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INNOVATION SPILLOVERS AS A DRIVER OF ECONOMIC DEVELOPMENT: EVIDENCE FROM REGIONS LOCATED IN CENTRAL AND EASTERN EUROPEAN UNION COUNTRIES

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Abstract. Innovation has been a core element in the economic development of countries worldwide. Although innovation often has a global impact, it is created in a particular location. This research focuses on regions from Central and Eastern European Union (EU) countries as they are in the process of catching up with more developed Western EU economies. This paper aims to explore the link between innovation level and economic development in Central and Eastern EU countries from a regional perspective as well as to examine the impact of innovation spread between these regions. The analysis applies spatio-temporal models for data on the regional innovation index and gross domestic product per capita from 2016 to 2022. The results of this research show that southeastern regions had, on average, a lower level of both innovation and economic growth than western and northern ones. The analysis also confirms the positive relationship between innovation and economic development in these regions. Finally, this research proves the existence of spatial innovation spillovers: the strongest effect in Polish (near its capital city's region) and Romanian regions while the weakest one in Slovenia, Bulgaria, and further from the capitals of Romania, Poland, and the Czech Republic.

Keywords: innovation spillovers, innovation level, economic development, economic growth, spatio-temporal analysis.

JEL Classification: C23, F63, O30.

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1. Introduction

Innovation improves the productivity, efficiency, and effectiveness of the economy, stimulating economic growth and determining competitiveness. Nowadays, in a globalised world, innovations appear with great frequency. There has been a radical increase in innovations, which are created on a daily basis. Scientists often describe the development of the innovation process using the example of a hockey stick. In the past, until the end of the 18th century, innovations were rare and were located in the flat part of the stick. Later, however, innovation processes, starting from the Industrial Revolution, developed rapidly – moving from the flat part of the hockey stick towards its end part – shaping an exponential curve. In fact, the ice hockey stick is often referred to as economic growth; it is clear that it has been driven by innovation. Innovation seems to be an indispensable element of the world, and the demand for it is increasing. There is more and more talk about the open innovation model, which contributes to the faster growth of new innovations.

Although innovation performance is mostly measured and compared at the national level, it indeed has a regional dimension. Innovation often has a global impact, but the process of creating innovation happens in a particular place. The innovation level of a particular country does not really say anything about its regions and their innovation performance. Since the EU is trying to decrease or eventually eliminate differences in economic development among its countries' regions through the cohesion policy, it seems logical to analyse innovation also in a regional manner. There are different stakeholders in the regional innovation creation process, including academia, institutions, businesses, civil society, and the natural environment. These all form a quintuple innovation helix framework, which describes the innovation process as comprehensive with interactions between all actors.

It is interesting how innovation is distributed across individual regions. One should note that individual regions have different economic characteristics and that their location matters for their development track. Innovations made in a particular place are believed to spread to others. This process, known as the innovation spillover effect, often results in increased knowledge and technological advancements. Although there is a Regional Innovation Scoreboard that provides the Regional Innovation Index, which comprehensively measures the innovation performance in EU regions, there is still a need for further analyses. Hence, the novelty of this paper is the regional focus on innovation and economic development, as well as the spillover effects that innovation may generate. Knowing the results of the innovation level in individual regions is vital to exploring their spatial patterns and how they influence each other.

This study aims to examine (1) the link between innovation and economic development, as well as (2) innovation spillovers in regions of Central and Eastern EU countries. The research hypothesis for innovation spatial spillovers implies that innovation in a particular territory can positively impact neighbouring areas.

2. Literature review

Innovation has been at the heart of an economic debate for many years. However, nowadays, the need for innovation seems to be even greater than ever before. Such a significant factor in economic development is also included in the 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015. Its ninth goal is to 'build resilient infrastructure, promote inclusive and sustainable industrialisation and foster innovation' (United Nations, 2015). Innovation and sustainable development are so interconnected that it is sometimes even called sustainable innovation (Afeltra et al., 2021; Hermundsdottir & Aspelund, 2021; Reficco et al., 2018; Szopik-Depczyńska et al., 2018). Thus, this concept refers to innovation that is in line with sustainable development, so it ensures economic growth, contributes to social development, and provides environmental protection (Cillo et al., 2019; Ghobakhloo et al., 2021; Sarpong et al., 2023).

Innovations are very often attached to a macro scale when they happen in a particular territory. They are not only the result of the global activities of international corporations but also, above all, they have their territorial dimension (Crescenzi et al., 2007; Crescenzi &

Rodríguez-Pose, 2011). One should not also forget about the crucial role of business activities (often innovative) conducted by small and medium-sized enterprises (SMEs) (Amoah et al., 2022; Batrancea et al., 2022; Hervás-Oliver et al., 2021). Thus, the ability to create and absorb innovations is very often considered a key factor contributing to the economic development of a given territory (Cantwell & Iammarino, 1998; Capello et al., 2011; Ding et al., 2025; Furman et al., 2002; Gorzelany-Dziadkowiec et al., 2019).

