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Spatial Heterogeneity and Spillovers of Employment in the EU Regions

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Abstract: *This paper focuses on the employment problem in the context of EU regions. Two main hypotheses were verified. The first hypothesis was related to the spatial heterogeneity problem, i.e., we hypothesised that relationship between the employment rate and the explanatory variables (GDP per inhabitant, educational attainment level and compensation of employees) may vary spatially. The second hypothesis dealt with the spatial autocorrelation, i.e., we assumed that the regional employment process is not isolated and that the neighbourhood of the regions also plays a significant role. As the main methodological tool the spatial regime models were applied. Spatial analysis of employment rate data indicated two spatial regimes. The results revealed the spatial instability of estimated parameters across the two regimes. Also, the spatial regional interconnections within both regimes were confirmed. Statistical significance of spillover effects of considered employment factors outlines the high importance of spatial spillovers.*

Keywords: Employment rate in EU regions; Spatial regimes; Spillover effects; Spatial heterogeneity; Spatial autocorrelation

JEL Classification: J21, C51, C10

Introduction

High-employment economy is one of the most challenging issues for economic development. European Union (EU) policy makers through the Europe 2020 strategy (European Commission, 2010) promoted social inclusion, in particular by its agenda for growth and jobs, whereby 75 % of the population aged 20-64 should have been employed by 2020. Fostering a high-employment economy delivering social cohesion

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was a part of inclusive growth priority declared by the Europe 2020. Also, in the current long-term EU strategy 2021-2027, the topic of employment is a part of a strategic goal „a more social Europe" presented by European Commission (European Commission, 2019).

It is also essential that the benefits of high-employment economy and consequently of economic growth spread to all parts of the EU, including its outermost regions, thus strengthening territorial cohesion too. Cohesion policy of the EU has invested heavily in reducing economic disparities across EU regions. Investment into innovation, education and digital and transport networks were financed, what help to create a single market that boosts growth, productivity and specialisation in areas of comparative advantage in all regions (European Commission, 2017). The effects of cohesion policy interventions not only positively affect the performance of the member states or regions in which they are implemented, but they also generate so called spatial spillovers elsewhere in the EU. Spatial spillovers are the effects of local economic processes in one region on processes in neighbouring ones. This can be positive, so that, e.g., economic growth in regions close to each other is self-reinforcing, or negative, so that a region grows at the expense of surrounding ones. Thus, spatial spillovers between regions are of major importance. For instance, it is assumed the impact of all cohesion policy programmes in 2007–2013 on the non-cohesion[1] countries. GDP in the non-cohesion countries is supposed to be higher than what it would have been without these programmes, due to the positive spillover they generate on the economies of the non-cohesion countries. In the long-run, these spillover benefits represent a substantial share of the total impact of the cohesion policy on the non-cohesion country economies. By 2023, the impact of the 2007–2013 programmes is estimated to be around 0.12% of GDP in non-cohesion countries, of which around a quarter is due to spillovers from spending in cohesion countries (European Commission, 2017). This effect is particularly pronounced for member states with strong trade links with cohesion countries or strong openness to trade in general.

It is clear that regional cohesion and economic convergence has always been a priority objective of the European Union. Despite the acceleration of the economic convergence process over the last decades, the gap between the EU member states is still sizeable. At the NUTS 2 (Nomenclature of Units for Territorial Statistics) regional level, the differences in economic growth and income among regions within and across countries are much more pronounced than the differences at the national level. While the development of an individual region is certainly correlated with the development of the respective country, the diversity of the regions with respect to their factor endowments, geographic location, sectoral structure and other aspects causes considerable heterogeneity in economic growth and income across regions (Landesmann and Römisch, 2006).

Empirical literature in the EU context includes many studies dealing with regional income convergence, but the common feature of most "earlier" studies in this area is the neglected aspect of spatial interactions – spatial spillovers (discussed above) as well as aspect of potential heterogeneity among regions. These two aspects, spatial effects, namely spatial autocorrelation and spatial heterogeneity are the main area of interest of spatial econometrics. Tools and models of spatial econometrics enable to take into account spatial dependencies, asymmetries in relations and the interaction of objects and data that are the subject of econometric modelling. The presentation of a "New Economic Geography" (NEG) theory is considered to be an important moment in the history of spatial econometrics. The contribution of NEG is to address questions such as (Venables, 2005): Why is economic activity distributed unevenly across space? What economic interactions are there between different geographical areas, and how do these shape income levels in the areas? How does the spatial organization of economic activity respond to exogenous shocks, such as technological change or policy measures? NEG models provide a framework for spatial analysis of economic data when examining issues such as regional convergence, regional concentration of economic activities and adjustment dynamics or innovation (Krugman, 1991; Fujita et al., 1999; Ottaviano and Puga, 1997; Venables and Puga, 1999; Anselin et al., 2000a; Anselin et al., 2000b; Acs et al., 2002).

Nowadays, the phenomenon of spatial autocorrelation and spatial heterogeneity is no longer neglected as markedly as it has been in recent decades. The ignorance of spatial correlation and the fact that regions are perceived as "islands" in the economic space lead to possible biased results and consequently misleading conclusions from empirical studies. The spatial aspects have been already incorporated, e.g., in many studies dealing with regional income convergence (Qin et al., 2017; Chocholatá and Furková, 2017; Lolayekar and Mukhopadhyay, 2019) at which it is assumed that spatial spillover effects will have a significant impact on income convergence of regions. Also, we can find several studies that handle issue of spatial heterogeneity and their results indicate that economic behaviour is unstable in space, and income convergence is characterized by multiple local equilibrium states – convergence clubs (Qin et al., 2017; Papalia and Betarelli, 2012; Pan et al., 2015; Furková, 2020).

