Regional and Spatial Concentration of Socio-economic Phenomena: Empirical Evidence from the Czech Republic[1]

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Abstract

Economic phenomena undoubtedly tend to form a large variety of agglomerations in space. It is thus natural to ask how significant these concentrations are, where they can be found and what the other aspects of these spatial arrangements are, including their practical implications. The main aim of this paper is to quantify the significance of spatial and regional concentration in respect to the overall inequality. In the empirical analysis economic variables are studied applying quantitative methods including specific ones such as Theil index decomposition and spatial autocorrelation. Contrary to the majority of thematically similar papers, this analysis is undertaken on a very detailed, municipal level which enables the authors to come to new, innovative, and more locally specific conclusions.

Keywords: *regional and spatial concentration, quantitative methods, spatial autocorrelation, Theil index decomposition, Czech Republic*

JEL Classification: R10, R12

Introduction

The significance of space is coming to be perceived as more important when studying socio-economic processes (Goodchild et al., 2000). However, the majority of methods developed in social sciences have been applied with little regard for spatially referenced data (Rey and Janikas, 2005). Similarly, few authors have

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focused on revealing the spatial and regional dimension of socio-economic inequality which is typically difficult to quantify. One of the reasons for the problematical quantification might be the fact that it is hindered by strong multi-causality and indivisibility of social processes defined by Harvey as 'socio-spatial confounding' (Harvey, 1973, p. 40). On the contrary, methods useful for quantification of the spatial and regional dimension have already been highlighted and published by Rey (2001), Rey and Janikas (2005), and by Novotný (2007).[2] This paper builds on the challenges posed by these authors and its main aims are:

(i) to utilise selected quantitative methods and come up with one coherent conceptual approach in order to

(ii) quantify the spatial and regional dimension of socio-economic inequality and

(iii) demonstrate its significance in the Czech Republic.

Despite the growing number of theoretical papers taking the spatial dimension into account, the empirical analyses have received much less attention. This paper sets out to contribute empirical research of spatial structure in detail, beginning at the municipal level (6 258 units). Importantly, working with municipal or other sub-regional units can reveal patterns usually hidden within a regional mean. This approach might also help to come up with new and innovative suggestions for practical implications of research.

The paper is organized as follows: In the following section, methodological background is briefly discussed. Utilised methods and theoretical background are not examined in greater detail though, for a methodologically and theoretically oriented paper see e.g. Netrdová and Nosek (2009) and Novotný (2006). The next part is devoted to empirical analysis of socio-economic data within the Czech Republic. All variables under analysis are studied by common and rather simple statistical methods first, followed by methods focusing predominantly on measurement of spatial and regional concentration (spatial autocorrelation and Theil index decomposition). The paper concludes with a discussion and some general comments.

Methodological Background

Identification and measurement of concentration of various processes and phenomena in space is one of the biggest challenges in social sciences. Several different statistical approaches, varying from simple statistical measures to specific

[2] A lot of methodological inspiration could be found in spatial econometrics literature (such as Anselin, Florax and Rey, 2004), New Economic Geography (Arthur, 1996; Venables, 1996; Krugman, 1998, etc.) or in studies attempting for holistic approach to regional development (e.g. Hampl, Blažek and Žížalová, 2008).

methods developed for spatial data analysis, are applied in this paper. The following part provides a short introduction to methods suitable for capturing the extent and type of spatial and regional concentration of economic phenomena.

The most commonly used non spatial statistical methods for measuring variability are variance and standard deviation. Unfortunately, these measures are inappropriate for comparison of more datasets because they are not scale invariant. Therefore, inequality is often measured by the dimensionless coefficient of variation. However, this coefficient is significantly dependent on mean which is considered to be its greatest weakness since the majority of geographical data is not distributed normally.[3] Dependence on mean makes the coefficient of variation considerably sensitive to high values in the considered distribution which evidently becomes a problem in the case of skewed distributions. For these reasons the Gini coefficient is typically applied for skewed data distributions (Gastwirth, 1972; Cowell, 1977; Lambert and Aronson, 1993). An advantage of this indicator is its independence of mean and rather low sensitivity to extreme values when compared with other inequality measures (Cowell and Flachaire, 2007).