There is indeed a relationship between innovation and economic growth, which is presented in the literature by different approaches. The first is a linear model of the innovation process, which implies that basic research as a result of the innovation process leads to applied research and inventions, which are transformed into innovations (Bush, 1945; Maclaurin, 1953). The most commonly studied link is between research and development (R&D) and patents, and then between patents and economic growth. Despite some criticism, this approach is still popular and used in scientific research (Ilyina et al., 2020; Rosenberg, 1994). Another one is related to evolutionary economics, which introduced new terms 'innovation systems' and 'learning region'. It truly refers to institutional settings and networks that, combined with social and structural dimensions, determine the innovation level of a given territory, and hence impact its economy (Cooke et al., 1998; Florida, 1995; Nelson & Winter, 1985). The last approach assumes that some processes are connected with innovation, e.g., the diffusion and assimilation of innovation or innovation clusters. They are based on the concept that innovation can be practically adopted, disseminated, and spread through different territories, enhancing economic development (Baptista, 2001; Fischer, 1989; Jaffe, 1986).

There are different studies on spillover effects: knowledge, technology, and innovation; hence, they are all interconnected. Studies on innovation and related topics confirm significant differences between regions, which can be more or less explained by the spillover effects (Audretsch & Feldman, 2004; Cabrer-Borras & Serrano-Domingo, 2007). However, spillovers very often exist between neighbouring regions with similar technological profiles within an individual country, as some cross-border difficulties might disrupt the transfer of knowledge (Greunz, 2003). Hence, sometimes these effects can only have a low level; nevertheless, the generation of innovation processes is mainly made in a region as an individual (Fritsch & Franke, 2004). Hence, the least innovative and developed regions should not count on the spillover effect because they do not have enough absorption capacity. First, they should work on improving the functioning of institutions, particularly in terms of education, training, and skills. Studies on EU regions confirmed that innovation transforms into economic development. However, the spillover effects also have their geographical limits with a radius of 200 km or even 300 km (Bottazzi & Peri, 2003; Rodríguez-Pose & Crescenzi, 2008).

3. Data and methods

The research relates to the economic development expressed in gross domestic product (GDP) per capita and innovation level expressed in regional innovation index (RII) across NUTS-2 regions in Central and Eastern EU from 2016 to 2022, which provides it with a spatial and temporal character. The data used in this research come from the European Statistical Office (EUROSTAT) database (https://ec.europa.eu/eurostat/data/database) – the GDP per capita level – and the Regional Innovation Scoreboard provided by the European Commission (https://projects.research-and-innovation.ec.europa.eu/en/statistics/performance-indicators/european-innovation-scoreboard/eis-2024#/ris) – the RII values.

The first stage of the study is to assess the spatio-temporal tendencies in formulating the considered processes. The study focuses on estimating and verifying the spatio-temporal model given by the Equation (1) (Schabenberger & Gotway, 2005; Szulc, 2007).

$$Y_{i,t} = \sum_{k=0}^{p}\sum_{m=0}^{p}\sum_{l=0}^{p}\theta_{kml}u_{1i}^{k}u_{2i}^{m}t^{l} + \eta_{i,t}, \tag{1}$$

where $\bar{u}_i = [u_{1i}, u_{2i}]$ is the vector of coordinates characterising the spatial location of the i^{th} region, wherein u_{1i} and u_{2i} are the longitude and latitude, respectively. The symbol t denotes time, $Y_{i,t}$ is the level of the dependent variable observed in the i^{th} region at time t, whereas θ_{kml} are the structural parameters of the model. Finally, p is the degree of the polynomial trend ($k + m + l \leq p$) and $\eta_{\,i,t}$ is the residual component.

The estimations of parameters related to variables u_{1i} and u_{2i} show changes in the values of processes towards the east and north, respectively. Besides the assessment of the spatial and temporal tendencies, the relation between neighbouring regions is considered. Moran's I statistic allowed for checking the significance of the spatial dependencies between the areas closest to each other. The Equation (2) presents the way how statistics are calculated (Moran, 1950; Schabenberger & Gotway, 2005):

$$I = \frac{1}{\sum_{i=1}^{NT}\sum_{j=1}^{NT} w_{ij,t}} \cdot \frac{\sum_{i=1}^{NT}\sum_{j=1}^{NT} w_{ij,t}\left[y_{i,t} - \bar{y}\right]\left[y_{j,t} - \bar{y}\right]}{\frac{1}{NT}\sum_{i=1}^{NT}\left[y_{i,t} - \bar{y}\right]^2} = \frac{NT}{S_0} \cdot \frac{\boldsymbol{z}^T\boldsymbol{W}^*\boldsymbol{z}}{\boldsymbol{z}^T\boldsymbol{z}}, \tag{2}$$

where $y_{i,t}$ denotes an observed value of the phenomenon in the i^{th} region at time t, $\boldsymbol{z}$ means a column vector with elements $z_{i,t} = y_{i,t} - \bar{y}$, and $S_0 = \sum_{i=1}^{NT}\sum_{j=1}^{NT} w_{ij,t}$ is a sum of the corresponding elements of the block weights' matrix $\boldsymbol{W}^*$ described with the Equation (3), NT = N * T stands for the number of observations (N regions in T years). The matrix $\boldsymbol{W}^*$ of spatial connections in this study is the matrix fixed in time (Szulc & Jankiewicz, 2018) and built based on the t nearest neighbours criterion, where k = 4. Moreover, the distance between spatial units is calculated as the Euclidean distance between the centres of the locations of regions.

