# Spatial Distribution of Regional Knowledge Bases in Slovakia

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## Abstract

*Knowledge bases have gain a cardinal importance in the recent literature concerning with the issue of knowledge creation, innovation process and promotion of competitiveness of regions. By using employment and firm´s level data the evolving structure of the knowledge bases in Slovak districts (LAU 1) is analysed. To identify the spatial concentration, clusters and spatial autocorrelation the Moran index and LISA index was used. Based on the historical formation of engineering knowledge base in Slovakia, mainly presented by manufacturing industry it was interesting to analyse the geographical patterns of symbolic knowledge base in Slovak district. The results suggest that geographical proximity is inevitable for symbolic knowledge base which has a tendency to locate in large metropolitan area. On the contrary, synthetic knowledge base is localised mainly in small industrial district close to small secondary technical and vocational school.*

**Key words:** knowledge bases, spatial distribution, regional innovation system, cluster analysis

**JEL Classification:** R10, R11, R58

## 1 Introduction

A globalized economy is distinctive for more intense competition between regions which are aiming to strengthen their regional capacity and regional competitiveness by exploiting their unique resources. A strategic viewpoint in the contemporary global economy now resides in the question how to develop such unique resources in order to invigorate competitiveness. Competitiveness is no longer based on conventional production factors, for instance labor, capital, equipment and raw materials that becoming available across the world for the same price but, as Maskell et al. (1998) have pointed out, the competitiveness is based on dynamic improvements and on creating and diffusing knowledge more speedily than other competitors. Thus, the most fundamental resource in the modern economy is knowledge and, accordingly, the most important process is learning. Knowledge is created through dynamic interactions between the actors themselves and between them and the surrounding environment (Nonaka, 2000). This learning process is not just getting access to information but it refers to building new competences and establishing new skills, mostly fine skills that are not easily acquired. Learning ability of individuals, firms, regions and countries is thus necessary for adapting to the quickly evolving market and for achieving innovation.

Globalisation brings also some limitation in terms of spatial mobility of knowledge. While information and codified knowledge is globally dispersed faster than even before, tacit knowledge is not immediately transferable because they are socially, locally and institutionally embedded. The only way to transfer this kind of knowledge is through a specific kind of social interaction of people within organisations and between them (Polanyi, 1966). For instance, tacit knowledge in the form of know-how or competence cannot be separated from the person or organisation containing it. Such kind of knowledge can only be learned through experience and cannot amply be transmitted in any form. This knowledge remains exclusively as tacit knowledge within the firm or region (Polanyi, 1966). Consequence of the present drive towards globalization is that codified knowledge is becoming more accessible and simultaneously tacit knowledge more significant for sustaining competitive advantage of nation, region and firm. However, the binary argument of whether knowledge is codified or tacit can be criticized for a restrictively narrow understanding of knowledge, learning and innovation (Johnson et al., 2002). There is a need to go beyond this simple dichotomy which would take into consideration the knowledge inputs in the processes of knowledge creation and innovation. These knowledge inputs contain different mixes of tacit and codified knowledge, qualifications and skills required by organisations and institutions involved in the process of knowledge creation and innovation. Each knowledge input is different in terms of its specific innovation challenges and pressures, which justify its different sensitivity to geographical distance and, accordingly, the importance of spatial proximity for localised learning. Asheim et al. (2011) distinguish three types of knowledge inputs or accurately said knowledge bases: synthetic, analytical and symbolic.