Nevertheless, our aim is not only to quantify the absolute value of inequality but also to explore its patterns in space. To attempt this, one has to apply different methods. The easiest way to capture spatial concentration is to map values of the studied variable into a cartogram (absolute/relative values, index of localization etc.) However, analysis of very detailed data, such as those related to municipalities, makes the final map very fragmented and hence difficult to interpret. Moreover, its interpretation strongly depends on the choice of intervals (number, gamut). This type of cartographic representation is generally more appropriate for larger spatial units.

The methods mentioned above are sufficient in answering basic questions about the concentration of phenomena in space but a lot of questions remain unanswered. The biggest and the most interesting one is the significance of spatial and regional concentration. The terms region and space stress two different concepts applied in this article: spatial concentration and regional concentration (relative regional inequality).

The first concept of spatial concentration tries to measure concentration of similar values of a studied variable in space – i.e. spatial clustering or autocorrelation. If there were no spatial patterns visible it could mean that the phenomenon in question does not have a significant spatial dimension (i.e. these variables are randomly distributed in space). On the other hand, if this variable formed

[3] More or less skewed distributions (Hampl, 1998; Novotný, 2004; Ulubasoglu and Hazari, 2004; Clauset, Shalizi and Newman, 2007; Novotný and Nosek, 2009).

large spatial clusters of similar values one could assert that this phenomenon is spatially clustered and its variability has a strong spatial dimension. The appropriate way to quantify spatial concentration is to use spatial autocorrelation, i.e. correlation of one variable with itself in space. One of several existing coefficients of global spatial autocorrelation which measure the extent and significance of spatial clustering can be used (Cliff and Ord, 1973; Anselin, 1988). The most popular is Moran's I coefficient which has many similarities with Pearson's correlation coefficient and is defined as:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - y)(y_j - y)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(y_i - y)^2}$$

where n represents the number of spatial units (municipalities in this paper), y_i stands for the value of the studied variable in *i-th* municipality, y for its mean and w_{ij} represents spatial weights matrix (Cliff and Ord, 1973).

The choice of the spatial weights matrix is of considerable importance in a spatial autocorrelation methodology (Spurná, 2008) and depends on geographical variables of the studied area.[4] The values of Moran's I range from +1 meaning strong positive spatial autocorrelation to –1 indicating strong negative spatial autocorrelation while values close to 0[5] indicate a random pattern (Fotheringham, Brunsdon and Charlton, 2000). When looking on formation of spatial clusters in detail local spatial autocorrelation methods such as LISA (Anselin, 1995) – the local equivalent of Moran's I – can be used. The mapped results of this analysis answer not only the question of whether any spatial pattern across studied area exists but also where the clusters are, what they look like, etc.

The second concept utilised in this paper, the concept of regional concentration, tries to quantify the share of overall inequality which could be attributed to different administrative levels. Relative share of inequality attributable to different administrative levels could be, then, defined as the share of the between-group (between-region) component of inequality in overall inequality.[6] To measure the

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[4] On the basis of previous research (Spurná, 2008; Netrdová and Nosek, 2009; Blažek and Netrdová, 2009), the distance-based spatial matrix with fixed cut-offs 10 km was chosen as fitting best to the territorial structure of the Czech Republic.

[5] More exactly, if the value of Moran's I is close to the expected value $I = -1/(n-1)$. However, by analyzing large datasets is the practical error insignificant.

[6] Overall inequality is understood as a sum of between-region and within-region components and ideally represents inter-personal inequality which is from obvious reasons (data cannot be obtained on a personal level) substituted by inter-municipal inequality.

relative significance of regional inequality specific methods need to be used. One of the methods which allows decomposition of inequality to the between-group and within-group component without residuum is the Theil index (Cowell and Jenkins, 1995; Shorrocks and Wan, 2005; Novotný, 2007; Netrdová and Nosek, 2009). The Theil index can be decomposed according to the following equation:

$$I_C = \left(\sum_{j=1}^{k} \frac{n_j}{n} \frac{y_j}{y} \ln \frac{y_j}{y} \right) + \left(\sum_{j=1}^{k} \frac{n_j}{n} \frac{y_j}{y} \sum_{i=1}^{n_j} \frac{y_{ij}}{y_j} \ln \frac{y_{ij}}{y_j} \right) = I_B + I_W \qquad (1)$$

where I_C represents the overall inequality between all municipalities, and I_B and I_W the between-region and within-region component respectively. Then y_j stands for the value of the studied variable in municipality j and y for its regional mean; y_{ij} represents the value of the studied variable of *i-th* municipality within region j and fraction n_j/n captures population share of municipality j of overall population.

