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# The Application Of Local Indicators For Categorical Data (LICD) In The Spatial Analysis Of Economic Development

## Abstract

*The paper makes an attempt to apply local indicators for categorical data (LICD) in the spatial analysis of economic development. The first part discusses the tests which examine spatial autocorrelation for categorical data. The second part presents a two-stage empirical study covering 66 Polish NUTS 3 regions.*

*Firstly, we identify classes of regions presenting different economic development levels using taxonomic methods of multivariate data analysis. Secondly, we apply a join-count test to examine spatial dependencies between regions. It examines the tendency to form the spatial clusters. The global test indicates general spatial interactions between regions, while local tests give detailed results separately for each region.*

*The global test detects spatial clustering of economically poor regions but is statistically insignificant as regards well-developed regions. Thus, the local tests are also applied. They indicate the occurrence of five spatial clusters and three outliers in Poland. There are three clusters of wealth. Their development is based on a diffusion impact of regional economic centres. The areas of eastern*

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*and north western Poland include clusters of poverty. The first one is impeded by the presense of three indiviual growth centres, while the second one is out of range of diffusion influence of bigger agglomerations.*

***Keywords***: *join-count test, spatial dependence, local indicators of spatial association (LISA), exploratory spatial data analysis (ESDA), economic development, taxonomic analysis*

## 1. Introduction

The problem of spatial dependence is more and more frequently discussed within the framework of spatial economic research. This particular concept is of high importance since it indicates the occurrence of the intensity of certain phenomena depends on their spatial location. In case of the majority of socio-economic phenomena the existence of positive spatial dependence is their natural property.

This observation was presented in the form of Tobler's First Law of Geography according to which "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970). Failure to include the existence of spatial dependence in economic research can lead to cognitive errors (Paelinck and Klaassen 1979, Anselin 1988, Haining 2003, Arbia 2006, LeSage and Pace 2009).

The aim of the paper is to identify classes of regions presenting diversified economic development levels and to apply a join-count test to examine spatial dependences as regards these classes. The study covers the situations of 66 Polish NUTS 3 regions (sub-regions) in 2011. The regions were divided into two groups presenting relatively low or relatively high levels of economic development. Groups were distinguished using taxonomic methods of multivariate data analysis.

The paper is divided into two main sections. The first section discusses statistical tests of spatial autocorrelation, presents their classification as regards a frame of reference and also data type, and it also explains tests for qualitative data in detail. The second section covers an empirical study; it presents the distinguished classes of regions and discusses the results of global and local join-count tests.

## 2. Tests of spatial autocorrelation for categorical data

The function of spatial autocorrelation is most often applied in the identification of spatial dependence with reference to socio-economic phenomena. Statistical tests, examining the statistical significance of spatial autocorrelation, are commonly included among the tools of exploratory spatial data analysis (ESDA). Anselin distinguished global and local tests of spatial autocorrelation (Anselin 1995). Global tests examine total spatial autocorrelation between regions, while local tests refer to the situations of individual regions; identifing spatial clusters and also outlier regions. The results of the studies can support planning of the regional development policy and spatial management.

The most frequently applied global statistical test of spatial autocorrelation is Moran's I test (Cliff and Ord 1973, 1981), while Geary's C (1954) and Getis-Ord's G (Getis and Ord 1992) tests were also proposed. Some of these statistics are also available as local indicators of spatial association (LISA). They examine quantitative data set, e.g. values of Gross Domestic Product (see Kopczewska 2006, pp. 69-70, Suchecki (Ed.) 2010, pp. 112-115, Suchecka (Ed.) 2014, p. 41).

In the field of economic research, territorial units are often classified in regard to their social and economic situations to examine regional diversification. Multivariate data analysis methods are frequently used for these purposes. Revealed classes can be equivalent (e.g. the economic profiles of regions) or ranked (e.g. the good, moderate or poor situations of regional labour markets). These classes as regards statistical measurement scales are realizations of non-metric variables such as, accordingly, nominal and ordinal variables (see Walesiak 1993). In this situation, a set of territorial units is described by qualitative (categorical) data.

In terms of qualitative data the measurement of spatial dependence in the global perspective, it is possible to follow the join-count test application (Cliff and Ord 1973, 1981, see also Kopczewska 2006, pp. 83-84, Suchecki (Ed.) 2010, pp. 110-112, Pietrzak et al. 2014). A local variant of the measure represents a family of local indicators for categorical data (LICD) (Boots 2003).