The knowledge base concept has been further developed by many authors who tried to describe variety of regions and industries in those regions. The most common method used in their works was mainly in-depth case studies (Asheim & Coenen, 2005, 2006; Coenen and Moodysson, 2009; Moodysson et al., 2008). Case studies seems to be appropriate framework for studying regional innovation system but as was suggested by Martin (2012) quantitative and more formalized research design can bring additional insights into the empirics of knowledge bases. The first attempt in this area was undertaken by Martin (2012). He developed a methodological approach to capture the knowledge base on the country level in Sweden by using occupation statistics. On the other hand Aslesen & Freel (2012) and Skokan (2012) used industrial classification systems reflecting the industry sector in which the employees are active and assigned NACE codes to each knowledge base. The present paper is in line with the last mentioned works and used the same methodology to probe the spatial organization of differentiated knowledge bases on district level in Slovakia. The main research question dealt with in this article is: *What is the spatial distribution of differentiated knowledge bases in Slovakia?*

With this perspective, this paper provides two main contributions to the knowledge base literature. First, it investigates local patterns of differentiated knowledge bases in Slovak district by adopting two complementary approaches. Cluster analysis is carried out to identify spatial trends of knowledge bases in the economy and then the spatial dependence across space is tested. The second contribution is related to using Slovak districts (LAU 1) as an observation levels. In spite of that a growing number of researchers have started to draw attention to the possibility of measurement of knowledge bases, no effort was made on measurement of knowledge bases for Slovakia, especially for lower administrative level. The need to bridge the gap has motivated this study. The paper is organised as follows. The next section presents the theoretical framework, followed by Section 3 that describes the methodology and the data used. Section 4 presents the survey results. Finally, the last section concludes.

## 2 Differentiated Knowledge Bases

The knowledge base typology was introduced by Asheim and Gertler (2005) taking into account the knowledge used as inputs into innovation processes. Asheim and Gertler claim that the innovation processes of firms and industries is strongly formed by their specific knowledge bases.

An analytical knowledge base is dominant in economic activities where knowledge creation is mainly based on formal modes, codified science and rational processes (Asheim and Gertler, 2005). Examples include genetics, biotechnology and information technology. In these sectors the geographical distance does not play important role as knowledge are based on a commonly accepted language that can be more easily codified and transferred. Thus, companies are mostly integrated in globally configured networks (Aslesen and Feel, 2012) and networks between them and universities or other research organization are very important (Asheim and Coenen, 2005; Gertler and Wolfe, 2006).

A synthetic knowledge base prevails in industries where incremental innovation dominated by the modification of existing products and processes is crucial. A good example for a sector with a synthetic knowledge base is manufacturing and automotive industry. Compared to the analytical knowledge base synthetic knowledge base required know-how, craft and practical skills for their knowledge production and circulation process (Asheim et al., 2011). Those skills are often provided by professional and polytechnics schools or by on-the-job training (Asheim and Coenen, 2006; Broekel and Boschma, 2011). Due to the fact, that learning process in synthetic knowledge bases is based on personal interaction tacit knowledge is particularly important in comparison the analytical type and geographical proximity is auxiliary.

The third category symbolic knowledge base is related to the creative industries that has become increasingly important components of modern post-industrial knowledge-based economies. Creative industries have starting to play an important role in fostering economic development as well as for determining successful integration into a rapidly changing global economy. They are characterised by knowledge incorporated and transmitted in aesthetic symbols, images, sounds and other. Symbolic knowledge is highly context-specific, as the interpretation of symbols, images, designs, stories and cultural artefacts is narrowly tied to a deep understanding of the habits and norms and ‘everyday culture’ of specific social groupings (Asheim et al., 2011). This shows that in symbolic knowledge bases geographical proximity is absolutely decisive (Mattes, 2014).

The basic idea of differentiated knowledge base approach is not to explain the level of competence or R&D intensity (high-tech or low-tech) but to characterize the nature of essential knowledge considering to be the base for innovative activity (Moodysson, 2007). This approach, compared to the OECD classification (low - tech, medium - tech, high - tech), does not consider important to classify one knowledge base as more advanced, complex and sophisticated than other knowledge base, or to consider science based knowledge (analytical) as more important for innovation and competitiveness of firms and regions than engineering based (synthetic) knowledge or artistic based knowledge (symbolic) (Laestadius, 2007). Table 1 provides a summary of the three knowledge bases. This distinction is intended as ideal-typical. However, in reality most activities contain more than one knowledge base and the degree to which certain knowledge base predominates varies between industries, firms and different types of activities within those firms and industries (Asheim et al., 2011).

