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Introduction

On September 21-22, 2015, 6th International Scientific Conference "Quality of Life 2015. Human and Ecosystems Well-being" was held in Wrocław.

The conference was a part of the cycle of the conferences on the topic of quality of life that have been organized by the Department of Statistics (Wrocław University of Economics) since 1999. The aim of the cycle is to participate in the still rising all over the word wave of scientific studies on quality of life: ethical background and definitions of quality of life, investigating (how to measure it), presenting the results of differences of quality of life over time and space, its interdependences with natural environment, mathematical methods useful for the methodology of measuring quality of life and finally – possible methods of improving it. The conferences are meant to integrate the Polish scientific community doing research on these topics as well as to make contacts with foreign scientists.

This year our honorary guest was Professor Filomena Maggino, past President of International Society for Quality-of-Life Studies (ISQOLS), who presented a plenary lecture.

We hosted about 30 participants, among them scientists from Spain, Romania, Italy and Japan. We had 24 lectures on such a variety of topics as carbon footprint and mathematical properties of some estimators. The common background of all of them was to better comprehend, measure and possibly to improve the quality of humans' life.

The present volume contains the extended versions of some selected lectures presented during the conference. We wish to thank all of the participants of the conference for co-creating very inspiring character of this meeting, stimulating productive discussions and resulting in some potentially fruitful cooperation over new research problems. We wish also to thank the authors for their prolonged cooperation in preparing this volume, the reviewers for their hard work and for many valuable, although anonymous, suggestions that helped some of us to improve their works.

Finally, we wish to thank the members of the Editorial Office of Wrocław University of Economics for their hard work while preparing the edition of this volume, continuous kindness and helpfulness exceeding their duties of the job.

Katarzyna Ostasiewicz

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CLUSTERS OF POVERTY IN POLAND

KLASTRY UBÓSTWA POLSCE

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Summary: The main objective of this paper is to study spatial autocorrelation of poverty in Poland using the synthetic measure. The analysis will be conducted on the level of subregions. Spatial analysis of the data has allowed to evaluate the overall similarity of subregions in Poland in the field of poverty. There were separated groups of similar subregions and subregions differing from neighboring subregions. There were used global and local Moran statistics and traditional method without using information regarding localization of the synthetic measure.

Keywords: global statistic, local statistic, poverty, subregions, Poland.

Streszczenie: Głównym celem artykułu jest analiza przestrzennej autokorelacji ubóstwa w Polsce z użyciem miary syntetycznej. Analiza jest przeprowadzana na poziomie podregionów. Analiza przestrzenna pozwoliła ocenić ogólne podobieństwo podregionów w Polsce ze względu na poziom ubóstwa w Polsce. Wyróżniono grupy podobnych podregionów i regionów różniących się od sąsiadów. W analizie zastosowano globalną i lokalną statystykę Morana oraz tradycyjną metodę, nie wykorzystującą informacji o lokalizacji zmiennej syntetycznej.

Słowa kluczowe: statystyka globalna, statystyka lokalna, ubóstwo, podregiony, Polska.

1. Introduction

Poverty is a phenomenon threatening households in whole Poland. However, this phenomenon is spatially differentiated by regions, voivodeships, subregions and even smaller territorial units. Poverty may be described by several variables concerning, inter alia, range and intensity of this phenomenon. In this situation, to describe the phenomenon a synthetic measure may be used. The main objective of this paper is to study spatial autocorrelation of poverty in Poland using the synthetic measure. The analysis will be conducted by subregions. Spatial analysis of the data will allow to evaluate the overall similarity of subregions in Poland in the field of poverty. Spatial autocorrelation can be considered as an indicator of clustering.

There will be separated clusters of similar subregions and subregions differing from neighboring subregions. There will be used global and local Moran statistics to achieve the aim of this paper. The results will be compared with results obtained using the traditional method, which means without using information regarding localization of the synthetic measure.

2. Data and methods

The analysis of poverty by subregions in Poland was based on data from *Social Diagnosis* [Social Monitoring Council 2013]. In the database there were included 12355 households divided into 66 subregions[1].

Poverty is a phenomenon studied in many ways. The problem appears at the beginning and is connected with defining poverty. All definitions can be fit into one of the following categories [Hagenaars, de Vos 1988]:

a) poverty is having less than an objectively defined, absolute minimum,

b) poverty is having less than others in society,

c) poverty is feeling you do not have enough to get along.

