous regions in terms of income have grown by a factor of 2.2 compared to the initial 2001 level, while the least prosperous regions have grown below the regional average and are relatively lagging behind.

Table 2 Log t-test results in East Central Europe (2001–2019)

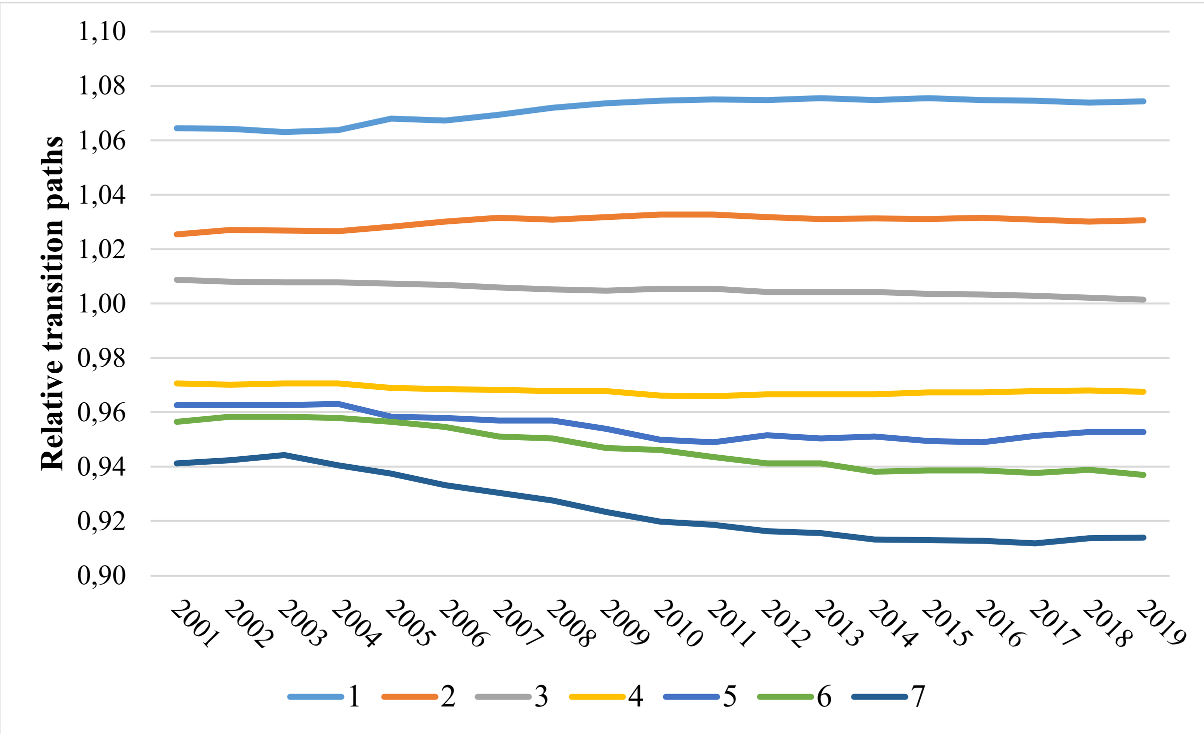
clubs	**number of units**	**beta (std. error)**	**t-value**	$\hat{\alpha}$	**GVA per capita**	
					2001	**2019**
Club1	5	0.088 (0.082)	1.077	0.044	185.05	213.74
Club2	15	0.110 (0.072)	1.524	0.055	127.52	136.54
Club3	58	0.125 (0.062)	2.016	0.063	108.73	101.64
Club4	52	0.081 (0.065)	1.252	0.040	75.65	71.83
Club5	34	0.073 (0.061)	1.196	0.037	69.88	61.65
Club6	25	0.104 (0.049)	2.138	0.050	65.97	52.64
Club7	9	0.229 (0.051)	4.473	0.115	56.95	41.53

Note: α – speed of convergence, Gross Value Added (GVA) per capita is based on ECE average. (Constant prices, constant PPP base year 2015.)
Source: authors' calculations

The majority of the beta values are between 0 and 2, so the results do not show absolute convergence within clubs; only relative (conditional) convergence explains the convergence within clubs and the differences between clubs in 2001–2019. Thus, convergence within each club is determined not only by the initial income position but also by other structural and geographical conditions of the economy (Cutrini, 2019; Cutrini & Mendez, 2023). The speed of convergence is fastest for Club3 and Club7 (6.3 and 11.5 per cent, respectively), while the others show lower values.

Figure 1 shows the relative income transitions of the seven convergence clubs over the period under review, as a percentage of the ECE average. All seven clubs show a clearly distinct performance path over the whole period. It can be concluded that already the initial income levels differ significantly and seem to strongly influence the paths of GVA per capita from 2001 to 2019.

Figure 1 Relative transition paths of the East Central European convergence clubs between 2001 and 2019 (average for the ECE region under study, GVA per capita)

