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Knowledge input and innovation in Visegrad Group (V4) regions: A spatial econometric approach

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Abstract. This paper argues that one of the reasons why innovation in one country leaves another behind could be its spatial geography. Questions relevant to R&D development and technological change are raised on how knowledge inputs affect innovation in the Visegrad Group (V4) (Czech Republic, Hungary, Poland, and Slovakia) and how these factors are spatially dependent. The study results show that regional knowledge inputs (R&D expenditure and R&D personnel) play an essential role in innovation development in Visegrad Group (V4). The study findings also emphasize the importance of R&D funding support in the public sector and R&D personnel capabilities in promoting innovation. This paper intends to make an initial contribution to innovation studies taking regions of Visegrad Group (V4) as the analyzed object and suggests the development of spatial modeling using more up-to-date data to yield more reliable and in-depth results.

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1. Introduction

1.1. Background and motivation

Central Europe underwent dramatic economic restructuring in a transition economy, which also affected its innovation system around the 1990s. It was also characterized by a decline in patenting activity, academic research, and R&D expenditure (Varga, 2007). Patent data is widely used to measure technological innovation, although not all inventions are patented and become genuine innovations in all industry sectors (Archibugi, 1992; Acs et al., 2002; de La Tour et al., 2011).

Figure 1 below shows the development of patent applications in the four countries of the Visegrad Group (V4) (Czech Republic, Hungary, Poland, and Slovakia) from 2004 to 2018. Two thousand and twelve was the last year in which patent development in Poland (POL) increased, before then fluctuating until 2018. The Czech Republic (CZE) recorded an increasing number of patent applications until 2013. In contrast, Hungary's (HUN) innovation performance continued to trend downward until 2018. Only Slovakia (SVK) has a stable trend despite being in the lowest position of the four countries.

According to Varga (2007), the decline in patenting activity in Hungary until the beginning of the millennium was due to the economic restructuring and the privatization of companies, which resulted in a dramatic decrease in R&D activity. However, as the years passed, Fig. 2 explains that R&D researchers, the primary resource of R&D activities in Hungary, steadily increased in numbers between 2004 and 2018. The same thing happened in the Czech Republic. These two countries left Poland behind regarding the ratio of R&D researchers. However, since 2016, the ratio of R&D researchers in Poland has increased dramatically. Slovakia has an average number of R&D researchers between Hungary and the Czech Republic, but since 2010 the trend has been downward.

Figure 3 shows one of the most critical aspects of R&D activity in terms of expenditure. R&D expenditure in the Czech Republic and Hungary

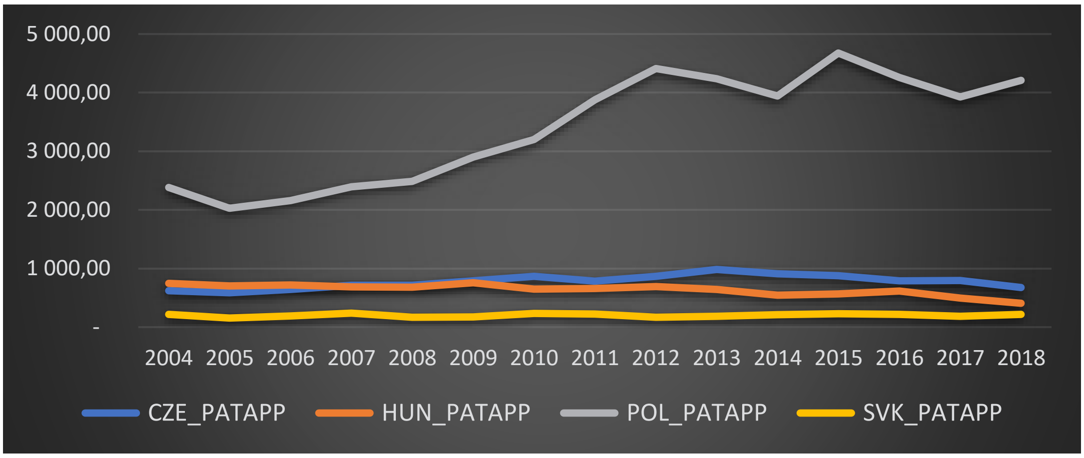

Fig. 1. Patent applications in Visegrad countries, 2004–2018 (in residents)

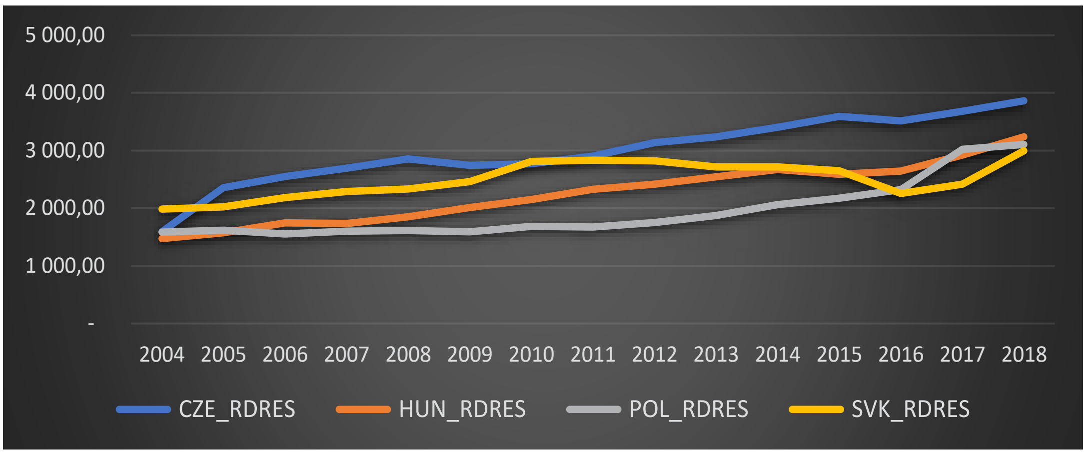

Fig. 2. R&D researchers in Visegrad countries, 2004–2018 (per million people)

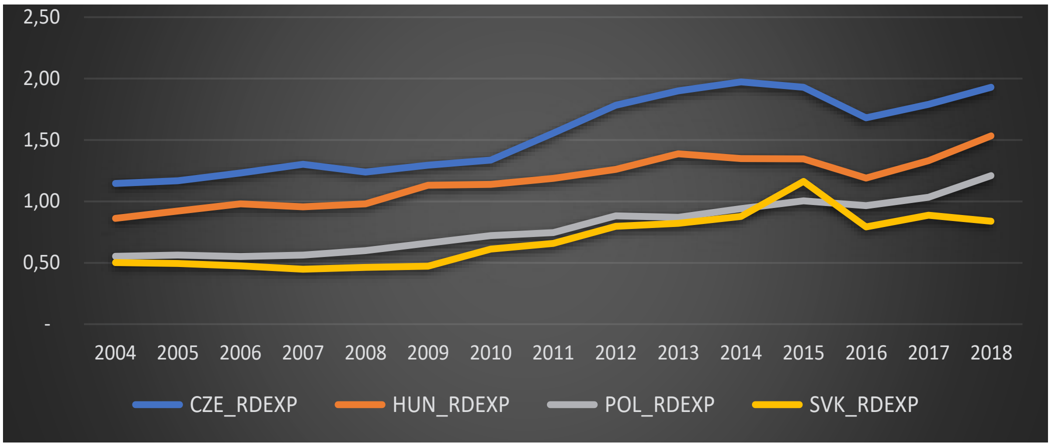

Fig. 3. Research and development expenditure in Visegrad countries, 2004–2018 (% of GDP)

tended to increase until 2015. Slovakia also experienced the same, especially after 2009. All three countries experienced the same pause in 2015 and simultaneously increased in 2016. On the other hand, with the highest innovation production, Poland has moderate R&D expenditure and a relatively stable upward trend.

These descriptions and facts raise some critical questions. First, what causes Poland to have high innovation, leaving the other three countries behind? Does knowledge input in Poland greatly influence its innovation? Even if so, why do the Czech Republic and Hungary, which have better input sources, not experience the same? Secondly, the Czech Republic and Hungary are similar in innovation though the Czech Republic is the only one of these two countries that is close to Polish territory, whereas Hungary is closer to Slovak territory. Slovakia borders all three countries but needs to catch up in innovation. How does spatial geography play a role in this?

This paper explores the spatial patterns of knowledge inputs and innovation in the Visegrad Group (V4) regions, where these regions have many close historical, cultural, social and economic links. The paper also highlights the associations and relationships between knowledge input factors and innovation development and how spatial attributes can explain the various dependencies and correlations in the NUTS-2 regions of the Visegrad Group (V4). Varga (2007) spatial econometric modeling is adopted to analyze the role of knowledge input factors in technological change in the Visegrad Group (V4) regions.

