SPATIAL CLUSTERS OF SELECTED POVERTY INDICATORS IN THE EUROPEAN UNION

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Abstract

Several poverty measures can be used in order to analyse poverty level in the society. All of them have their advantages as well as shortcomings. The goal of this paper is to analyse spatial distribution of poverty levels from the viewpoint of several poverty indicators. Different approaches yield different results and hence, poverty levels based on different indicators will be estimated and compared (we will focus mostly on monetary poverty, subjective perception of poverty and material deprivation). Analyses are based on spatial statistical methods (mainly global and local spatial autocorrelation coefficients). The results indicate that all investigated variables are positively spatially autocorrelated, i.e. similar values are clustered together. The available data further indicate that regions with high levels of poverty are clustered in the Eastern (Romania and Bulgaria, and the region of Eastern Slovakia) and South-Western parts of the EU, and low values are concentrated in the Northern and Central part of the European Union.

Key words: Poverty, deprivation, spatial statistics.

JEL Code: I32, R11, R15.

Introduction

Poverty assessment can be based on several concepts. Absolute poverty concept is based on the determination of a level of poverty which is fixed in terms of the welfare indicator used and is also fixed in time and for all the individuals who are considered in these comparisons (Ravallion, 1992). The concept of relative poverty is used frequently in developed countries, whereas the concept of absolute poverty is more common in less developed countries. One of the ways of determining the level of poverty is to compare the living standard of an individual with a common living standard in society (Hagenaars and van Praag, 1985), determining a fixed ratio between the level of income (or another indicator of poverty) of an individual and median or average income in the whole society (Ravallion, 1998). Relative poverty refers to the position of an individual or household compared with the average income in the country, while absolute poverty refers to the position of an individual or household in relation to a poverty line whose real value is fixed over time (World Bank, 1993).

Regardless of the concept, individual poverty level depends on a set of variables. The aim of this paper is to analyse to what extent selected poverty measures are spatially clustered in the European Union[1].

The development of methods for spatial data analyses allows the application of such methods in various fields including social sciences. During the last decade a number of poverty analyses involving methods for spatial data analyses have been published (see e. g. Chattopadhyay, Majumder and Jaman, 2014; Lawson and Elwood, 2014; Thongdara et al., 2012; Zelinsky and Stankovicova, 2012 etc.).

1 Methodology

1.1 Observation Units and Description of Data

The sample includes data for all available regions at NUTS-2 (in some cases at NUTS-1) level.

The following poverty indicators are used in the analyses:

- ***Disposable per capita income:*** the total income of a household, after tax and other deductions, that is available for spending or saving, divided by the number of household members. Disposable per capita income is measured in terms of purchasing power standard based on final consumption per inhabitant.
- ***Percentage of the population at risk of poverty or social exclusion*** defined as percentage of persons who are: at risk of poverty or severely materially deprived or living in households with very low work intensity as a share of the total population, expressed in numbers or shares of the population, and its sub-indicators:
- ***At-risk-of-poverty rate*** (after social transfers) is defined as the share of persons with an equivalised disposable income below the risk-of-poverty line, which is set at 60% of the national median equivalised disposable income after social transfers. The disposable income is defined as gross income less income tax, regular taxes on wealth, compulsory social insurance contributions, while the gross income is the total monetary and non-monetary income received by the household over a specified

[1] Several studies on poverty levels, incomes/wages and associated phenomena including countries clustering in the European Union have been published by the Czech and Slovak scientists recently (see e.g. Bartosova and Forbelska, 2012; Bilkova, 2009; Langhamrova and Fiala, 2013; Loster and Pavelka, 2013; Marek, 2013; Megyesiova, Lieskovska and Baco, 2013; Pivonka and Loster, 2013; Sipkova, 2013; Stankovicova, Vlacuha and Ivancikova, 2013).

income reference period. Income is measured at household level, and in order to gain equivalised disposable income, the total disposable income of a household has to be divided by equivalised household size according to the modified OECD scale (giving a weight of 1.0 to the first adult, 0.5 to other persons aged 14 or over and 0.3 to each child aged less than 14).

