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Contact to corresponding author: michaela.chocholata@euba.sk, University of Economics in Bratislava, Faculty of Economic Informatics, Department of Operations Research and Econometrics, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia
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Michaela Chocholatá
University of Economics in Bratislava, Slovakia

Andrea Furková
University of Economics in Bratislava, Slovakia

The analysis of employment rates in the context of spatial connectivity of the EU regions

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Abstract
Research background: The main objective of this paper is to analyse the employment rates in the context of spatial connectivity of the EU regions. Employment rate is declared as one of the important indicators of the strategic document Europe 2020. The achievement of high levels of employment in individual regions plays therefore an important role.
Purpose of the article: The aim of the paper is to verify the possible spill-over effects within the EU regions and their territorial interconnection in the context of employment rates.
Methods: Analysis is based on tools of the Exploratory Spatial Data Analysis (ESDA) to consider spatial connectivity of the EU regions.
Findings & Value added: The results show that the statistically significant clusters of regions with high employment rates are situated mainly in the central, northern and north-western part of the EU while the clusters with low values are located mainly in Greece, Spain, Italy, Portugal, Bulgaria, Romania and some French regions.

Introduction

After the crisis, in 2010, Europe has adopted a strategy for smart, sustainable and inclusive growth — Europe 2020: Europe's growth strategy (European Commission, 2010; Balcerzak, 2015). Declaring five headline objectives (concerning employment, research and innovation, climate change and energy, education, and combating poverty) this strategic document helps to define where the European Union (EU) wants to be by 2020. It is worth mentioning that all the specified targets are mutually linked. Concerning the inclusive growth, a key issue is played by achieving a high levels of employment.

Analysing the labour market, especially the levels of unemployment across various regions has attracted researchers' attention for a long time. As pointed out e.g. by Perugini and Signorelli (2004), only recently researchers have started to prefer analysing the employment indicators. Numerous studies have been presented concerning the (un)employment performance in the various regions of the EU based on the use of different theoretical and empirical approaches.

During the last years, the analyses based on spatial approaches have played a significant role. From the recent studies dealing with the European regions following studies could be mentioned. Niebuhr (2003) analysed spatial interaction and regional unemployment in European countries during 1986–2000 based on measures of spatial autocorrelation and spatial econometric methods. She proved the high degree of spatial association among analysed European labour markets. Cracolici *et al.* (2009) investigated the spatial structure of provincial unemployment disparities of Italian provinces for the year 2003. Lottmann (2012) tried to explain the regional unemployment differences in Germany 1999–2007 based on spatial panel data analysis. Pietrzak and Balcerzak (2016) performed a spatial analysis of the impact of entrepreneurship and investment of the unemployment rate for the Polish sub-regions. Perugini and Signorelli (2004) analysed the regional employment and convergence of the European regions, Franzese and Hays (2005) dealt with the employment spill-overs in the EU using the spatial econometric models, and Monastiriotis (2007) dealt with the spatial association and its persistence for various socio-economic indicators in the case of Greek regions. Pavlyuk (2011) investigated the differences in employment rates in Latvian regions based on instruments of spatial analysis and spatial econometrics. Pagliacci (2014) analysed the regional performances with regard to Europe 2020 main objectives based on the Principal Component Analysis (PCA) and Exploratory Spatial Data Analysis (ESDA) confirming the large territorial imbalances across the EU–27. All these mentioned papers confirmed both the necessity to include the space dimension into the analysis and the existence of disparities across analysed regions.

The main objective of this paper is to investigate the significance of spatial linkages as well as the existence of the disparities for the employment rates (expressed in %) of population aged 15–64 across 252 NUTS 2 (Nomenclature of Units for Territorial Statistics) regions of EU countries based on ESDA including visualisation techniques via graphs, maps and calculations of two types of spatial autocorrelation indicators (Moran's *I* and Getis-Ord statistics).

After the brief introduction, the rest of this paper is organized as follows. The Section 2 deals with research methodology, Section 3 presents results, Section 4 contains discussion and Section 5 concludes.