According to the first category of definitions, poverty is absolute, according to the second category – is relative and according to the third category may be absolute or relative, or somewhere in between. Another difference between the categories is that the third category defines poverty subjectively, while the first and second define poverty to be an objective situation.

The choice of certain poverty definition implies a certain way of poverty measurement, i.e. we have several choice possibilities of the poverty threshold, equivalence scales etc. The description of poverty methodology is available in foreign [Hagenaars, van Praag 1985; Atkinson et al. 2002] and Polish literature [Panek 2011].

Poverty may be described by several variables. The most popular measures used in poverty studies are headcount ratio (also known as at-risk-of-poverty rate) and the median poverty gap ratio among the poor (also known as relative median at-risk-of-poverty gap). At-risk-of-poverty rate measures the share of individuals (persons, households or families) with income below poverty threshold and relative median at-risk-of-poverty gap measures the difference between the median income of the poor individuals and the poverty threshold, expressed as a percentage of this threshold [*Laeken indicators*… 2003].

Poverty is connected with income inequality: the greater the inequality, the more poor individuals. For this reason, inequality measures are taken into account in the poverty study. Often used measures are Gini coefficient and income quintile share ratio. The Gini coefficient is defined as the relationship of cumulative shares of the population arranged according to the level of equivalised disposable income,

[1] There have been 72 subregions since January 1st, 2015.

to the cumulative share of the equivalised total disposable income received by them. The income quintile share ratio is defined as the ratio of total income received by the 20% of the population with the highest income (top quintile) to that received by the 20% of the population with the lowest income (lowest quintile) [*Laeken indicators*… 2003].

Based on calculated values of mean income and Gini coefficient Sen index can be computed [Rusnak 2007]:

$$IS = \mu(1 - G), \tag{1}$$

where: μ – mean income; G – Gini coefficient.

The higher values of Sen index, the greater welfare.

Hellwig's method allows to create ranking objects (in our case – subregions in Poland) described by more than one variable. On the basis of the matrix of standardized input variables the reference object is determined. Coordinates of the reference object are determined by the following formula [Hellwig 1968]:

$$z_{0j} = \begin{cases} \max\limits_i z_{ij} \mid j \in S \\ \min\limits_i z_{ij} \mid j \in D \end{cases}, \tag{2}$$

where: S – set of stimulants; D – set of destimulants; z_{ij} – standardized value for i-th object and j-th variable.

Then we calculate for each object its distance from a reference object, using Euclidean distance as given by formula:

$$d_{i0} = \sqrt{\sum_{j=1}^{m} \left(z_{ij} - z_{0j}\right)^2}, \; i = 1, 2, \ldots, n. \tag{3}$$

Finally, synthetic measure is defined as:

$$q_i = 1 - \frac{d_{i0}}{d_0}, \tag{4}$$

where:

$$d_0 = \bar{d}_0 + 2s_0, \tag{5}$$

whereby:

$$\bar{d}_0 = \frac{1}{n}\sum_{i=1}^{n} d_{i0} \tag{6}$$

and

$$s_0 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(d_{i0} - \overline{d}_0\right)^2}. \tag{7}$$

Values of synthetic measure (formula 4) belong to the interval [0, 1] and only in exceptional cases go beyond this range – this particular place when the object dramatically lags behind developmentally from remaining in the test area. A higher value of this measure indicates a better position of the object. The division of objects into classes can be made on the basis of statistical criteria using the arithmetic mean $\overline{q}$ and standard deviation s_q of the synthetic measure [Nowak 1990]:

$$\begin{aligned}
&\text{cluster1}\left(\text{low level}\right): q_i < \overline{q} - s_q \\
&\text{cluster2}\left(\text{lower average level}\right): \overline{q} - s_q \le q_i < \overline{q} \\
&\text{cluster3}\left(\text{higher average level}\right): \overline{q} \le q_i < \overline{q} + s_q \\
&\text{cluster4}\left(\text{high level}\right): q_i \ge \overline{q} + s_q
\end{aligned} \tag{8}$$

This is a classic way of division of territorial units into groups. If we have in database information about the localization of studied variable (in our case – synthetic measure), we will lose this information. This information may relate to area boundaries or neighbors. Explorative spatial data analysis (ESDA) uses information about values of studied variable and additionally about localization. ESDA is often used to visualization and quantitative analysis of spatial data. ESDA techniques are an efficient way to test the existence of spatial autocorrelation processes. Measures of spatial autocorrelation allow to evaluate correlation of variables regarding spatial location. Spatial autocorrelation means that geographically close observations are more similar than distant observations. ESDA techniques were used in Poland, inter alia, in the analyses of blood donation [Ojrzyńska, Twaróg 2011], land prices [Pietrzykowski 2011] or budget incomes [Wolny-Dominiak, Zeug-Żebro 2012].