The values of the global test are determined jointly for all regions and the statistical properties of the test are well known (Cliff and Ord 1973, 1981). One of the most important issues while using a join-count test is to select the type of an adjacency matrix. This significantly affects the analysis results. A contiguity matrix is most frequently used, while other approaches can be, for example, based on applying the *k*-nearest neighbours method.

Let assume that "white" (W) means a relatively poor economic situation, while "black" (B) – a relatively good economic situation of a region. In the case of a two-colour map, the idea of join-count statistics consists in counting the white-white (WW), white-black (WB) and black-black (BB) types of neighbourhoods (Cliff and Ord 1973, 1981):

$$BB = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_i x_j \tag{1}$$

$$WW = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(1-x_i)(1-x_j) \tag{2}$$

$$BW = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - x_j)^2 \tag{3}$$

where: $x_i$, $x_j$ take the value of 1 for a region belonging to the black class (B) and the value of 0 for a region belonging to the white class (W), $w_{ij}$ – an element of an adjacency matrix.

In case of positive spatial autocorrelation occurrences the neighbourhood of units marked by the same colour should be the dominating one over the neighbourhood of units having different colours. Otherwise, a negative correlation can be adopted. If "one-colour" neighbourhoods are not dominant over the "two-colour" ones, it indicates the random distribution of a variable.

While examining statistical properties of join-count test, one of two following assumptions regarding a binary non-metric variable is assumed. The first one assumes that each territorial unit is assigned by realizations of a random variable of Bernoulli distribution $b(p), p \in (0,1)$, where p is the probability of occurring 1, similarly like in sampling with replacement. The second one assumes that the random variable records in each localization, the value 1 or zero with equal probability (similarly like in sampling without replacement).

For both assumptions, it was proved that BB and BW statistics demonstrate asymptotic normal distributions (Cliff and Ord 1973, 1981). In the test standardized BB and BW statistics are used:

$$Z_{BB} = \frac{BB - E(BB)}{\sqrt{Var(BB)}}, \quad Z_{BW} = \frac{BW - E(BW)}{\sqrt{Var(BW)}}. \tag{4}$$

A determination of the values of $Z_{BB}$ and $Z_{BW}$ statistics requires knowledge of the moments of their distributions which differ according to the sampling method. In sampling with replacement, distribution moments of BB statistics are given in (5), while for BW in (6) (Cliff, Ord 1973).

$$E(BB) = \frac{1}{2} p^2 S_0,$$
$$Var(BB) = \frac{1}{4}\left[p^2 S_1 + p^3 (S_2 - 2S_1) + p^4 (S_1 - S_2)\right] \tag{5}$$

$$E(BB) = \frac{1}{2} p(1-p) S_0,$$
$$Var(BB) = \frac{1}{4}\left[p(1-p)S_2 + 4p^2(1-p)^2 (S_2 - 2S_1)\right] \tag{6}$$

where:

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij},$$
$$S_1 = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} (w_{ij} + w_{ji})^2,$$
$$S_2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\right)^2.$$

While sampling without replacement, the procedure is much more complicated (see Cliff and Ord 1973, pp. 5-6). The hypothesis regarding the lack of statistical significance of spatial autocorrelation is rejected, if the value of the $Z_{BW}$ statistics is located in left-hand rejected area or the value of $Z_{BB}$ statistics is located in right-hand rejected area.

A different way of testing thehypothesis of the lack of spatial autocorrelation is proposed in permuation approach. An a priori given number of colour permutations on the map is performed. Then for each permutation, the values of the BB and BW statistics are calculated. In the next steps an empirical distribution of both statistics is determined using so-called pseudo-levels of significance:

$$p_{BB} = \frac{\#\left(BB_{perm} \geq BB_{obs}\right) - 1}{k+1},$$
$$p_{BW} = \frac{\#\left(BW_{perm} \geq BW_{obs}\right) - 1}{k+1}, \qquad (7)$$

where $BB_{obs}$ and $BW_{obs}$ mean the values of statistics for real spatial arrangement of colours, while $BB_{perm}$ oraz $BW_{perm}$ mean the values for permutation arrangements ($k$ – the number of permutations).