Research methodology

This section of the paper provides a brief review of spatial statistical methods used in the empirical part of this study. In general, spatial association means that the values of a variable in nearby locations are more similar than values in locations that are far away. Spatial dependence in a data set imply that observations at location *i* depend on other observations at locations $j \neq i$ and formally it can be formulated as follows:

$$y_i = f\left(y_j\right), \quad j = 1, 2, \dots, N, \quad j \neq i \tag{1}$$

where *N* is the number of spatial units in the data set. If nearby observations (locations) are similar in variable values under the consideration, we can conclude that the overall pattern performs spatial autocorrelation, in this case a positive spatial autocorrelation. On the other hand, negative spatial autocorrelation is related to the situation when observations that are nearby tend to be different in variable values than observations that are far away. There is no spatial autocorrelation when variable values are not related to the location. A crucial step of spatial autocorrelation examination is the determination of nearby locations. Formally, spatial structure of observations is usually expressed in the form of $N \times N$ spatial weight matrix **W,** where each element w_{ij} represents the „spatial influence“ of location *j* on location *i*. The design of the matrix **W** usually follows a binary matrix idea or geographic, economic closeness measures, for example, physical distance or contiguity between locations can be used. Consequently, the relationship can have a binary form (1 — neighbour, 0 — not neighbour) or variable. In order to exclude "self-influence of the locations", diagonal elements of the spatial weight matrix are set to zero. Two common approaches to spatial weight matrix construction are weights based on boundaries and weights based on distance.

Spatial weights based on boundaries

The degree of spatial influence is very often determined by the shared boundaries of the locations. The most common spatial weights based on boundary principle are called spatial contiguity weights. Following chess notation, we distinguish weights referred to as the rook, the bishop and the queen contiguity case (for more details see e.g. Getis, 2010; Smith, 2014). Next, this spatial weights approach is presented in more details, because the queen contiguity weights were used in empirical part of our study.

The queen contiguity weights simply denote whether locations share a boundary or not. Two locations are considered to be neighbours in this case, if they share any part of a common boundaries. When the set of boundary points of location *i* is denoted as *bnd*(*i*), then the queen contiguity weights can be given as follows:

$$w_{ij} = \begin{cases} 1, & bnd(i) \cap bnd(j) \neq \emptyset \\ 0, & bnd(i) \cap bnd(j) = \emptyset \end{cases} \tag{2}$$

The consequent matrix based on this approach produces symmetric spatial weight matrix.

Spatial weights based on distance

If distance itself is a relevant criterion of spatial influence, the spatial weights based on the distance are appropriate. In this case, the spatial weight matrix construction requires the centroid (or central point distances) d_{ij} between each pair of spatial locations *i* and *j*. The family of methods based on distance contains radial distance weights, power distance weights, exponential distance weights or *k*–nearest neighbour weights (for more details see e.g. Getis, 2010; Smith, 2014). The option of distance metrics (e.g. Euclidian distance, Arc distance) is an important aspect of this approach. As the *k*–nearest neighbour weights are the second option in our empirical analysis, we briefly present corresponding important details.

In contrast to the queen contiguity case, the *k*–nearest neighbour weights approach is not resulting to symmetric matrix **W**. The procedure of the construction can be summarized as follows:

Let centroid (or central point) distances from each spatial location *i* to all units $j \neq i$ are ordered as: $d_{ij(1)} \leq d_{ij(2)} \leq \ldots \leq d_{ij(N-1)}$. Next, for each location $k = 1, \ldots, N-1$, the set $B_k(i) = \{j(1), j(2), \ldots j(k)\}$ includes the *k* closest locations to *i*. For given *k*, the *k*–nearest spatial neighbour weight matrix has spatial weights of the following form:

$$w_{ij} = \begin{cases} 1, & j \in B_k(i) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Usually spatial weights are normalized in order to create proportional weights. The most common standard approach is row normalized weights in which the rows of the matrix **W** are cumulated to unity.

Global and Local Measures of Spatial Autocorrelation

Spatial autocorrelation can be detected by global and local measures of spatial association, e.g. Moran's *I*, Geary's *C* or Getis-Ord statistics. Moran's *I* and Getis-Ord statistics are the basis of our employment spatial dependence analysis and this topic will be dealt with in next subsection.