The key element of spatial analyses is spatial weights matrix. This matrix is usually defined as $n \times n$ row-standardized first order contiguity matrix. "First order contiguity" means regions bordering with studied territorial unit are neighbors. Weights matrix is created by standardization to one of binary neighborhood matrix. In binary matrix value one means that units have common border, zero – units do not have common border. Row-standardization means that for each row i we have $\sum_{j=1}^{n} w_{ij} = 1$. In the empirical research there are often used standardization involving the assumption that w_{ij} are equal to $\frac{1}{n}$, when a region has n neighbors.

For testing global spatial autocorrelation global Moran's I statistic is used, which is given by formula [Kopczewska 2011]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}, \quad (9)$$

where: x_i, x_j – values of variables in spatial unit i and j; $\bar{x}$ – mean of the variable for all units; n – total number of spatial units that are included in the study, w_{ij} – element of spatial weight matrix W. Spatial matrix should be row-standardized to one spatial weights matrix. Global Moran's I statistic takes values ranging from [−1,1]: positive, when tested objects are similar, negative, when there is no similarity between them and approximately equal to 0 for a random distribution of objects. Significance tests base on theoretical moments or permutation approach (numerical approach to testing for significance of a statistic). Significance tests have been characterized in details by Anselin [2005].

The graphical presentation of Moran's statistic is Moran's I scatter plot. This graph depicts a standardized variable (x-axis) and the spatial lag of this standardized variable (y-axis). The spatial lag is a summary of the effects of the neighboring spatial units, obtained by means of a spatial weights matrix. In other words, spatial lag is weighted average of neighboring values of a location [Anselin et al. 2013]. The analyzed variable and its spatial lag are standardized, therefore "outliers" may be easily visualized as points further than two units away from the origin. They are "outliers" in the sense that they unduly influence the rest of the analysis [Anselin, Bao 1997][2]. The Moran's I value is interpreted as a regression coefficient and is displayed as the slope of the line in the scatter plot (for a row-standardized weight matrix only). The four quadrants correspond to the four types of spatial association. The lower left and upper right quadrants indicate spatial clustering of similar values: low values (that is, less than the mean) in the lower left (LL) and high values in the upper right (HH). Respectively, clusters of low and high values are potential cold spots and potential hot spots. The upper left and lower right quadrants indicate a spatial association of dissimilar values: low values surrounded by high neighboring values (LH) for the former, and high values surrounded by low values for the latter (HL) [Anselin 1995]. Points in the LH and HL quadrants are potential spatial outliers. Described four types of association are shown in Figure 1, where standardized variable is denoted by *stdX* and spatial lag by $L(X)$.

Local Moran's statistics provide information about a position of each observation relative to its neighbors. In the case of non-standardized values of the variable and row-standardized weight matrix, the local Moran is given by:

$$I_i = \frac{\left(x_i - \bar{x}\right)\sum_{j=1}^{n} w_{ij}\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 / n}, \quad (10)$$

where all elements of the formula are defined as in the global Moran's I.

[2] Potentially influential observations may be identified using various measures of influence, e.g. DFFITS, Cook's distance, DFBETAS.