It is well known, the variables used to assess convergence or divergence are measures generally tied to per capita GDP (Barro and Sala-i-Martin, 1991) and to its two components namely employment rate and productivity. Econometric estimates unanimously agree that, in recent years in Europe, the convergence of per capita GDP has been very slow and has instead fostered the formation of clusters of homogeneous regions as already mentioned in the previous paragraph. These clusters of regions are internally convergent but diverge with respect to each other, and this has been due exclusively to the trend in the employment rate and therefore to the characteristics of the labour market (Overman and Puga, 2002; Combes and Overman, 2004). A number of studies have paid attention especially to unemployment rate performance in the various regions of the EU based on the different theoretical and empirical approaches. Only recently, studies began to appear where employment rates were the preferred indicator (Perugini and Signorelli, 2004). These authors analysed the regional employment and convergence for the European regions. Among the other empirical works on regional employment analysis taking into account the spatial context, we can mention, e.g., Franzese and Hays (2005) who dealt with the employment spillovers in the EU, Monastiriotis (2007) who dealt with the spatial association and its persistence for various socio-economic indicators in case of the Greek regions. Also, Pavlyuk (2011) investigated the differences in employment rates in Latvian regions based on instruments of spatial analysis and spatial econometrics. Furková and Chocholatá (2019) and Furková and Chocholatá (2021) used the Spatial Durbin Model (SDM) and geographically weighted regression (GWR) in order to verify territorial interconnections within the EU regions in the context of employment rates. Majchrowska and Strawiński (2021) analysed the spatial dependencies in the relationship between employment and minimum wage for local Polish labour markets revealing significant heterogeneities in the model. The spatio-sectoral heterogeneity and population–employment dynamics was studied by Alamá-Sabater et al. (2022) who presented some implications for territorial development in Spanish region. Wu and Hua (2023) used the SDM model to study the impact of different variables on employment in Chinese provinces and draws some interesting conclusions. They divided the analysed sample into coastal and inland areas based on their location. In order to promote high-quality employment, they recommend to apply targeted policies under regional differences.

One of the motivating factors in this paper is the gap among empirical studies on regional employment regarding spatial interconnections among regions. The novelty of the study consists on simultaneous consideration of both spatial autocorrelation and spatial heterogeneity. This approach enables the specification of spatial regimes as well as to assess the spatial spillovers. To the best of our knowledge, this, in connection with the problem of regional employment, is very rare approach and enables to suggest more specified place-based policies. The aim of this paper will be the verification of the role of region location in the EU regional employment process modelling. Empirical part of the paper will include verification of two main hypotheses:

Hypothesis 1: Hypothesis of spatial heterogeneity, i.e., we assume that the relationship between the dependent variable (employment rate) and the explanatory variables (GDP per inhabitant, educational attainment level and compensation of employees) may vary spatially. Instead of fixed values of regression parameters for all regions, it is assumed that their values may be different for spatial unit groups, which we refer to as spatial regimes.

Hypothesis 2: In addition to spatial heterogeneity problem, we hypothesize that the regional employment process in individual regimes is influenced by employment in neighbouring regions. We assume that there is global level of spillovers of employment determinants under consideration.

Spatial econometric and spatial regime models will be applied as the hypotheses validation tool. The models will be used to quantify and to test statistical significance of the direct, indirect and total impacts of selected explanatory variables. Following spatial partitioning of these impacts and their statistical significance, we will try to answer the question what level of neighbourhood degree still matter in the regional employment process modelling.

After the introduction, the rest of the paper is organized as follows: section 2 deals with main theoretical issues concerning both spatial effects and spatial regimes, section 3 presents empirical results and the paper closes with concluding remarks and policy implications.

Materials and Methods

This chapter will provide a brief overview of main methodological aspects of our analysis. The first part will deal with spatial dependence (spatial autocorrelation) and spatial spillovers, and topics related to the spatial heterogeneity and spatial regimes will be the content of the second subchapter.

Spatial autocorrelation and spatial spillover effects

Spatial autocorrelation can be identified as the situation when the value taken by a given variable is related to the value by the same variable located nearby. In order to judge the form of the spatial dependence as well as the intensity of this relation, an information how the observations (regions, states, etc.) are linked among themselves in space is needed. The structure of spatial links is usually described by a spatial weights matrix **W**. This matrix formalizes the relative proximity between the observations and various approaches are known for specification of this matrix (for more details see, e.g., Anselin and Rey, 2014). The measurement of the spatial autocorrelation can be done by global and local spatial autocorrelation statistics such as Moran´s *I* statistic, Geary´s *c* statistic or family of Getis-Ord statistics.

Spatial econometrics offers a group of spatial autoregressive models which explicitly allow for spatial dependence through spatially lagged variables. Well–known SAR (Spatial Autoregressive) model[2], assumes spatial spillover effects within the spatial lag of dependent variable (global spillover). In the spatial context, the spillover effect means that for a particular observation the data generating process is influenced by the nature of the dependent variables related to the nearby observations. These effects are of real importance and the researchers try to measure their extent and impact. The spatial econometrics provides sufficient instruments for the measurement of these effects. Let us start with formulation of SAR model, in matrix notation, the model can be written as:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \boldsymbol{\iota}_N \alpha + \mathbf{X}\beta + \mathbf{u} \tag{1}$$

where $\mathbf{y}$ is the $N \times 1$ vector of the observed dependent variable for all N locations, $\mathbf{X}$ denotes a $N \times k$ matrix of exogenous explanatory variables (k represents the number of explanatory variables), $\boldsymbol{\iota}_N$ represents $N \times 1$ vector of ones associated with the intercept α, $\boldsymbol{\beta}$ is $k \times 1$ vector of unknown parameters to be estimated, $\mathbf{u} \sim N(0, \sigma_u^2 \mathbf{I}_N)$ is $N \times 1$ vector of random errors, σ_u^2 is random error variance and $\mathbf{W}$ is N dimensional spatial weights matrix. Spatial autoregressive parameter ρ indicates the direction and the strength of spatial dependence.