The share of the between-group component in overall inequality (formula 2) then gives the desired extent of relative significance of regional inequality. This relation uncovers the relative importance of a regional level on the overall inequality.

$$I_{RELATIVE} = \frac{I_B}{I_B + I_W} = \frac{I_B}{I_C} \qquad (2)$$

The last two methods, even though methodologically very different, could lead to similar conclusions (Rey, 2001; Netrdová and Nosek, 2009). The first one tries to find spatial patterns independently of the administrative definition of regions while the second one stresses the relative significance of predefined units (regions). However, when combined interesting and more complex information about relative significance of spatial and regional concentration can be found.

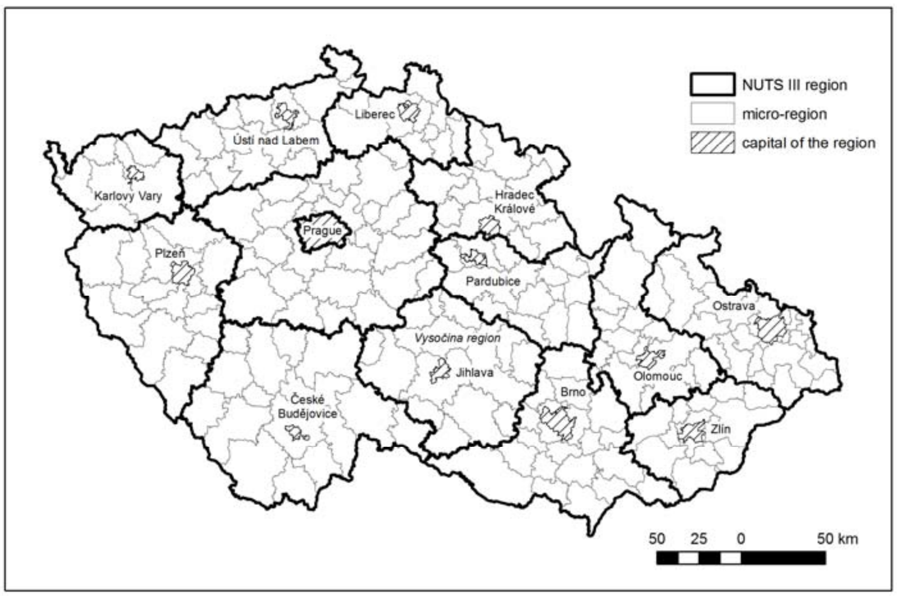
Empirical Analysis of Selected Socio-economic Variables

In this section, four selected socio-economic variables are analyzed within the Czech Republic by the methods discussed in previous section. The analysis needed to be undertaken on a very detailed level which is a prerequisite when using methods such as spatial autocorrelation. Thus, only the data which are available on the municipal level could be used. Consequently, the data are analyzed on three levels of administrative units: municipal (LAU II, 6 258 units) – micro-regional (206 units) – meso-regional (NUTS III, 13 units).[7] The applied

[7] In the Czech terminology micro-regional level corresponds with ‘ORP’ and meso-regional level with ‘kraje’.

regionalization of the Czech Republic with the names used in the text is demonstrated in Figure 1. The variables were chosen with respect to assumed differences in patterns of spatial and regional concentration. Authors are aware of limitations of applied quantitative methods as well as of partial character of all analyses which were not meant to comprehend spatial aspects of studied variables exhaustively. Despite analyses in this paper being predominantly of illustrative nature, the results may be considered as scientifically relevant and should be elaborated in future, more rigorous and complex, research.

F i g u r e 1
Administrative Units in the Czech Republic



Source: Visualisation by ArcMap 9.3.

Socio-economic variables entering the analysis are introduced in Table 1. After discussing the basic statistical parameters of studied variables the authors try to apply several different statistical methods to measure their spatial and regional concentration. Methods are applied in logical order starting with the most common ones and ending with methods specially evolved or adjusted to quantify spatial and regional concentration.