**Tab. 1 Differentiated knowledge bases**

| | **Analytical knowledge** | **Synthetic knowledge** | **Symbolic knowledge** |
|---|---|---|---|
| **Rationale for knowledge creation** | Developing new knowledge about natural systems by applying scientific laws; know why | Applying or combining (in novel ways) existing knowledge; know how | Creating meaning, aesthetic qualities, affect; know who |
| **Development and use of knowledge** | Scientific knowledge, models, deductive | Problem-solving, inductive, custom production | Creative process |
| **Importance of geographical proximity** | Negligible, meaning relatively constant between places | Helpful (auxiliary), meaning varies substantially between places | Critical, meaning highly variable between place, class and gender |
| **Actors involved** | Collaboration within and between research units | Interactive learning with customers and suppliers | Learning-by-doing in studio, project teams |
| **Knowledge types** | Strong codified knowledge content, highly abstract, universal | Partially codified knowledge, strong tacit component, more context specific | Strong semiotic knowledge content, some forms highly context-specific |
| **Outcome** | Drug development | Mechanical engineering | Advertising |

Source: Asheim and Gertler (2005), Asheim et al. (2011), Martin (2012)

The theoretical framework presented above suggests that industries where tacit knowledge prevails are more spatially bound in the learning and innovation processes than industries based on strong codified type of knowledge. Besides, analytical knowledge based industries have a tendency to locate in close proximity to universities, synthetic knowledge based industries are located in proximity to lead users or in non-urban areas, specialised clusters (e.g. industrial districts), while industries drawing on a symbolic knowledge base are overwhelmingly an urban phenomena (Asheim et al., 2005) The paper attempts to verify these assumptions by exploring a large scale dataset gathered from ELIS database in 2012.

## 3 Methodology

Mapping the spatial distribution of knowledge base is challenging issue. The most common method used in many works used mainly in-depth case studies. (Asheim & Coenen, 2005, 2006; Coenen & Moodysson, 2009; Moodysson et al., 2008) Case studies seems to be appropriate framework for studying regional innovation system but as was suggested by Martin (2012) quantitative and more formalized research design can bring additional insights into the empirics of knowledge bases. The first attempt in this area was undertaken by Martin (2012). He developed a methodological approach to capture the knowledge base on the country level in Sweden by using occupation statistics. Occupation statistics reflect the set of activities or tasks applied by employees at their workplace thereby reflect the type of knowledge embodied in these employees. On the other hand Aslesen & Freel (2012) used industrial classification systems reflecting the industry sector in which the employees are active and assigned NACE codes to each knowledge base. This approach includes all workers of an economic sector, whether they have science-based occupation or arts-based occupation, while underestimates for example science-based employees working in arts-based economic sector. On the contrary, occupational analysis captures actual skills and activities applied at the workplace but ignores the production-consumption chain of for example science-based products, where also arts-based workers are involved. Therefore both approaches may bring contradictory results and thus provide biased pictures of the organisational patterns of knowledge bases. Combining these two metrics would be more appropriate, but such methodological accuracy depends on the availability of data (Bertacchini and Borrione, 2013). Owing to data availability the industry-based approach is applied to define three knowledge bases in Slovakia. To run the analysis we apply classification brought forward by Aslesen and Freel (2012), who assign different industries to the three knowledge bases (Table 2). Industries are identified according to NACE code rev. 1

**Tab. 2 NACE codes assigned to each knowledge base**

| Knowledge base | NACE code |
|---|---|
| Analytical | 244, 331 334, 335, 30, 313, 32, 332, 333,73,803 |
| Synthetic | 241,242,243,245,2461,2462,2463,2566,247,29,311,312,314, 315,316,34,352,354,335,642,72,74202,74203,74209,743,65, 66,67,70,10,11,12,13,14,15,20,21,23,25,26,27,28,351, 3662,3663,37,17,18,19,361,362,363,364,365,3661,2464,2465 |
| Symbolic | 9211,922,9231,9234,924,74201,744,74872,74873 |