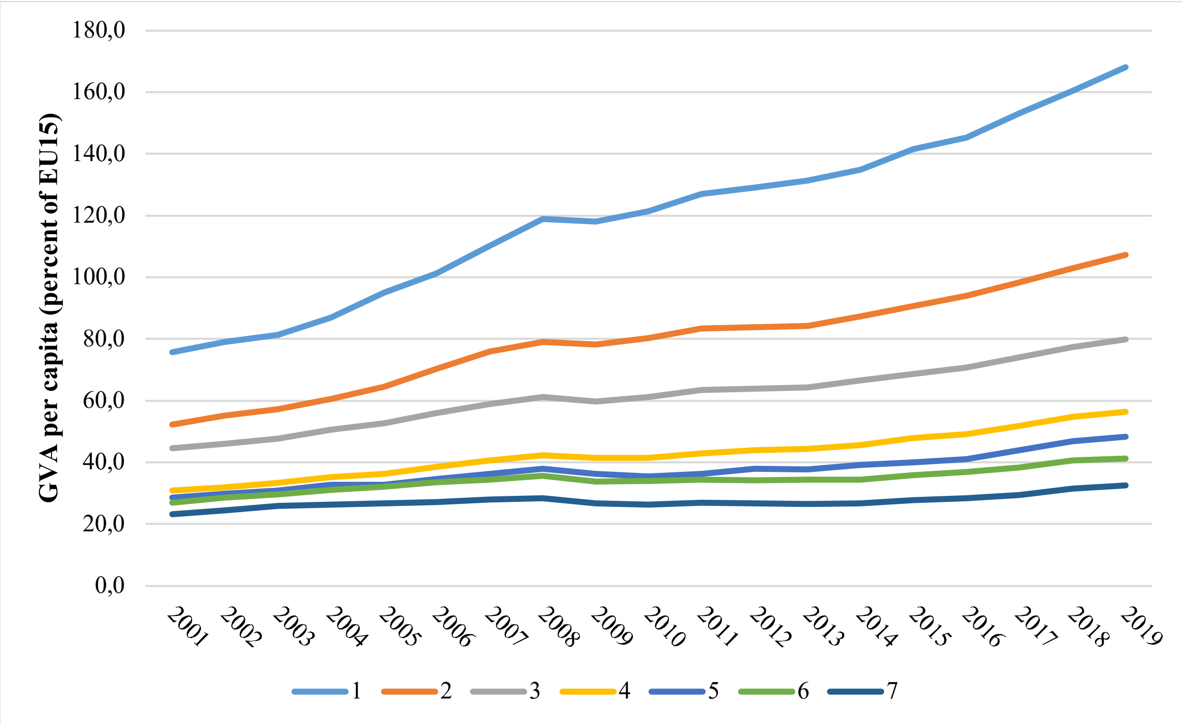


Source: authors' elaboration

There are visible relative changes in the trajectories, especially from the period 2007–2009 (the beginning of the economic crisis), with high-income (above average) regions becoming even richer, while low-income regions below average became even poorer and fell behind over the period under review. It is also observed that the relative decline in the least developed regions (especially Club 7) is larger than the increase in the higher income groups. The average relative transitions show that the GVA per capita of each convergence club is not converging, that the differences between clubs are stable over the period under review and that persistent inequalities are typical in the period after the economic crisis of 2007–2008.

Comparing the average income paths of the convergence clubs with the EU15 average, Club 1 reached it in 2007 (2019: 168.1 per cent) and Club 2 reached it in 2018 (2019: 107.4 per cent), while Club 3 has shown a very weak and slow convergence towards the benchmark over the period (2019: 80.0 per cent). The three clubs cover almost 60 per cent of the ECE population (only 7.3 per cent for Club 1 and 15.4 per cent for Club 2). The other convergence clubs show a distant growth and position, with no significant convergence (Fig. 2).

Figure 2 Economic performance of each convergence club as a percentage of the EU15 (2001–2019)



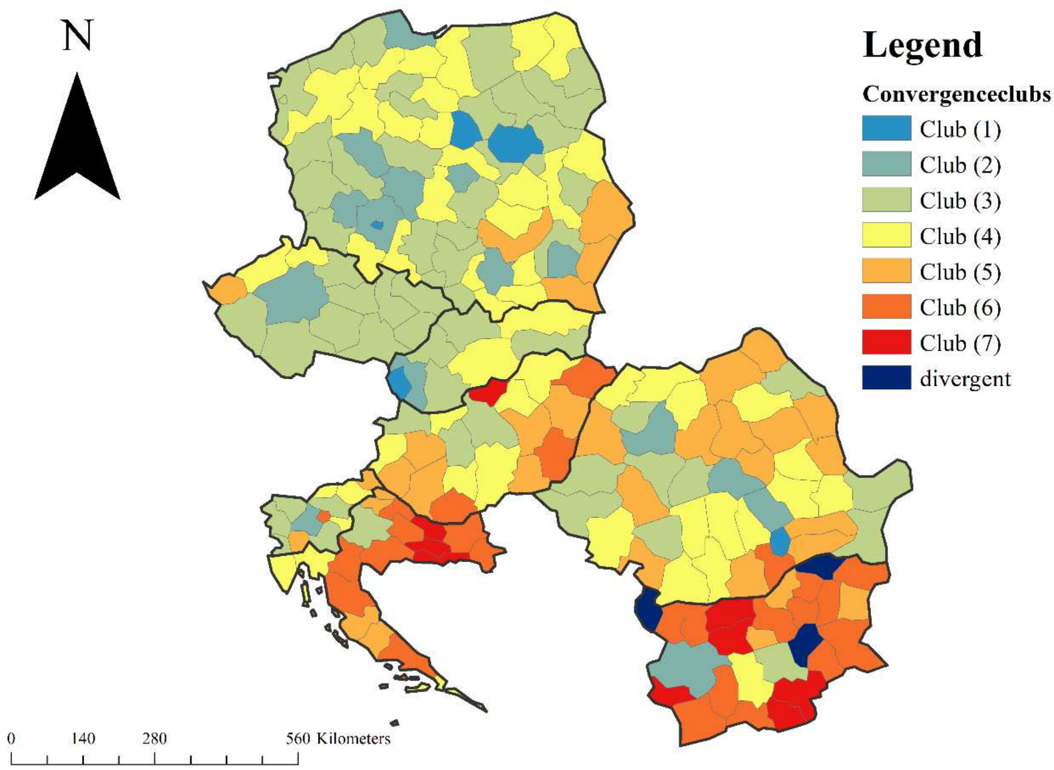
Source: authors' elaboration

Club 1, with its steadily increasing advantage in terms of income, includes only metropolitan areas, with three capital regions (Warsaw, Bucharest, Bratislava) and the Polish cities of Wroclaw and Plock (Fig. 3). Club 2 also includes urban and metropolitan areas, where high-equilibrium income paths are also observed. In addition to Prague, Sofia, Ljubljana, Gdansk, Krakow, Lodz, Poznan, some Romanian (e.g. Cluj, Brasov), Polish (Rzeszowski, Wroclawski) and Slovak (the metropolitan agglomeration of Trnava) regions are also included in this club. Polish regions account for more than half of the group. Club 3 also includes metropolitan areas (Budapest, Zagreb and Katowice) and regions with major cities (e.g. Constanta, Timis, South

Moravia, Szczecin, Győr-Moson-Sopron, Kosice). The Polish, Czech and Slovak regions are overrepresented in the group of middle income path. Particularly striking is the spatial distribution in Czechia (70 per cent of the country is covered by this classification) and Western Slovakia. The results of the log t-test clustering so far clearly point to the role of size dependency and the multi-speed existence of metropolitan areas in East Central Europe.