- ***Severe material deprivation rate*** represents the share of the population lacking at least 4 items among the 9 following: the household could not afford: i) to face unexpected expenses; ii) one week annual holiday away from home; iii) to pay for arrears (mortgage or rent, utility bills or hire purchase instalments); iv) a meal with meat, chicken or fish every second day; v) to keep home adequately warm, or could not afford (even if wanted to): vi) a washing machine; vii) a colour TV; viii) a telephone; ix) a personal car.
- ***Percentage of population living in households*** with very low work intensity, i.e. households where working-age adults (18-59) work less than 20% of their total work potential during the past year.

1.2 Global and Local Measures of Spatial Autocorrelation

Measures of spatial autocorrelation quantify the existence of clusters in the spatial arrangement of a given variable, while global and local versions of almost all measures can be estimated.

(Global) Moran's I is the most known statistics widely used to test for the presence of spatial dependence in observations taken on a lattice. Under the null hypothesis that the data are independent and identically distributed normal random variates (Li, Calder and Cressie, 2007).

Moran (1950) proposed a test statistic to assess the degree of spatial autocorrelation between adjacent locations:

$$I^0 \equiv \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\delta_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}, \text{ where} \qquad (1)$$

X_i is the variable of interest,

δ_{ij} is an indicator such that δ_{ij} =1 if the i^{th} and j^{th} locations are "adjacent" (defined a priori), and δ_{ij} =0 otherwise.

Later, Cliff and Ord (1981) proposed a statistic to test for a more general form of spatial dependence:

$$I \equiv \frac{\mathbf{Z}'\mathbf{W}\mathbf{Z}}{\mathbf{Z}'\mathbf{Z}} \text{, where} \qquad (2)$$

W is the spatial weight matrix.

While the global spatial autocorrelation measure (Moran's I) analysis yields one statistics to summarize the pattern of poverty in the whole study area, i.e. it assumes homogeneity (Sowunmi, 2012). Using local spatial autocorrelation measure we can find clusters also at a local level even if there is no global spatial autocorrelation or no spatial clustering (Zhang, Mao and Meng, 2010). Local Moran's *I* is the best known local indicator of spatial autocorrelation. Local Moran's I can be used to evaluate the clustering in individual units by calculating Local Moran's I for each spatial unit and evaluating the statistical significance for each region (Wang et al., 2012). Local Moran' *I* (Anselin, 1995) is:

$$I_i \equiv \frac{z_i}{m_2}\sum_{j=1}^{n} w_{ij} z_j \text{, where} \qquad (3)$$

z_i, z_j are deviations from the mean,

w_{ij} are the spatial weights between observations *i* and *j*,

m_2 is the second moment given: $m_2 = \frac{\sum_{i=1}^{n} z_i^2}{n}$ (a consistent, but not unbiased estimate of the variance).

All estimations and calculations are performed in R software (R Core Team, 2012) using package 'spdep' (Bivand et al., 2013). Administrative boundaries layer are downloaded from Eurostat web-site (Eurostat, 2014). Contiguity-based spatial weight matrix is used in estimations.

2 Results and Discussion

According to the Moran's I spatial autocorrelation coefficient all variables are significantly positively spatially autocorrelated, i.e. similar values are clustered together.

From Fig. 1 (left) it is obvious that there is a strong degree of positive spatial autocorrelation with very low levels of income in the Eastern part of the European Union and significantly high level of income in the central part of the European Union.