Global and local statistics of spatial autocorrelation are a part of the ESDA. The tools of ESDA (see Haining, 2003; Bivand, 2010) enable gaining spatial pattern information in the given data. A detailed analysis of global and local spatial association can be done by statistical, graphical or mapping procedures. Global measures of spatial autocorrelation enable the users to test the global spatial autocorrelation of the variable they are interested in, i.e. to test for the presence of general spatial trends in the distribution of an underlying variable over a whole space. The term 'global' means that all components of the spatial weight matrix are considered in the calculation and it yields just one value of spatial autocorrelation statistic. Local indicators have been suggested to further analyse local spatial patterns, they assess the spatial autocorrelation association of the particular unit with its neighbouring areal units.

Global Moran's *I* statistic indicates the correlation between the underlying variable and so called spatial lag of this variable and it is formally given by the expression (Viton, 2010):

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2} \tag{4}$$

where x_i denotes the underlying variable value for location *i*, x_j denotes the underlying variable value for location *j*, $\overline{x}$ represents the mean of the variable, *N* is the number of spatial locations and w_{ij} are the components of spatial weight matrix which was discussed before. Spatial autocorrelation is considered to be present when the computed spatial autocorrelation statistic (4) takes a larger number in comparison to what we expect under the null hypothesis of no spatial autocorrelation, i.e. under the spatial randomness. The question is what can be considered to be significantly larger. The point of departure of the statistical testing is the distribution of the test statistic. One possibility is the random permutation test. According to this procedure, the calculated value of *I* is evaluated relative to the set of all possible values that could be obtained by randomly permuting the observations over the locations in the data set. The resulting empirical distribution function is the basis for the testing of statistical significance. A problematic issue of this testing approach can be the fact that Moran's *I* statistic must be calculated for *N*! permutations. Even in the case of small *N*, it can cause computing difficulties. Close approximation to the permutation distribution provides Monte Carlo approach where random sampling is based on a reasonable number of the permutations (for more details see, e.g. Fisher & Wang, 2011).

The value of Moran's *I* statistic approaching approximately zero indicates the absence of spatial autocorrelation, positive spatial autocorrelation (the statistic has a positive value) implies that similar values of observed variable tend to cluster over the space and negative spatial autocorrelation (negative value of statistic) implies that different values are clustered in the space.

During the past two decades, various local spatial autocorrelation statistics have been developed. As a local version of Moran's *I* statistic, LISA (Local Indicators of Spatial Association) has been proposed by Anselin (1995) to further analyse local spatial patterns. In this case, particular location *i* is fixed. The local Moran's I_i statistic for the location *i* is defined as (Feldkircher, 2006):

$$I_i = \frac{(x_i - \bar{x})}{\frac{1}{N}\sum_{k=1}^{N}(x_k - \bar{x})^2}\sum_{j=1}^{N} w_{ij}(x_j - \bar{x}) \tag{5}$$

where all variables were defined before. Each location has an associated test statistic and spatial pattern (spatial clustering) can be visualised by the Moran scatterplot and LISA cluster map. These graphical tools enable to detect which of the spatial unit has a statistically significant relationship with its neighbours, and show the type of relationship (*high-high* and *low-low* — positive spatial associations or *high-low, low-high* — negative spatial associations).

The local versions of family Getis-Ord statistics, $G_i(d)$ and $G_i^*(d)$ provide additional information of spatial association that may not be evident when using only global statistics. As well as in previous case, the statistic is calculated for each location. Getis and Ord (1992) defined $G_i(d)$ statistic as follows:

$$G_i(d) = \frac{\sum_{j=1}^{N} w_{ij}(d)x_j}{\sum_{j=1}^{N} x_j}, \quad j \neq i \tag{6}$$

where $\{w_{ij}(d)\}$ denotes a symmetric binary matrix **W**, ones for all relations defined as being within the distance *d* of a given location *i* and all other relations are set to zero (including the link of location *i* to itself). This statistic defined by formula (6) measures the degree of spatial dependence that stems from the concentration of weighted points and all other weighted points included within a radius of distance *d* from the original weighted point. Getis and Ord (1992) first focused on physical distances, but “distance” can be also interpreted as e.g. conceptual distance, travel time or other measures that make possible the *N* points to be located in a space. $G_i^*(d)$ statistic in contrast to $G_i(d)$ statistic, it contains also the value x_i itself and also neighbourhood values. In Ord and Getis (1995), the statistics $G_i(d)$ and $G_i^*(d)$ were modified in order to include variables that do not have a natural origin and the modification was done for non–binary weights as well.