$$\boldsymbol{W}^* = \begin{bmatrix} \boldsymbol{W}_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{W}_T \end{bmatrix}. \tag{3}$$

The Moran's I statistic relates to the occurrence of spatial autocorrelation. The positive and statistically significant value of the this statistic shows that the processes in the neighboring regions are at a similar level. The negative value of this statistic indicates the difference in the levels of the considered processes in the neighboring spatial units. The random position of the values of the phenomenon is verified if the Moran's I statistic is statistically non-significant.

The analysis of the relationship between economic development and the innovation level starts with the estimation and verification of the base model described according to the following Equation (4):

$$\ln(GDP)_{i,t} = \sum_{k=0}^{p}\sum_{m=0}^{p}\sum_{l=0}^{p}\theta_{kml}u_{1i}^{k}u_{2i}^{m}t^{l} + \beta_1\ln(RII)_{i,t} + \eta_{i,t}, \tag{4}$$

where $\ln(GDP)_{i,t}$ is the natural logarithm of the Gross Domestic Product per capita in the i^{th} region at time t and $\ln(RII)_{i,t}$ denotes the natural logarithm of the regional innovation index (RII) of the i^{th} spatial unit at time t. The remaining factors are already described in Equation (1). After testing the spatial autocorrelation, the Lagrange Multiplier tests (in base and robust versions) are conducted to estimate the spatial autoregression (SAR) model. Equations (5)–(6) present the LM statistics (Anselin et al., 2004):

$$LM_{lag} = \frac{1}{T_2}\left(\frac{\boldsymbol{e}^T\boldsymbol{Wy}}{\hat{\sigma}^2}\right)^2, \tag{5}$$

$$RLM_{lag} = \frac{1}{T_2 - T_1}\left(\frac{\boldsymbol{e}^T\boldsymbol{Wy}}{\hat{\sigma}^2} - \frac{\boldsymbol{e}^T\boldsymbol{We}}{\hat{\sigma}^2}\right)^2. \tag{6}$$

The statistical significance of at least one of the calculated statistics allows for estimating the spatial autoregression model, which is the basis for the designation of the spatial spillover effects. The model, based on which the spillovers are calculated, has the following form – Equation (7):

$$\ln(GDP)_{i,t} = \sum_{k=0}^{p}\sum_{m=0}^{p}\sum_{l=0}^{p}\theta_{kml}u_{1i}^{k}u_{2i}^{m}t^{l} + \rho\boldsymbol{W}^{*}\ln(GDP)_{i,t} + \beta_1\ln(RII)_{i,t} + \beta_2\boldsymbol{W}^{*}\ln(RII)_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where $\boldsymbol{W}^{*}\ln(GDP)_{i,t}$ and $\boldsymbol{W}^{*}\ln(RII)_{i,t}$ are the average values of the GDP per capita and regional innovation index from neighbouring units and $\varepsilon_{i,t}$ denotes the random component; the remaining factors are as above. Enriching the SAR model with the spatial lag of the independent variables (in this study, only the spatial lag of RII) transforms it into the Spatial Durbin Model (SDM). The SDM model can be modified to the following Equation (8) (Elhorst, 2017):

$$\ln(GDP)_{i,t} = \left(\boldsymbol{I} - \rho\boldsymbol{W}^{*}\right)^{-1}\sum_{k=0}^{p}\sum_{m=0}^{p}\sum_{l=0}^{p}\theta_{kml}u_{1i}^{k}u_{2i}^{m}t^{l} +$$

$$\left(\boldsymbol{I} - \rho\boldsymbol{W}^{*}\right)^{-1}\left(\beta_1\boldsymbol{I} + \beta_2\boldsymbol{W}^{*}\right)\ln(RII)_{i,t} + \left(I - \rho\boldsymbol{W}^{*}\right)^{-1}\varepsilon_{i,t}. \tag{8}$$

The expression $\left(\boldsymbol{I} - \rho\boldsymbol{W}^{*}\right)^{-1}\left(\beta_1\boldsymbol{I} + \beta_2\boldsymbol{W}^{*}\right)$ allows for the determination of direct and indirect effects resulting from the impact of the innovation level on the GDP. Models (7) and (8) are estimated using the Maximum Likelihood (ML) method.