Source: author´s own elaboration based on Aslesen & Freel (2012)

Spatial distribution of knowledge bases in Slovak districts (LAU 1) is carried out by cluster analysis and then spatial autocorrelation is calculated to identify regularities in the spatial pattern. Cluster analysis technique is used to summarize clusters of objects which resemble each other and which are different in some respects from individual in other clusters (Everitt et al., 2011). Porter (2003) defines cluster as a geographically proximate group of interconnected companies, suppliers, service providers and associated institutions in a particular field, linked by externalities of various types. The methodology in the present paper is derived from the study conducted by Bertacchini and Borrione (2013). Their approach differs from the cluster methodology proposed by Porter (2003) such that cluster refers to a group of district of comparable specialization levels instead of being a geographic concentration of interconnected companies (Bertacchini and Borrione, 2013). Similarly, the paper applied Ward´s hierarchical approach to produce exclusive clusters. At the beginning of this method every clusters consist exactly of one object in our case district. The most similar pair of clusters is then merged together until only one single cluster remains. The aim of Ward method is to find at each stage those two clusters whose merger gives the minimum increase in the total variance (Romesburg, 2004). In order to choose an optimal number of clusters, five indices were applied: Root Mean Square Standard Deviation Index (RMSSTD), Dunn's Index (DUNN), Davies-Bouldin's Index (DB), Pseudo F Index (CHF), Pseudo T-square Index (PTS). For more information see Wilkinson et al. (2012).

In the present case each Slovak district (LAU 1) is characterized by their specialization in the three knowledge bases. To assess which district specializes on which knowledge base the location quotients (LQ) was applied. LQ compares the relative specialization of a place in an industry regarding the national average and is defined as:

$$LQ = \frac{\frac{X^k}{X}}{\frac{X_B^k}{X_B}}$$

*where $X^k$ is the number of employees in knowledge base k in country; $X_B{}^k$ is the total number of employees in district B in knowledge base k; X is the total employment in country; $X_B$ is the total employment in district B*

This technique is used to find out whether certain knowledge base has a smaller or larger presence in a local economy compared with the corresponding national economy, measured by employment active in knowledge based industries (Martin, 2012). An LQ above 1 indicates that the share of employment in the district B exceeds the share of employment in the country. If it is below 1, the share of employment in the district B is smaller than in the country as a whole.

Cluster analysis is beneficial for detecting homogenous group of districts with similar patterns of specialization. The Global Moran Index is subsequently used to detect spatial dependence of knowledge bases across Slovak districts. The Global Moran Index is defined as:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

*where $N$ is the number of districts; $w_{ij}$ is the matrix of spatial weights; $x_i$ is the value of the observed phenomenon in the district i; $x_j$ is the value of the observed phenomenon in the district j; $\bar{x}$ is the arithmetic mean of the variable x.*

Positive value of the index represents spatial clustering across districts of specialization in the chosen knowledge bases, while negative value indicates that districts have dissimilar level of specialization in the chosen knowledge bases. As the Moran Index provides one statistic and evaluates only global spatial autocorrelation, local indicator of spatial association (LISA) was also calculated. The LISA for each district gives an indication of the extent of significant spatial clustering of similar values around that district (Anselin, 1995).