After Club 3, Club 4 is the group with the second largest number of regions (nearly 26%), where country affiliation can also be an important club-shaping factor. Geographically concentrated, below-average regions appear in particular in Northern and Eastern Poland (mainly in the case of regions between metropolitan areas) and in the Carpathian regions of Romania, but are also scattered in the eastern part of Slovakia and Slovenia, as well as in Hungary, Croatia and Bulgaria. In Czechia and Slovenia, the peripheral areas are more affected by this classification, while in Bulgaria and Croatia the second tier cities (Plovdiv, Rijeka) are included in Club 4. The main characteristic of the fifth lagging club is the absence of external (EU) and internal borders and the geographical location close to the borders, which is evident in all the countries surveyed except Slovakia. In addition to the external peripheries, internal peripherality is also evident (e.g. in Hungary, Romania and Poland).

Figure 3 Convergence clubs in East Central Europe based on gross value added per capita (2001–2019)

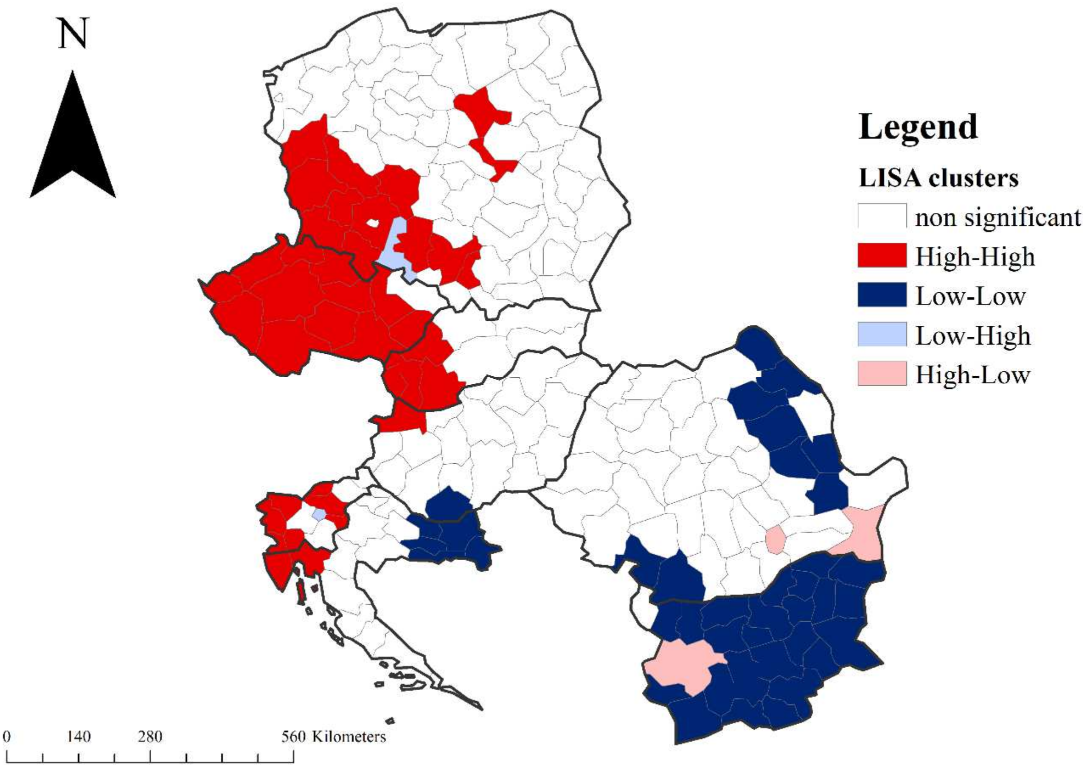


Source: authors' elaboration

The deprived income peripheries of Club 6 present a spatially coherent and spectacular picture. They cover particularly extensive areas in Bulgaria and Croatia, while some of the regions concerned are also found in Hungary, Slovenia and Romania. Closeness to borders and spatial proximity are important club-shaping factors for Club 6. Club 7 covers the smallest number of peripheral regions (9 regions), with Bulgarian and Croatian regions constituting the majority. The geographical distribution of the club is characterised by the same features as in the previous club. Particularly striking is the significant difference between Sofia and its immediate neighbours Lovech and Kyustendil, or Nógrád, near the Budapest metropolitan area, which indicates the lack of spatial spillovers. The divergent regions (not close to the other clubs) are found in Bulgaria, with low-income Vidin, Silistra and Sliven forming this group.

As neighbourhood effects are assumed to play a role in the formation of ECE convergence clubs, the spatial analysis was complemented with the Local Moran's I analysis in order to highlight the relationship between neighbourhood effects and income inequality. The Global Moran's I value for GVA per capita is 0.431 (z-score: 9.405), which is highly significant ($p<0.05$). This means that a characteristic spatial clustering of incomes is observed in the ECE region under study. (Fig. 4)

Figure 4 Local autocorrelation pattern of GVA per capita (Local Moran's I, 2019)