The paper is organized as follows. The first section provides background to the study and reviews recent literature on innovation, particularly in Central and Eastern Europe (CEE). The second section describes the methodological approach. The third section describes the geographic distribution of innovation in the Visegrad Group (V4) regions along with the knowledge input factors that potentially support it. The fourth section presents the results of the analysis of the influence of knowledge inputs on innovation in the Visegrad Group (V4) regions. The fifth section summarizes the findings and provides recommendations.

1.2. Literature review

Regions have been a widely studied unit of analysis for exploring knowledge production. This approach arises from the fact that many innovative firms form specific spatial patterns in a region that then benefits from the knowledge spillover from the presence of these innovative firms (Rodríguez-Pose & Crescenzi, 2008; Buesa et al., 2010). Regional forms of innovation activity also emerge from universities and public research institutes, all of which form regional innovation systems. The effective combination of industrial agglomeration and knowledge spillovers from regional R&D activities contribute to regional innovation efficiency. Their role determines the success of knowledge production in the region (Benneworth & Hospers, 2007; Benneworth et al., 2009; Asheim et al., 2016; Brown et al., 2020; Theeranattapong et al., 2021).

Since the accession of Central and Eastern European (CEE) countries to the European Union, significant issues related to convergence and gaps in competitiveness and income have emerged. Since then, many studies have been conducted in the CEE regions to see how this convergence occurs (Matkowski et al., 2016; Loewen & Schulz, 2019;). For example, Filippetti and Archibugi

(2011) estimated the impact of the 2008 crisis on innovation performance and convergence in the EU regions. The 2008 crisis reversed the innovation output convergence of the 2004–2008 period. Furthermore, in a recent study on the resilience of innovation performance in the euro area, Filippetti et al. (2020) confirmed that innovation performance has had better resilience since the 2008 crisis, when innovation performance has been associated with performance in employment. The study concludes that countries affected by large shocks that have disrupted innovation can recover and adapt quickly by maintaining learning capabilities over time. The same reasoning also provides opportunities for less-developed regions to advance and develop innovation systems. Kravtsova & Radosevic (2012) and Radosevic (2012) emphasize the importance of regional policy design specific to the CEE regions by promoting collaboration and networking. The study of regional innovation policy continues to grow in CEE regions, where the main focus is how the CEE regions can create innovation support programs and what the policy implications are for the region).

The innovation paradox arises when innovation is associated with less-developed regions. These regions require significant R&D investment for innovation but have relatively low capabilities in funding efficiency. There is a stark contrast when Eastern European regions are compared to the more-developed Western European regions. Many challenges arise in addressing regional innovation issues, especially in less-developed regions. These are closely related to the quality of regional innovation governance and the capabilities of various regional innovation resources (McCann & Ortega-Argilés, 2013, 2014; Morisson & Doussineau, 2019; Trippl et al., 2019). Kravtsova & Radosevic (2012) point out that innovation levels in Eastern European countries tend to be low, with human resources in the R&D sector contributing to this problem. The low productivity in producing innovation outputs is closely related to the low capacity in the Eastern European region. In a recent study, Kirankabeş & Erkul (2019) analyzed knowledge productivity at the NUTS-2 level in the CEE regions. Regional knowledge capacity in 2001–12 tended to increase, although the 2008 crisis contributed to a decline in innovation productivity. The efficiency of regional innovation resources was found to decrease, but the recovery of knowledge capacity and capability in the CEE regions was maintained until recent years (Hájek & Stejskal, 2018; G. H. Popescu, 2014; D. I. Popescu et al., 2019).

2. Research materials and methods

2.1. Spatial econometric characteristics

Spatial interactions between different locations expand the branch of econometrics, giving rise to the concept of spatial econometrics, which focuses on investigating spatial dependences (Espoir & Ngepah, 2021; Wang et al., 2019; Wei et al., 2019; Zhang et al., 2021). Spatial analysis and modeling methods are applied to reveal the spatial characteristics of a set of observational data. Spatial modeling reflects a measure of the change in a condition in a region if the average condition in another adjacent region changes (Anselin et al., 1997, 2009; Y. Liu et al., 2018). Data analysis and Exploratory Spatial Data Analysis (ESDA) techniques are commonly used to explore spatial autocorrelation by considering spatial dependence and heterogeneity (Dai et al., n.d.; J. Liu et al., 2013).

Spatial-geospatial linkages between observations can be described by a spatial weight matrix ($\boldsymbol{W}$), which is an essential part of spatial modeling. The spatial weight matrix is a non-negative matrix that describes the neighborliness in an observational dataset. In a spatial weight matrix, the location of observations appears in the form of non-zero rows and columns, and the elements indicate the relationship between observations. One indicator of ESDA measurement is Global Moran's I (e.g., Liu et al., 2018). The spatial correlation of the analyzed variables is expressed using the Global Moran's I scatterplot map. The threshold of Moran's I is from -1 to 1. A positive Moran's I value implies a positive spatial correlation and more significant spatial agglomeration characterized by values close to 1, and vice versa (Dai et al., 2010; Wang et al., 2015; Liu et al., 2018). Local spatial correlation patterns are expressed by spatial autocorrelation (Anselin, 2005; Anselin & Florax, 2012; Yu et al., 2017; Y. Liu et al., 2018b). The significance of Moran's I can be calculated and standardized from the z value at a certain threshold of $-1.96 < z < 1.96$ (Franchi et al., 2013; Yan et al., 2018; Zhan et al., 2021).

Local Indicators of Spatial Association (LISA) analysis is applied to the Global Moran's I statistic to test the spatial association of independent variables and dependent variables (Anselin, 1988; Anselin & Florax, 2012; Bednář & Halásková, 2018; Bivand & Wong, 2018; Lyke, 2018; Song et al., 2020; Ali, 2021; Tao & Chen, 2022). A positive Local Moran's I value indicates that the analyzed variables have a spatial relationship that resembles the values around the location. There are two spatial groupings, namely High-High and Low-Low. High-High clusters indicate that locations with high values are surrounded by neighbors with high values. Low-Low clusters indicate that low-value locations are surrounded by neighbors with low values. A negative Local Moran's I value indicates that a particular variable at a location is very different spatially from its neighbors. There are two spatial groupings, namely High-Low and Low-High. A High-Low cluster indicates that a high-value location is surrounded by other low-value locations. Conversely, a Low-High cluster indicates that a low-value location is surrounded by other high-value locations.

2.2. Spatial Lag Model (SLM) and Spatial Error Model (SEM)

The spatial Lag Model (SLM) is a spatial regression estimation model that includes spatial lag variables that can explain the effects of spatial dependence due to spillover effects and externalities. It is what distinguishes SLM from Ordinary Least Square (OLS). In addition, SLM also aims to overcome disturbances due to spatial autocorrelation. The term "lag" refers to a particular subset of the data that affects spatial data in neighboring locations. In the SLM spatial regression model, the spatial autoregressive coefficient (ρ) is substantial in explaining the association of one spatial data observation with its neighbors. An evaluation must be done to prove that $\rho \neq 0$ expresses the existence of spatial autocorrelation (Wang et al., 2019; Benedetti et al., 2020; Sannigrahi et al., 2020; Cai & Hu, 2022; Gu & You, 2022

Equation 1 expresses the Spatial Lag Model (SLM)

$$Y = \alpha + \rho \boldsymbol{W} Y + \beta X + \varepsilon$$

where: α is the intercept; ρ is the spatial autoregressive coefficient/parameter; WY is the spatial lag variable, β is the regression coefficient for the independent variable X; ε describes the error.

The Spatial Error Model (SEM) spatially models the autocorrelation in the errors (ε). The error is expressed by multiplying the spatial weight matrix by the spatial error coefficient (λ). To test the presence of spatial autocorrelation in the model, the spatial error coefficient (λ) must be proven with the hypothesis $\lambda \neq 0$.

Equation 2 expresses the Spatial Error Model (SEM):

$$Y = \alpha + \beta X + \varepsilon; \text{with } \varepsilon = \lambda \boldsymbol{W} \varepsilon + \xi$$

where: α is the intercept; β is the regression coefficient for the independent variable X; εi describes the error vector; λ is the spatial error coefficient; W is the spatial weight matrix; ξ is the modified error vector.