Now, we can see that model (1) includes endogenous interaction effects among the dependent variable ($\mathbf{Wy}$). Just spatial lags of dependent and/or explanatory variables cause problems with parameter interpretation in spatial econometric models. In classical linear regression model, a change in a given explanatory variable k, denoted by x_{ik} allows to retrieve its marginal effect on the behaviour of the dependent variable and this marginal effect is simply equal to the parameter β_k for all observations i. This is no longer the case of spatial econometric models. Now, a variation in variable x_{ik} causes a change in the value y_i which leads to a variation in the value $y_j$for the observations located around i which in turn causes a change in the value y_i and so on. In other words, the expected value of the dependent variable in the ith location is no longer influenced only by exogenous location characteristics, but also by the exogenous characteristics of all other locations through a spatial multiplier $\left(\mathbf{I}_N - \rho \mathbf{W}\right)^{-1}$ (for more details see LeSage and Pace, 2009). The marginal effect can be separated into two parts, the first part is related to the direct effects and the second part measures the indirect effects. LeSage and Pace (2009) based on spatial multiplier and consequently on the matrix $\mathbf{S}_k\left(\mathbf{W}\right)$ proposed a following summary average measures of marginal effects:

$$\overline{M}_{total} = N^{-1} \boldsymbol{\iota}_N^{\mathrm{T}} \mathbf{S}_k\left(\mathbf{W}\right) \boldsymbol{\iota}_N \tag{2}$$

$$\overline{M}_{direct} = N^{-1} \mathrm{tr}\left(\mathbf{S}_k\left(\mathbf{W}\right)\right) \tag{3}$$

$$\overline{M}_{indirect} = \overline{M}_{total} - \overline{M}_{direct} \tag{4}$$

where $\boldsymbol{\iota}_N$ is a vector of 1 dimension $N \times 1$ and $\mathbf{S}_k\left(\mathbf{W}\right)$ for SAR model (1) is defined as

$$\mathbf{S}_k\left(\mathbf{W}\right) = \left(\mathbf{I}_N - \hat{\rho}\mathbf{W}\right)^{-1} \left(\mathbf{I}_N \hat{\beta}_k\right) \tag{5}$$

Spatial multiplier and the matrix (5) are the key issues for the spatial spillovr effects calculations. The diagonal elements of the matrix (5) provide information about direct impacts and non – diagonal elements of this matrix represent indirect impacts. It is clear that the calculation of (2), (3) and (4) strongly depends on the estimation of spatial autoregressive parameter ρ, estimation of associated parameter β_k and the specification of spatial weights matrix $\mathbf{W}$. Estimation of spatial autoregressive models requires special estimation methods. The topics related to the estimation of spatial econometric models, other model specifications and also inferences regarding the statistical significance of individual impacts can be found in, e.g., LeSage and Pace (2009).

Spatial heterogeneity and spatial regimes

Since the consideration of the spatial autocorrelation has been quite popular in modelling of the spatial relationships, the incorporation of the spatial heterogeneity is scarce. Spatial heterogeneity reflects the structural instability in space, i.e., that the modelled relationship among the dependent variable and explanatory variables is not consistent across the whole analysed area but varies spatially. We can find studies indicating different relationships in e.g., northern and southern regions, eastern and western regions, urban and rural regions. Ertur and LeGallo (2008) distinguish two possible ways of differences: space-varying parameters and/or space-varying variances. In general, parameters can vary across group of regions (spatial regimes) or in a more general case these can vary even across individual regions (for more information see e.g., Fotheringham et al., 2002; Furková and Chocholatá, 2021).

Spatial regimes can be specified in different ways. Besides a priori specification of spatial regimes based on e.g., belonging to a geographical zone, the Exploratory Spatial Data Analysis (ESDA) instruments like Getis-Ord statistics $G_i(d)$ or Local Indicators of Spatial Association (LISA) indicators enabling to detect the clusters of similar values are useful as well (Ertur and LeGallo, 2008). Debarsy and Ertur (2006) further present a survey of some studies with endogenous way of determination of spatial regimes.

Regarding the simplified specification of two spatial regimes (N_1 and N_2 represent the number of regions included in regimes 1 and 2, respectively, while $N_1 + N_2 = N$) with spatial parameters varying across these spatial regimes, the corresponding spatial lag model then becomes as follows (Anselin and Rey 2014):

$$\begin{bmatrix}\mathbf{y}_1\\ \mathbf{y}_2\end{bmatrix}=\begin{bmatrix}\rho_1\mathbf{W}_1 & \mathbf{0}\\ \mathbf{0} & \rho_2\mathbf{W}_2\end{bmatrix}\begin{bmatrix}\mathbf{y}_1\\ \mathbf{y}_2\end{bmatrix}+\begin{bmatrix}\mathbf{I}_{N_1} & \mathbf{0}\\ \mathbf{0} & \mathbf{I}_{N_2}\end{bmatrix}\begin{bmatrix}\alpha_1\\ \alpha_2\end{bmatrix}+\begin{bmatrix}\mathbf{X}_1 & \mathbf{0}\\ \mathbf{0} & \mathbf{X}_2\end{bmatrix}\begin{bmatrix}\beta_1\\ \beta_2\end{bmatrix}+\begin{bmatrix}\mathbf{u}_1\\ \mathbf{u}_2\end{bmatrix} \tag{6}$$