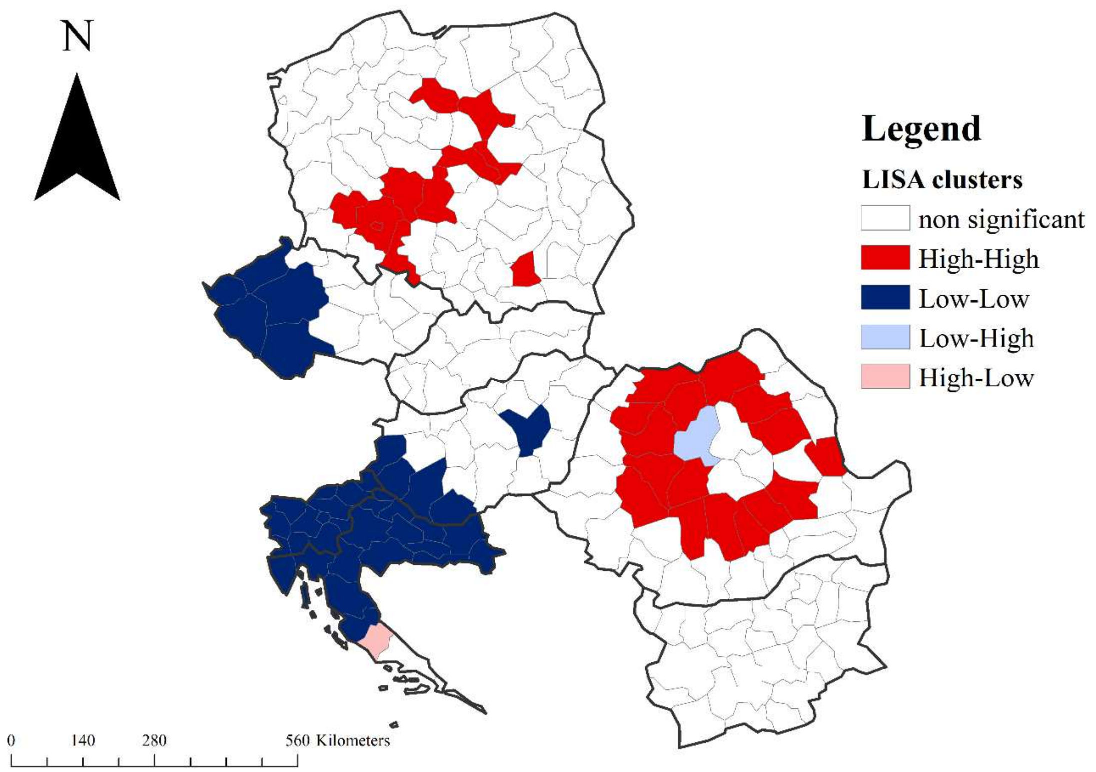


Source: authors' elaboration

The local clusters confirm the cluster results of the log t-test, but due to the specificity of the method, it basically only describes the centre-periphery relations. Neighbourhood effects show on the one hand the east-west relations, for example the coherent core area of Club 3 is clearly visible (Poland, Czechia, Slovakia, western parts of Slovenia), and on the other hand the relative backwardness of the eastern Romanian, eastern Croatian and Bulgarian regions. In addition to the country effects (Czechia, Bulgaria), there are several cases where geographical proximity effects are beneficial (in the regions between Warsaw and Plock, Osrednjeslovenska [Ljubljana], Bratislava, Prague, Katowice, Wroclaw, Poznan, along the cities and urban regions of Poznan), but there is also a lack of spillover effects, for example in Sofia, Bucharest and Constanta.

The spatial autocorrelation pattern of economic growth between 2001 and 2019 (Global Moran's I = 0.567, z-score: 6.121) partly indicates similar generalities: spatial imprints of metropolitan and country effects (Fig. 5). The spillover of growth mainly in Poland indicates the impact of metropolitanisation and the coherent growth zone of western Romanian (mainly Transylvanian) regions.

Figure 5 Local autocorrelation pattern of economic growth (Local Moran's I, 2001–2019)



Source: authors' elaboration

The country effects appear along the low growth path, with Croatia and Slovenia being almost entirely in low-low income (LL) areas. In addition, regions in south-western Hungary and western Bohemia appear in the LL group. The cross-section of static and dynamic characteristics indicates the spatial correlation of neighbourhood effects, which is partly expected and partly nuanced: western Bohemia and Slovenia are characterised with the low growth dynamics of advanced western regions, while low income/high dynamics are mainly present in eastern Romania (the two 'traditional' convergence directions), low income/low dynamics are present in eastern Croatia and south-western Hungary, and high income/high dynamics are present along the large urban regions of Poland.

Club formation in East Central Europe

The results so far indicate significant differences between income clubs, but the club convergence hypothesis is not proven. This requires a proper description of the club-forming effects of initial and structural factors. This was done by running ordinal logistic regression based on the solution of Bartkowska and Riedl (2012).

The model in Table 3 is diagnostically appropriate, showing a good fit (pseudo R-square = 0.677), and most of the explanatory phenomena indicate significant effects in all categories. The table points to the probability of belonging to a particular club for each variable (marginal effects on probabilities), with all other variables considered constant.

As to most of the indicators included in the ordinal logistic regression (initial GVA per capita, employment rate, active population growth, market services, urban areas, remote areas), a unit increase in a given variable contributes to the chances of belonging to higher income clubs (1, 2 and 3), while decreasing the chances of belonging to lower income clubs (4–7).

The ordinal logit regression results show that initial income level has the strongest effect among the initial conditions, with a unit improvement of 148.6 percent increasing the probability of belonging to Club 3, for example, and 93.6 percent decreasing the probability of belonging to Club 5. Initial income level is a strong determinant of club formation across all clubs. Employment rate is a similar, but less strong and less significant, determinant of club membership (significant only for Clubs 3–6, with $p<0.10$). The signs of high tech patent activity are opposite to the ones of initial GVA and employment, but appear to be insignificant factors in the formation of ECE convergence clubs. The growth of the active population is correlated with the income development of convergence clubs, with significant increases in Clubs 1–3 and significant decreases in Clubs 4–7.

Table 3 Marginal effects on probabilities (ordered logit regression)

	convergence clubs						
variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
initial conditions							
initial GVA per cap	0.007* (0.004)	0.121*** (0.046)	1.486*** (0.306)	–1.512*** (0.236)	–0.936*** (0.215)	–0.309*** (0.091)	–0.038** (0.018)
employment rate	0.000 (0.000)	0.000* (0.000)	0.006** (0.003)	–0.010** (0.005)	–0.004** (0.002)	–0.001* (0.001)	–0.000. (0.000)
patent activity	–0.000 (0.000)	–0.001 (0.001)	–0.010 (0.008)	0.007 (0.002)	0.006 (0.005)	0.002 (0.002)	0.000 (0.000)
population growth	0.001 (0.000)	0.009*** (0.004)	0.112*** (0.024)	–0.092** (0.047)	–0.070*** (0.018)	–0.023*** (0.007)	–0.003** (0.001)
structural characteristics							
manufacturing	–0.000 (0.000)	–0.000 (0.000)	–0.004 (0.005)	0.003 (0.001)	0.002 (0.003)	0.001 (0.001)	0.000 (0.000)
market services	0.000 (0.000)	0.001* (0.001)	0.014** (0.006)	–0.010** (0.005)	–0.009** (0.004)	–0.003** (0.001)	–0.000* (0.000)
public and other services	–0.000 (0.000)	–0.004*** (0.002)	–0.049*** (0.011)	0.037*** (0.010)	0.031*** (0.008)	0.010*** (0.003)	0.001** (0.001)
geographic controls							
urban areas	0.004 (0.004)	0.061 (0.052)	0.343*** (0.116)	–0.221* (0.125)	–0.143*** (0.041)	–0.040*** (0.014)	–0.005* (0.002)
remote areas	–0.000 (0.00)	–0.008* (0.005)	–0.110* (0.060)	0.086* (0.002)	0.080* (0.050)	0.029 (0.021)	0.004 (0.003)
threshold values	–94.386	–91.493	–88.252	–86.167	–84.470	–82.181	–
number of regions	5	15	58	52	34	25	9