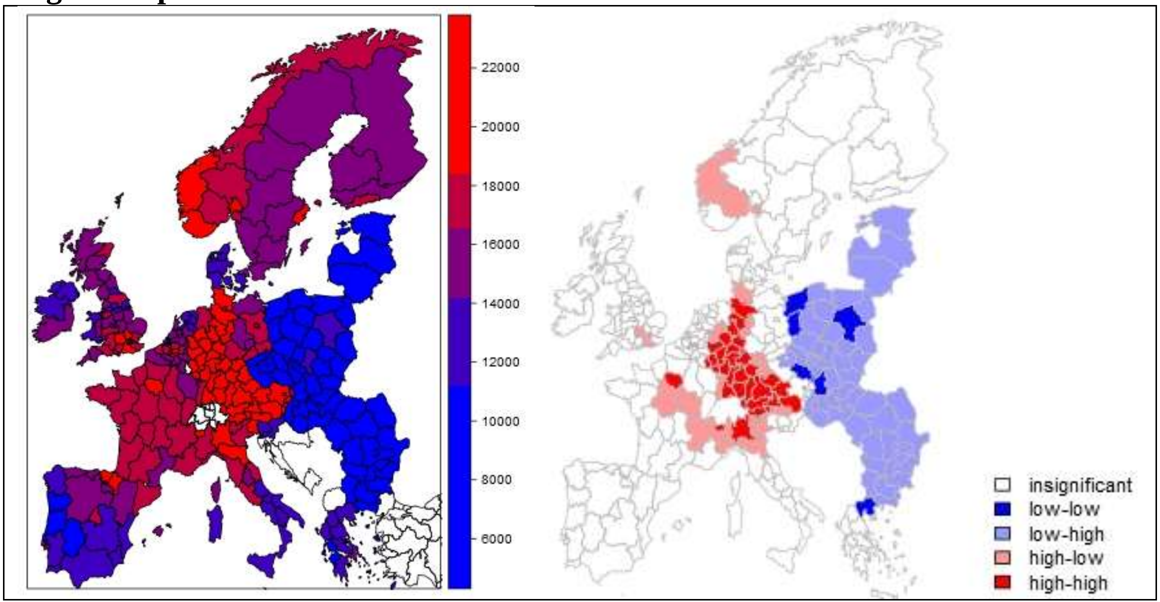
Tab. 1: Moran's I spatial autocorrelation coefficient

Variable	Moran's I	p-value
Disposable income	0.79825	< 0.0001
At-risk-of-poverty rate	0.50568	< 0.0001
At-risk-of-poverty rate or social exclusion	0.72892	< 0.0001
Very low work intensity	0.46742	< 0.0001
Severe material deprivation	0.86507	< 0.0001

Source: Own construction

The right part of Fig. 2 depicts significant local spatial autocorrelation coefficients and it is obvious that in the Eastern part of the EU low values of disposable income are more often surrounded by high values and only in few cases low values are surrounded by low values. These results indicate that there is a number of regions with significantly lower values of disposable income. On the other hand, in the central part of the EU high values are more often surrounded by high values than high values surrounded by low values.