2.3. Data and analysis method

In this study, a spatial econometric analysis approach using cross-sectional data is applied in consideration of the large number of studies showing that this approach is robust enough to estimate the impact of regional knowledge spillovers (Anselin, 1988; Anselin & Florax, 2012; LeSage, 2015; Naveed & Ahmad, 2016; Debarsy et al., 2018; Agasisti et al., 2019; Qin et al., 2019; Stojcic, 2021). The most recent data available in EUROSTAT for patent application data (available until 2012 at the NUTS-2 and NUTS-3 regional levels). Data on R&D expenditure and R&D personnel are more up to date in those databases. Since the main variable to be examined is patent application data, the data for the other three variables are also restricted to the same year. The cross-sectional dataset generated 34 regional observations at the NUTS-2 level in the Visegrad countries. Some data were found to be missing during the data collection process. GERPUB data for the Lubuskie region (Poland) were unavailable, so this region was excluded from the analysis. However, the number of degrees of freedom was considered acceptable for decision-making. The patent application data used is the total value in units per million population. Human resources for R&D use total R&D personnel and researchers in full-time equivalent (FTE) units. For R&D expenditure, it is separated into two sectors, namely the business sector and the public sector. Public R&D expenditure is an amalgamation of two entities: government-owned public research institutes and university research institutes.

Variable operationalization is shown in Table 1: The basic equation model applied is:

$$\ln PATAPP = \alpha + \beta 1 \, lnGERDBUS + \\ + \beta 2 \, lnGERDPUB + \beta 3 \, lnRDPR + \varepsilon$$

where: *PATAPP* is a proxy for technological change or innovation, *GERDBUS* is R&D expenditure for the business sector; *GERDPUB* is public-sector R&D expenditure covering the government and university sectors; and ε is a stochastic error. The analysis was carried out for the cross-section unit with many individual observations. $\beta 1$ measures

Table 1. Variable Operations

Variable	Definition	Measurement unit
PATAPP	Patent applications to the EPO by priority year by NUTS 3 regions [PAT_EP_RTOT__custom_2729431]	Per million inhabitants
RDEXP	GERD by sector of performance and NUTS 2 regions in all sectors	Million euro
GERDBUS	GERD by sector of performance and NUTS 2 regions in Business enterprise sector	Million euro
GERDPUB	GERD by sector of performance and NUTS 2 regions in Higher education sector	Million euro
RDPR	R&D personnel and researchers by sector of performance, sex and NUTS 2 regions in all sectors	Full-time equivalent (FTE)

Source: own elaboration

the influence of research from the business sector or industry on innovation. *β2* is a measure of the influence of public research, which includes research from public research institutes and universities on innovation. β3 measures the influence of human resources on R&D activities, namely workers and researchers in the R&D field on innovation. The positive and significant coefficients *β1, β2* and *β3* indicate a strong positive effect of different knowledge inputs on innovation.

The analysis is divided into two groups: *spatial description analysis* and *spatial regression analysis.* Spatial description analysis aims to see the spatial distribution of patent application variables, R&D personnel and researchers, R&D spending for the business sector, and R&D spending for the public sector. The results of this analysis will be displayed in the form of a thematic map divided based on the category of natural breaks. It also displays correlations between variables through a scatterplot correlation matrix and a few other spatial description hints. The empirical analysis was performed using the spatial regression method with *Geoda* software.

3. Results and discussion

3.1. Spatial distribution of patent applications, R&D expenditures, and R&D personnel in Visegrad Group (V4) regions

Figure 4 shows a map of the distribution of patent applications in 34 regions of Visegrad Group (V4). Four regions have a high density of patent applications: three regions in the Czech Republic (one of which is Prague) and one region in the Hungarian region (the capital, Budapest). These regions generated a minimum of 27 patent applications per million inhabitants in 2012. The next density level is the area that produced 13–27 patent applications per million inhabitants in 2012, namely four regions in Poland (one of which is the capital, Warsaw) and one region in the Czech Republic. The remaining 25 regions have fewer than 13 patent applications per million inhabitants. In 2012, the Czech Republic produced the most patent applications.

Figure 5 shows a map of the distribution of total R&D personnel and researchers (RDPR) in 34 regions of the Visegrad Group (V4). Three regions have a high density of R&D personnel/researchers, namely one region in the Czech Republic (Prague), one region in Hungary (in the region of the capital city, Budapest), and one region in Poland (in the region of the capital city, Warsaw). These regions had a minimum of 21,800 full-time equivalents of R&D personnel and researchers in 2012. The next

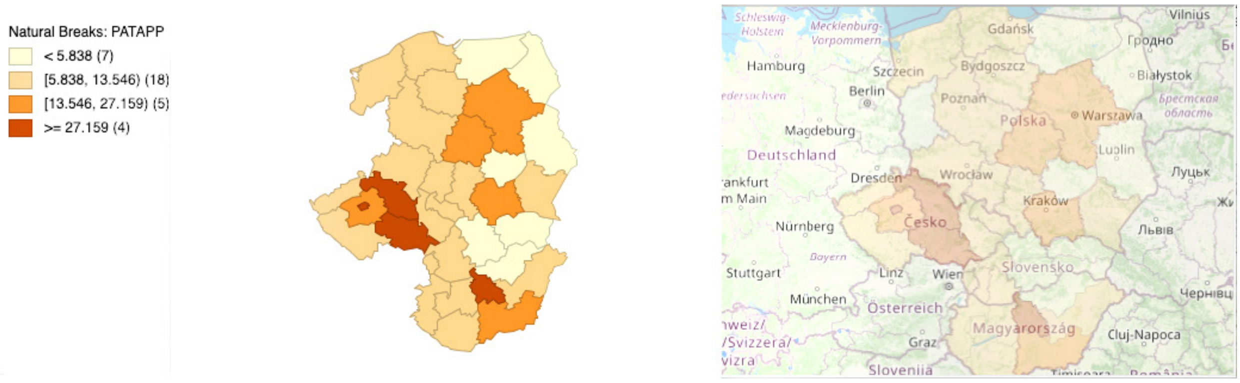

Fig. 4. The spatial distribution of patent applications (PATAPP)

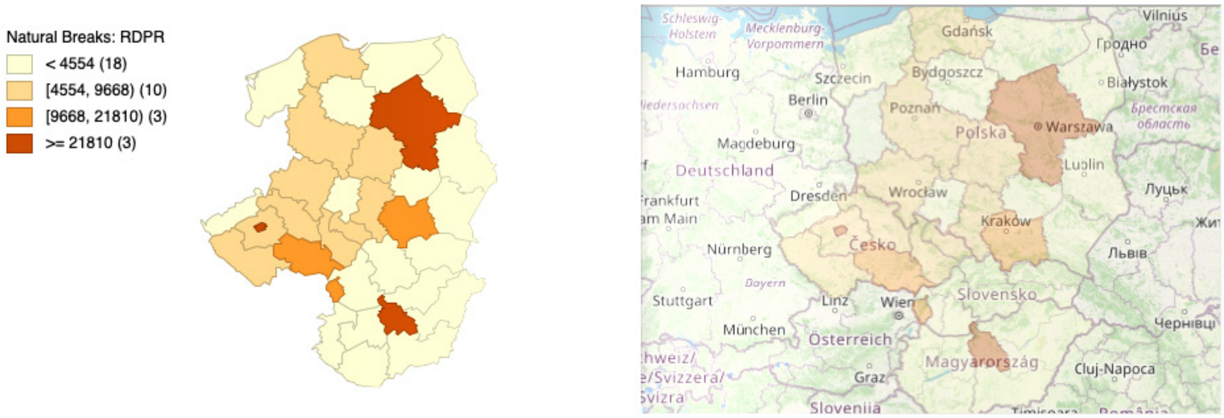

Fig. 5. Spatial distribution of total R&D personnel and researchers (RDPR)

highest density level is an area with a minimum of 9,600 full-time equivalents of R&D personnel and researchers in 2012, comprising one region in the Czech Republic, one region in Poland and one region in Slovakia (the region's capital city of Bratislava). The remaining 28 regions have R&D personnel and researchers of fewer than 4,500 full-time equivalents.

Figure 6 shows a map of the spatial distribution of business sector R&D spending (GERDBUS) in 34 NUTS-2 regions in the Visegrad Group (V4). Three regions have a high density of business sector R&D spending: one region in the Czech Republic (Prague), one region in Hungary (the nation's capital), and one region in Poland (the nation's capital). These regions had business sector R&D expenditures of over 364 million euros in 2012. The next highest density level is the regions with business sector R&D expenditures of over 221 million euros in 2012, i.e., three regions in the Czech Republic. The remaining 28 regions had business sector R&D expenditures of below 221 million euros in 2012.

Figure 7 shows a map of the spatial distribution of public sector R&D spending (GERDPUB) in 34 NUTS-2 regions in the Visegrad Group (V4). It should be noted that this R&D expenditure is a combination of government and university R&D spending. Two regions have a high density of public sector R&D spending, i.e., one region in the Czech Republic (Prague) and one region in Poland (the nation's capital). These regions had public sector R&D expenditures of over 610 million euros in 2012. The next highest density level is the regions with public sector R&D expenditures of over 234 million euros in 2012, i.e., one region in the Czech Republic, one region in Hungary (the nation’s capital), and one region in Poland. The remaining 29 regions had public sector R&D expenditures of below 234 million euros in 2012.