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Pseudo R-Square (Nagelkerke) is 0.677. The parallel regression assumption is not violated. V4 dummy (CZ, HU, PL and SK) is included and significant (not reported). Standard errors are reported in parentheses.
Source: authors' calculations

Structural characteristics confirm the same correlations. The results show that the share of market services in the economy has a positive significant effect on the likelihood of belonging to higher income clubs and a negative impact on the likelihood of belonging to lower income clubs. Public and other services have the opposite effect on the probability of regions' participation, with a unit increase in public services increasing participation in Clubs 4–7 and decreasing participation in Clubs 1–2 and 3. The manufacturing sector has the same sign as the public and other sectors (decreases the probability of high-income club membership and increases the probability of belonging to low-income clubs) but does not show a significant effect on club formation. The spatial agglomeration characteristic of the ECE region (urban areas) is the second strongest significant determinant of club formation, clearly favouring high-income clubs. The role of transport geography accessibility, which reflects spatial interactions, is also a significant factor in club formation, supporting participation in higher income clubs.

DISCUSSION

Our research basically shows that in the new millennium, the ECE region is not experiencing global overall convergence and that there are clearly distinct convergence clusters in the geographical space in terms of gross value added per capita between 2001 and 2019. Based on the von Lyncker and Thoennessen club merging algorithm, seven geographic convergence clubs have been identified in the ECE region, which show a clearly distinct steady-state condition. Relative (conditional) convergence is observed within each club, which can be explained by the ordinal logistic regression method by including initial and structural as well as geographic-institutional factors.

During the period under review, the income paths of convergence clubs are clearly separated and persistent regional income gaps emerge. At the same time, the relative transition paths in GVA per capita started to widen already before the economic crisis of 2007–2008, and were further exacerbated by the crisis. This contradicts Cutrini's (2019) results for the EU27 at the regional level, with divergent processes starting earlier in the ECE region. The behaviour of convergence clubs follows Myrdal's (1957) circular cumulative causation theory and Krugman's (1991) new economic geography theory. The high-income (mainly urban metropolitan) clubs increase their incomes (the first two convergence clubs), while the low-income clubs (the bottom three clubs) become even poorer by 2019. Convergence clubs confirm the presence of different development (low and middle income) traps in the ECE region (Iammarino et al., 2020). The persistent behaviour of income paths is consistent with the characteristics of higher agglomeration regions (Bartkowska & Riedl, 2012; von Lyncker & Thoennessen, 2017; Cutrini, 2019; Cutrini & Mendez, 2023).

The distribution of the resulting multi-speed convergence clubs also reflects the urban-rural inequality at the lower aggregation level, similar to the results of von Lyncker and Thoennessen (2017), Bartkowska and Riedl (2012), Cutrini (2019) and Szakálné Kanó and Lengyel (2021). An important feature is that centre regions do not show a uniform development path (Smetkowski, 2018), but rather can be considered as multi-speed. Particularly striking are the

Budapest and Zagreb regions in Club 3, which lag behind other metropolitan areas, and the Katowice-centred Upper Silesian urban area, which has the largest population in the initial period. In ECE convergence clubs, which also describe the centre-periphery situation, our results show that population agglomeration is one of the causes of cumulative causality, in which case it can be reasonably assumed that it also means the drain of educated active population from underdeveloped spaces (Smetkowski & Wójcik, 2012; Smetkowski, 2018; Cutrini, 2019). According to our analysis – and confirming the theory of the new economic geography – urban-rural divisions and related spatial interactions thus contribute to the increase of regional inequalities (Gerritse & Arribas-Bel, 2018) and will lead to a further deepening of metropolisation and marginalisation in the future as well.

The formation of convergence clubs and the process of club convergence are mostly related to initial conditions, including initial GVA per capita. This is most consistent with the results of von Lyncker and Thoennessen (2017) and slightly different from the ordered logistic regression outputs of Bartkowska and Riedl (2012) and Cutrini (2019). The sign of patent activity, which we used as a proxy for human capital in the ordered logistic regression, is as expected but it is not a significant explanatory factor for club convergence. This is in line with the results of Iammarino et al. (2020), who argue that the process of innovation is a region–specific phenomenon and as such does not represent a general 'panacea' for regional economic performance. On the other hand, the convergence of the knowledge economy is not typical in the ECE region for complex reasons: the weakness of national innovation systems, the persistent technology gap between old and new Member States, R&D imports, the weakness of institutional capacities and the weak innovation readiness of firms (Veugelers, 2011; Rodríguez-Pose & Wilkie, 2017; Karbowski, 2017; Papava, 2018).

Structural characterics factors seem to be less influential determinants in explaining club convergence (similarly to von Lyncker & Thoennessen, 2017). Our results confirm the structural economic characteristics of the ECE region in line with the research work of Capello and Cerisola (2023). The effect of the market service sector in promoting club convergence and regional disparities is a reflection of the economic evolutionary processes of the period characterising this stage of development in ECE regions (Capello & Cerisola, 2023). According to calculations by Iammarino et al. (2020), employment rate in the sector increases the escape from the trap of middle-level development. This, although our research takes a different approach, is ultimately in line with our calculation: staying in developed clubs is facilitated, while leaving low-income clubs is supported by increased sectoral role. Employment rate in public and other services supports trapping, especially in low-income regions (Iammarino et al., 2020), which is a partially parallel result to our analysis. Higher non-market (i.e. public and other) services lead to 'sheltered' economies, protected from cyclical downturns but unable to take advantage of cyclical periods (Iammarino et al., 2020).

Cutrini (2019) has identified the presence of the manufacturing sector as a key determinant of club convergence in the EU, facilitating the positions of developed regions. Industrial efficiency gains have a prominent role in the regional transformation of East Central Europe in the new millennium (Capello & Cerisola, 2023), while Smetkowski (2015) argues that the presence (unsuccessful renewal or transformation) of traditional industrial regions is a major development constraint in the region.