Local Getis-Ord statistic can be viewed as an indicator of local clustering of similar values around particular location *i*. Positive values of statistic indicate clustering of high values (so called hot spots) and a negative value indicates a cluster of low values (so called cold spots).

The testing of statistical significance of local measures of spatial autocorrelation follow a similar idea as testing procedures of global measures. In order to yield pseudo significance levels, a conditional random permutation test can be used. The randomisation is conditional in terms of that the value x_i associated with observation *i* is fixed in the permutation and the remaining values are randomly permuted over the locations. The resulting empirical distribution is the base for statistical testing (for details see e.g. Fisher & Wang, 2011).

Results

The empirical part of this paper is based on the employment rates (expressed in %) of population aged 15-64 across 252 NUTS 2 regions of EU countries obtained from the web page of the statistical office of the European Union (Eurostat) over the 2010–2016 period (see http://ec.europa.eu/eurostat/data/browse-statistics-by-theme). In order to avoid the problem with isolated regions, the total number of 272 NUTS 2 regions had to be reduced, we excluded 20 regions of Cyprus, France, Finland, Greece, Italy, Malta, Portugal and Spain. The analysis was performed using free downloadable software for the geographic data analysis called GeoDa (https://geodacenter.asu.edu/software/downloads). The corresponding shapefile was retrieved from the web page of Eurostat (http://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units) and the set of analysed NUTS 2 regions was selected in GeoDa.

The development of the employment rates for the complete set of analysed regions is demonstrated in Figure 1, containing the box plot as well as the descriptive statistics of the analysed indicator during 2010–2016 period. The mean values did not change dramatically; the average employment rate firstly rose from 65.28% in 2010 to 65.30% in 2011 and the slow decline to 65.22% in 2012 was followed by moderate growth to 67.72% in 2016. However, there are huge differences across analysed regions spanning from minimum values of approx. 39%–40% to maximum of 78%–79 %. Furthermore, based on Figure 1, it is possible to identify 1 to 3 lower outliers (these correspond to regions in the southern part of Italy). Regarding the interquartile range (IQR) denoting the middle 50 % of the data, it can be concluded that it indicated the increasing variability of the employment rates in 2010–2013 followed by slowly decreasing variability of the analysed indicator.

Figure 2 illustrates the evolution of the countries' average employment rates 2010–2016 to see the performance of the indicator across the individual analysed EU countries. The lowest employment rates were identified for Greece, where the rates went down below the 50% in 2012–2015. The highest employment rates (above 70% during the whole analysed period) were in Austria, Germany, Denmark, Netherland and Sweden. Since in some countries the average employment rates remained almost constant (e.g. Austria, Belgium, Finland, France, Italy, Luxemburg, Romania), in other countries the rates went extremely up (e.g. Czech Republic, Estonia, Hungary, Lithuania, Latvia) and we can identify also countries with sharp downward trend followed by the rise of employment rates during the analysed period (e.g. Greece, Croatia, Ireland, Spain, Portugal and Slovenia).

To gain further information about the employment rate disparities across analysed regions, the natural breaks map and quantile map for 2016 were constructed[1] (Figure 3). Following the Jenks natural breaks algorithm, which considers four classes, we can identify 15 regions with low levels of employment rates located in southern parts of Spain, Italy and Greece. However, as it is shown in Figure 3 (left), there are 103 regions with high employment rates located mainly in the central, northern and north-western part of the EU. The quantile map (Figure 3 right) gives another insight into the employment rate distribution over space containing 4 classes with approx. equal number of regions. Based on both maps, one can identify huge differences in employment rates also inside the analysed countries, e.g. in Slovakia between the capital city region (Bratislavsky kraj) with the employment rate of 74.9% and the eastern region (Vychodne Slovensko) with only 59.1% of employed people.