Figure 8 shows the correlation between the dependent variable and independent variables. The aim is to see the strengths and weaknesses of the relationship between the independent variables and the dependent variable. Based on Fig. 5 above, the RDPR variable has a positive correlation with the PATAPP variable with a significance below 5% alpha and a correlation strength of 61.9% (strong correlation). Meanwhile, in Fig. 5, bottom left, the public sector R&D expenditure variable (GERDPUB) has a positive correlation with PATAPP with a significance below 5% alpha but with a correlation strength of 38.1% (weak

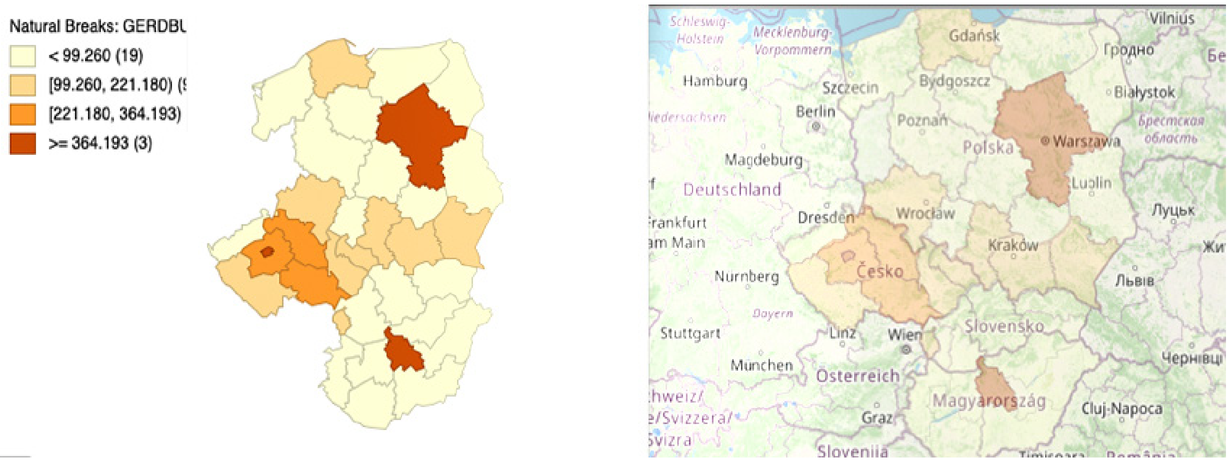

Fig. 6. Spatial distribution of business sector R&D spending (GERDBUS)

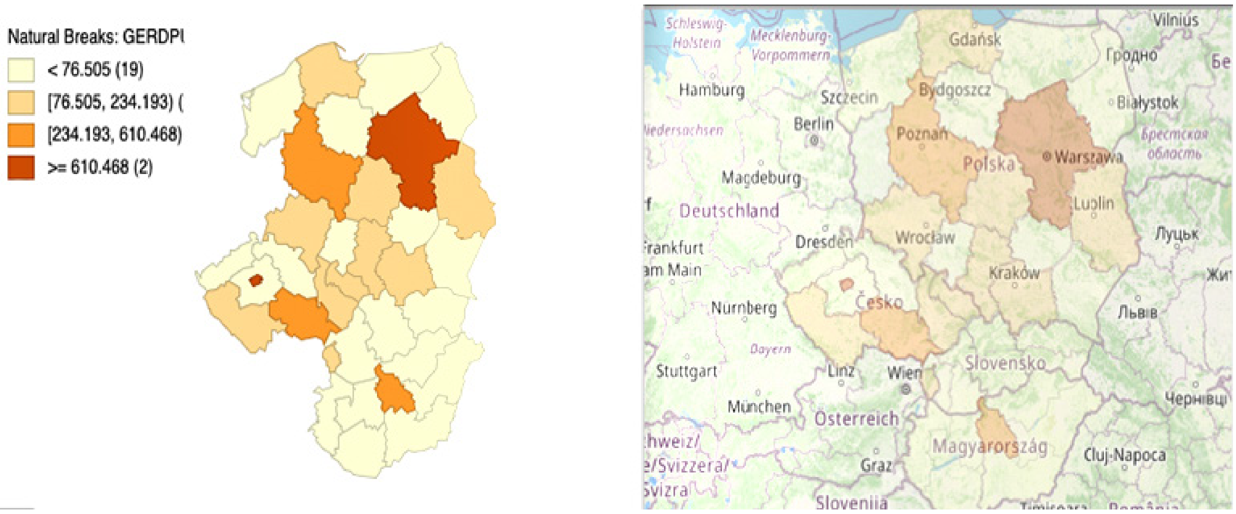

Fig. 7. Spatial distribution of public sector R&D spending (GERDPUB)

correlation). The business sector R&D expenditure variable (GERDBUS) positively correlates with PATAPP with a significance below 5% alpha and a correlation strength of 73.3% (strong correlation). This correlation plot shows that the independent variables RDPR and GERDBUS strongly correlate with PATAPP. In contrast, the GERDPUB variable has a weak correlation. All these independent variables are positively correlated with PATAPP.

Before conducting the regression analysis, a weight matrix was prepared to look at the contiguity between regions. The queen contiguity weighting type was selected for this procedure. Based on Fig. 9, the average number of neighbors in the NUTS-2 regions is 4–5. There is one region that has the most neighbors (eight neighbors), which is in Slovakia.

Figure 10 displays spatial autocorrelation based on Moran's I global univariate statistical analysis with 999 permutations. It is noted that only the GERDPUB and RDPR variables have negative spatial autocorrelation with pseudo-p values of less than 5% alpha (0.033 for GERDPUB) and less than 10% alpha (0.063 for RDPR). The degree of spatial correlation between these two variables is -0.16 (for GERDPUB) and -0.17 (for RDPR). The scatterplot graph for GERDBUS also shows negative spatial autocorrelation. Its pseudo-p value of 0.430 is greater than 10% alpha, indicating the absence of spatial autocorrelation. The z-values of these three variables are at the threshold of "$-1.96 < z < 1.96$".

Furthermore, Figure 11 shows the spatial correlation scatterplot graph for the dependent variable PATAPP. Moran's I value is positive (0.021), but the pseudo-p value is 0.285 (greater than 10% alpha), indicating the absence of spatial autocorrelation.

The next step is to identify the spatial autocorrelation of the dependent variable by transforming the PATAPP value into lnPATAPP.