These three statistics (BB, WW, BW) can be also used for testing the local dependencies (in relation to each single unit). However, using local tests is more difficult than using a global test. The first issue is that the neigbourhood matrix is determined separately for each region, using, for example, the contiguity matrix or k-nearest neighbours matrix. The second problem is that the statistical properties of the local test are unknown. Thus, the significance of spatial dependencies can not be statistically validated.

## 3. Classes of regions presenting different levels of economic development

Comparative studies examining situations of regions and territorial diversification frequently use taxonomic methods proposed in the field of multivariate data analysis (see e.g Chojnicki and Czyż 1973, Grabiński, Wydymus and Zeliaś 1989, Strahl (Ed.) 2006). The first group of these methods tends to distinguish internally homogenous and externally separable classes of units. This is the domain of cluster analysis (Hair et al. 2006, Everitt and Dunn 2001, Florek et al. 1951, Kolenda 2006, pp. 74-109). This approach is useful, among others, in the situation when the purpose of the study is to identify clusters featuring, for example, a similar job market structure, a similar economic profile, etc. (see e.g. Markowska 2012, Strahl (Ed.) 2006).

**Figure 1. The 16 Polish NUTS 2 regions (dark bold line) divided into 66 NUTS 3 regions (grey line)**


Source: http://stat.gov.pl/statystyka-regionalna/jednostki-terytorialne/nomenklatura-nts/nts-3-3559/.

The second group covers methods used to arrange the units in accordance with a superior criterion. These methods determine the positions of units in comparison to the other units. International literature most frequently indicates factor analysis in the field (Hair et al. 2006, Everitt and Dunn 2001). Polish literature proposes a family of linear arrangement methods (see e.g. Hellwig 1968, Grabiński 1984, Pluta 1976). One of the extensions of this concept is the TOPSIS method (Technique for Order of Preference by Similarity to Ideal Solution) proposed by Hwang and Yoon (1981) with further developments by Yoon (1987), Hwang, Lai and Liu (1993).

The second approach will be applied in the following study. The purpose of the research is to examine regional diversification of the economic development level in Poland in 2011. The study covers the situation of 66 Polish NUTS 3 regions, located in 16 NUTS 2 regions (Figure 1).

Economic development refers to the production level, economic growth, entrepreneurship, as well as the willingness to invest, and also the situation in regional job markets. The intention of the authors was to construct a set of variables which account for all the issues. In the first step the statistical data availability was examined. The set of variables also had to meet the following application criteria: comparability, clear definition of the research problem, measurability and usefulness in the description of phenomena for NUTS 3 regions, and also formal criteria: relatively high statistical variation and low statistical correlation. Table 1 presents the final set of diagnostic variables.

**Table 1. The set of diagnostic variables**

| No | Name of variable | Unit |
|---|---|---|
| 1 | *Per capita* Gross Domestic Product | PLN |
| 2 | National economy entities included in the REGON register per 10,000 inhabitants | Entity |
| 3 | *Per capita* investment outlays in enterprises | PLN |
| 4 | Average monthly gross salaries and wages | PLN |
| 5 | Registered unemployment rate | % |

Source: Authors' own elaboration.

In the next step, the TOPSIS method was applied to examine the development levels of Polish NUTS 3 regions. One of the main advantages of this method is comparing the situations of units to a positive ideal pattern as well as a negative ideal pattern (see Łuczak and Wysocki 2011, Wysocki 2010).