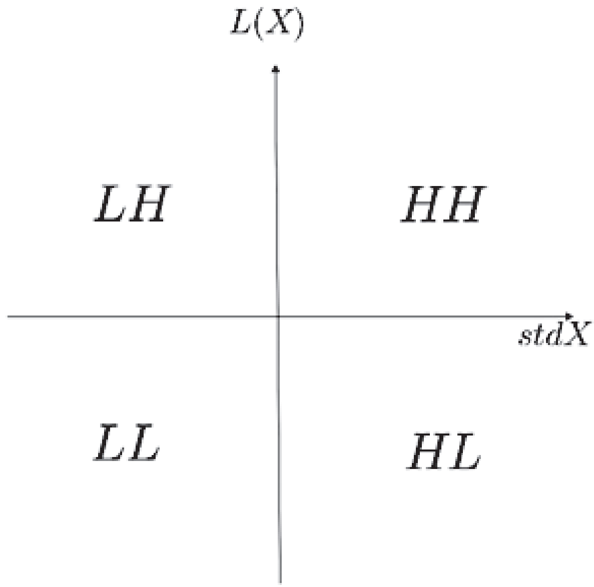

Figure 1. Moran's scatter plot

Source: own work.

Significance tests are based mostly on conditional randomization or permutation approach to yield empirical so-called pseudo significance levels[3]. Small p-value (e.g. $p < 0.05$) and $I_i > 0$ indicate statistically significant positive spatial autocorrelation (observation is a hot spot or cold spot), large p-value (e.g. $p > 0.95$) and $I_i < 0$ indicate statistically significant negative autocorrelation (observation is a spatial outlier). Absolute value of local Moran's I_i can be interpreted as degree of similarity/diversity [Kopczewska 2011].

In our analysis global Moran's statistic allows to evaluate general similarity/diversity of subregions due to the range of poverty (measured by synthetic measure) and local Moran statistics allow to answer the question whether the given subregion is similar/different from subregions in vicinity.

3. Results

All calculations and graphs were made in R [R Development Core Team 2015] using `spdep` [Bivand 2015b] and `maptools` [Bivand 2015a] packages. The map of Poland with division into subregions is available on the Eurostat website http://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units.

[3] More information about conditional randomization or permutation approach in Anselin [1995].

The study was conducted based on database of *Social Diagnosis* project for 2013. Database contains information about more than 12000 households, inter alia, information about their income. We used modified OECD equivalence scale in order to compare income of households with different size and composition. This scale is [Hagenaars et al. 1994] equal to one for first adult, 0.5 for each additional adult in household and 0.3 for each person of 14 years or younger. Poverty threshold was set at 60% of the median equivalised income.

To study poverty by subregions in Poland, six diagnostic variables were selected:

X_1 – at-risk-of-poverty rate,
X_2 – relative median at-risk-of-poverty gap,
X_3 – income quintile share ratio,
X_4 – Gini coefficient,
X_5 – mean income,
X_6 – Sen index.

Variables from initial list were tested due to the level of variability and correlation with other variables from the list. All of the variables had required the level of variability, because none of the variables had coefficient of variation lower than or equal to 10%. Using Hellwig's parametric method, three variables: X_1, X_4, X_6 were the so-called satellite variables (they were too strongly correlated with other variables from the list) and therefore these variables were deleted from the list. The values of the variables from the final list were standardized before further calculations. Variables X_2 and X_3 were destimulants and variable X_5 was stimulant. Values of synthetic measure were calculated in the next step and, based on them subregions were divided into groups using classic way (formula 8). The results of the subregions grouping are shown in Figure 2.

It can be noticed that there are similarities regarding poverty level. The lowest poverty level (the highest values of synthetic measure) is in four neighboring subregions from southern Poland (Bielski, Gliwicki, Rybnicki and Tyski), in two subregions bordering with Warszawa (subregions: Warszawsko-wschodni and Warszawsko-zachodni) and in one subregion bordering with Poznań (Poznański subregion), and also in big cities (Szczecin, Wrocław, Trójmiejski subregion, i.e. Gdańsk, Gdynia and Sopot). The worst material situation is in three subregions from eastern Poland (Bialski, Lubelski, Przemyski) and in a few subregions scattered across Poland.

In the next step an analysis was conducted to evaluate the correlation of synthetic variable in regard to spatial location. First of all the spatial weight matrix was set for 66 subregions in Poland. The subregions were considered as neighbors if they had a common boundary. Spatial links in weight matrix are shown in Figure 3.

The number of nonzero links is equal to 312 and average number of links is 4.73. There are five the least connected subregions with one link (Kraków, Łódź, Poznań, Wrocław and Trójmiejski subregions) and one the most connected subregion with nine links (Sandomiersko-jędrzejowski).