Descriptive statistics in Table 1 provide basic but useful information of economic phenomena. Mean and median serve only to show the absolute values. Moreover, large differences between mean and median (such as in the case of employment in agriculture) can indicate skewed distribution with fewer large observations and a lot of minima (Hampl, 1971). Variance informs us about absolute levels of variability and it is the highest in the case of entrepreneurial activity. Standardization by mean (i.e. coefficient of variation) gives a more realistic view on variability levels. However, the most convenient and the most often used coefficient for measuring inequality is the Gini coefficient especially since it is much less dependent on outlying observations. The highest observed inequality shows employment in agriculture, the lowest the economically active population.

Table 1

Descriptive Statistics of Selected Socio-economic Variables (Municipal Level, 6 258 Units)

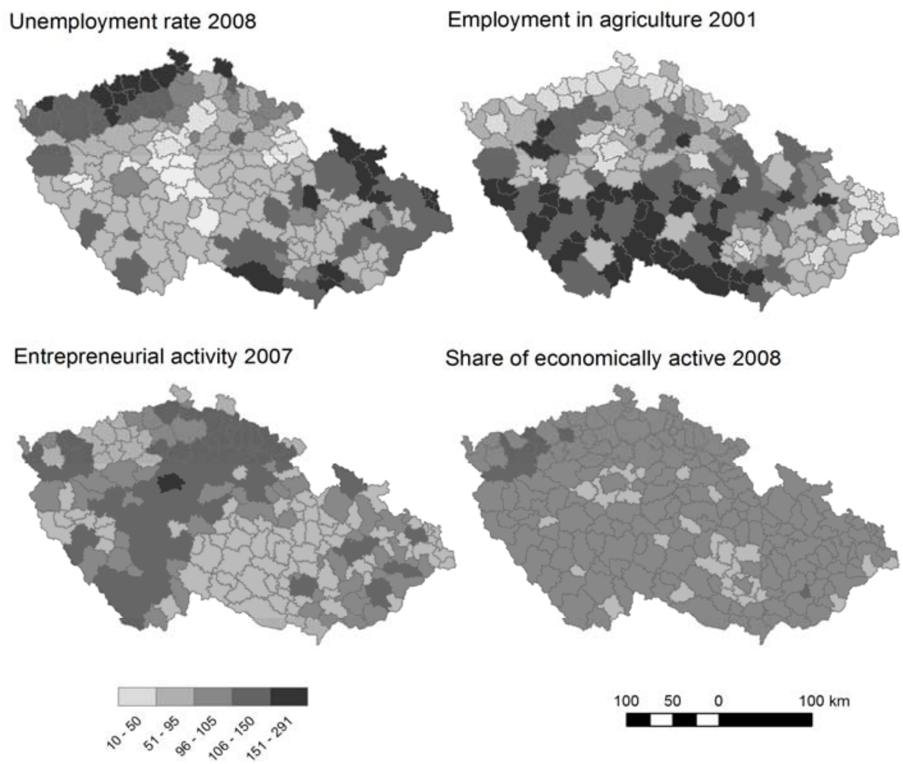
Data	Source	Year	Mean	Median	Variance	Coefficient of variation	Gini coefficient
Unemployment rate[1]	Ministry of Labour and Social Affairs of ČR	2008	6.34	5.71	11.54	0.536	0.289
Employment in agriculture[2]	Census 2001	2001	2.25	1.10	8.16	1.268	0.575
Entrepreneurial activity[3]	Czech Statistical Office	2007	16.72	16.07	14.56	0.228	0.128
Economically active population[4]	Ministry of Labour and Social Affairs of ČR	2008	0.49	0.49	0.005	0.140	0.039

Note: Data are weighted by population sizes and economically active in the case of employment in agriculture.
[1] Unemployment rate refers to the share of the number of unemployed in evidence of Ministry of Labour and Social Affairs of ČR on population.
[2] Employment in agriculture comprises economically active population in NACE categories A and B.
[3] Entrepreneurial activity is defined as number of registered entrepreneurs per 100 capita.
[4] I.e. share of economically active on overall population.

Source: Basic descriptive statistics were computed with the software package SPSS and with Microsoft Excel.