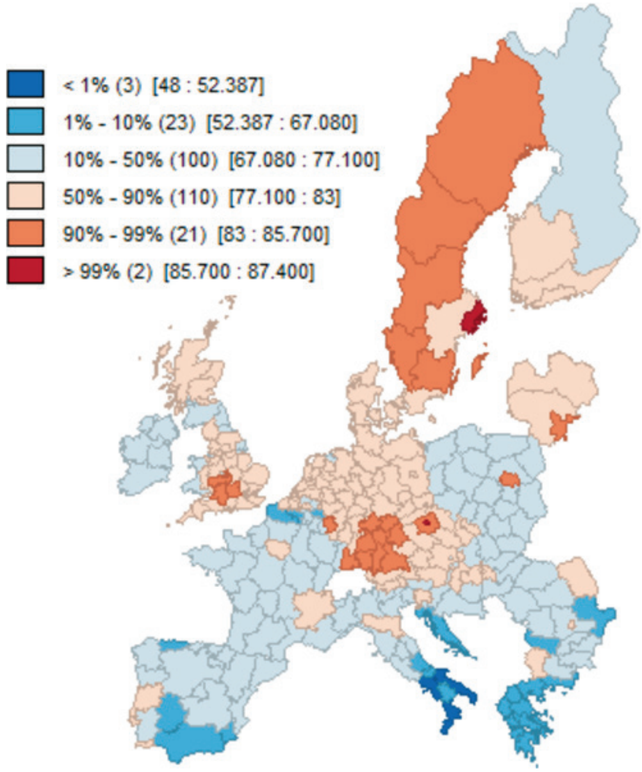
where $\mathbf{y}_1\ (N_1\times 1)$ and $\mathbf{y}_2\ (N_2\times 1)$ are the vectors of the dependent variable $\mathbf{y}\ (N\times 1)$, $\mathbf{X}_1\ (N_1\times k)$ and $\mathbf{X}_2\ (N_2\times k)$ are the matrices of exogenous explanatory variables, $\mathbf{W}_1\ (N_1\times N_1)$ and $\mathbf{W}_2\ (N_2\times N_2)$ denote the regime weights. Spatial autoregressive parameters ρ_1 and ρ_2 for the individual spatial regimes indicate that there are spillovers inside each regime, but no spillovers between regimes. Symbols $\boldsymbol{\beta}_1\ (k\times 1)$, $\boldsymbol{\beta}_2\ (k\times 1)$ denote the vectors of regression parameters in individual spatial regimes and $\mathbf{u}_1\ (N_1\times 1)$, $\mathbf{u}_2\ (N_2\times 1)$ are vectors of error terms. Furthermore, we assume the groupwise heteroskedasticity with homoskedastic errors within regimes, i.e., $\mathrm{E}\left[\mathbf{u}_1\mathbf{u}_1^{\mathrm{T}}\right]=\Sigma_1=\sigma_1^2\mathbf{I}_{N_1}$ and $\mathrm{E}\left[\mathbf{u}_2\mathbf{u}_2^{\mathrm{T}}\right]=\Sigma_2=\sigma_2^2\mathbf{I}_{N_2}$. Parameters of model (6) can be estimated by the spatial maximum likelihood method (SML). As pointed out by Anselin and Rey (2014), the assumption of the groupwise heteroskedasticity enables to estimate separate equations for each group (regime).

Data and empirical results

The data for analysis comprises the regional data for the 259 NUTS 2 regions[3] of the EU retrieved from the Eurostat database (http://ec.europa.eu/eurostat/), namely: the employment rates (in %) of population aged 25-64 in 2018 as a variable of interest (dependent variable) and other three variables as explanatory variables – GDP in euro per inhabitant (GDP) in 2017, educational attainment level (in %) of population aged 25-64 with the upper secondary, post-secondary non-tertiary and tertiary education (EDU) in 2017 and compensation of employees per thousand employees[4] (COM) in 2016. The cross-sectional data in this study were used in form of natural logarithms. The GeoDa software package and R studio environment were used for analyses.

As a preliminary step, the ESDA approach was applied to explore the structure of the analysed employment rates data. The percentile map in Fig. 1 illustrates the unequal distribution of the analysed dependent variable over space and enables to identify some disparities across regions inside the analysed countries, as well. Based on Fig. 1 it can be concluded, that, in general, the regions with higher (lower) employment rates tend to be located together, but on the other hand, it is also possible to identify some regions with higher employment rates surrounded by regions with lower level of employment rates. While the regions of high employment rates are located mostly in central and northern part of the EU, the low employment regions can be found mostly in western, southern and eastern part of the EU. Huge disparities across regions of individual countries could be found e.g., in Italy, Bulgaria, Romania and Poland.

Figure 1: Percentile map for the employment rates (in %) of population aged 25-64 in 2018



Source: authors' calculations in GeoDa

Fig. 1 further enables to observe the division of regions into high-employment regions (northern and central part of the EU) and the regions with lower employment rates (western, southern and eastern part of the EU) suggesting the spatial heterogeneity and thus possible existence of the spatial regimes.