It is important to underline that, despite the socio-economic transformation of the ECE region, the initial conditions of the new millennium have fundamentally determined the trajectories of the income clubs, and clearly continue to have a lasting impact on them.

Neighbourhood effects indicate a distinctive spatial pattern, but provide a complex picture in explaining club convergence in East Central Europe. The spatial autocorrelation results partially confirm the significant phenomenon of metropolisation, similar to the work of Smetkowski and Wójcik (2012), Crespo Cuaresma et al. (2014), Smetkowski (2018), Gorzelak (2020). The polycentric development that fosters the emergence of convergence clubs is only static or dynamic in countries with larger populations. At the same time, spatial autocorrelation results adequately mediate marginalisation processes and the circular cumulative causation backwash effects of Myrdal (1957), with slow growth also restraining the growth of neighbours. This is also reflected in the distribution of convergence clubs, similar to Smetkowski (2015) (e.g. in Bulgaria or Eastern Croatia) and Ayouba and LeGallo (2019). The breakdown of national borders (as barriers) in East Central Europe shows partial positive local externalities, in fact, the spatial orientation towards the West is significantly reflected in the organisation of economic space and the formation of convergence clubs. This further supports Gorzelak's (2020) picture of regional transformation for the ECE region (i.e. the presence of 'leaders' and 'winners' spaces). Moreover, based on Rodríguez-Pose and Tselios (2015) and Annoni and Rubianes (2016), the spatial autocorrelation results are also hypothesized to be influenced by macro-level socio-economic policies and national institutions, which is supported by our results. In addition to 'traditional' socio-economic interactions (knowledge spillovers, labour flows, economies of scale, etc.), national and supranational institutional structures are also important shapers of regional development, especially during the transformation of the ECE region (Cutrini, 2019; Gorzelak, 2020). All these features, as expressed by spatial autocorrelation studies, add complexity to the phenomenon of regional club convergence in the ECE region.

CONCLUSION

In our study, we investigated the presence of economic convergence clubs and club convergence at NUTS3 level for Gross Value Added per capita in the East Central European region. In doing so, we aimed to contribute to the understanding of the transformation and convergence in East Central Europe in the new millennium.

The novelty of our analysis lies in the fact that the investigated phenomenon has not yet been examined in the extended East Central European region using such a complex and integrated quantitative methodological framework.

For this purpose, we first applied the log t-test of Phillips and Sul and the von Lyncker–Thoennessen cluster merging algorithm in order to delineate regions (convergence clubs) with similar income steady-state conditions. Subsequently, ordinal logistic regression was used to detect the factors influencing the formation of income-based clubs.

Our results show that there is no global convergence within the ECE region, with seven geographically distinct convergence clubs in the first two decades of the new millennium. In other words, the region shows ‘multi-speed’ economic development, with significant and persistent differences between income clubs. Our results show that regions with almost a quarter of the population have reached the average GVA per capita of the EU15, while for 40 percent of the population in the ECE region no substantial improvement or convergence is expected. The geographic distribution of clubs does not necessarily follow ‘traditional’ inequalities, with centres and peripheries also showing ‘multi-speed’ development. So our first hypothesis is confirmed.

The emergence of ECE convergence clubs, despite the transformation processes, is fundamentally determined by the characteristics of the initial period (initial development, changes in active population, agglomeration characteristics, spatial interactions, economic structure characteristics, neighbourhood relations). All these results are consistent with those reported in the international literature and confirm the club convergence hypothesis in the ECE region. Thus our second hypothesis is confirmed.

Although our analysis is not based on GDP calculated at traditional purchasing power parity, the results certainly point to differentiated spatial paths behind regions of regional policy interventions. It is important to highlight that these paths go beyond NUTS2 regions, but also beyond NUTS3-based (e.g. urban-rural) delimitations. In our view, the results point to a persistent phenomenon of spatial and temporal dependence of economic development, which is a real problem in the ECE region.

Our results confirm that both EU and national regional policies must abandon the 'one-size-fits-all' approach and instead be tailored to the specific characteristics of convergence clubs through place-based interventions. In developed metropolitan regions, sustaining growth should be supported through smart specialisation and digitalisation, whereas in peripheral, low-income areas, overcoming structural disadvantages requires targeted investments in (transport) infrastructure and human capital. Furthermore, strengthening cross-border cooperation based on spatial proximity is essential for enabling lagging regions to catch up. The effectiveness of cohesion policy depends not only on the volume of financial resources, but also on the implementation of appropriate structural reforms, such as improving institutional quality (Iammarino et al. 2020).

Although the empirical scope of this study is limited to data available up to 2019, subsequent developments – including the COVID-19 pandemic, escalating geopolitical tensions, and increasing inflationary pressures – may have significantly influenced regional economic dynamics across Europe. These events could have altered the pace and spatial patterns of convergence in certain areas. Nevertheless, we maintain that the structural patterns and spatial mechanisms identified in this study remain valid (core-periphery divide, agglomeration advantages, structural economic weaknesses in lagging regions), providing a robust theoretical and methodological foundation for comparative and longitudinal analyses in the post-2019 period.

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REFERENCES

Alexiadis, S. (2013). *Convergence Clubs and Spatial Externalities*. Springer. https://doi.org/10.1007/978-3-642-31626-5

Annoni, P., & Rubianes, A. C. (2016). Tree-based approaches for understanding growth patterns in the European regions. *Region*, 3(2), 23-45. https://doi.org/10.18335/region.v3i2.115

Annoni, P., de Dominicis, L., & Khabirpour (2019). Location matters: A spatial econometric analysis of regional resilience in the European Union. *Growth and Change*, 50(3), 824-855. https://doi.org/10.1111/grow.12311

Anselin, L. (1995). Local Indicators of Spatial Association – LISA. *Geographical Analysis*, 27 (2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Ayouba, K., & Le Gallo, J. (2020). *Report on spatiotemporal ESDA on GDP, income and educational attainment in European regions*. Retrieved from https://hal.inrae.fr/hal-02789469

Barro, R.J., & Sala-I-Martin, X. (2004). *Economic growth* (2nd ed.). The MIT Press.