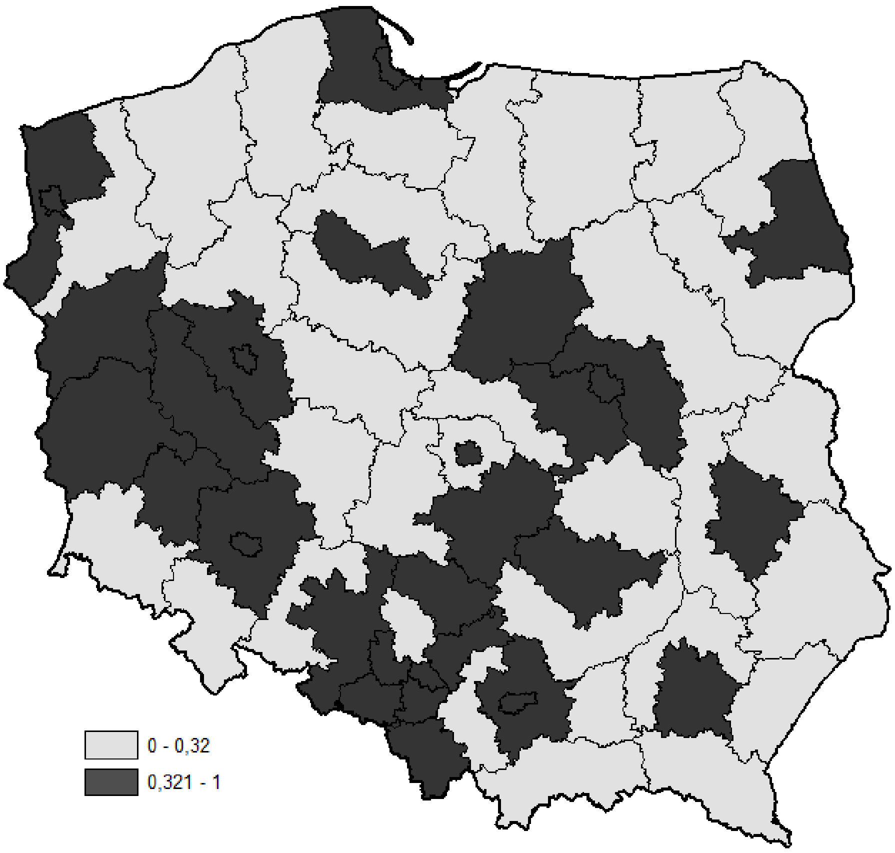
There were proposed a few ways of defining features of pattern-object, depending on the aim of the research and emipirical knowledge (see e.g. Hellwig 1968, Pluta 1976). In the presented study the positive ideal pattern takes the form of an artificial object which represents the highest real reached values of variables having a positive impact (stimulants) and the lowest real reached values of variables having a negative impact (destimulants). The negative ideal pattern is calculated inversely. The majority of selected variables indicate stimulants of economic development. Only unemployment depicts structural or economic difficulties with regional labour market.

Next, the data was normalized using unitization with zero minimum. After normalization the variables take values in the range [0.0, 1.0]. Then the values of variables with negative impact (registered unemployment rate) were translated into variables exerting a positive impact by subtracting the value of 1.

Following the above, Euclidean distances between each region (*i*th region) and the positive ideal pattern (*PIP*) and also between each region (*i*th region) and the negative ideal pattern (*NIP*), were calculated. Then the values of the synthetic measure for each region ($SM_i$) were calculated (Hwang and Yoon 1981):

$$SM_i = \frac{NIP_i}{NIP_i + PIP_i} \tag{8}$$

**Figure 2. Two classes of NUTS 3 Polish regions presenting different levels of economic development**




Source: Authors' own elaboration on the basis of data provided by Local Data Bank of the Central Statistical Office of Poland (BDL GUS).

The synthetic measure takes its values in the range of [0.0, 1.0], where 1 is determined for a region presenting the most favourable values of variables, while 0 is presented by a region with the most unfavourable values. The highest value (0.998) was recorded for the city of Warsaw (the Mazowieckie NUTS 2 region); the capital city of Poland. The second position was taken by the city of Poznań (0.703) located in the Wielkopolskie NUTS 2 region. The rest of regions took values in the range [0.654, 0.182]. The lowest value was recorded for Ełcki region, located in the Warmińsko-Mazurskie NUTS 2 region.

In the next step, on the basis of recorded values of the synthetic measure, regions were assigned to classes presenting different levels of economic development. Division criteria were presented in Nowak (1990, pp. 95-102). In the following study, due to the occurrence of the outlier value recorded by the city of Warsaw, the median value was used to distinguish classes of regions. Figure 2 presents the classification of NUTS 3 regions. The first class identifies a relatively low level (white colour), while the second class refers to a relatively high level of economic development (black colour).

There are visible clusters characterized by the low level of economic development, e.g. in the northern Poland (apart from Trójmiejski and its surrounding Gdański NUTS 3 region). Clusters featuring a relatively high level of economic development, in western Poland, southern Poland and also central Poland are also observed. Additionally, we can notice outlier well-developed regions, e.g. Białostocki and Lubelski sub-regions in eastern Poland.

## 4. The global join-count test in examining spatial dependence

The application of the join-count test will verify conclusions made in the previous section which were based on the visual analysis of the regional diversification of economic development levels in Poland. Table 2 presents the analysis results.