The short-term effects are designated as the matrix of partial derivatives of the dependent variable $\left(\ln(GDP)\right)$ with respect to the independent variable $\left(\ln(RII)\right)$ in spatial unit 1 up to unit N at a particular point in time (Equation (9)). They denote the effect of a change in a certain explanatory variable in a particular spatial unit on the dependent variable of all other units in the short term (Elhorst, 2017):

$$\left[\frac{\partial \ln(GDP)}{\partial \ln(RII)_1} \cdots \frac{\partial \ln(GDP)}{\partial \ln(RII)_N}\right] = \left(\boldsymbol{I} - \rho \boldsymbol{W}^*\right)^{-1}\left(\beta_1 \boldsymbol{I} + \beta_2 \boldsymbol{W}^*\right). \tag{9}$$

The diagonal elements of the matrix $\left(\boldsymbol{I} - \rho \boldsymbol{W}^*\right)^{-1}\left(\beta_1 \boldsymbol{I} + \beta_2 \boldsymbol{W}^*\right)$ define the direct impacts of a change in the i^{th} observation *RII* (denoted by RII_i) on GDP_i, i.e., on the values of the Gross Domestic Product in the same i^{th} spatial unit. The average of the sum across the i^{th} row of this matrix represents the average impact on individual observation GDP_i resulting from changing the regional innovation index by the amount across all observations – Average Impact to an Observation. In turn, the average of the sum down the j^{th} column of the matrix yields the average impact over all GDP_i from changing the RII by an amount in the j^{th} observation – Average Impact from an Observation (LeSage & Pace, 2009). The indirect effects as the spatial spillovers are identified based on the non-diagonal elements of the considered matrix.

4. Empirical results

The empirical analysis starts by assessing the spatio-temporal tendencies in the formation of GDP per capita and innovation levels in the NUTS-2 regions of the selected countries from the Central and Eastern EU countries. Figure 1 presents the spatial differentiations of GDP per capita in the extreme years of the investigation: 2016 – map (a) and 2022 – map (b). The highest level of economic development in both years occurred in almost all Czech regions, Estonia (EE00), the Capital Region of Lithuania (LT01), Slovenia's regions and Warszawski stołeczny (PL91). Most areas in Romania (excluding the București-Ilfov region – RO08) and Bulgaria (excluding the Yugozapaden region – BG41) were on the other side, where GDP per capita was at the lowest level. The highest diversification of the economic situation was noted across regions from Poland, where they were arranged between three of the four given groups. In general, a certain tendency in the spatial differentiation of GDP per capita levels can be observed. The eastern and southern regions were characterised by lower economic development than those in the western and northern parts.

Figure 2 contains maps illustrating the spatial distribution of the innovation level measured by the Regional Innovation Index in 2016 (a) and 2022 (b). In both years, the highest innovation level was observed in almost all Czech regions, Estonia (EE00), regions from Slovenia, the Capital Region of Lithuania (LT01) and Warszawski stołeczny (PL91). Most regions in Bulgaria and Romania were characterised by very low values of the considered phenomenon. Again, the most significant differences between regions regarding the described process within the country were identified in Poland.

When comparing the spatial variations of the Regional Innovation Index with GDP per capita, it can be seen that they are similar. Regions with high and very high values of RII were situated in the southern and western parts of the investigated area. Based on these distributions, one can presume that there was a significant relationship between the innovation level and economic development across NUTS-2 regions in the selected EU countries.

It is worth noting that the majority of countries' capital regions (City of Zagreb – HR05, Warszawski stołeczny – PL91, the Capital Region of Lithuania – LT01, Budapest – HU11, Bu-