Fig. 1: Disposable Income

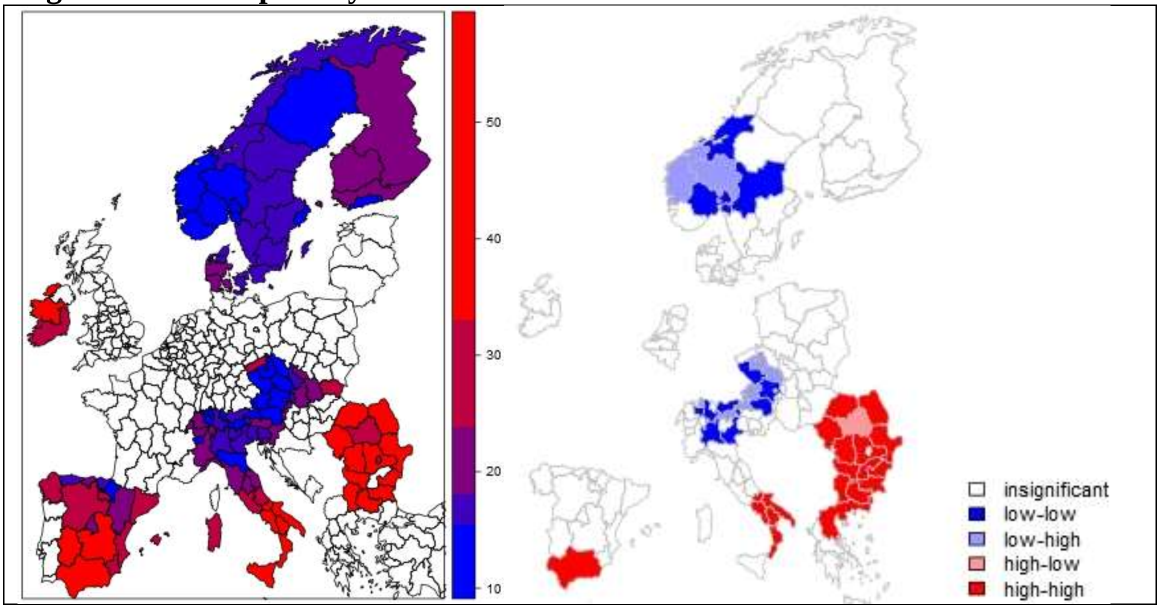


Source: Own construction (left: spatial distribution of the variable; right: local spatial autocorrelation)

As for the aggregate indicator of poverty (at-risk-of-poverty or social exclusion rate), one has to be very careful when interpreting spatial clustering due to lack of data. The available data indicate that regions with high levels of the indicator are clustered in the Eastern (Romania and Bulgaria, and the region of Eastern Slovakia) and South-Western parts of the EU (see Fig. 2). Low values are concentrated in the Northern and Central part of the

European Union. Unfortunately Eurostat does not publish data on Germany and France, and hence the data set does not offer a complete information. Local spatial autocorrelation coefficients indicate similar results – in the Southern part of the EU regions with high values of the aggregate poverty measure are surrounded by regions with high values, exceptionally regions with higher values are surrounded by regions with low values.