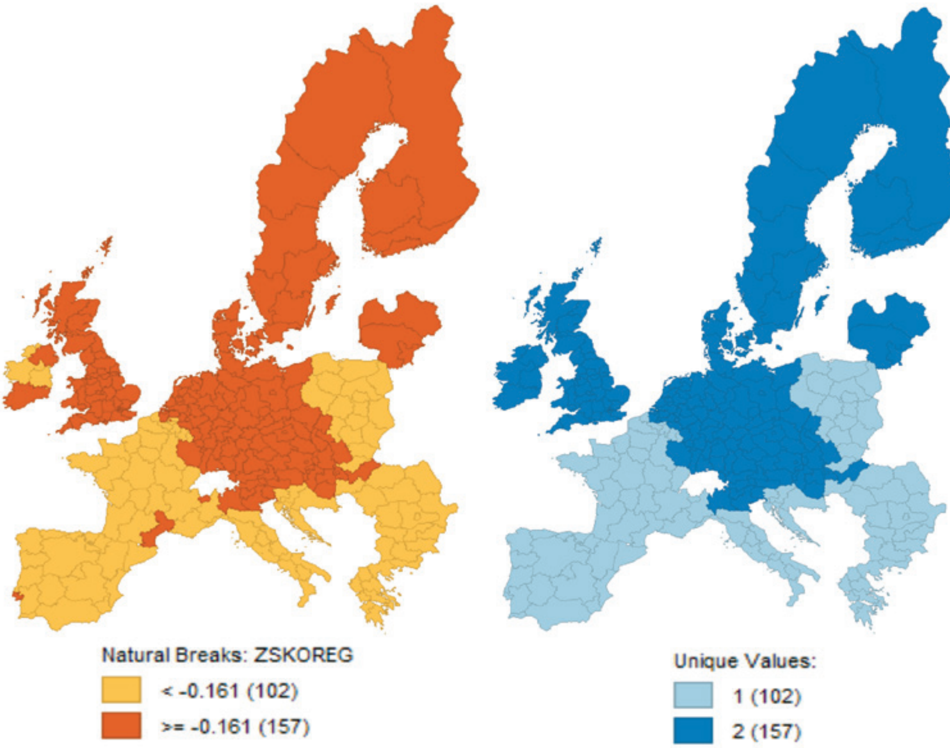
In this context, several questions arise, namely whether groups of regions – spatial regimes are justified, how many groups to choose, how many regions each regime should contain, that is, what actually determines individual regimes. Economic theory does not provide unique rule how to create such groups of regions. However, some authors (e.g., Fischer and Stirböck, 2004; Debarsy and Ertur, 2006) mainly in the context of economic convergence clubs, distinguish between exogenous and endogenous ways of determination of spatial regimes. The first category includes approaches where the criteria for creating regimes are, e.g., affiliation to the geographical zone, the institutional system or threshold levels of relevant economic indicators. On the other hand, empirical literature also presents a survey of several methods which can be used for the endogenous determination of spatial regimes. This group includes, for example, Exploratory Spatial Data Analysis (ESDA) tools. The selected ESDA statistics appear as a suitable tool for determining spatial regimes because they allow to detect spatial interactions between regions and we can take the information into account when dividing regions into groups.

We decided to use endogenous way for identifying spatial employment regimes using ESDA tools (Getis – Ord statistics $G_i(d)$ and Natural Breaks Maps). We preferred this approach because the determination of spatial regimes for instance based on the unique values of employment rates and quantile maps, does not take spatial interregional dependencies into account. First, the values of the decision variable, the values of local Getis-Ord statistics for employment rates were calculated and then we used the Jenks Natural Breaks algorithm to determine the breaking point for regimes determination.

The information from the Getis – Ord statistics $G_i(d)$, as a measure of the spatial clustering, was used to identify the spatial regimes. The values of the Getis – Ord statistics $G_i(d)$ were calculated based on the queen contiguity spatial weights (see e.g., Anselin and Rey, 2014). The calculated *z*-values of $G_i(d)$ statistics for the employment rates enabled to split the regions into two spatial regimes (Fig. 2a).

The Jenks Natural Breaks algorithm, i.e., the Natural Breaks Map (for more details see Jenks, 1977 and De Smith et al., 2009) appears to be a suitable tool for dividing regions into groups. The natural break map uses a non-linear algorithm to group regions to maximize within-group homogeneity. It is essentially a clustering algorithm in one dimension to determine the breakpoints that provide the groups with the largest internal similarity. Compared to the quartile map, the natural breaks criterion is better at grouping extreme observations. Interestingly, unlike quantile maps, the number of observations in each category can be highly unequal. Thus, based on this approach, the break point was identified to be -0.161[5], i.e., regions with lower values of the *z*-values of $G_i(d)$ statistics form the regime 1, whereas the regions with values of -0.161 and higher belong to the regime 2. Since there arise some isolated regions (BE24 – Prov. Vlaams-Brabant, IE04 – Northern and Western, IE06 – Eastern and Midland in regime 1 and FRJ1 – Languedoc-Roussillon, PT17 – Área Metropolitana de Lisboa, ITC2 – Valle d'Aosta/Vallée d'Aoste in regime 2), the spatial regimes were modified as given by the unique values map in Fig. 2b. Finally, regime 1 thus consists of 102 regions located mostly in southern, western and eastern part of the EU, regime 2 comprises the 157 regions from the central and northern part of the EU.

Figure 2: Specification of two spatial regimes – **a** natural breaks map (z-score of $G_i(d)$ statistics for employment rates) and **b** unique values map



(a) **(b)**

Source: authors' calculations in GeoDa

Following the classical specific-to-general approach (see Florax et al., 2003), as the first step the linear regression models for individual regimes were estimated by the ordinary least squares (OLS) method. Estimation results for both regimes can be found in Table 1, columns: Linear model. All the estimated parameters for both regimes were statistically significant indicating positive impact of GDP in Euro per inhabitant (ln GDP) and educational attainment level (ln EDU) variables onto the employment rates (both regimes). Also, the results indicated the negative impact of compensation of employees (ln COM) for regime 1 and positive impact for regime 2. The statistical significance of the Moran's I for residuals of both regimes as well as the Lagrange Multiplier (LM) test statistics enabled to reject the null hypothesis of non-spatial dependence which means that the OLS estimates could be misleading. Based on the LM test statistics' values, the model SAR is clearly preferred for regime 1. As for the regime 2, the LM test results enabled no clear-cut conclusion about the type of the spatial model, but due to assumption of the presence of the global spillover effects, we decided to estimate the SAR model for regime 2, as well. The estimation of the SAR models was done by the SML method, the corresponding results are gathered in Table 1, columns: SAR model. Almost all estimated parameters (with exception of parameter α in regime 1 and parameter $\beta_1(\ln \text{GDP})$ in regime 2) were statistically significant. Statistical significance of the spatial autoregressive parameter ρ together with the values of the *LR* test statistics confirm the adequate use of the spatial model in case of both regimes.