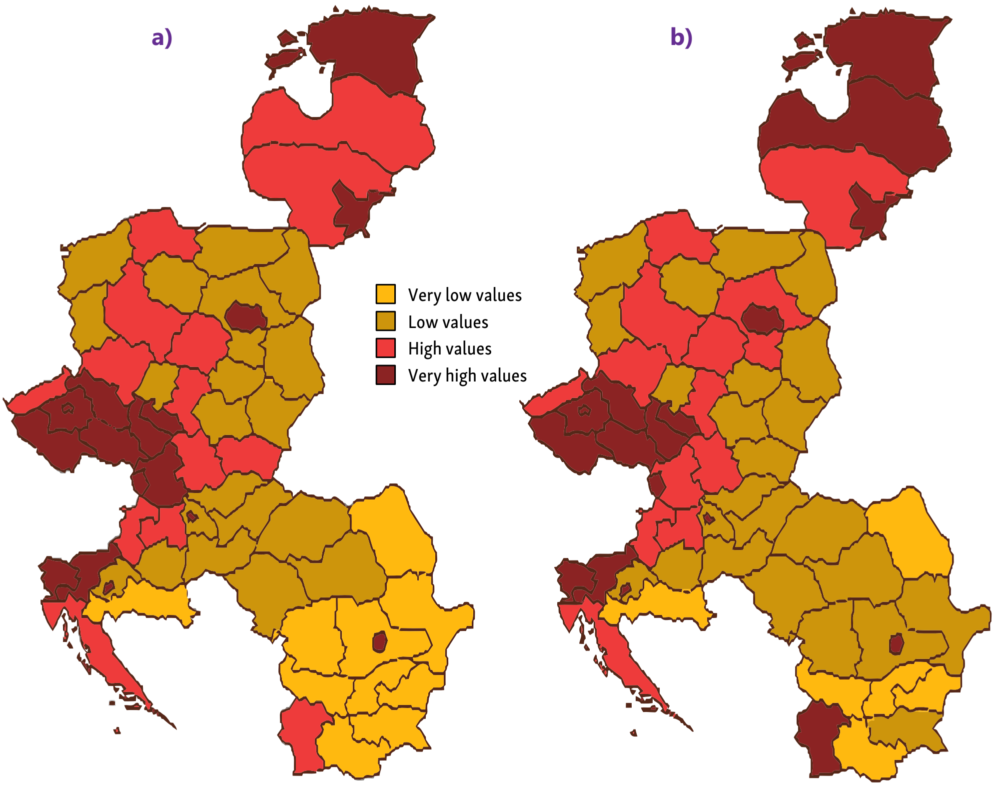

Figure 1. The spatial differentiation of the Gross Domestic Product per capita across selected NUTS-2 regions in the years 2016 (a) and 2022 (b) (source: own elaboration)

curești-Ilfov – RO08, Prague – CZ01, Yugozapaden region – BG41) were placed in the groups of very high and high values of the presented processes. Moreover, the neighbouring regions showed similar values in terms of both GDP per capita and innovation level. The visible clusters of regions (maps from Figures 1 and 2) with similar economic development and innovation potential may indicate the occurrence of spatial dependence between neighbouring areas.

Time is the second dimension considered in this study. Figure 3 shows the tendency of the average values of GDP per capita and the RII from 2016 to 2022 in the area mentioned above. There was only one breakdown in both presented lines. It happened in 2020, in the upward trend of economic development, which was undoubtedly related to the COVID-19 pandemic. In the case of the innovation level, the disruption of the positive tendency occurred in 2018. Despite the one-year stop in the upward trend, the economic development and innovation level across NUTS-2 regions in Central and Eastern EU improved between 2016 and 2022. The GDP grew from 11913 EUR to 18369 EUR per capita. The average value of the Regional Innovation Index in 2016 was 57.91 and grew in 2022 to 64.21.

Table 1 presents the descriptive statistics of the GDP per capita and the Regional Innovation Index from 2016 to 2022. The statistics are calculated for values of variables transformed into their natural logarithms because such variables are used in the model estimation.

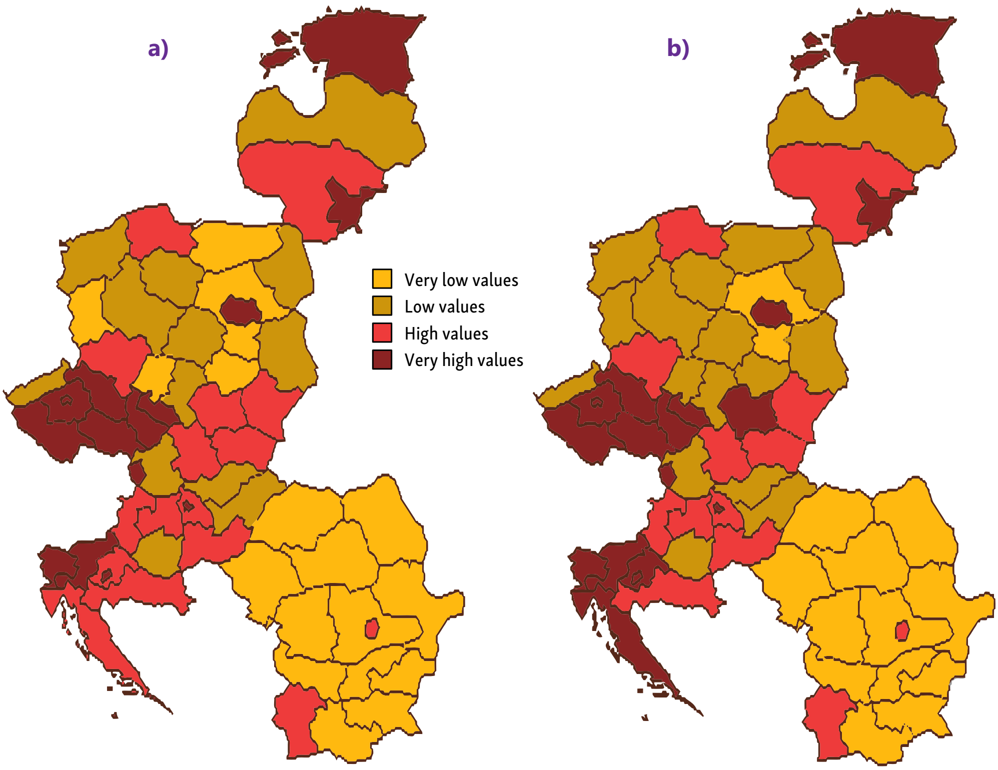

Figure 2. The spatial differentiation of the Regional Innovation Index across selected NUTS-2 regions in the years 2016 (a) and 2022 (b) (source: own elaboration)