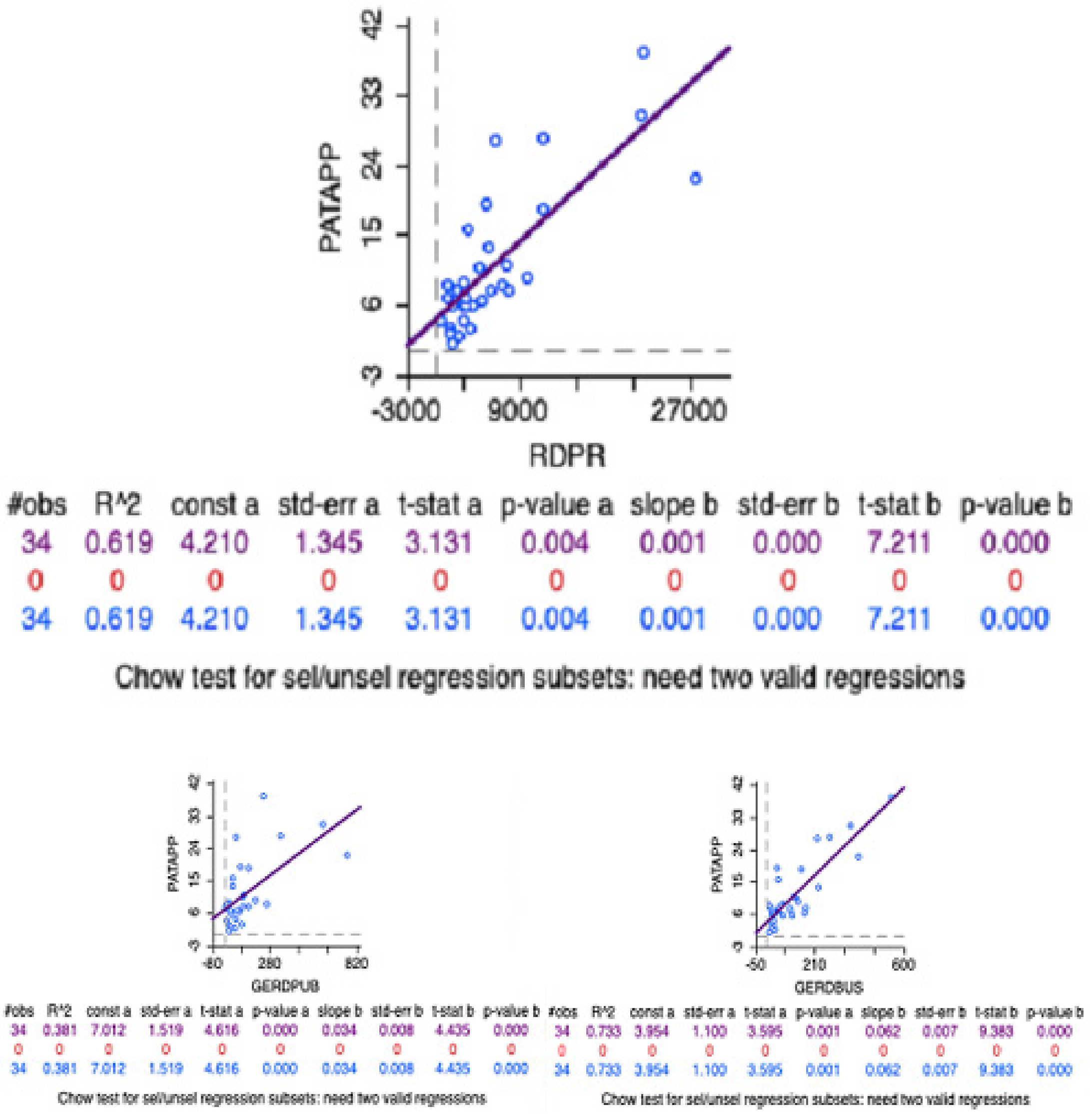

Fig. 8. Scatterplot graph of correlation between independent variable and dependent variable

Property	Value
type	queen
symmetry	symmetric
file	WEIGHT_QUEEN_V4.gal
id variable	POLY_ID
order	1
# observations	34
min neighbors	1
max neighbors	8
mean neighbors	4.59
median neighbors	5.00
% non-zero	13.49%