Table 1: Estimation results – OLS and SAR models

Estimation	**Regime 1**		**Regime 2**	
	Linear model	**SAR model**	**Linear model**	**SAR model**
	OLS	SML	OLS	SML
α	2.1273***	0.3516	2.5985***	1.1339***
β_1 (ln GDP)	0.1727***	0.1328***	0.0167*	0.0130
β_2 (ln COM)	-0.1303***	-0.1027***	0.0299***	0.0269***
β_3 (ln EDU)	0.1988***	0.1264***	0.3384***	0.2953***
ρ	–	0.5621***	–	0.3891***
R–squared	0.3118	–	0.3195	–
Log likelihood	–	124.3125	–	294.6885
Tests				
Moran's *I* (residuals)	6.3070***	–	6.5522***	–
LM (lag)	40.4163***	–	19.0100***	–
Robust LM (lag)	8.7557***	–	8.7510***	–
LM (error)	31.9266***	–	37.9929***	–
Robust LM (error)	0.2661	–	27.7338***	–
LR test	–	35.793***	–	19.373***

*Notes: Symbols ***, **, * indicate in whole paper the rejection of H_0 hypothesis at 1 %, 5 % and 10 % level of significance, respectively.*
LR – Likelihood Ratio, LM – Lagrange Multiplier.

Source: authors' calculations in R

However, the formulation of the SAR model includes the spatially lagged dependent variable (**Wy**) and thus assumes the presence of the global spillover effects (i.e., that changes in *i*-th region will cause series of responses in other/all regions), which indicates that the assessment of the individual parameter estimates and corresponding interpretation is being more complicated. Since, as pointed out by Le Sage and Pace (2009), the impact of changes in the explanatory variable differs over individual regions, they suggested the summary average measures of these effects. The summary impact estimates (average direct impact, average indirect impact and average total impact) were calculated based on formulas (2) – (5) and together with parameter estimates (from the corresponding SAR model) are summarized in Table 2. Testing the statistical significance of these summary measures of impacts was based on a simulation approach (Le Sage and Pace, 2009). Apart from the explanatory variable ln GDP in regime 2, all the impacts associated with individual explanatory variables, were statistically significant (Table 2).

Let us consider the SAR model estimates for individual explanatory variables. The estimate for the first explanatory variable, ln GDP, yields 0.1328 and 0.0130 in regime 1 and regime 2, respectively. However, the corresponding average direct impacts are different and equal 0.1481 and 0.0136 in regime 1 and regime 2, respectively. The positive differences of 0.0153 and 0.0006, respectively, indicate the feedback effects among regions. The average total impacts of 0.3032 and 0.0213 in regime 1 and regime 2, respectively mirror that 1 % rise in the GDP will lead to average rise of employment rate of 0.3032 % and of 0.0213 %, respectively. Positive impact of the GDP level on the employment rate is in accordance with our expectations and was confirmed by several empirical studies, e.g., by Pavlyuk (2011), Furková and Chocholatá (2019), Furková and Chocholatá (2021).

As for the second explanatory variable, ln COM, the signs and interpretation of estimated parameters in individual regimes are not so unambiguous. The controversial effect of the compensation of employees (or wages) on the employment rate is pointed out by e.g., Belman and Wolfson (2016) who emphasised that the results are country- and time-specific as well as sensitive to the work force qualification and wage level. Since in regime 1, comprising in general regions with lower level of employment rate, its impact is negative (-0.1027), results for regime 2 (regions with higher employment rates) indicate the positive impact of 0.0269. The average direct, indirect and total impacts are depending on the type of regime, negative and positive, respectively. Since in regime 1 the 1 % rise in the compensation of employees (COM) will cause an average decline of employment rate of 0.2346 %, the 1 % increase of COM in regime 2 entails on average 0.0441 % increase of employment rate.

The third explanatory variable, ln EDU, has the positive impact on the employment rate in both analysed regimes. Unlike the first two explanatory variables, the impact of this variable is higher for the regime 2 in comparison to regime 1. This indicates that the 1% increase of the population with considered level of education will lead to an average increase of employment rate of 0.2886% (regime 1) and of 0.4833% (regime 2), respectively. While for regime 1 the ratios of direct and indirect impacts on the total impact were almost the same (49% and 51%, respectively), the results for regime 2 indicated clearly a higher portion of total impact attributable to direct impacts (64%) compared to the 36% assignable to indirect impacts.

It is appropriate to draw attention to the constant ratios of direct and indirect effects to the total effect for each explanatory variable (see the lower part of Table 2) These proportions are constant because the SAR model contains only a spatially lagged dependent variable and no spatially lagged explanatory variables, so the value of the dependent variable in a given region is affected only by its values in neighbouring regions. However, for instance, compared to the Spatial Durbin Model, which contains not only a spatially lagged dependent variable but also spatially lagged explanatory variables, and thus the value of the dependent variable in a given region is influenced not only by its values in neighbouring regions and explanatory variables in a given region, but also by the values of explanatory variables in neighbouring locations.