As it is shown in Figure 3, the regions with similar employment rates tend to be located together. To assess the statistical significance (insignificance) of clustering, we can test for spatial autocorrelation. As it was mentioned above, two types of spatial weights were used to characterize spatial neighbourhoods — queen contiguity weights (2) and 8-nearest neighbour weights[2] (3). The values of the global Moran's I (4) during 2010–2016 based on both types of spatial weights are displayed in Figure 4. The global Moran's I values were higher in the case of queen contiguity weights (0.75–0.79) than for 8-nearest neighbour weights (0.61–0.71). Furthermore,

[1] Due to the limited space, the paper contains maps only for 2016, maps for the 2010–2015 period can be provided by the authors upon request.

[2] The calculation was based on arc distance metrics.

it is worth mentioning that the number of neighbours according to used weight matrices was different. We identified 1 to 11 neighbours for individual regions with the highest frequency of 5 neighbours (8 and more neighbours had only 13 regions) following the queen contiguity weights and the constant number of neighbours following the 8-nearest neighbour weights. The values of global Moran's *I* statistics in both cases were higher than the expected value $\mathrm{E}(\mathrm{I}) = -1/(N-1) = -0.0040$ which confirms the positive spatial autocorrelation[3]. It means that there is a statistically significant tendency of geographical clustering of regions with similarly high/low values.

LISA cluster maps of employment rate in 2016 (Figure 5) with regard to the local Moran's *I* statistics (5) statistically significant at 0.05 significance level, using both types of spatial weights mentioned above, enable to identify the statistically significant clusters. As it is shown in Figure 5, there is a large number of regions with the significant positive spatial autocorrelation identified, and only a small number of regions with the significant negative spatial autocorrelation. Concerning the regions with a negative spatial autocorrelation, the results based on different weight matrices are very similar. Regarding positive spatial autocorrelation, there are more expanded clusters with the 8-nearest neighbour weights. Regions with statistically significant positive spatial autocorrelation (64 regions of *high-high* type and 37 regions *low-low* type following the queen case contiguity; 94 regions of *high-high* type and 49 regions *low-low* type following the 8-nearest neighbour weights) denote the similar value of employment rate as their neighbouring regions. Regions with statistically significant negative spatial autocorrelation (1 region of *low-high* type and 3 regions *high-low* type following the queen case contiguity; 3 regions of *low-high* type and 4 regions *high-low* type following the 8-nearest neighbour weights) have the different level of employment rate in comparison to their neighbours.

Furthermore, based on both types of weights, we tried to find the clusters based on local Getis-Ord statistics (6) and to identify the statistically significant[4] hot spots and cold spots. The maps depicted in Figure 6 show that the hot spots and cold spots almost correspond to the regions with the positive autocorrelation of *high-high* type and *low-low* type from Figure 5, respectively.

[3] Randomization approach involving 999 permutations was used to prove the statistical significance of results.

[4] Randomization approach involving 999 permutations was used to prove the statistical significance of results.

One of the limitations of the local Getis-Ord statistics is that it is not able to detect the negative spatial autocorrelation. Literature in general recommends using both these statistics in the analysis of spatial autocorrelation in order to interpret the results correctly.

Discussion

The results of our research are in line with some other studies analysing the employment rates (Monastiriotis, 2007; Perugini & Signorelli, 2004; Pagliacci, 2014), confirming the large territorial disparities among analysed regions. We proved that the location plays an important role in assessment of employment rates level across the 252 NUTS 2 EU regions. Concerning the policy implications, it is not so unambiguous, since as pointed out e.g. by Monastiriotis (2007), one has to keep in mind that the spatial spill-overs concerning the employment do not need to link to similar processes based on other indicators, e.g. income (Chocholatá & Furková, 2017), tertiary educational attainment (Chocholatá, 2018) or patent applications at the European Patent Office (Furková, 2016). Although the dissimilarity in the spatial patterns across different indicators can present a limitation for policy makers to face complex problems through a properly chosen policy instruments, the results of the ESDA analysis for individual indicators (e.g. employment rate presented in this paper) can serve to some orientation for policy makers to apply more place-based policies (see e.g. Barca *et al*., 2012).