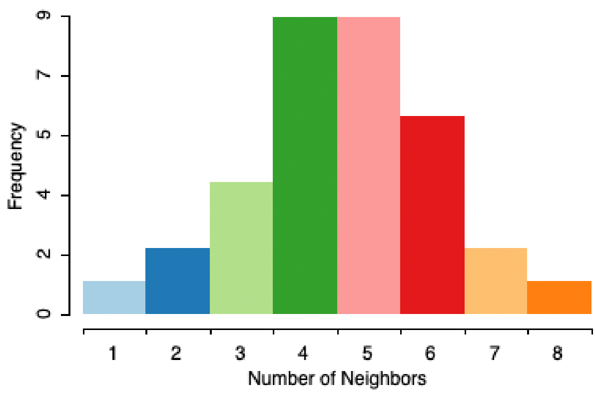

Fig. 9. Neighborhood tables and graphs

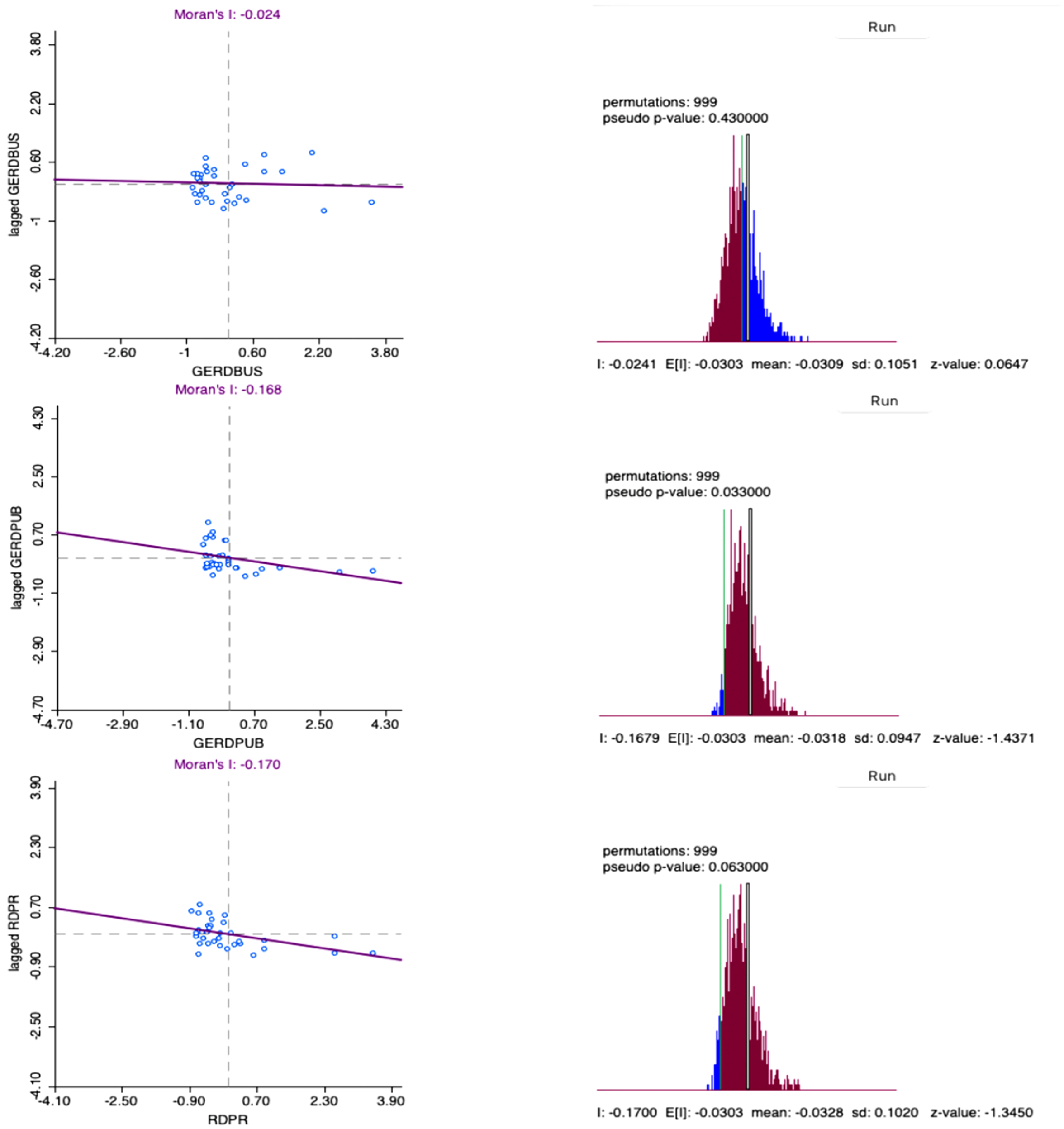

Fig. 10. Moran's I scatterplot of GERDBUS, GERDPUB and RDPR

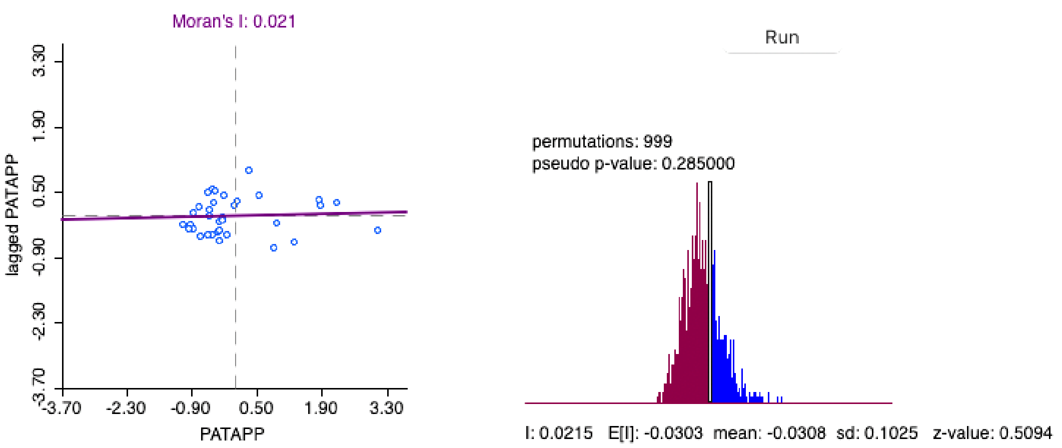

Fig. 11. Moran's I scatterplot of PATAPP

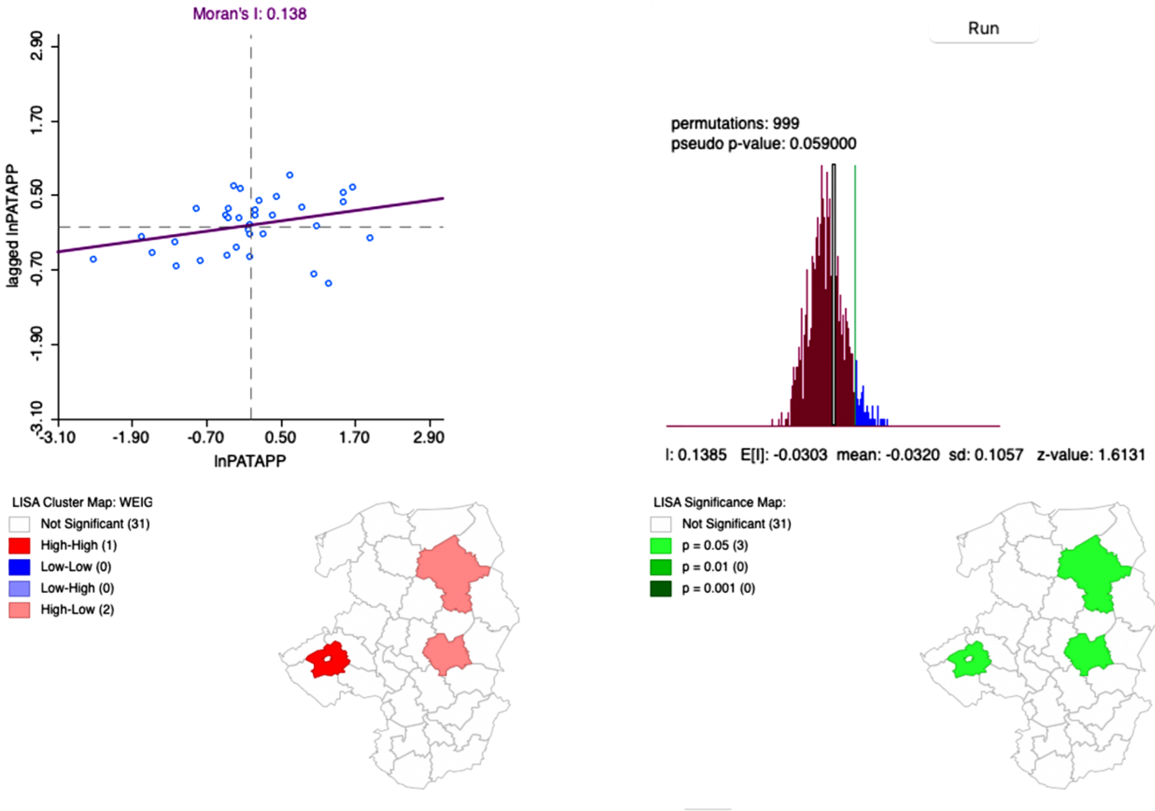

Fig. 12. Moran's I statistics of lnPATAPP

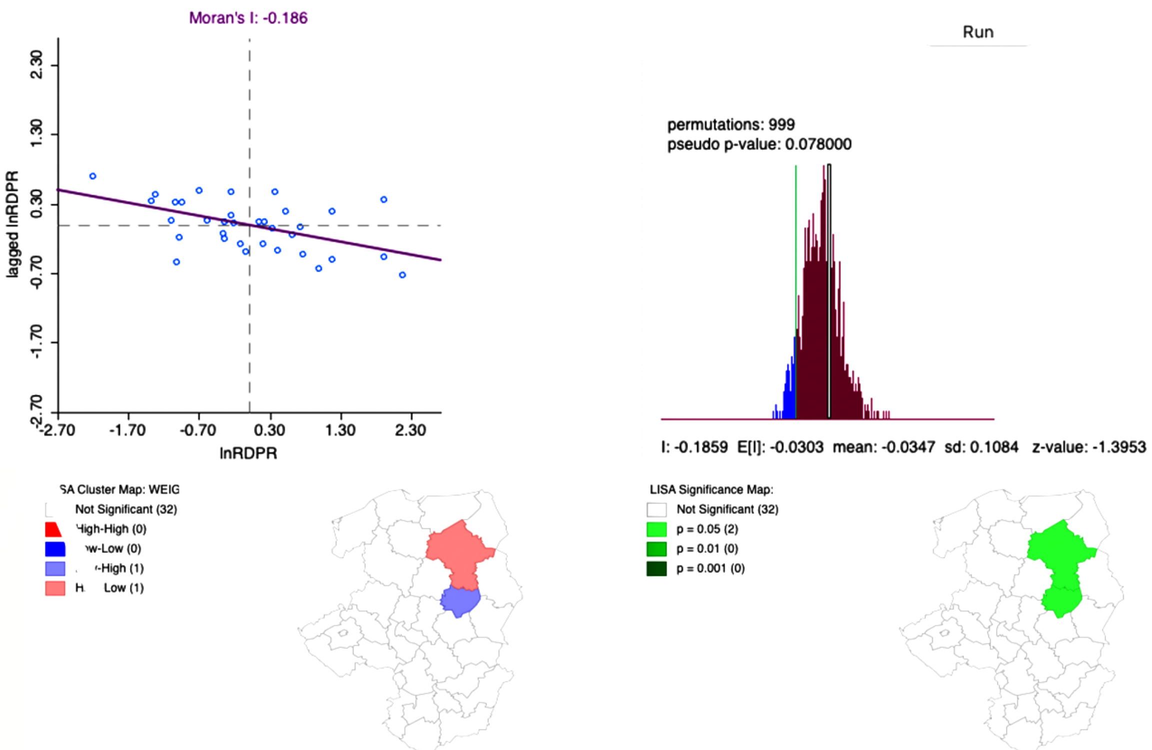

Fig. 13. Moran's I scatterplot and spatial distribution of lnRDPR

The new Moran's I scatterplot graph (Fig. 12) shows an increase in the Moran's I value to 0.14, and the pseudo-*p* value is now smaller than 10% alpha, indicating the presence of spatial autocorrelation at a 10% significance level.

Figure 12 also shows that innovation in the Visegrad countries is generally spatially concentrated in national capitals. Of the four countries, only Poland and the Czech Republic can be categorized as countries whose regions have high innovation concentrations. Looking at the LISA significance map, three regions in these two countries are highly significantly concentrated in innovation, namely PL12_Mazowieckie and PL21_Malopolskie in Poland and CZ02_Strední Cechy in the Czech Republic. One of these Polish regions is Warsaw, the country's capital, and the other is Prague, the capital of the Czech Republic. The LISA map also shows that only CZ02_Strední Cechy is spatially concentrated with clustering features with other regions around it. In other words, the High-High cluster category here indicates that the CZ02_Strední Cechy region is an area of high innovation activity and is surrounded by other regions with a high level of innovation. The two regions in Poland are categorized into the diffuse High-Low cluster category. This means that although the two regions in Poland have a high concentration of innovation, the regions around them have a low level of innovation. Meanwhile, the remaining 31 regions on the LISA map do not show significant values.

Figure 13 shows Moran's I value for the variable lnRDPR (R&D personnel) is -0.19, and the pseudo-p value is 0.078, which is smaller than alpha 10% indicating the presence of spatial autocorrelation at the 10% significance level. The negative sign in Moran's I indicates that R&D personnel in the Visegrad regions tend to be dispersed rather than clustered (like Moran's I for the innovation variable in Fig. 9). The LISA significance map shows this dispersion tendency. Two regions in Poland have significance at 5% alpha, while the remaining 32 are not significant. The two regions have different clusters. The PL12_Mazowieckie region is categorized as High-Low, which means that the density of R&D personnel in this region is pretty high but is not matched by the density of R&D personnel in the neighbouring regions. Another region is PL33_Swietokrzyskie, whose R&D personnel are categorized as a Low-High cluster, which means this region has a low concentration of R&D personnel, but the neighbouring regions have more highly concentrated R&D personnel.