**Table 2. Global join-count test results**

| Type of tested relation | Statistics | Expected value | Variance | Z-value |
|---|---|---|---|---|
| WW | 10.4591 | 8.1230 | 0.6968 | 2.798 |
| BB | 8.8863 | 8.1230 | 0.6968 | 0.914 |
| BW | 13.6545 | 16.7538 | 2.0044 | –2.189 |

Source: Authors’ own calculation using spdep package (Bivand et al. 2014) of R-CRAN.

The results of join-count test are not obvious in both cases, i.e. examining of black-to-black and white-to-white relations. The test proved the occurrence of a positive spatial dependence in case of regions displaying a low level of socio-economic development. Therefore, regions featuring a low development level show a tendency towards spatial clustering.

Spatial clustering of poor regions can indicate that these regions present a slow, however, ongoing withdrawal of resources such as enterprises, human capital, etc. It results in the advancing deterioration of the situation in the regions grouped in such a spatial cluster. It also brings about the expansion of spatial cluster boundaries to more regions featuring a low development level. This situation is difficult to change and, additionally, it will probably keep advancing by further decrease in the level of development compared to well developed regions.

The results of the join-count test for black-to-black relation are not obvious. Contrary to visual assessment of the result of the taxonomic analysis presented in Figure 2, the join-count test results indicate insignificant spatial dependence for regions characterized by a relatively high development level. The global test shows an overall situation and can be affected by outlier regions. The study needs to be supplemented by a detailed analysis of spatial dependence.

## 5. The application of local join-count tests in examining spatial clusters

Specifying the value of local indicators for categorical data (LICD) seems to be a natural complement of the results of the global join-count test. It can become a tool for spatial cluster identification, especially in the situation when the global join-count test indicates the statistical insignificance of spatial dependence.

In the first step the contiguity matrices were determined for each region. Furthermore, 25% of regions showing the highest values of BB and WW statistics (Equations 1-2) were selected. It was assumed that for these regions there is the highest possibility of occurrence of local positive spatial dependencies.

On the basis of local join-count test statistics, five types of regions were distinguished. Figure 3 shows the analysis results. The A-type areas include the NUTS 3 regions that had the highest values of WW statistics, while the B-type areas recorded the lowest values of WW statistics. The C-type areas cover the NUTS 3 regions with the highest values of BB statistics, while the D-type areas had the lowest values of BB statistics. The E-type areas show high values of BW statistics. The white areas display statistical insignificance of BB, WW and BW statistics.

The test results revealed five spatial clusters showing different economic and spatial relations between NUTS 3 regions. The largest cluster consists of A-type NUTS 3 regions located in the eastern Poland and B-type regions. This cluster includes NUTS 3 regions of eastern, south eastern and also north eastern Poland of A-type and their B-type neighbours. This cluster comprises almost

25% of the country's total area and approximately 20% of the total population. It represents an area with the highest share of the agricultural sector in relation to other parts of Poland. The Podkarpackie, Lubelskie, Podlaskie and Świętokrzyskie NUTS 2 regions also belong to the poorest regions within the European Union. Their per capita GDP is much below the national average, while the unemployment rate is much above the national average.

The second spatial cluster was formed in north western Poland. The Koszaliński NUTS 3 region of A-type establishes the core of this cluster and its surrounding regions of B-type determine the spatial borders of this cluster.