Bartkowska, M., & Riedl, A. (2012). Regional convergence clubs in Europe: Identification and conditioning factors. *Economic Modelling*, 29(1), 22–31. https://doi.org/10.1016/j.econmod.2011.01.013

Baumol, W. J., & Wolff, E. N. (1988). Productivity growth, convergence, and welfare: Reply. *American Economic Review*, 78(5), 1155–1159.

Baumol, W. J. (1986). Productivity growth, convergence and welfare: What the long run data show. *The American Economic Review*, 76(5), 1072–1085.

Bourdeau-Lepage, L. (2007). *Advanced services and city globalization on the Eastern fringe of Europe*. Belgeo. Retrieved September 25, 2020, from http://journals.openedition.org/belgeo/11703

Bourdin, S. (2013). Pour une approche géographique de la convergence: Les inégalités régionales dans l'Union européenne et leur évolution. *L'Espace géographique*, 42, 270-285. https://doi.org/10.3917/eg.423.0270

Capello, R., & Cerisola, S. (2023). Industrial transformations and regional inequalities in Europe. *The Annals of Regional Science*, 70, 15–28. https://doi.org/10.1007/s00168-021-01097-4

Capello, R., & Fratesi, U. (2013). Globalization and endogenous regional growth. In Crescenzi, R., & Percoco, M. (Eds.), *Geography, institutions and regional economic performance. Advances in spatial science* (pp. 15–37) Springer-Verlag. https://doi.org/10.1007/978-3-642-33395-8_2

Capello, R., & Perucca, G. (2013). *Do Eastern European regions move towards an endogenous growth pattern? A diachronic perspective of regional success factors*. GRINCOH Working Paper Series, Paper No. 1.15.

Consolidated version of the Treaty on the Functioning of the European Union (2012). Official Journal of European Union. C326/47, 1-390. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A12012E%2FTXT

Crespo-Cuaresma, J., Doppelhofer, G., & Feldkircher, M. (2014). The determinants of economic growth in European regions. *Regional Studies,* 48(1), 44-67. https://doi.org/10.1080/00343404.2012.678824

Cutrini, E., & Mendez, C. (2023). Convergence clubs and spatial structural change in the European Union. *Structural Change and Economic Dynamics,* 67, 167-181. https://doi.org/10.1016/j.strueco.2023.07.009

Cutrini, E. (2019). Economic integration, structural change, and uneven development in the European Union. *Structural Change and Economic Dynamics*, 50, 102–113. https://doi.org/10.1016/j.strueco.2019.06.007

Diemer, A., Iammarino, S., Rodríguez-Pose, A., & Storper, M. (2022). The Regional Development Trap in Europe. *Economic Geography*, 98(5), 487–509. https:/doi.org/10.1080/00130095.2022.2080655

Durlauf, S. N., & Johnson, A. P. (1995). Multiple Regimes and Cross-Country Growth Behaviour. *Journal of Applied Econometrics*, 10(4), 365-384.

ESPON (2023). *ESPON Database*. Retrieved from https://database.espon.eu/

European Commission (2017). *Competitiveness in low-income and low-growth regions: The lagging regions report*. Publications Office of the European Union, Brussels.

Eurostat (2023). *Regional statistics by NUTS classification*. Eurostat. Retrieved from https://ec.europa.eu/eurostat/web/regions/database

Eurostat (n.d.). *Territorial typologies manual - metropolitan regions*. Eurostat. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Territorial_typologies_manual_-_metropolitan_regions

Ezcurra, R., & Del Villar, A. (2021). Globalization and spatial inequality: Does economic integration affect regional disparities? *The Annals of Regional Science*, 67(2), 335-358. https://doi.org/10.1007/s00168-021-01050-5

Fischer, M. M., & Stirböck, C. (2006). Pan-European regional income growth and clubconvergence: Insights from a spatial econometric perspective. *The Annals of Regional Science*, 40, 693–721. https://doi.org/10.1007/s00168-005-0042-6

Friedrich-Eckey, H., & Türck, M. (2007). Convergence of EU-Regions. A Literature Report. *Investigaciones Regionales – Journal of Regional Research*, 10, 5-32.

Galor, O. (1996). Convergence? Inferences from Theoretical Models. *The Economic Journal,* 106(437), 1056-1069.

Gerritse, M., & Arribas-Bel, D. (2018). Concrete agglomeration benefits: do roads improve urban connections or just attract more people? *Regional Studies*, 52(8), 1134−1149. https://doi.org/10.1080/00343404.2017.1369023

Gorzelak, G. (2020). Regional Policies in East-Central Europe. In Fischer, M., & Nijkamp, P. (Eds.), *Handbook of Regional Science* 2nd edition (pp. 1087-1114.) Springer-Verlag. https://doi.org/10.1007/978-3-662-60723-7

Iammarino, S., Rodríguez-Pose, A.,, & Storper, M. (2017). *Why Regional Development matters for Europe's Economic Future*. Working papers DG for Regional and Urban Policy Publications. Office of the European Union.

Iammarino, S., Rodríguez-Pose, A., Storper, M., & Diemer, A. (2020). *Falling into the middle-income trap? A study on the risks for EU regions to be caught in a middle-income trap*. Publications Office of the European Union. https://doi.org/10.2776/02363

Karahasan, B.C. (2020). Winners and losers of rapid growth in Turkey: Analysis of the spatial variability of convergence. *Papers in Regional Science*, 99(3), 603-644. https://doi.org/10.1111/pirs.12496

Karbowski, A. (2017). Institutional underpinnings of the development of knowledge subsystems in Central and Eastern Europe. *Ekonomista*, 1, 30-46.

Krugman, P. (1991). *Geography and trade*. MIT Press.

Le Gallo, J., & Ertur, C. (2003). Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980-1995. *Papers in Regional Science*, 82: 175-201. https://doi.org/10.1111/j.1435-5597.2003.tb00010.x

Le Gallo, J., & Fingleton, B. (2021). Regional growth and convergence empirics. In Fischer, M. M., & Nijkamp, P. (Eds.), *Handbook of regional science* (pp. 680–706). Springer.

Le Gallo, J. (2004). Space-time analysis of GDP disparities among European regions: a Markov chains approach. *International Regional Science Review*, 27(2), 138-163. https://doi.org/10.1177/0160017603262402

Li, F., Guangdong, L., Weishan, O., Jing, O., & Haitao, M. (2018). Identifying Economic Growth Convergence Clubs and Their Influencing Factors in China. *Sustainability,* 10, 2588. https://doi.org/10.3390/su10082588

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2), 407–437. http://dx.doi.org/10.2307/2118477

Monfort, P. (2020). *Convergence of EU regions redux recent trends in regional disparities*. Working Papers 2/2020. Publications Office of the European Union.