Table 2: Summary average measures of direct, indirect and total impacts

	Regime 1			Regime 2		
	ln GDP	*ln COM*	*ln EDU*	*ln GDP*	*ln COM*	*ln EDU*
Parameter estimate ($\beta_1, \beta_2, \beta_3$)	0.1328	-0.1027	0.1264	0.0130	0.0269	0.2953
Average direct impact ($\overline{M}_{direct}$)	0.1481***	-0.1146***	0.1410***	0.0136	0.0282**	0.3093***
Difference $\overline{M}_{indirect}$ and parameter estimate	0.0153	-0.0119	0.0146	0.0006	0.0013	0.0140
Average indirect impact ($\overline{M}_{direct}$)	0.1551**	-0.1200**	0.1476***	0.0077	0.0159**	0.1740***
Average total impact ($\overline{M}_{total}$)	0.3032***	-0.2346***	0.2886***	0.0213	0.0441**	0.4833***
$\overline{M}_{direct}/\overline{M}_{total}$	49%	49%	49%	64 %	64 %	64 %
$\overline{M}_{indirect}/\overline{M}_{total}$	51%	51%	51%	36 %	36 %	36 %

Source: authors' calculations in R

Table 3: Spatial partitioning of impacts

Regime 1									
Order of **W**	*ln GDP*			*ln COM*			*ln EDU*		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
$\mathbf{W}^0$	0.1328***	0	0.1328***	-0.1027***	0	-0.1027***	0.1264***	0	0.1264***
$\mathbf{W}^1$	0	0.0746***	0.0746***	0	-0.0577***	-0.0577***	0	0.0710***	0.0710***
$\mathbf{W}^2$	0.0106***	0.0314***	0.0419***	-0.0082**	-0.0243**	-0.0325**	0.0101***	0.0298***	0.0399***
$\mathbf{W}^3$	0.0016**	0.0219**	0.0236**	-0.0013*	-0.0170*	-0.0182*	0.0016**	0.0209**	0.0224**
$\mathbf{W}^4$	0.0018	0.0115	0.0133	-0.0014	-0.0089	-0.0103	0.0017*	0.0109*	0.0126*
$\mathbf{W}^5$	0.0006	0.0069	0.0074	-0.0004	-0.0053	-0.0058	0.0005	0.0066	0.0071
$\mathbf{W}^6$	0.0004	0.0038	0.0042	-0.0003	-0.0029	-0.0032	0.0004	0.0036	0.0040
Σ	0.1478	0.1501	0.2978	-0.1143	-0.1161	-0.2304	0.1407	0.1428	0.2834
Regime 2									
Order of **W**	*ln GDP*			*ln COM*			*ln EDU*		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
$\mathbf{W}^0$	0.0130	0	0.0130	0.0269**	0	0.0269**	0.2953***	0	0.2953***
$\mathbf{W}^1$	0	0.0051	0.0051	0	0.0105**	0.0105**	0	0.1149***	0.1149***
$\mathbf{W}^2$	0.0005	0.0015	0.0020	0.0011*	0.0030*	0.0041*	0.0116**	0.0331**	0.0447**
$\mathbf{W}^3$	0.0000	0.0007	0.0007	0.0001	0.0015	0.0016	0.0011*	0.0163*	0.0174*
$\mathbf{W}^4$	0.0000	0.0003	0.0003	0.0001	0.0005	0.0006	0.0010	0.0057	0.0067
$\mathbf{W}^5$	0.0000	0.0001	0.0001	0.0000	0.0002	0.0002	0.0002	0.0025	0.0027
$\mathbf{W}^6$	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0009	0.0010
Σ	0.0135	0.0077	0.0212	0.0282	0.0158	0.044	0.3093	0.1734	0.4827

Source: authors' calculations in R

Since the matrix (5) can be written as a linear combination of powers of spatial weights matrix **W** (see e.g., Le Sage and Pace, 2009; Anselin and Rey, 2014), we are able to assess the impact attributable to each power of **W**. Spatial partitioning of impact estimates (direct, indirect and total) associated with the spatial weights matrices **W** of orders 0 to 6 for individual explanatory variables for both regimes are gathered in Table 3. Lines denoted by Σ indicate how much of the average direct, indirect and total impact, respectively we have accounted for using the orders 0 to 6 of **W**. As we can see, the direct impact corresponding the $\mathbf{W}^0$ equals to the adequate parameter estimate from SAR model, thus the difference between average direct impact and parameter estimate indicates the feedback effect. Concerning e.g., the explanatory variable ln GDP in regime 1, it means that the spatial partitioning of direct impact (orders 0 to 6 of **W**) explains 0.1478 of the 0.1481 direct impact. We can also see that direct spatially partitioned impacts disappear rapidly with increasing neighbourhoods, while indirect spatially partitioned impacts decline much more slowly. The statistical significance of all individual types of spatially partitioned impacts could serve as an indicator to which degree of the neighbourhood to examine the decomposition of impacts.

Conclusion and policy implications

This paper was aimed at the employment problem in the context of EU regions. We hypothesised that relationship between the employment rate and the explanatory variables (GDP per inhabitant, educational attainment level and compensation of employees) may vary spatially. At the same time, we assumed that the regional employment process is not isolated and that the neighbourhood of the regions also plays a significant role. Our empirical results indicated that both spatial effects (spatial autocorrelation and spatial heterogeneity) should not be avoided when the problem of regional employment is dealt with. Based on the initial spatial analysis of employment rate data, two spatial regimes were indicated (regime 1 – regions with lower level of employment and regime 2 – regions with higher level of employment). Consequently, these two regimes were handled and separate spatial econometric models (SAR) were estimated.