Our employment rate analysis was based on the selected ESDA tools and therefore the evidence concerning spatial regional interconnections was provided. A majority of studies does not exploit the advantages of the ESDA and the issues regarding spatial autocorrelation are neglected. From this point of view, our study can be considered to be a contribution to nowadays widely applied approaches of the employment rate analyses.

Conclusions

This paper presents the spatial analysis of one of the inclusive growth indicators — the employment rate — given as a percentage of population aged 15-64 among 252 NUTS 2 EU regions during 2010–2016. In order to investigate the influence of location on the employment rate, graphic visualisation (box graph, column graph) and ESDA tools were used. Application of these tools, as well as mapping of the values, showed the existence of disparities across the analysed regions. The analytical ESDA tools of global Moran's *I* statistic, local Moran's *I* statistic and local Getis-Ord statistic enabled to detect statistically significant clusters of regions with high employment rates situated especially in the central, northern and north-western part of the EU while the clusters with low values were located especially in Greece, Spain, Italy, Portugal, Bulgaria, Romania and some French regions. The results proved the significant impact of location on the employment rate in individual regions, and they can provide valuable information for both the EU policy makers and national authorities to support concrete regions in order to minimize the present disparities. Furthermore, it is important to mention that the existence of positive spatial autocorrelation indicates that the higher employment rates in one region will positively influence the employment rates in neighbouring regions. With regard to the presence of spatial spill-overs, Pagliacci (2014) and Barca *et al.* (2012) stress the importance of more place-based policies. It appears to be important for policy makers to concentrate on interventions that will address exactly the causes of disparities than just to rely on redistributing resources from wealthier regions to poorer ones (Monastiriotis, 2007). On the other hand, concerning the importance of the spatial linkages implied by the European integration, the supranational (EU) policymaking in this area plays a vital role (Franzese & Hays, 2005).

As we have already mentioned, ESDA analysis has confirmed our spatial autocorrelation assumption of the regional employment rates. The subject of our spatial analysis was the global indicator — employment rates (expressed in %) of population aged 15–64 across 252 NUTS 2 EU regions. This can be perceived as a certain limitation of our study, because more detailed insight into particular elements of employment rate would be useful. It would be appropriate to perform analogous spatial analysis separately for employment by sex, age, economic activity or educational attainment levels. Moreover, the choice of spatial units can be considered as a problematic issue of the analysis. The levels of administrative units play a crucial role as for the strength and impact of spatial spill-over effects. We have chosen the EU regions at NUTS 2 level rather than other territorial levels (e.g. national level) because these administrative units are defined by the European commission as the appropriate units for the evaluation of the regional convergence process. Of course, the information resulting from studies based on the e.g. NUTS 3 levels can also provide very useful information for regional policy makers.

Identified clusters based on the local Getis–Ord and Moran´*I* statistics also invoke a question concerning another important spatial aspect of the analysis — spatial heterogeneity. In the course of further research, we in-tend to focus on modelling the regional employment rate taking into account both spatial effects, spatial autocorrelation as well as spatial heterogeneity. The estimation of the spatial econometric models will be the base for the quantification and spatial decomposition of the employment rate spatial impacts. We suppose this topic will be the subject of our further research.

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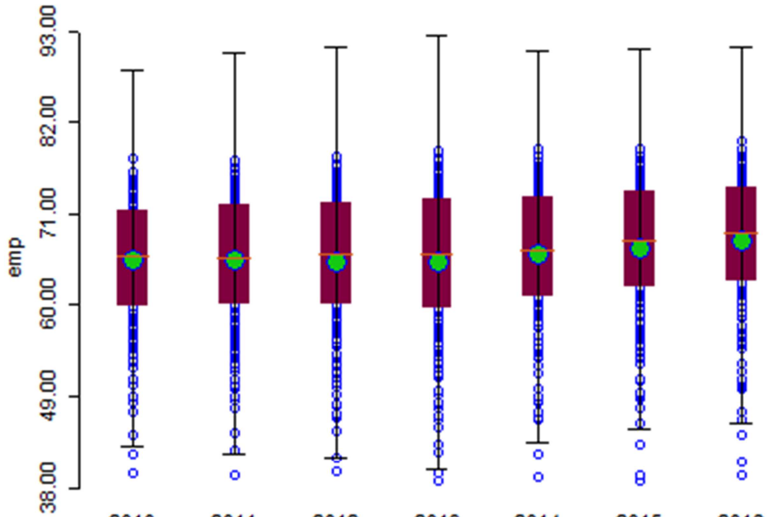
Annex