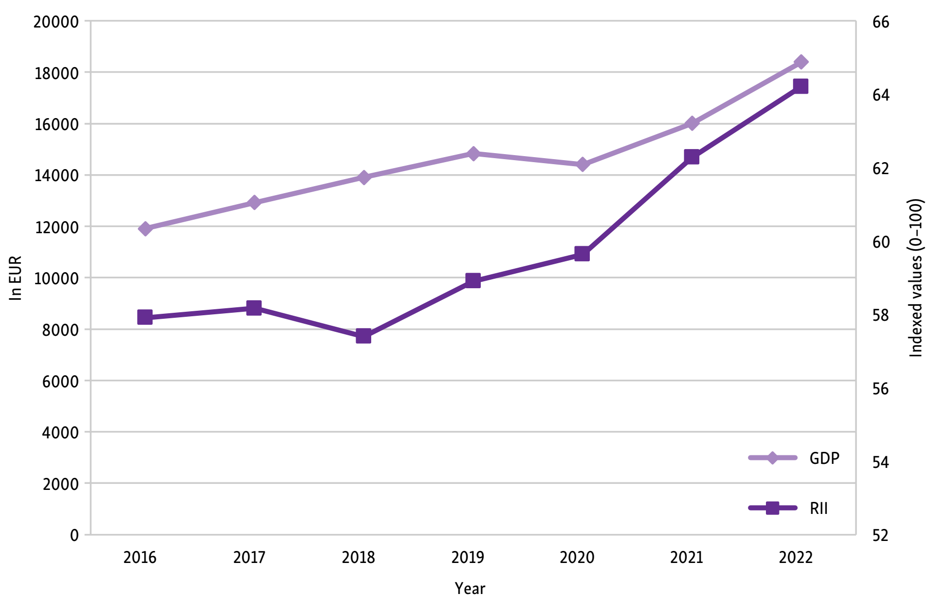

Figure 3. The time tendencies of the average values of GDP per capita and RII across selected NUTS-2 regions in the period of 2016–2022 (source: own elaboration)

As observed, the mean value of GDP per capita is higher than its median, unlike the RII. Moreover, the volatility of the variables is low. The coefficient of variation is lower than 10 per cent for each. The positive skewness of GDP per capita indicates that most values are clustered around the left tail, while the outliers are placed around the right tail of the distribution. The negative skewness is evident in the case of the Regional Innovation Index, meaning that there are outliers with the lowest values of this phenomenon. However, the absolute value of the skewness coefficient for both phenomena is less than one, indicating that the skewness is excellent. The kurtosis coefficient values (0.3390 for GDP per capita and 0.1499 for RII) show that the distributions are close to normal. Despite the desirable values of skewness and kurtosis, the Jarque-Bera (JB) test indicates that the distributions of the analysed variables do not conform to a normal distribution., as the p-values (values in brackets) related to the JB statistics are lower than the adopted significance level of 0.05. Nevertheless, the large dataset can be the cause of the significance of the JB statistics.

Table 1. The descriptive statistics of the GDP per capita and the Regional Innovation Index in the period of 2016–2022

Statistics	GDP per capita	Regional Innovation Index
Mean	9.4764	4.0159
Median	9.4255	4.0320
Standard deviation	0.4610	0.3995
Coefficient of variation	0.0486	0.0995
Skewness	0.4861	–0.4620
Kurtosis	0.3390	0.1499
Normality test (JB)	18.8602 (0.0001)	15.5882 (0.0004)

Table 2 presents the results of the estimation and verification of the spatio-temporal trend models for the GDP per capita and RII values. The negative estimate of the statistically significant parameter θ_{100} indicates that the economic development of regions across the considered area averagely decreased from west to east (see the left part of Table 2). In turn, the positive estimate of the parameter θ_{010} shows that the economic situation was improving on average, moving towards the north. Moreover, in the case of GDP per capita, the statistical significance of the positive value of parameter θ_{001} denotes that the economic situation in the considered regions averagely increased between 2016 and 2022. Analogous changes in the spatio-temporal distribution can be concluded in the case of the innovation level. The values of the RII were averagely increasing towards the north and west, and also during the considered period. The Moran test for the occurrence of spatial autocorrelation shows different results depending on the analysed phenomenon. Considering the spatio-temporal tendencies the Moran's *I* statistics is statistically significant only for the innovation level distribution. The positive value of *I* means that the innovation level in neighbouring regions is similar. In the model estimated for GDP per capita, the residuals do not show spatial autocorrelation, which is a signal that the spatio-temporal trend is sufficient to describe the spatial structure of this phenomenon. The spatio-temporal models generally confirm the presumptions made based on Figures 1–3.