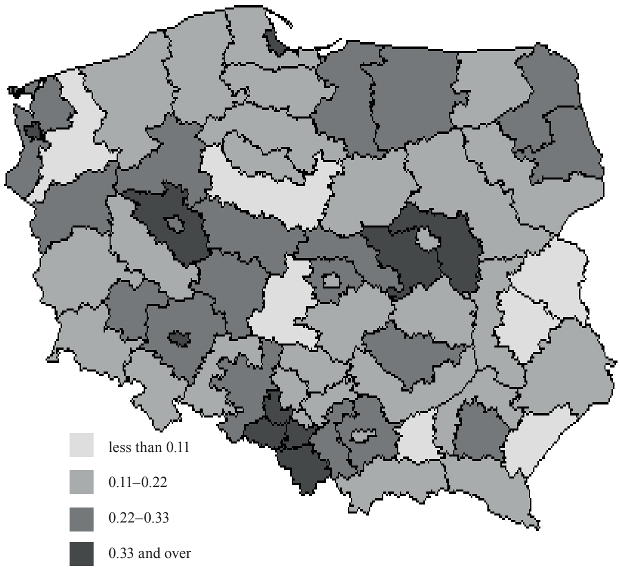

Figure 2. Spatial differentiation of poverty by subregions in Poland

Source: own calculations based on [Social Monitoring Council 2013], © EuroGeographics for the administrative boundaries.

Figure 3. Spatial links in weight matrix

Source: own calculations based on [Social Monitoring Council 2013], © EuroGeographics for the administrative boundaries.

In the next step Moran's *I* global statistic was calculated using the test under randomization. Moran's *I* is statistically significant (p-value at 0.011) and indicates poor spatial autocorrelation ($I = 0.177$). (This means that there is a small similarity between neighboring subregions in terms of poverty. Moran's global statistic is shown in Moran's scatter plot (Figure 4).

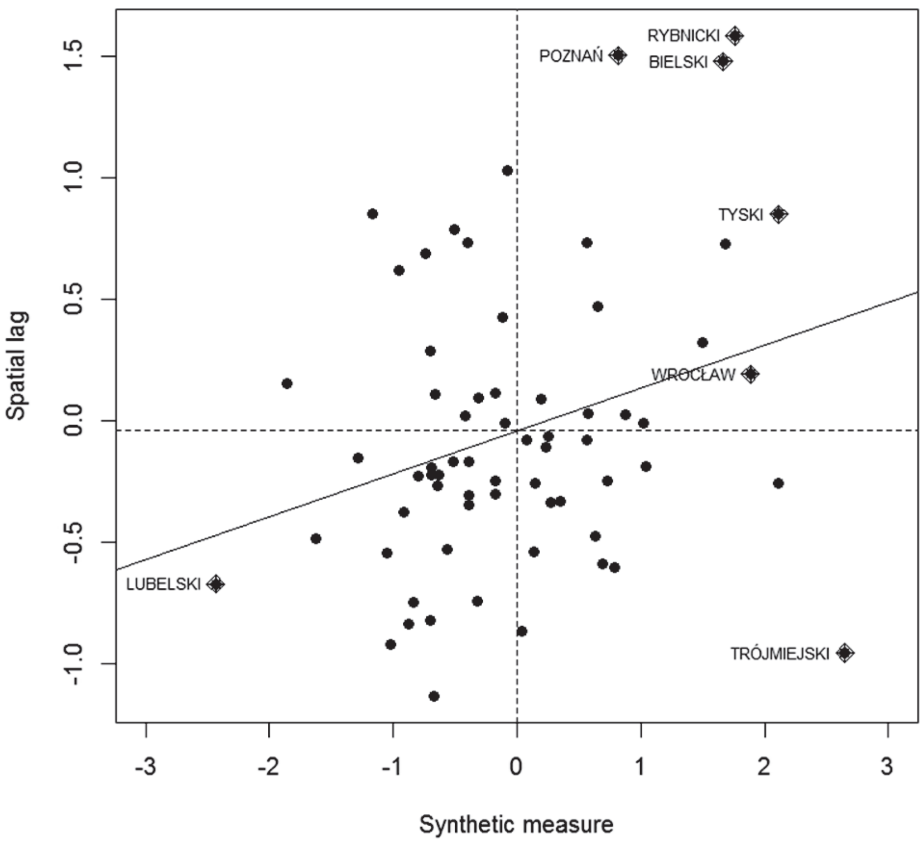

Figure 4. Moran's scatter plot for synthetic measure

Source: own calculations based on [Social Monitoring Council 2013], © EuroGeographics for the administrative boundaries.