Furthermore, Figure 14 and Figure 15 below show something different. They show R&D expenditure for two different sectors: the business sector (Fig. 14) and the public sector (Fig. 15). Based on Moran's I scatterplot, R&D expenditure

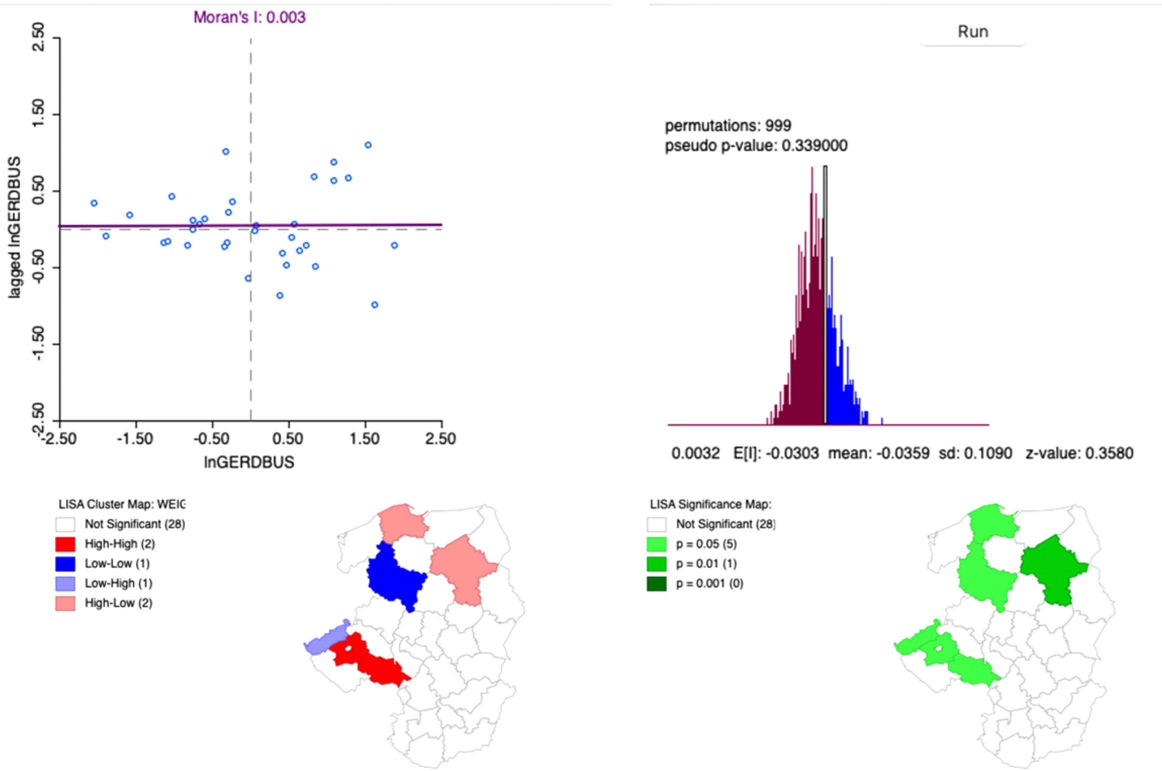

Fig. 14. Moran's I scatterplot and spatial distribution of lnGERDBUS

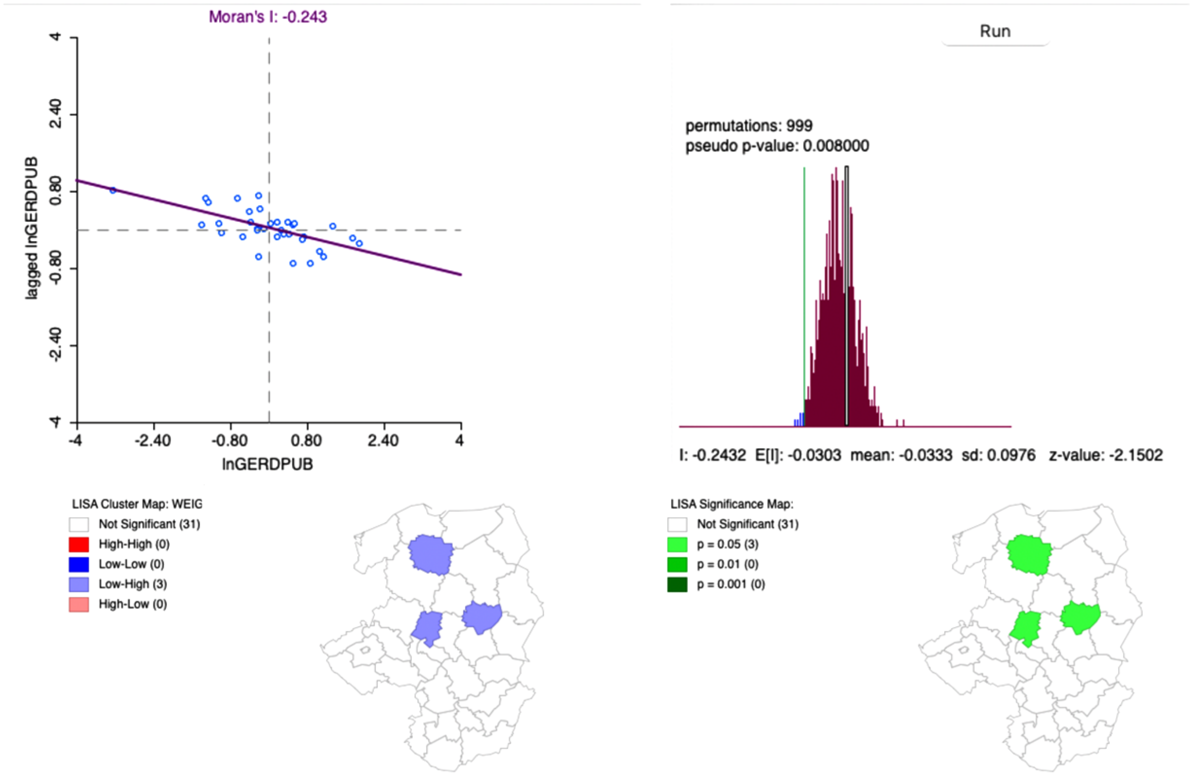

Fig. 15. Moran's I scatterplot and spatial distribution of lnGERDPUB

in the business sector in the shows no indication of spatial dependence. It is indicated by the very low Moran's I value of -0.003. In contrast, R&D expenditure in the public sector indicates negative spatial dependence between regions where Moran's I value is -0.243. The pseudo-p value is 0.008, which is smaller than 1% alpha, indicating the presence of spatial autocorrelation at the 1% significance level. These two negative Moran's I values suggest that R&D expenditure in the business and public sectors tends to be dispersed rather than clustered. The LISA significance map of R&D expenditure in the business sector shows an interesting point: five regions are significant at 5% alpha and one region is significant at 1% alpha. In addition, the clustering of this variable also varies. PL63_Pomorskie and PL12_ Mazowieckie are in the High-Low cluster category, while PL41_Wielkopolskie is in the Low-Low category, all three being regions in Poland. Next, there are two regions in the Czech Republic in the High-High category, CZ06_Jihovýchod, and CZ02_ Strední Cechy, while one region is in the Low-High category, CZ04_Severozápad. Unfortunately, this description does not indicate that business sector R&D expenditure in the Visegrad Group (V4) regions is spatially dependent.

On the other hand, R&D expenditure in the public sector (Fig. 15) shows a different illustration. Three regions have significant values on the LISA significance map: PL61_Kujawsko-Pomorskie, PL33_ Swietokrzyskie and PL52_Opolskie. Interestingly, these three regions are in Poland, while the other 31 regions are insignificant for this variable. These three regions are in the Low-High cluster category, meaning that public sector R&D spending in these regions is low but surrounded by other regions with higher values.

3.2. The effect of R&D spending and R&D personnel on patent applications in Visegrad Group (V4) regions

The first stage starts by running a classical regression with the original data without transformation. The results show that only the coefficient of the variable GERDBUS is significant, while the other two are not (Table 2). Simultaneously, all variables are significant, and the Adj R2 value is 0.71. The model also has no symptoms of multicollinearity or heteroscedasticity. All diagnoses of classical assumption problems reject the null hypothesis. Unfortunately, the diagnosis of spatial dependence does not show significant probabilities. Therefore, a step of data transformation into natural logarithm

Table 2. Results of classical regression without data transformation

Variable	Coefficient	Std-error
Constant	36.338	11.997
GERDBUS	0.0499	0.0191**
GERDPUB	-0.0113	0.0149
RDPR	0.0005	0.0006
R-squared	0.7390	
Adj R-squared	0.7129	
Ll	-995.753	
AIC	207.151	
SC	213.256	
Regression Diagnostics		
	DF	Value
Jarque–Bera	2	46.454
Breusch–Pagan test	3	25.138
White	9	126.182
Moran's I (error)	-0.0305	0.0756
LM (lag)	1	0.7592
Robust LM (lag)	1	26.456
LM (error)	1	0.0061
Robust LM (error)	1	19.525
LM (SARMA)	2	27.116

Source: own work

Note: ***, **, * indicate the rejection of H0 at 1, 5 and 10% significance level.

AIC: Akaike information criterion; SC: Schwarz criterion; Ll: likelihood function, LM: Lagrange Multiplier

Table 3. Results of classical regression with data transformation

Variable	Coefficient	Std-error
Constant	-33.627	13.182
lnGERDBUS	0.3536**	0.1545
lnGERDPUB	-0.2565**	0.1171
lnRDPR	0.6032**	0.2349
R-squared	0.6247	
Adj R-squared	0.5872	
Ll	-24.193	
AIC	56.386	
SC	624.915	
Regression Diagnostics		
	DF	Value
Jarque–Bera	2	0.4981
Breusch–Pagan test	3	57.407
Koenker–Basset test	3	6.4395*
Moran's I (error)	0.1526	1.7142*
LM (lag)	1	4.3531**
Robust LM (lag)	1	3.0947*
LM (error)	1	16.582
Robust LM (error)	1	0.3998
LM (SARMA)	2	4.7529*

Source: own work

Note: ***, **, * indicate the rejection of H0 at 1, 5 and 10% significance level.