Figure 1. Box plot of employment rate



	2010	2011	2012	2013	2014	2015	2016
min	39.8000	39.4000	39.9000	38.9000	39.2000	38.9000	39.6000
max	77.7000	77.5000	77.8000	78.6000	78.9000	78.9000	79.7000
Q1	59.9500	60.1500	60.0500	59.7000	61.1000	62.1500	62.8000
median	65.6500	65.4000	65.9000	66.0000	66.5000	67.5500	68.6000
Q3	71.3000	72.2000	72.4000	72.7500	72.9000	73.6000	74.1000
IQR	11.3500	12.0500	12.3500	13.0500	11.8000	11.4500	11.3000
mean	65.2810	65.3011	65.2224	65.2601	66.0563	66.8043	67.7159
s.d.	7.1003	7.5991	8.0956	8.4673	8.2125	8.0501	7.8941

Figure 2. Performance of countries' average employment rates 2010–2016 in %

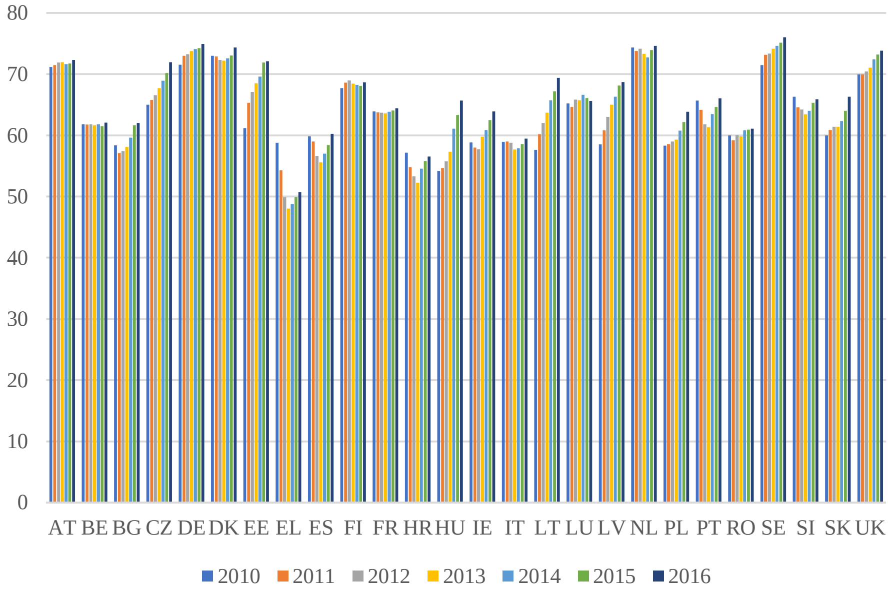


Figure 3. Natural breaks (left) and quantile (right) maps of employment rate in 2016