While the overall pattern of spatial association is clearly positive, as indicated by the slope of the regression line (Moran's *I*), thirty observations show an association between dissimilar values: 14 in the upper left quadrant and 16 in the lower right quadrant. Seven selected subregions may be considered as "outliers" (Bielski, Lubelski, Poznań, Rybnicki, Trójmiejski, Tyski and Wrocław subregions). Five of them (Bielski, Lubelski, Rybnicki, Trójmiejski and Tyski subregions) have values of synthetic measure (horizontal axis) approx. two standard deviations away from the mean and simultaneously these subregions have quite far values for the spatial lag (vertical axis). Bielski, Rybnicki and Tyski subregions are potential hot spots (subregions with high values with similar neighbors) and Lubelski subregion is a potential cold spot (subregion with low values with similar neighbors). Finally, Trójmiejski subregion is a potential spatial outlier. Poznań and Wrocław subregions have not quite far values for synthetic measure (Poznań) or for spatial lag (Wrocław). For this reason, they have less chance to be hot spots.

Table 1 contains the local Moran statistics I_i and p-value of local Moran statistics.

Table 1. Values of local Moran's I_i in subregions

Subregion	I_i	$Pr\ (z > 0)$
1	2	3
Bialski	**0.959**	**0.011**
Białostocki	−0.046	0.518
Bielski	**2.497**	**0.000**
Bydgosko-toruński	0.742	0.136
Bytomski	−0.203	0.670
Chełmsko-zamojski	**0.774**	**0.032**
Ciechanowsko-płocki	−0.072	0.568
Częstochowski	0.300	0.207
Elbląski	−0.303	0.750
Ełcki	0.088	0.415
Gdański	−0.599	0.888
Gliwicki	**1.244**	**0.002**
Gorzowski	−0.182	0.652
Grudziądzki	0.136	0.334
Jeleniogórski	0.135	0.377
Kaliski	−0.016	0.501
Katowicki	−0.299	0.723
Kielecki	−0.072	0.540
Koniński	−0.006	0.491
Koszaliński	0.001	0.486
Krakowski	−0.411	0.848
Kraków	−0.518	0.695
Krośnieński	0.589	0.078
Legnicko-głogowski	−0.039	0.520
Leszczyński	−0.051	0.540
Lubelski	**1.664**	**0.001**
Łomżyński	0.121	0.374
Łódzki	−0.482	0.834
Łódź	−0.405	0.654
Nowosądecki	0.177	0.345
Nyski	0.045	0.444

1	2	3
Olsztyński	−0.094	0.565
Opolski	0.020	0.463
Ostrołęcko-siedlecki	0.184	0.287
Oświęcimski	0.417	0.155
Pilski	0.018	0.459
Piotrkowski	0.068	0.400
Poznań	1.241	0.101
Poznański	0.488	0.119
Przemyski	0.580	0.108
Puławski	0.245	0.214
Radomski	−0.029	0.515
Rybnicki	**2.825**	**0.000**
Rzeszowski	−0.036	0.514
Sandomiersko-jędrzejowski	0.351	0.117
Sieradzki	−0.285	0.794
Skierniewicki	−0.117	0.613
Słupski	0.054	0.436
Sosnowiecki	−0.020	0.505
Stargardzki	***−1.008***	***0.981***
Starogardzki	0.144	0.370
Suwalski	−0.026	0.508
Szczecin	−0.553	0.782
Szczeciński	0.311	0.318
Tarnobrzeski	**0.640**	**0.032**
Tarnowski	**0.797**	**0.028**
Trójmiejski	***−2.574***	***0.995***
Tyski	**1.821**	**0.000**
Wałbrzyski	0.159	0.378
Warszawa	−0.078	0.536
Warszawski wschodni	−0.202	0.686
Warszawski zachodni	−0.009	0.494
Włocławski	0.201	0.288
Wrocław	0.365	0.350
Wrocławski	0.017	0.464
Zielonogórski	−0.008	0.494

Source: own calculations based on [Social Monitoring Council 2013], © EuroGeographics for the administrative boundaries.