## 4 Empirical Analysis of Knowledge Bases in Slovak District

Ward´s hierarchical method has identified six clusters according to their LQ values. Table 3 shows, that each cluster has different degree of specialization for each knowledge base. Figure 1 displays the spatial distribution of clusters. Cluster 1 and 2 include 21 and 20 districts respectively and confirms strong geographical localization of synthetic knowledge base in the industrial district or in non-urban areas. Districts Partizánske (LQ=1.49), Bánovce nad Bebravou (LQ=1.79), Púchov (LQ=1.76) have a strong specialization in synthetic knowledge base. These districts possess a small secondary technical and vocational schools which are in close connection with nearer firms. District Partizánske is rooted on the path-dependent formation of footwear manufacturing. Bánovce nad Bebravou hosts number of companies in footwear, clothing and manufacturing sector; especially the large multinational company Hella Slovakia operating in development and manufacture of lighting and electronic components for the automotive industry. District Púchov hosts textile and clothing firm Makyta, one of the world´s major manufacturers of high quality drinking glasses Rona and firm Continental Matador Rubber active in tire manufacturing. In these sectors, knowledge creation is mostly engineering based and aims at solving concrete, technical problems (Martin, 2012). Other districts Brezno (1.44), Detva (1.37), Poltár (1.54) have also strong specialization in synthetic knowledge base. The biggest company in the distric Brezno is Iron factory Železiarne Podbrezová which is involved in the education and professional training of their future employees. Therefore, that factory founded two schools which are situated near factory. This suggests that, for these knowledge base, the core knowledge involves know-how experience and skills that are hard to transfer and probably less applicable in distant locations (Aslesen and Freel, 2012). District Detva is well-known for its industrial park - Areal PPS as a result of strategic intention of the company PPS Group. The company's core business is the manufacturing of medium large and medium heavy welding constructions. The District Poltár is one of the least and the most sparsely populated districts of Slovakia with strong glass-making tradition. Knowledge from this realm embodied in local people was one of the reasons for establishing the company Slovglass Poltar in 1833 which is a legacy of communist-era consolidation of the industry. In a nutshell, synthetic firms in Slovakia are mostly represented by heavy industry sector with a great deal of knowledge embodied in people but also in technologies. Synthetic knowledge based industry are located in more sparsely populated district with non-urban character than firms in the symbolic knowledge base.

**Tab. 3 Clusters of three knowledge bases, 2012**

| | | **LQANAL** | **LQSYMB** | **LQSYNT** | **Population density** |
|---|---|---|---|---|---|
| Cluster 1 | Mean | 0,14 | 0,56 | 1,50 | 133,05 |
| n=21 | SD | 0,15 | 0,16 | 0,31 | 209,11 |
| Cluster 2 | Mean | 0,14 | 0,61 | 0,87 | 91,00 |
| n=20 | SD | 0,09 | 0,17 | 0,18 | 36,54 |
| Cluster 3 | Mean | 0,46 | 1,15 | 0,93 | 366,29 |
| n=14 | SD | 0,23 | 0,51 | 0,18 | 537,96 |
| Cluster 4 | Mean | 1,23 | 0,83 | 1,00 | 170,00 |
| n=18 | SD | 0,31 | 0,34 | 0,27 | 171,35 |
| Cluster 5 | Mean | 3,22 | 0,32 | 0,83 | 81,00 |
| n=2 | SD | 0,20 | 0,03 | 0,40 | 38,18 |
| Cluster 6 | Mean | 2,82 | 2,33 | 1,05 | 1749,25 |
| n=4 | SD | 0,67 | 0,76 | 0,30 | 1543,77 |

Source: author´s own elaboration

Second, clusters 4-6 are characterized by a high concentration of analytical knowledge base. It is worth noticing that cluster 6 is also characterized by noticeable specialization in symbolic knowledge base. A strong specialization on economic activities where analytical knowledge is important can be found in Bratislava III (1.52), Nitra (1.62), Prešov (1.69) and Banská Bystrica (1.45) district. The reason why Bratislava III is included in this category is without doubt its higher education infrastructure with particular focus on medical research. The most of the life sciences and biotechnology capacity is held in Slovak Medical University in Bratislava collaborating with a number of research intensive companies and research institutions e.g. Cancer Research Institute of the Slovak Academy of Sciences and Institute of Molecular Physiology and Genetics. There are also some medical technology companies and high-tech companies collaborating with universities and research institutes. A significant analytical knowledge base can be identified in Nitra district. Typical chemical business segments in the district are medicament development and in vitro diagnostics with large multinational companies Pharmagal – bio and Mevak. These firms are engaged in cooperation with international partners, suggesting that the knowledge created in analytical based industry is more codified and transferable between distant partners (Aslesen and Freel, 2012). Besides, Nitra hosts University of Agriculture which is a member of international agrarian cluster. University collaborates with research Institution for Animal Reproduction and the Archaeological Institution of the Slovak Academy of Sciences. Strong R&D infrastructure and the absorption of scientific knowledge through industry–university collaborations is a precondition for economic success. District Prešov and Banská Bystrica appear in the same category. Banská Bystrica hosts two of the most important manufacturers working in the sphere of biotechnology and pharmaceutical industry Biotika and Evonik Ferma. Prešov district is characterized by a large service sector and a number of high-tech companies.