However, none of these statistical methods says much about spatial or regional concentration of studied variables. The easiest way to capture it is to chart data into a map. Cartograms, as a very basic method, are useful in identifying the biggest regional concentrations. Nevertheless, a cartogram can be used only when having data aggregated into regional entities. If the cartogram were processed on municipal level the resulting map would be difficult to interpret. Moreover, an interpretation of a cartogram depends significantly on a selection of intervals which may easily result in hiding existing concentrations. In addition, cartograms depicting different variables can hardly be compared with each other because they do not allow more exact quantifying of the extent and significance of the concentration visible on the map. Despite all the shortcomings of cartograms, it is usually a first step when analyzing spatial and regional concentrations. Examples of cartograms are shown in the following Figure 2.

F i g u r e 2
Cartograms on Micro-regional Level (206 Units)



Note: Values are standardised by the Czech Republic mean which is represented by a value of 100.
Source: Authors' calculations (see Table 1) in Microsoft Excel and visualisation by ArcMap 9.3.

The cartogram with unemployment rate shows that unemployment is concentrated in North-western Bohemia and Moravia; the difference between Bohemia (the western part of the Czech Republic) and Moravia (the eastern part of the Czech Republic) is visible at first sight. The cartogram with employment in agriculture identifies rather strong concentrations of low employment in agriculture in North-western Bohemia, North-eastern Moravia and in regions adjoining big cities. In the case of entrepreneurial activity it is clear that the biggest regional concentration can be found around Prague while Bohemia-Moravian borderland has a very low concentration of entrepreneurial activity. Regional variability seems to be rather high in the case of employment in agriculture and the unemployment rate, while in the case of entrepreneurial activity cartogram suggests rather low variability and almost no variability in economic activity.

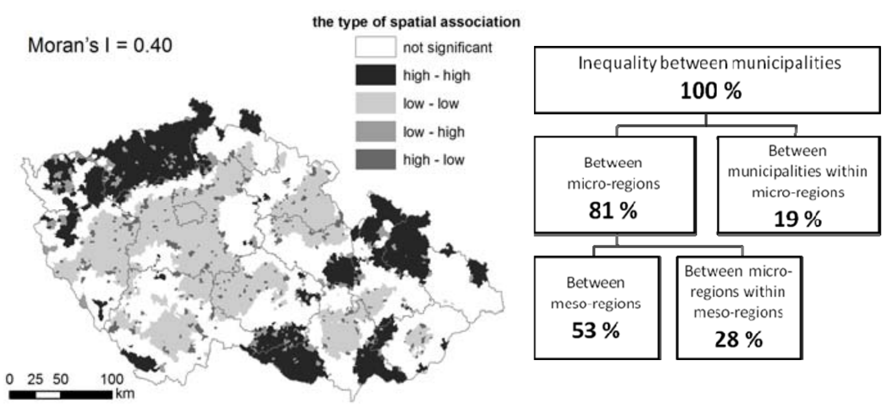
From cartographic analysis it seems that there will be no spatial or regional dependence in the case of the economically active population which is very similar across the whole republic and there should not be any significant clusters. Unemployment rate and employment in agriculture, on the other hand, might be the most significantly spatially and regionally anchored. However, for uncovering spatial concentrations as well as for measuring the significance of regional concentrations more precisely one has to use different methods such as the Theil index decomposition and spatial autocorrelation. Computations of all spatial autocorrelation analyses are performed with software package GeoDa 0.9.5-i (Beta)[8] (Anselin, 2003; Anselin, Syabri and Kho, 2004), the results of LISA analysis are visualized by GIS software ArcMap 9.3. Theil index and its decompositions are calculated manually in Microsoft Excel using formulae (1) and (2) mentioned earlier in the text. Results are discussed in detail and separately for each variable by applying both methods jointly.

Unemployment Rate

The first variable under analysis is the unemployment rate. Results obtained both by spatial autocorrelation (LISA cluster map and Moran's I) and Theil index decomposition in 2008 can be observed from Figure 3 below.

F i g u r e 3

Unemployment Rate Results in 2008 (Municipal Level, 6 258 Units)



Note: The type of spatial association high-high means that above-mean values are surrounded by above-mean values etc. All identified types of spatial association are significant at 1% level as well as the values of Moran's I. Inference is based on the permutation approach with 999 permutations in GeoDa. Distance based weight matrix (spatial weights from x-y coordinates, Euclidean distance metric, distance threshold 10 km) is used.