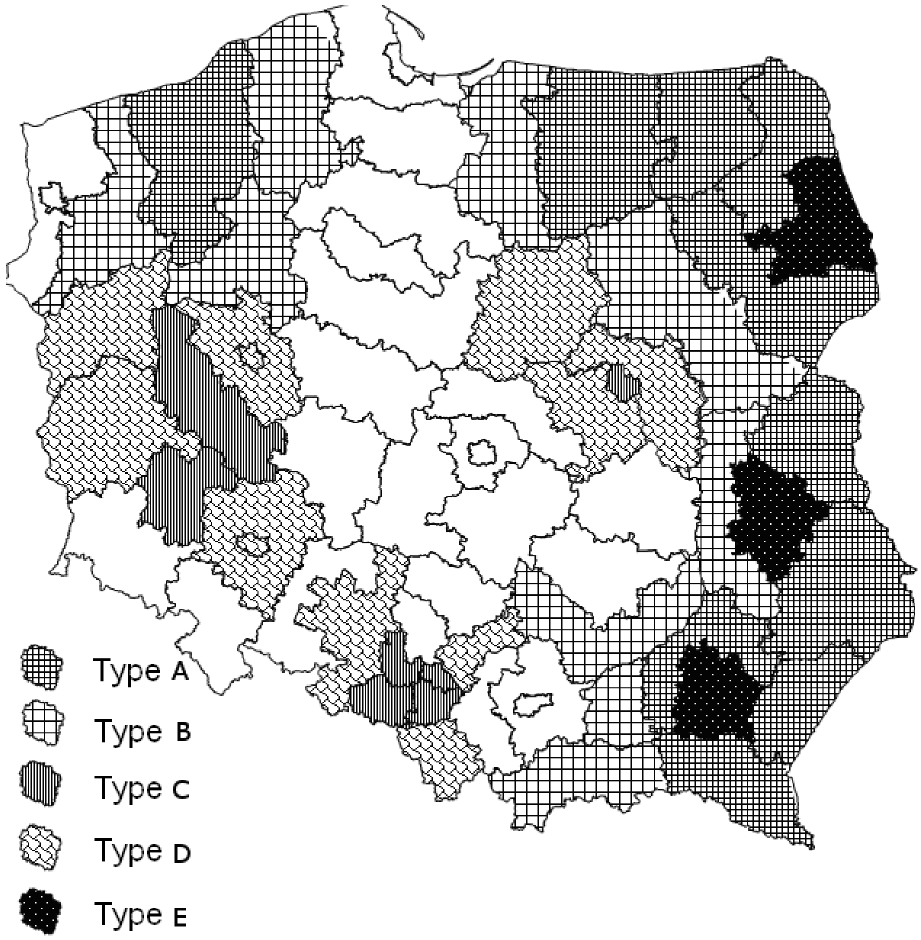
The next three spatial clusters display high economic development. Each of them consists of a well developed NUTS 3 region (or regions) of C-type with neighbouring D-type regions. The strongest economically is the spatial cluster located in central Poland with the core of the city of Warsaw. This cluster includes a greater part of the Mazowieckie NTS 2 region.

The second spatial cluster covers the most industrialized area of Poland. This cluster is formed by selected NUTS 3 regions of the Opolskie and Śląskie NUTS 2 regions. The third, and also the biggest spatial cluster includes NUTS 3 regions located in the middle of western Poland. The cluster covers the area of the Lubuskie and also a part of the Wielskopolskie and Dolnośląskie NUTS 2 regions.

The E-type areas such as the Białostocki, Lubelski and Rzeszowski NUTS 3 regions show a relatively good economic development level. All of them are located in the eastern Poland, within economically poor NUTS 3 regions. They can be defined as outliers due to their negative spatial dependences with reference to their neighbouring regions.

They establish local growth centres and are unable to form economic clusters. They do not constitute economic support for their neighbouring regions and negatively affect their situations. Outliers contribute to draining neighbouring regions due to the fact that they are a place of concentration of investment outlays and one-way flows of well qualified human resources, etc. This leads to the deterioration of situations of the other regions forming the eastern spatial cluster.

**Figure 3. Local join-count tests results – five types of regions according to economic development levels and spatial dependences**




Source: Authors' own elaboration.

## 6. Conclusions

The paper made an attempt to apply a join-count test to the analysis of spatial dependences between classes of regions displaying different economic development levels. Two approaches were included in the study. The first one examined the overall spatial interactions, while the second one concerned the particular situations of regions.

The global join-count test indicated statistically significant spatial dependence exclusively for NUTS 3 regions featuring a low level of economic development. In case of NUTS 3 regions showing relatively high development levels, the test indicated the statistical insignificance of spatial dependence.

The results pointed out the strengths and weaknesses of the global join-count test. It shows an overall situation in spatial clustering. The presence of outliers, i.e. extremely well or poorly developed regions which display statistical significance of spatial dependence of BW statistics, can significantly influence the test results.

Local join-count test facilitates more extensive analysis of the studied issue. The application of local indicators of spatial association (LISA) can indicate convergence processes, regions exceptionally exposed to poverty, processes of forming metropolitan areas etc.