Third, cluster 3 and 6 include districts with strong specialization in symbolic knowledge base. District Košice I (1.46), III (1.35) and district Bratislava I (2.56), IV (3.24), V (2.06) are considered as institutionally thick districts with dense network of support cultural institutions (Chaminade and Plechero, 2002). This higher specialization may be caused by the fact that these districts are territorial administrative centers where universities, museums and other important cultural institutions are localized. The most urbanized and densely settled district Bratislava I is the centre of cultural production in Slovakia. The dominant industries are fashion design, music visual and performing arts and publishing software (Chovanec and Rehák, 2012). Bratislava hosts a large number of local and international record companies, the publicly funded radio and television (RTVS) and all other major television channels have their headquarters in this district. Košice I, II districts have a strong institutional environment, reflecting the role of Košice as a regional cultural hub. Selected investment projects related to ECoC - Kosice 2013 has gradually changed Košice city from an industrial one into a creative one. A significant symbolic knowledge base can also be identified in Banská Štiavnica (2.11). Banská Štiavnica is the second smallest district in the terms of population and population density is also very low. But as the old medieval mining centre with its natural and cultural heritage Banská Štiavnica is justly inscribed on UNESCO's World Heritage list. As an important center of recreation and tourism there are also a number of small businesses focusing mainly on architecture, advertising and art creation. The cases of Bratislava, Košice and Banská Štiavnica districts demonstrate that symbolic knowledge production is often dominant in metropolitan regions but as was pointed out by Tödtling and Trippl (2005) symbolic base can equally occur in institutionally thin peripheral regions.

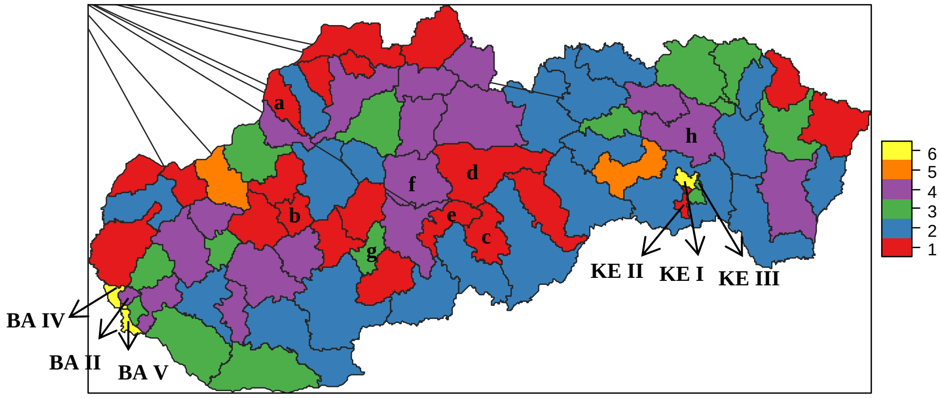
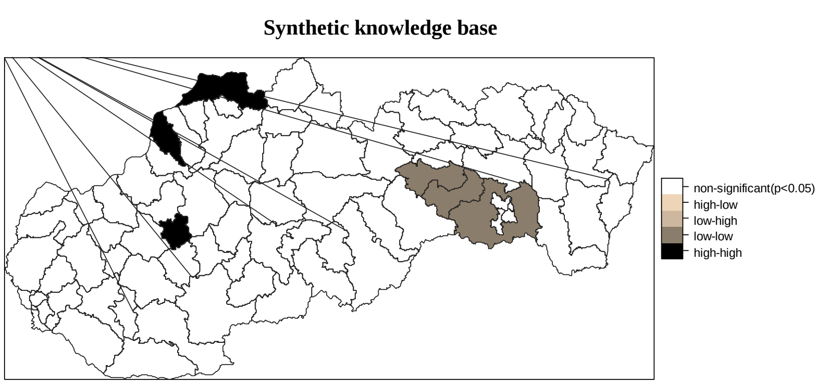
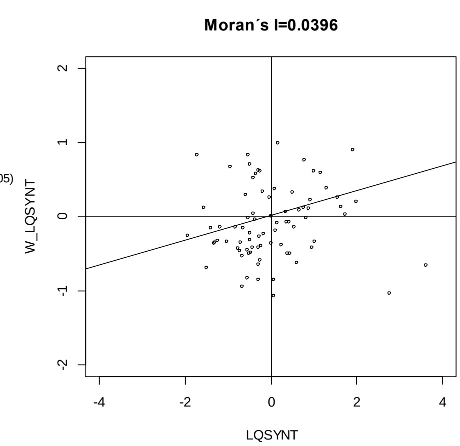