Table 2. The results of the estimation and verification of the spatio-temporal trend models for GDP per capita and Regional Innovation Index (source: own calculations)

Parameter	GDP per capita			Regional Innovation Index		
	Estimate	p-value	Significance	Estimate	p-value	Significance
θ_{000}	8.6727	< 2e-16	***	3.6794	< 2e-16	***
θ_{100}	–0.0459	< 2e-16	***	–0.0524	< 2e-16	***
θ_{010}	0.0300	0.0000	***	0.0273	0.0000	***
θ_{001}	0.0662	0.0000	***	0.0157	0.0407	**
R^2	0.3277			0.3822		
Moran test	I = 0.0317 (0.1380)			I = 0.2072 (0.0000)		

Next, the relationship between innovation level and economic development is studied. Table 3 presents the results of the estimation and verification of the base OLS model, including the spatio-temporal trend factor. Because the phenomena are expressed in the natural logarithm, the parameter β_1 is responsible for the elasticity of the considered dependence. The parameter β_1 is statistically significant, which makes the relationship between the Regional Innovation Index and GDP per capita relevant. Its positive value (β_1 = 0.8522) indicates that a one per cent increase in the RII in a given region causes around a 0.85% increase in its GDP per capita, on average.

It is worth noting that the parameter θ_{100} became insignificant when compared with the spatio-temporal trend model for GDP per capita. On the other hand, the Moran's I statistic has increased to 0.0978. In connection with the statistical relevance of Moran's I, the spatial autocorrelation in the model residuals has been concluded. Compared with the model estimated above, the change in the roles of the spatial trend factor and spatial autocorrelation shows that the dependence between neighbouring regions is more important than the tendency in space when considering the relationship between economic development and innovation level. Moreover, the results of LM tests indicate the possibility of estimating the spatial autoregression (SAR) model (the RLM_{lag} statistic is statistically significant), which is a starting point for evaluating short-term spatial spillovers.

Additionally, the Variance Inflation Factor test values (VIF) for all explanatory variables indicate no collinearity between them, and neither of these should be excluded from the model.

Hence, Table 4 shows the results of the estimation and verification of the SAR model enriched with the spatial lag of RII, which transforms the SAR model into a Spatial Durbin Model (SDM). The parameter β_1 remains statistically significant, and its estimate is above zero. The relationship is a bit stronger than in the OLS model. The relevance of the spatial parameter ρ confirms that the dependence between neighbouring regions is important, considering the link between economic development and the innovation level in the studied area. The parameter β_2 is also statistically significant, which denotes that the average innovation level observed in neighbouring regions influences economic development in the given region.

The significance of parameters β_1, β_2 and ρ allows for calculating the short-term spillovers resulting from the diffusion of innovations. The residuals of the model do not show spatial autocorrelation, which proves their random character. The Jarque-Bera (JB) test only indicates that the residuals do not have the character of a normal distribution, but this is the effect of the large dataset used for the model estimation.

Table 3. The results of the estimation and verification of the OLS relationship model (source: own calculations)

Parameter	Estimate	Std. Error	t Statistics	p-value	Significance
θ_{000}	5.5373	0.2508	22.0820	< 2e-16	***
θ_{100}	–0.0013	0.0040	–0.3170	0.7515	
θ_{010}	0.0068	0.0037	1.8150	0.0702	*
θ_{001}	0.0529	0.0065	8.1110	0.0000	***
β_1	0.8522	0.0414	20.5910	< 2e-16	***
R^2	0.6647				
VIF test	u_1 = 1.4630				
	u_2 = 1.1350				
	t = 1.0100				
	ln(RII) = 1.6190				
Moran test	I = 0.0978 (p-value = 0.0006)				
LM_{lag}	0.7428 (p-value = 0.3888)				
RLM_{lag}	26.0796 (p-value~0)				

Table 4. The results of the estimation and verification of the Spatial Durbin Model (source: own calculations)

Parameter	Estimate	Std. Error	z Statistics	p-value	Significance
θ_{000}	5.5100	0.5322	10.3536	< 2.2e-16	***
θ_{100}	–0.0160	0.0049	–3.2322	0.0012	***
θ_{010}	0.0118	0.0039	3.0422	0.0023	***
θ_{001}	0.0471	0.0073	6.4397	0.0000	***
β_1	0.9565	0.0430	22.2269	< 2.2e-16	***
β_2	–0.53535	0.08927	–5.9968	2.013E-09	***
ρ = 0.1939*** (p-value = 0.0080)					
Nagelkerke pseudo-R^2	0.6902				
Moran test	I = 0.0142 (p-value = 0.2985)				
AIC	65.0850				
JB	16.8520 (0.0002)				

The first aim of calculating spatial spillovers is to denote regions that are innovation leaders whose innovation development has a relatively strong impact on the economic growth of others. The spatial distribution of the strength of the impacts of the innovation level of a given country on the economic situation in all other regions is shown in Figure 4. Regions with the strongest impact on others are located mainly in Poland and Romania. Mostly, these are the regions with big cities (regions Warszawski stołeczny – PL91 and București-Ilfov – RO08) or urban agglomerations (Wielkopolskie region – 41, Śląskie region – PL22). Furthermore, the regions that strongly influenced others are located near the countries' capitals, i.e., Střední Čechy (CZ02) and Sjeverna Hrvatska (HR06). On the other hand, regions situated in Slovenia and Bulgaria showed the weakest impact on others. Moreover, this group has regions located further away from the capitals of Romania, Poland and the Czech Republic.