The local Moran's I_i are significant for 11 subregions: nine of them (bold values in Table 2) are surrounded by subregions with similar values (Bialski, Bielski, Chełmsko-zamojski, Gliwicki, Lubelski, Rybnicki, Tarnobrzeski, Tarnowski and Tyski subregions) and two of them (bold and italic values in Table 2) are surrounded by subregions with different values (Stargardzki and Trójmiejski subregions). These two subregions are spatial outliers. Statistically significant local statistics are shown in Figure 5.

Figure 5. Subregions with signicicant local Moran's I_i

Source: own calculations based on [Social Monitoring Council 2013], © EuroGeographics for the administrative boundaries.

On the basis of local Moran's I_i and subregions belonging to quarters in Moran's I scatter plot spatial regimes are identified (Fig. 6), i.e. subregions with substantially similar or dissimilar distribution of the analysed variable [Szubert 2014].

Spatial cluster of high values (hot spot) is formed by subregions from southern Poland (Bielski, Gliwicki, Rybnicki and Tyski subregions) and spatial cluster of low values (cold spot) – by subregions from eastern and south-eastern Poland (Bialski, Chełmsko-zamojski, Lubelski, Tarnobrzeski and Tarnowski subregions). The spatial outliers are Stargardzki and Trójmiejski subregions. The other values of local Moran's I_i are not statistically significant. Local Moran statistics confirm the results obtained based on scatter plot. The indicated potential cold spots, hot spots and spatial outliers are in fact statistically significant "outliers". It should be noted that on the basis of scatter plot not every significant local statistics were identified.

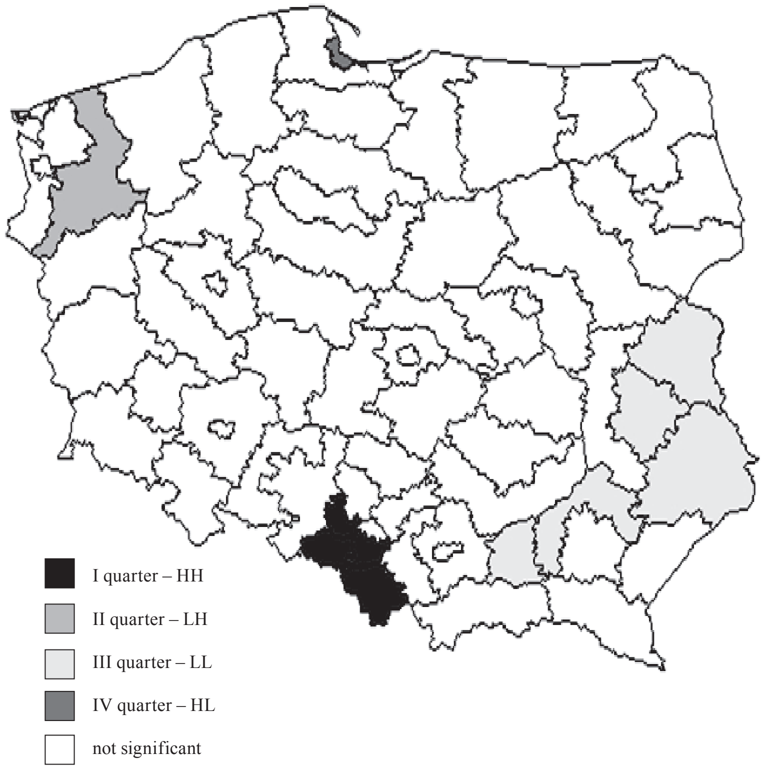

Figure 6. Spatial regimes

Source: own calculations based on [Social Monitoring Council 2013], © EuroGeographics for the administrative boundaries.

4. Conclusions

The analysis of poverty was performed in two versions: using traditional method and spatial autocorrelation statistics. The poverty has been described by synthetic measure in both cases. Based on a classic way (division into the groups using mean and standard deviation of synthetic measure) it can be concluded that four subregions from southern Poland form a cluster the least at-risk-of-poverty subregions. The extended analysis on information about neighboring subregions confirms these results, but additionally shows that there is a cluster of five the poorest subregions from eastern and south-eastern Poland.

Using spatial methods allows to conduct a more complete analysis. In contrast to traditional methods spatial autocorrelation does not ignore information about localization of variable. Spatial methods allow a fuller definition of the connections and dependencies between territorial units and they allow to define spatial structures.

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