The empirical part of the paper brings interesting findings and might be helpful when regional employment policies are specified. Firstly, the results revealed the spatial instability of estimated parameters across regimes. Secondly, spatial interconnections within both regimes were also confirmed and due to this fact the main focus was on interpretation of average impacts (direct, indirect and total) and their spatial partitioning. Huge differences have arisen when magnitudes and mathematical character (indicating the direction) of individual parameters across regimes are discussed. Although the impact of GDP on the employment rate seems to be positive in both regimes, its magnitude is noticeably higher for the regime 1 in comparison to the regime 2. As for the compensation of employees, the results are even more interesting since both the magnitude and indicated direction differ across regimes. We suppose that the opposite directions could be caused by various reasons, such as structural factors of an economy, work force qualification or wage level. Our results related to regime 1 predict that higher level of compensation of employees would lead to lower employment. Regime 1 covers a larger number of less developed regions, such as the regions of southern Italy, part of the Greek, Spanish and Portuguese regions, as well as most of the regions of the post-socialist countries. In many of these regions, the share of low-paid workers (labour-intensive industries) is likely to be significant and therefore employment is expected to decline. In labour-intensive industries labour costs form a substantial proportion of total production costs and low-paid workers become expensive. The opposite situation was found for regime 2 (higher share of advanced regions) where industries other than labour-intensive industries are likely to dominate. Thus, employment may even increase as compensation for employees increases.

As the third determinant of employment, educational attainment level was considered. A higher level of education for the regions of both regimes appears to be a very important factor of employment. Once again, we see significant differences between the two regimes. In particular, the value of educational attainment level parameter in regime 2 is significantly higher. Regime 2 includes higher share of advanced regions and thus probably a higher proportion of knowledge intensive industries. For regime 2 regions, therefore, a highly educated workforce is a very important factor in increasing employment. The lower, but also positive impact of education on employment for regime 1 regions may have been partly explained by a previous discussion with regard to compensation of employees. The regions with a higher incidence of labour-intensive industries are unlikely to reap the benefits of a highly skilled workforce as effectively as advanced regions where the share of knowledge-intensive industries is higher.

Finally, beneficial findings can be gained from estimates of the spatial autoregressive parameter. Spatial regional links within both regimes appear to have a positive effect on employment levels. This external determinant in explaining regional employment should not be excluded from the regression equation. Similarly, as compared to all previous internal determinants, some differences in spatial processes between the two regimes were also revealed. The spatial interactions of regions belonging to the regime 1 regions appear to be stronger than in regime 2. This is also reflected in the 51% ratio of the average indirect impact to the total impact (36% for regime 2). Also, the statistical significance of spillover effects of some employment factors up to the fourth order of the neighbourhood (regime 1) outlines the high importance of spatial spillovers.

Overall, our analysis shows considerable spatial parameter instability and thus the resulting differences in the effects of individual employment determinants. This information might be very useful for the design and implementation of regional employment policies. Our results suggest that the instruments as well as the objectives of regional labour market policies should be more heterogeneous considering individual groups of regions. Based on the above discussion, we have seen, for example, that in the more developed regions, a very effective tool for enhancing employment is to increase the share of highly educated people. Although, this was partly the case in the first group of regions (regime 1), in this group of regions, it is probably necessary to focus initially on structural regional aspects and problems arising from the high incidence of labour-intensive industries.

For a long time, EU cohesion policy has focused on correcting disparities between countries and regions. Within the EU, place-based policies are already being implemented through several programs (e.g., Interreg) and this should be continued. Place-based policies refer to enhance the economic performance of specific areas, usually less developed areas – regions in order to improve their economic performance. However, such a policy can also be targeted at more developed regions, by encouraging their further development. For example, the development of existing business or innovation clusters makes it possible to spread these positive effects to the surrounding regions. Such a conclusion is also indicated by the results of our analysis, as the spatial spillover effects were verified.

This paper has tried to contribute to the empirical econometric modelling of regional employment. Simultaneous consideration of both spatial effects can be considered as the main virtue of this study. To the best of our knowledge, this, in connection with the problem of regional employment, is very rare approach. Nevertheless, certain shortcomings of the analysis and challenges for further research may be apparent. The regional employment modelling presents a comprehensive problem and to include all relevant determinants is very challenging. In this regard, we see further possible improvements of this analysis. In addition, the implementation of multiple local regressions at the regional level may bring other interesting findings and clarify even more the existing problem of spatial heterogeneity.

Declarations

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Conflicts of interest/Competing interests

There is no conflict of interest/Competing interests.

Availability of data and material

The data that support the findings of this study are openly available in the website of Eurostat (http://ec.europa.eu/eurostat/).

Code Availability

The computer program results are shared through the tables and figures presented in the manuscript.

Authors' Contributions

Michaela Chocholatá: Conceptualization, Methodology, Software, Formal analysis, Visualisation, Writing - Original Draft, Writing - Review & Editing.
Andrea Furková: Conceptualization, Methodology, Software, Formal analysis, Visualisation, Writing - Original Draft, Writing - Review & Editing.

NOTES

[1] The Cohesion Fund is aimed at member states whose Gross National Income (GNI) per inhabitant is less than 90 % of the EU average. It aims to reduce economic and social disparities and to promote sustainable development.

[2] We pay an attention to SAR model in relation to our application part of the paper.

[3] Island regions were excluded from the entire group of NUTS 2 regions (based on the NUTS 2016 regulation). Also, the region of Estonia was excluded due to the unavailability of part of the data (compensation of employees).

[4] Income of households in millions of Euro divided by the number of employees in thousands.

[5] Due to the number of NUTS 2 regions included in the analysis, we did not consider more than two regimes. If we assumed more than two regimes (divided based on the Jenks algorithm), some regimes might contain an insufficient number of regions for econometric estimation.

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