**Fig. 1 Spatial distribution of clusters**
Source: author´s own elaboration

*Note: a-Púchov, b-Partizánske, c-Poltár, d- Brezno, e- Detva, f-Banská Bystrica, g-Banská Štiavnica, h- Prešov, KE – Košice, BA- Bratislava*

The Moran index indicates positive spatial autocorrelation of LQ values in synthetic knowledge base (0.0396). However, this value is lower than in analytical (0.1115) and symbolic knowledge base (0.4214). This might let us presume that districts specialized in symbolic knowledge base are more located to each other, whereas concentration of synthetic knowledge base is more homogeneously spread across whole country. The values of the local indicator of spatial association (LISA) illustrate the spatial concentration and agglomeration for the chosen knowledge bases and for each district. According to value of LISA five scenarios can occur. The first is when district with high value of LQ is located close to district with high value too (known as hot-spots), the second is locations of low-value with neighbours (cold spot), the third is location with high values with low-value neighbours (potential spatial outliers), the fourth with low values with high-.value neighbour and the last scenario when the value of LISA has no significance (Kanó and Vás, 2013). Despite the fact, that large part of LISA is not significant the most relevant districts where each knowledge base has a hot spot are shown on the maps (Figure 2). The values of LISA show that synthetic knowledge base has a hot spot in district Partizánske and Púchov. The cold spots, where the neighbouring districts have similarly low values of LQ, can be identified in Eastern Slovakia. Not surprisingly, clusters with higher level of symbolic knowledge bases are formed in Bratislava districts and its agglomerations. In many others district the location has no significant local autocorrelation. Analytical knowledge base is also geographically concentrated in Bratislava districts. Thus, there is an overlapping cluster in analytical and symbolic knowledge bases around Bratislava agglomeration.