Fig. 2: At-risk-of-poverty or social exclusion rate

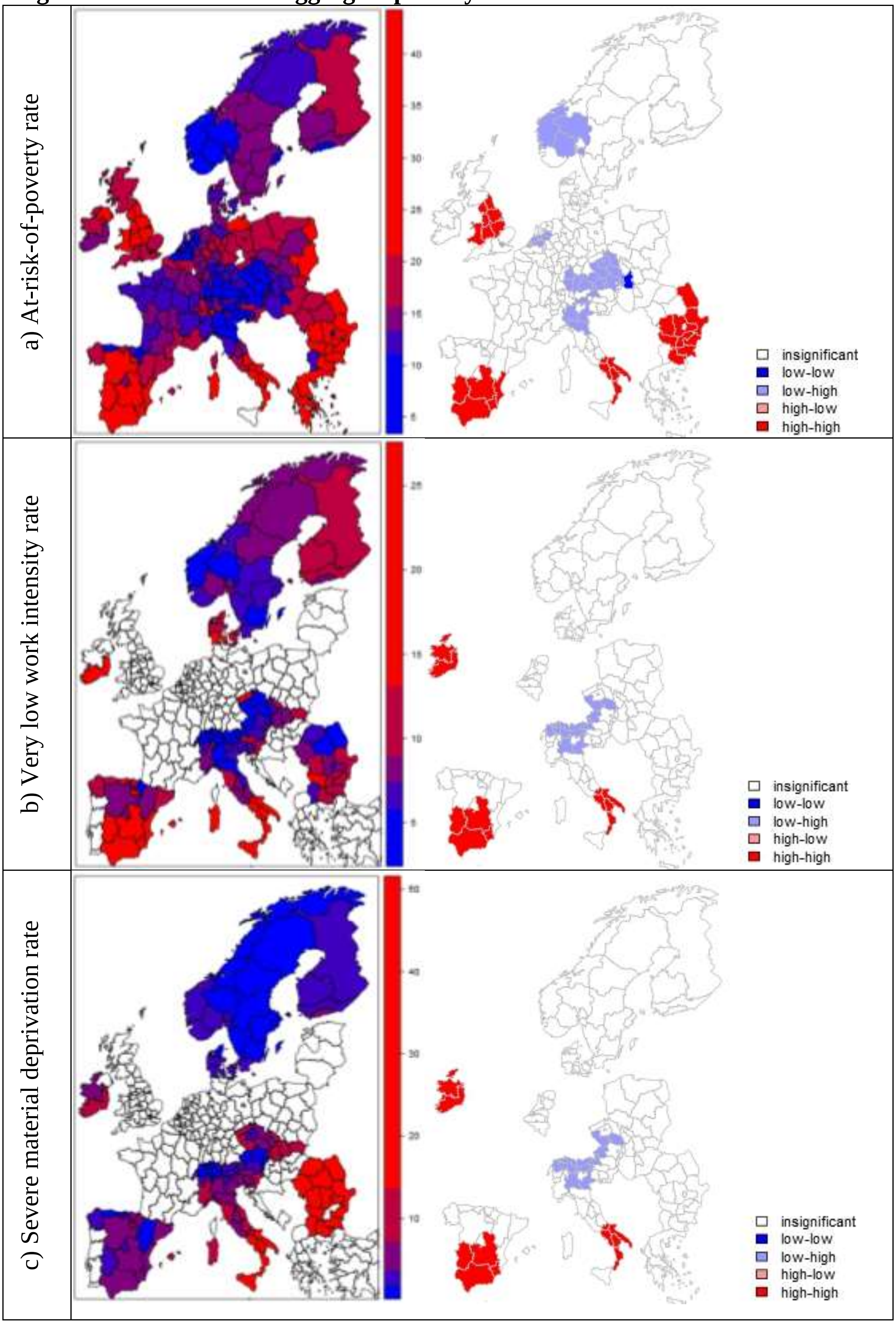


Source: Own construction (left: spatial distribution of the variable; right: local spatial autocorrelation)

As already mentioned, the aggregate poverty indicator consists of three sub-indicators (see Fig. 3). At-risk-of-poverty rate (Fig. 3a) is one of the most used measures of poverty, but it has both advantages and disadvantages. As income levels differ across countries, international comparisons are doubtful or in some cases even senseless. For instance, compare two countries: country A with median personal income of EUR 6,000/year and 13% at-risk-of-poverty rate and country B with median personal income of EUR 20,000/year and 15% at-risk-of-poverty rate. According to a simple comparison of poverty rates, country B would be perceived as a country with higher poverty level. On the other hand median personal income in country B is more than three-times higher than in country A.

The highest at-risk-of-poverty rates are concentrated in the Southern and Eastern parts of the EU. Distribution of local spatial autocorrelation coefficients of at-risk-of-poverty rates is similar to the distribution of the aggregate poverty indicator. The results further indicate similar distributions of local spatial autocorrelation coefficients of all sub-indicators (see Figures 3a, 3b and 3c).

Fig. 3: Sub-indicators of aggregate poverty measure



Source: Own construction (left: spatial distribution of the variable; right: local spatial autocorrelation)

Conclusion

The article presents a simple analysis of spatial distribution of poverty in the European Union. The analyses are based on Global and Local Moran's coefficients of spatial autocorrelation.

According to the Moran's I spatial autocorrelation coefficient all variables are significantly positively spatially autocorrelated, i.e. similar values are clustered together. Further there is a strong degree of positive spatial autocorrelation with very low levels of income in the Eastern part of the European Union and significantly high level of income in the central part of the European Union. The available data indicate that regions with high levels of at-risk-of-poverty rate or social exclusion are clustered in the Eastern (Romania and Bulgaria, and the region of Eastern Slovakia) and South-Western parts of the EU. Low values are concentrated in the Northern and Central part of the European Union.

One of the most significant limitations of this study is the fact that regional data on poverty are published in a very limited way and hence a complete information is not provided.

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