Moran, P.A.P. (1948). The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society*, B10, 243–251.

Myrdal, G. (1957). *Economic Theory and Underdeveloped Regions*. Gerald Duckworth.

OECD (2023). *Regional Database*. OECD. Retrieved from https://doi.org/10.1787/region-data-en

Papava, V. (2018). Catching Up and Catch-Up Effect: Economic Growth in Post-Communist Europe (Lessons from the European Union and the Eastern Partnership States). *European Journal of Economic Studies*, 7(2), 109-125. https://doi.org/10.13187/es.2018.7.109

Phillips, P. C., & Sul, D. (2009). Economic transition and growth. Journal of Applied *Econometrics*, 24(7), 1153–1185. https://doi.org/10.1002/jae.1080

Phillips, P.C., & Sul, D. (2007). Transition modeling and econometric convergence tests. *Econometrica*, 75(6), 1771–1855.

Pintera, J. (2024). Regional convergence in the European Union – Factors of growth between the great recession and the COVID crisis. *Economic Systems*, 48(1), 101169. https://doi.org/10.1016/j.ecosys.2023.101169i

Quah, D. T. (1996). Empirics for economic growth and convergence. *European Economic Review*, 40(6), 1353–1375. https://doi.org/10.1016/0014-2921(95)00051-8

Rey, S.J. (2019). Spatial Dynamics and Space-Time Data Analysis. In Fischer, M., & Nijkamp, P. (Eds.), *Handbook of Regional Science* (pp. 1365-1384). Heidelberg Springer.

Ridao-Cano, C., & Bodewig, Ch. (2018). *Growing United: Upgraiding Europe's Convergence Machine*. International Bank for Reconstruction and Development/The World Bank.

Rodríguez-Pose, A., & Ketterer, T. (2020). Institutional change and the development of lagging regions in Europe. *Regional Studies,* 54(7), 974–986. http://doi.org.10.1080/00343404.2019.1608356

Rodríguez-Pose, A., & Tselios, V. (2015). Toward inclusive growth: Is there regional convergence in social welfare? *International Regional Science Review*, 38(1), 30–60. https://doi.org/10.1177/0160017613505201

Rodríguez-Pose, A., & Wilkie, C. (2017). Innovation and competitiveness in the periphery of Europe. In Huggins, R., & Thompson, P. (Eds.): *Handbook of Regions and Competitiveness Contemporary Theories and Perspectives on Economic Development* (pp. 351-380). Edward Elgar Publishing.

Sichera, R., & Pizzuto, P. (2019). ConvergenceClubs: A Package for Performing the Phillips and Sul's Club Convergence Clustering Procedure. *The R Journal*, 11(2), 142-151.

Single European Act (1987). Official Journal of the European Communities, L (169), 1-19. Retrieved from https://eur-lex.europa.eu/resource.html?uri=cellar:a519205f-924a-4978-96a2-b9af8a598b85.0004.02/DOC_1&format=PDF

Smetkowski, M., & Wójcik, P. (2012). Regional convergence in Central and Eastern European countries: A multidimensional approach. *European Planning Studies*, 20(6), 923–939. https://doi.org/10.1080/09654313.2012.673560

Smetkowski, M. (2015). Spatial patterns of regional economic development in Central and Eastern European countries. *Geographia Polonica*, 88(4), 539–555. https://doi.org/10.7163/GPol.0033

Smetkowski, M. (2018). The role of exogenous and endogenous factors in the growth of regions in Central and Eastern Europe: the metropolitan/non-metropolitan divide in the pre- and post-crisis era. *European Planning Studies*, 26(2), 256–278. https://doi.org/10.10)80/09654313.2017.1361585

Solow, R. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65–94.

Szakálné Kanó, I., & Lengyel, I. (2021). Convergence Clubs of NUTS3 Regions of the V4 Group. *E&M Economics and Management*, 24(4), 22–38. https://doi.org/10.15240/tul/001/2021-4-002

Treaty Establishing the European Community (Consolidated Version), Rome Treaty (1957). Retrieved from https://www.refworld.org/legal/agreements/eu/1957/en/40087

Veugelers, R. (2011). Assessing the potential for knowledge-based development in the transition countries of Central and Eastern Europe, the Caucasus and Central Asia. *Society and Economy*, 33(3), 475–504. https://doi.org/10.1556/SocEc.33.2011.3.3

von Lyncker, K., & Thoennessen, R. (2017). Regional club convergence in the EU: Evidence from a panel data analysis. *Empirical Economics*, 52(2), 525–553. https://doi.org/10.1007/s00181-016-1096-2

Appendix 1 List of variables

variable	definition	source
Initial GVA per capita	GVA divided per population (PPP, constant price, base year 2015, logs, 2001)	OECD Regional Database
population growth	growth of active population (15-64) between 1995 and 2000	ESPON, own calculation
employment rate	employment rate in percent of total population (2001)	ESPON, Eurostat Regional Database, own calculation
patent activity	high tech patent per million capita (2001)	OECD Regional Database, own calculation
manufacturing	gross value added in manufacturing sector as a share of total gross value added (2001)	ARDECO Database, own calculation
market services	gross value added in Wholesale and retail trade; transport; accommodation and food service activities; information and communication and financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities sector as a share of total gross value added (2001)	Eurostat Database, own calculation
public services and other services	gross value added in Public administration and defence; compulsory social security; education; human health and social work activities; arts, entertainment and recreation, repair of household goods and other services sector as a share of total gross value added (2001)	Eurostat Database, own calculation
urban areas (dummy)	dummy variable of predominantly urban regions (NUTS level 3 regions where more than 80 % of the population live in urban clusters) (1–yes, 0–no)	Eurostat Database, own calculation
remote areas (dummy)	dummy variable of remote regions (A predominantly rural or intermediate regions is considered remote if less than half of its residents can drive to the centre of a city of at least 50 000 inhabitants within 45 minutes) (1–yes, 0–no)	Eurostat Database, own calculation
V4 dummy	dummy variable of NUTS3 regions in V4 countries (Czechia, Hungary, Poland, Slovakia) (1–yes, 0–no)	own calculation