Source: Authors' calculation (see Table 1) in GeoDa 0.9.5-i (Beta) and Microsoft Excel and visualisation by ArcMap 9.3.

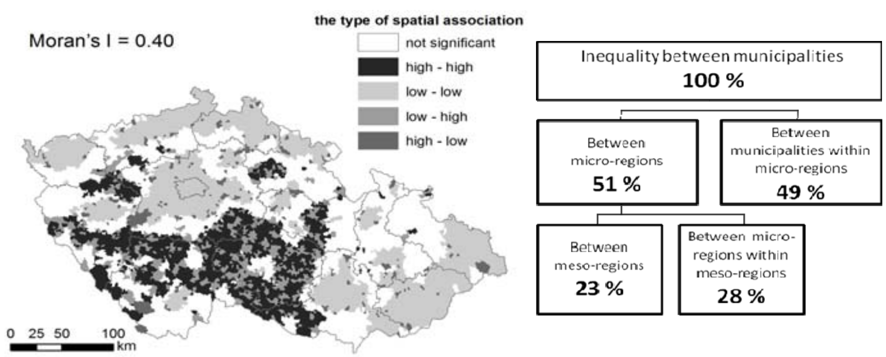
Unemployment rate has shown very high spatial and regional dimension. Concentration of this phenomenon in space as well as on all regional levels can be probably elucidated by the dependence of unemployment rate on the job market which is one of the main constituting principles of the utilised regional units. More than one half of the observed inequality can be attributed to differences between meso-regional units while differences between micro-regions account for more than 80% of overall variability. Only 19% of observed inequality remains within micro-regional borders (between municipalities within micro-regions) hence little would be lost if the analysis took place only on the micro-regional level. Concentrations are predominantly of areal type, unemployment concentrating in old industrial regions (Northern Moravia and Silesia and Northern Bohemia) and in Southern Moravia. Low unemployment concentrations can be found in the form of radial axes in the direction from Prague towards Liberec, Plzeň, České Budějovice, and partly towards Brno.

Employment in Agriculture

The concentration of employment in agriculture in 2001 shows specific features. The spatial concentration is the same as the concentration of unemployment rates.

Figure 4

Employment in Agriculture in 2001 (Municipal Level, 6 258 Units)



Note: See Figure 3.

Source: Authors' calculation (see Table 1) in GeoDa 0.9.5-i (Beta) and Microsoft Excel and visualisation by ArcMap 9.3.

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[8] GeoDa 0.9.5-i (Beta) is a freeware software package for exploratory spatial data analyses including spatial autocorrelation analyses developed by Anselin (Anselin 2003; Anselin, Syabri and Kho, 2004). For more information see the official website https://www.geoda.uiuc.edu/.

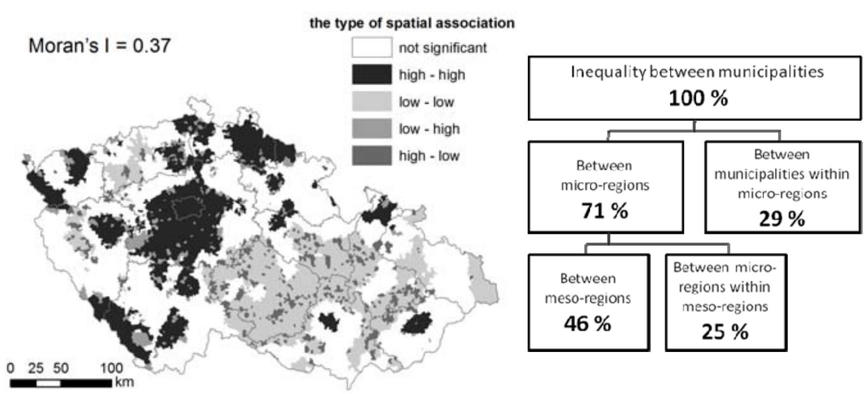
However, the share of respective regional levels is much lower. This is caused by concentrations which run across regional borders. These concentrations do not respect regional boundaries since they depend heavily on land quality and other physical variables (elevation etc.) and not only on functional relations between municipalities (core vs. hinterland) and job markets. One half of the observed inequality can be attributed to differences between micro-regions and thus the second half of the inequality remains on the municipal level within micro-regions. Meso-regions account for only about one fifth of the overall inequality. In this case then, regional analysis would not be sufficient. From LISA analysis (Figure 4) one can find that concentrations of higher employment in agriculture can be found in peripheral regions (especially Vysočina), presumably due to a lack of job opportunities in other sectors.