In turn, Figure 5 shows the spatial differentiation of the strength of addiction to economic development in regions based on the changes in innovation levels in all others. Almost all regions from the Czech Republic and Croatia were the least susceptible to the influence of others. Moreover, the economic development of Lithuanian regions, Latvia and Estonia showed little dependence on the diffusion of innovations from other units. It could result from staying at a higher level of innovation, which is more critical for their economic development. On the other hand, the economic development of regions located in the southeastern part of the considered area (belonging to Romania and Bulgaria) and most Polish regions were strongly affected by the innovation levels in others.

A clear pattern can be observed by comparing the maps in Figures 4–5. Most regions where the innovation level strongly influenced economic development in others also showed the weakest sensitivity to innovation changes beyond their boundaries. Interestingly, the regions of Prague (CZ01), the City of Zagreb (HR05), the Capital Region of Lithuania (LT01) and Budapest (HU11) are not indicated as those that were imitated by others in terms of innovation. It could be a result of the vast differences in economic development between these capital cities (or regions with the capital) and the remaining units. The relatively poorer areas may not be ready to adopt the innovative solutions proposed by the richer ones.

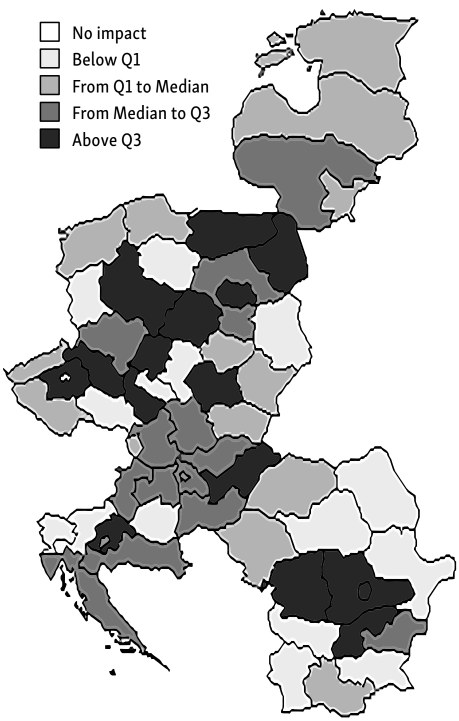

Figure 4. The distribution of the average impacts of changes in the innovation level in a given region on the GDP per capita in all other regions (source: own elaboration)

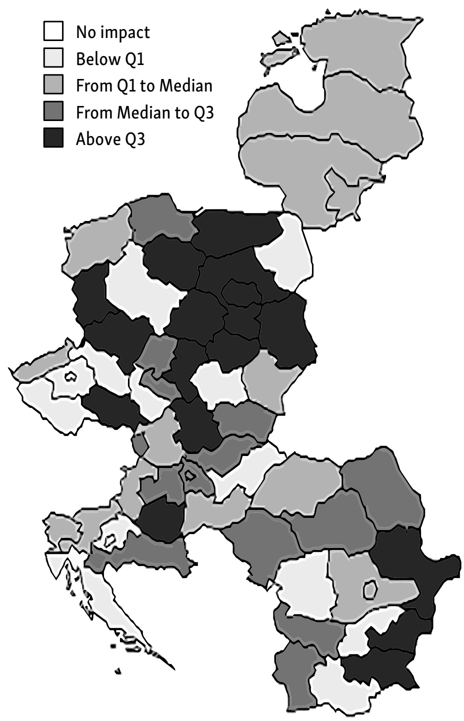

Figure 5. The distribution of the average dependence of GDP per capita in a given region on the innovation level in all other regions (source: own elaboration)

5. Conclusions

Innovation is indeed a significant stimulus of economic growth. Central and Eastern EU countries are still involved in the process of catching up with the Western EU economies that are, on average, more economically developed, with higher levels of innovation and economic growth. Hence, this paper took a closer look at them, analysing their regions in order to see the performance in economic development and, more importantly, innovation level.

A particular spatial tendency characterised the analysed regions of selected EU countries: the southeastern part of them had, on average, a lower level of economic growth than those located in the west and north. Hence, the spatial distribution of the innovation level in Central and Eastern EU countries was similar to the economic growth. The values of both economic growth and innovation levels increased from 2016 to 2022. In addition, they also, on average, increased towards the north and west. In addition, the analysis proved that innovation positively influenced economic growth in studied regions.

The study also confirmed the existence of the spillover effects, which were the strongest in Polish and Romanian regions, in particular, including big cities or urban agglomerations. Interestingly, some regions strongly influenced others, like some regions near Prague. In contrast, regions with the weakest impact on others were mainly located in Slovenia and Bulgaria and further away from the capitals of Romania, Poland, and the Czech Republic. The least susceptible regions regarding innovation level affecting economic development were those located in almost all areas of the Czech Republic, Croatia, and the whole territory of Lithuania, Latvia, and Estonia. The opposite situation was noted in Bulgaria, Romania, and almost all of Poland. Since in some regions, there were some significant differences in economic development across regions noted (Prague, Zagreb, the capital region of Lithuania, and Budapest), the relatively less developed areas did not succeed in following them in the innovation adaptation.

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