The results of local join-count tests indicated the occurrence of five spatial clusters in Poland. Two of them can be seen as areas of poverty, while three of them can be classified as clusters of wealth. These clusters cover the industrialized area of southern Poland and also two areas presenting the best developed service sector in Poland. These clusters can develop due to the diffusion of innovations and other support given by regional economic centres.

The widest area is covered by regions which form clusters of poverty. The biggest one is located in the eastern Poland and spreads from the Elbląski to Nowosądecki NUTS 3 region. The majority of its regions have a poor economic situation which is also impeded by three local growth centres which take over the potential and current sources of development. These centres contribute to economic disparities in eastern Poland. The second poverty cluster covers regions located in north western Poland. This area is out of range of diffusion influence of the cities of Szczecin and the Trójmiejski NUTS 3 region.

This preliminary study can be a starting point for further research. One of the difficulties in using local join-count tests is that their statistical properties are unknown and their results cannot be validated. The second issue is considering the situations of Polish regions without reference to neighbouring foreign regions. There are macro-regions, e.g. Nysa Euro-region consisted of neighbouring regions of Poland, Germany and Czech Republic, in which cross-border cooperation exists and strong spatial relations occur. The third problem is to determine the number of related units for which the local join-count test is applied. In the study, the k-nearest neighbour method was applied. But this method can pose problems when considering regions located near the country borders.

The last problem concerns the level of territorial division, type of territorial units and their internal structure. NUTS 3 regions were analyzed in the study due to statistical data availability of the main economic statistics, e.g.

GDP, investment outlays etc. But NUTS 3 regions are territorial units established for statistical purposes, they are not administrative units. In Poland, they usually cover a few neighbouring districts located in the territory of the same province. Thus, a NUTS 3 region is usually not economically homogeneous because each of its districts realizes its individual economic development plan. The development levels and directions, and progress rates can significantly differ within the NUTS 3 unit. The second type of NUTS 3 regions covers administrative units which function independently and, in Poland, include the biggest agglomerations. Comparing different units showing different internal structures affects the analysis results, "a 5-ton elephant is not equal to 5 tons of ants". In all the situations, additional theoretical, empirical, and simulation studies are recommended.

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## Streszczenie

## ZASTOSOWANIE LOKALNYCH WSKAŹNIKÓW DLA DANYCH JAKOŚCIOWYCH (LICD) W PRZESTRZENNEJ ANALIZIE ROZWOJU GOSPODARCZEGO

*W artykule podjęto próbę zastosowania lokalnych wskaźników dla danych jakościowych (LICD) w przestrzennej analizie rozwoju gospodarczego. W pierwszej części omówiono testy służące do badania autokorelacji przestrzennej na podstawie danych jakościowych. W drugiej części zaprezentowano dwu etapowe badanie empiryczne obejmujące 66 polskich regionów klasy NUTS 3.*

*Najpierw zidentyfikowano klasy regionów prezentujące różny poziom rozwoju gospodarczego, z wykorzystaniem taksonomicznych metod wielowymiarowej analizy statystycznej. Następnie zastosowano test join-count w celu określenia przestrzennych zależności między regionami. Bada on tendencje do tworzenia się klastrow przestrzennych. Test globalny wskazuje ogólne interakcje przestrzenne między regionami, natomiast testy lokalne dają szczegółowe wyniki w odniesieniu do poszczególnych regionów.*

*Globalny test join-count ujawnił przestrzenne grupowanie się regionów o niskim poziomie rozwoju gospodarczego, nie potwierdził jednak zależności przestrzennych w odniesieniu do regionów dobrze rozwiniętych. Z tego względu badanie uzupełniono o zastosowanie lokalnego testu join-count. Ujawnił on występowanie pięciu klastrów* *przestrzennych i trzech regionów odstających. Zidentyfikowane zostały trzy klastry bogactwa. Ich rozwój bazuje na dyfuzyjnym oddziaływaniu regionalnych centrów wzrostu. Obszar Polski wschodniej oraz pólncno-zachodniej zajmują klastry biedy. Sytuacja pierwszego z nich jest pogarszana przez trzy indywidualne centra wzrostu, natomiast drugi klaster znajduje się poza zasięgiem dyfuzyjnego wpływu większych aglomeracji.*

***Słowa kluczowe****: test join-count, zależność przestrzenna, lokalne wskaźniki zależności przestrzennych (LISA), eksploracyjna analiza danych przestrzennych (ESDA), rozwój gospodarczy, analiza taksonomiczna*