Entrepreneurial Activity

Both spatial and regional concentration of entrepreneurial activity in 2007 is significant. Moran's I is slightly lower when compared with unemployment rate and employment in agriculture. The regional concentration is not as strong as in the case of unemployment rate although almost half of the overall inequality could be attributed to differences between meso-regional units and almost two thirds to micro-regional units. Differences between municipalities within micro--regional are responsible for only 29% of the overall inequality. Locally, clusters can be found surrounding big cities and an axis might emerge in the north-south direction going through Prague (Figure 5).

F i g u r e 5

Entrepreneurial Activity in 2007 (Municipal Level, 6 258 Units)



Note: See Figure 3.

Source: Authors' calculation (see Table 1) in GeoDa 0.9.5-i (Beta) and Microsoft Excel and visualisation by ArcMap 9.3.

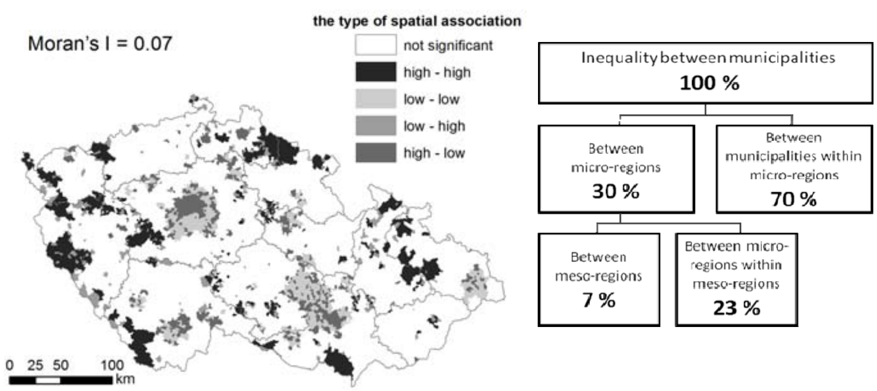
Moravia is far less entrepreneurial when compared with Bohemia, Brno and Zlín being the only two exceptions. The Bohemia-Moravian borderland (the whole Vysočina region) forms a large concentration of low entrepreneurial activity.

The Economically Active Population

By far the lowest spatial and regional concentrations can be observed in the case of the economically active population in 2008. Moran's I is significant but very low when compared with other variables and the majority of the overall inequality remains on the municipal level (70% between municipalities within micro-regions). Differences between meso-regions are responsible only for 7% of the overall inter-municipal inequality. From LISA analysis (Figure 6), there are visible only few small concentrations of high-high type and one larger concentration of low-low type in the Bohemia-Moravia borderland. The reason for the rather insignificant spatial and regional dimension of inequality in this case is presumed to be very low variability in general (see Table 1).

F i g u r e 6

The Economically Active Population in 2008 (Municipal Level, 6 258 Units)



Note: See Figure 3.

Source: Authors' calculation (see Table 1) in GeoDa 0.9.5-i (Beta) and Microsoft Excel and visualisation by ArcMap 9.3.

Discussion and General Typology

All variables proved to have a significant spatial or regional dimension with the only exception being the economically active population. This might be caused by the very low variability of economic activity. The significance of spatial or regional dimension of three other variables is not only formal due to the large datasets with more than 6 000 units under analysis. The spatial or regional distribution of these variables substantially differs from random distribution no matter which method was employed – for empirical demonstration and comparison of empirically and randomly distributed data see Nosek and Spurná (2008).