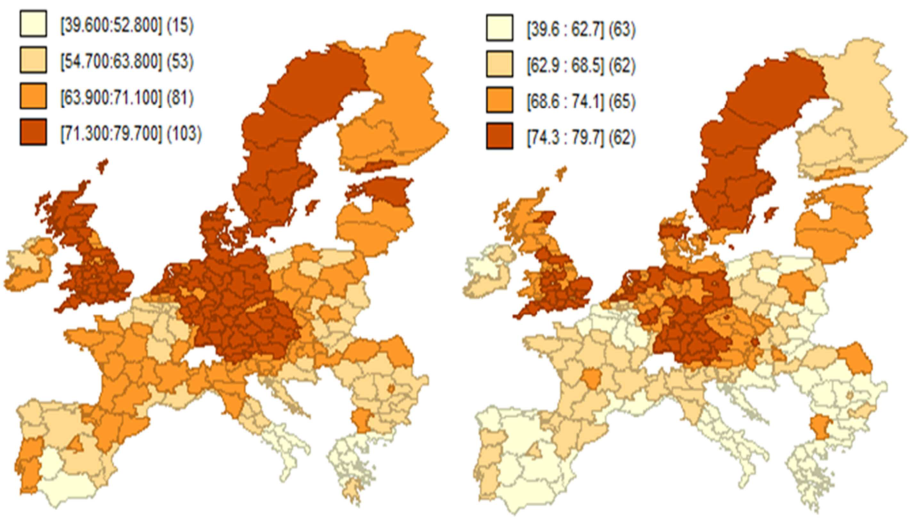


Figure 4. Moran's *I* statistics of employment rates 2010–2016

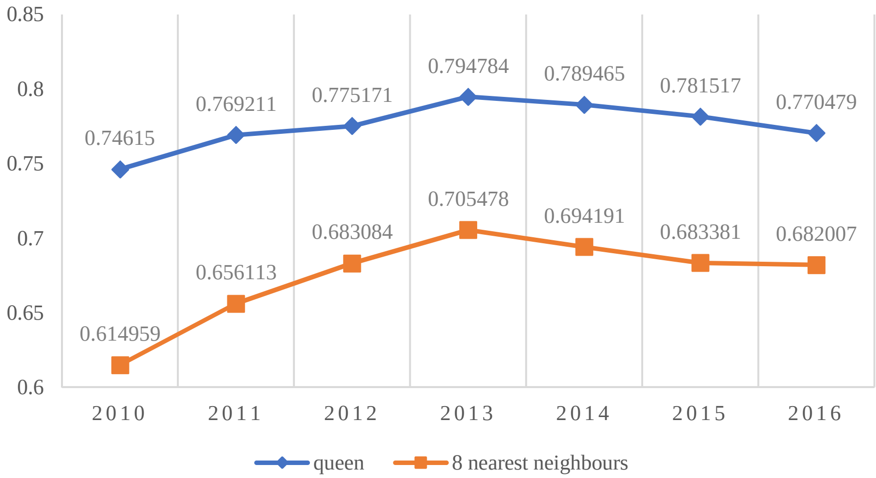


Figure 5. LISA cluster map of employment rate in 2016 — spatial weights: queen (left) and 8 — nearest neighbours (right)

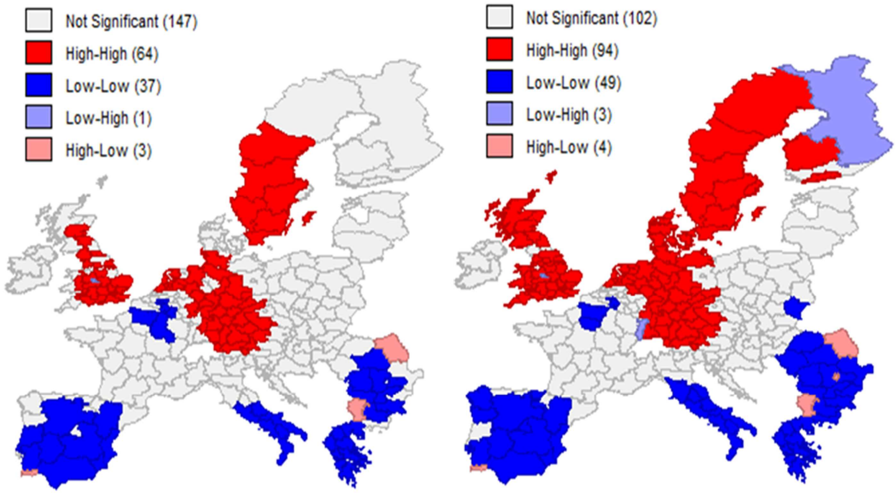


Figure 6. Local Getis-Ord cluster map of employment rate in 2016 — spatial weights: queen (left) and 8 — nearest neighbours (right)