AIC: Akaike information criterion; SC: Schwarz criterion; Ll: likelihood function, LM: Lagrange Multiplier

Table 4. Spatial lag regression results

Variable	Coefficient	Std-error
w_lnPATAPP	0.4734***	0.1458
Constant	-4.9169***	1.1948
lnGERDBUS	0.2294*	0.1345
lnGERDPUB	-0.2258**	0.0989
lnRDPR	0.7180***	0.1999
R-squared	0.6992	
Ll	-21.4126	
AIC	52.8252	
SC	60.457	
Regression Diagnostics		
	DF	Value
Breusch–Pagan test	3	4.1299
Likelihood Ratio Test	1	5.5608**

Source: own work
Note: ***, **, * indicate the rejection of H0 at 1, 5 and 10% significance level.
AIC: Akaike information criterion; SC: Schwarz criterion; Ll: likelihood function, LM: Lagrange Multiplier

Table 5. Spatial Lag regression results

Variable	Coefficient	Std-error
w_lnPATAPP	0.4734***	0.1458
Constant	-4.9169***	1.1948
lnGERDBUS	0.2294	0.1345
lnGERDPUB	-0.2258**	0.0989
lnRDPR	0.7180***	0.1999
R-squared	0.6992	
Ll	-21.4126	
AIC	52.8252	
SC	60.457	
Regression Diagnostics		
	DF	Value
Breusch–Pagan test	3	4.1299
Likelihood Ratio Test	1	5.5608**

Source: own work
Note: ***, **, * indicate the rejection of H0 at 1, 5 and 10% significance level.
AIC: Akaike information criterion; SC: Schwarz criterion; Ll: likelihood function, LM: Lagrange Multiplier

(ln) form was chosen to obtain a better classical regression model. The results show that two of the three explanatory variables (lnGERDPUB and lnRDPR) partially have a significant effect on lnPATAPP, despite the decrease in Adj R2 to 0.59 (Table 3).

Table 4 shows that, of the three variables set in this spatial modeling, only two knowledge input variables have significant effects in the Visegrad Group (V4) regions, namely lnGERDPUB and lnRDPR. In contrast, the variable lnGERDBUS has no effect on innovation in the Visegrad Group (V4) regions. The variable lnGERDPUB significantly affects lnPATAPP at 5% alpha (with a negative coefficient), while the variable lnRDPR has a significant positive effect at 1% alpha. In the second modeling estimation with the spatial lag method, the R2 value also increased to 0.70, better than the OLS regression model (Adj R2 = 0.58). The diagnostic report shows that this model has no heteroscedasticity problem. The estimation also makes an important point about the existence of significant spatial autocorrelation between innovation in a region and in other regions. The rho value indicates this spatial autocorrelation in the model.

In Moran's I analysis, the significance map (three regions significant at 5% alpha), and the LISA cluster map, the innovation pattern in the Visegrad Group (V4) regions is characterized by spatial dependence. The reasonably low Moran's I value (0.14) and a probability of only 10% indicating the low spatial dependence of innovation in the Visegrad Group (V4) regions may be suspect as to whether it indicates low or no spatial autocorrelation of innovation in the Visegrad Group (V4) regions. Although Moran's I analysis aims to detect spatial dependence and leads to a fundamental spatial analysis framework, which type of spatial autocorrelation or spatial heterogeneity is most suitable must be further proven through modeling estimation. Therefore, regression modeling using the LM test aims to answer the question of which type of spatial autocorrelation should be used (Acs et al., 2002; Li et al., 2007; Fotheringham, 2009; Dubé & Legros, 2014).

From the regression modeling estimation results, where further decisions are taken to conduct spatial regression analysis based on the LM (lag) test results, the coefficient (*rho*) is 0.4734. This figure measures the change (high or low) of innovation in region j if the average innovation in other regions changes. Thus, the estimation of modeling with the spatial lag method produces the best regression model.

The mathematical model is expressed as follows:

$$\widehat{lnPATAPP} = -4.9169 + 0.4734\boldsymbol{W}lnPATAPP + \\ + 0.2294\, lnGERDBUS - 0.2258\, lnGERDPUB + \\ + 0.7180\, lnRDPR$$

The estimation results shown with the spatial lag regression model above indicate the interaction between regional knowledge inputs and innovation in the Visegrad Group (V4) regions. The estimation results show that the industrial R&D expenditure variable does not impact innovation in the Visegrad Group (V4) regions. Meanwhile, public R&D expenditure (government and universities) has a significant effect on innovation but with a negative relationship ($p<0.05$). The correlation between public R&D expenditure and innovation (outlined in the description analysis section) shows a weak positive relationship (only 38%). However, in the modeling estimation, both with OLS and spatial lag method, the coefficient of GERDPUB is negative. As indicated by the negative Moran's I value, the inclusion of spatial characteristics in the model may have contributed to this difference. However, further testing to prove this should be conducted.

The R&D personnel variable was also found to have a significant positive effect on innovation in Visegrad Group (V4) regions. According to Filippetti et al. (2020), innovation performance in the CEE regions show improved results when associated with good labor performance. Although there are many shocks in the innovation process, given the significant influence of R&D personnel in innovation in the Visegrad Group (V4) regions, it has the potential to accelerate the recovery of the country or region in the event of a shock or crisis. Therefore, learning that can gradually improve the quality of R&D personnel, funding support for R&D for physical infrastructure, and training and incentives for R&D personnel all need to be encouraged to promote innovation in the Visegrad Group (V4) regions.

Furthermore, referring to what Kravtsova & Radosevic (2012) and Radosevic (1999, 2012) stated about the importance of designing specific policies to enhance innovation through collaboration and expansion of R&D networks matches the study's findings in this paper. Strong support for R&D personnel in a region, whether from government agencies or universities, will significantly boost regional innovation. Then, the spatial effect will work to influence innovation in other regions around it. Nevertheless, when discussing the innovation paradox, especially in less-developed regions, there is something to keep in mind. Investment in R&D infrastructure should be linked to investment in R&D personnel, as this will ultimately relate to the effectiveness and efficiency of funding. This then leads to the governance capability of regional R&D resources in a regional innovation system (RIS). Governance issues have become a real issue in innovation policy design in less-developed regions (McCann & Ortega-Argilés, 2013, 2014; Morisson & Doussineau, 2019; Trippl et al., 2019).

4. Conclusion

This paper first examines the spatial dependence of knowledge inputs (R&D expenditure and R&D personnel) and innovation (patent applications), which is clearly illustrated in section three. From the spatial distribution of innovation, only three countries have regions of high innovation density: the Czech Republic, Hungary and Poland. In terms of knowledge inputs, the three countries have a high intensity of R&D personnel factors. However, the Czech Republic and Poland are more similar in R&D expenditure support to each other than to Hungary. Spatial dependence was analyzed by looking at the scatterplot and spatial distribution of Moran's I of all the variables analyzed. The findings suggest that innovation is generally highly concentrated in the region around the capital city, particularly in the Czech Republic and Poland. The R&D expenditure proxy is separated into two types, namely business R&D and public R&D, to see how they differ. However, only public R&D expenditure significantly impacts innovation in the Visegrad Group (V4) regions and, interestingly, has a negative relationship.

Modeling estimates were conducted using the LM test to assess the presence of spatial autocorrelation of regional innovation between regions. Classical regression was run using data transformation and showed significant LM (lag) test results. It is a critical spatial framework in the modeling of this study. Estimation using the spatial lag method revealed three essential findings on innovation in the Visegrad Group (V4) regions. First, changes in innovation in a region are spatially significantly influenced by innovation in other regions. Second, R&D investment support in the public sector significantly impacts innovation. Unfortunately, the negative relationship shown in the model cannot be analyzed in depth in this study. Third, R&D personnel is the essential resource for innovation. These three inputs significantly affect innovation. Innovation productivity is more stable and quickly recovered, even in times of crisis, if regions have an ethos of lifelong learning embedded in their R&D personnel. Therefore, a particular policy push to improve the capacity and capability of regional R&D resources is necessary and should be supported by balanced R&D funding.

This study has obvious limitations, especially the issue of data availability. Nonetheless, it has shown a clear contribution to the study of innovation in the Visegrad Group (V4) regions. The spatial analysis applied in this paper can be a fundamental reference for future studies that take the Visegrad Group (V4) regions as their subject. However, future studies should consider a broader range of data sources to provide more valid and in-depth research results.

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