Two variables showed both a strong spatial and regional dimension. Only employment in agriculture tends to cluster significantly across regional borders. However, this is not very surprising since agricultural production also depends on the physical attributes of the studied area. The biggest spatial and regional dimension was found in the case of the unemployment rate. Put another way, this suggests that the probability of being unemployed depends most, from the studied variables, on your spatial/regional location. The Prague metropolitan region proved to form clusters in all variables under analysis. In some cases it also indicated potential development axes in north-south direction (from Liberec to Plzeň and České Budějovice). On the other hand, the Vysočina region proved to be a region lacking, often forming 'negative' clusters. When the results are compared with cartograms (see Figure 2 and the beginning of the empirical section) there are a lot of discrepancies which highlight the importance of spatial statistics methodology even though the basic assumptions were shown to be correct.

Generally, the results can be split into four basic categories. Firstly, we have data which tend to have both a significant spatial and regional dimension (both spatially and regionally anchored). This category comprises variables which are not only concentrated in space but these concentrations are usually found within regional boundaries. When studying socio-economic data this would probably be the most frequently studied category. In the empirical analysis in this paper, the unemployment rate and entrepreneurial activity fall under this category. However, spatial concentration can also arise from a mismatch between the regional boundaries used to organize the data and the boundaries of the actual socio-economic process under study (Rey, 2001). In other words, physical conditions might be more important than basic (core-periphery) socio-economic processes. This type of data, such as employment in agriculture, would fall into the second category (spatially anchored). The third category represents data with insignificant levels of inequality in both the spatial and regional dimension. In this category one would find data which are more or less independent of their location in space. In other words, one cannot talk about an ecological mistake. This is typical for less complex data (such as demographic data) or data with very low variability. In this paper, the only variable belonging to the third category is the economically active population. The last category is not represented by empirical data. This category is only theoretical since a regional concentration implies at least some spatial concentration. Theoretically, however, data with few extreme values likely to skew the mean would be insignificantly spatially autocorrelated but would have high regional concentration at the same time and might probably fall into this category. The general typology of patterns is summarized in Table 2.

T a b l e 2

General Typology of Resulting Patterns

	Regional Concentration HIGH	**Regional Concentration LOW**
Spatial autocorrelation HIGH	BOTH SPATIALLY AND REGIONALLY ANCHORED *- Unemployment rate* *- Entrepreneurial activity*	SPATIALLY ANCHORED *- Employment in agriculture*
Spatial autocorrelation LOW		BOTH SPATIALLY AND REGIONALLY INDEPENDENT *- The economically active population*

Source: Own construction.

Conclusion

In this paper, authors utilised selected quantitative methods and tried to come up with one coherent conceptual approach. This approach was supposed to lead to quantification of the spatial and regional dimension of socio-economic inequality which was demonstrated on the example of the Czech Republic. Methods applied in order to achieve these goals had to fulfil specific criteria which were met only in the case of spatial autocorrelation and the Theil index decomposition.

Both spatial autocorrelation and Theil index decomposition, despite each primarily having a different purpose, can give similar results when studying the geographical dimension of variability. Moreover, they complement each other very well and it seems fruitful to apply both methods jointly. In addition to indicating the significance of the spatial and regional dimension, Theil index decomposition can quantify the contribution of the respective regional level while the LISA analysis can specify the contribution of specific locations and uncover potential development axes as well as regions lagging behind. Both methods can thus be applied as one coherent concept when studying the extent of the spatial and regional dimension in socio-economic inequality research.

The empirical findings can be generalized into four categories. It is clear that the majority of the studied variables would fall into the first category both with significant spatial and regional dimensions. It might even be one of the properties of economic phenomena in general. However, there will still be some socio-economic processes dependent more on the physical environment or other factors not relating to socio-economic regions. In future research, it would be interesting to try to classify more socio-economic processes and compare them with other processes such as demographic ones.

The authors hope that this theme provides great potential and there are many avenues for future research. There are not many research projects focusing on a spatial level that detailed. This approach can be especially fruitful when utilised transnationally. Potential development axes as well as areas with potentially successful international cooperation can be revealed. Research studying the importance of national borders, for instance in the context of the European integration process, might bring interesting results. The significance of European regions could also be assessed, which could lead to a more effective cohesion policy. There are also a lot of opportunities to develop the methodology. Other spatial methods such as geographically weighted regression, the Gini index decomposition or various network analyses can be applied. Great potential might also be seen in implementing such empirical findings into political practice, although this remains a controversial topic.

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