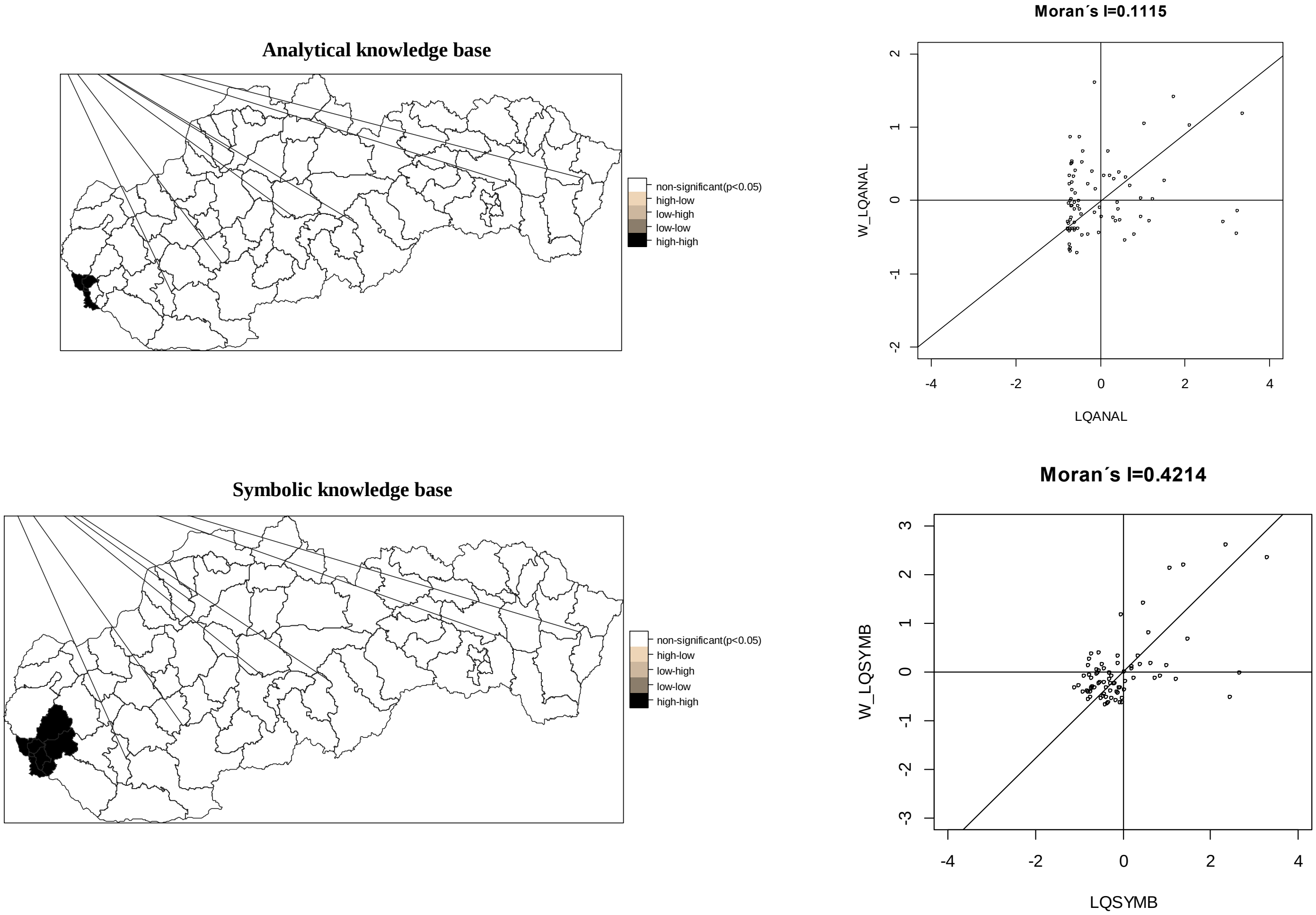



**Fig. 2 LISA and Moran's scatter plot of LQ values of differentiated knowledge bases**
Source: author´s own elaboration

# 4 Conclusion

This paper has presented a mapping of spatial distribution of knowledge bases in Slovakia at district level (LAU 1). Spatial distribution of knowledge bases was carried out by cluster analysis and then spatial autocorrelation was calculated to identify regularities in the spatial patterns. The analysis explored the relevance of geographical proximity in symbolic knowledge base. In line with the knowledge base literature, analysis confirm agglomerating tendency of symbolic knowledge base in large urban centres. Strong specialization on symbolic knowledge base is particularly in Košice I, III districts and Bratislava I, IV, V districts. Further, data show emergence of synthetic knowledge based industries within the traditional industrial centres and more sparsely populated districts especially in Poltár and Púchov. The largest areas in terms of population density still remain the main loci of analytical knowledge based industries given the tight linkages with public or private research organisations providing education and a skilled labour force. The gained results are in line with the characteristics of the regional industries identified by reviewing the literature. This approach is thus appropriate for further research questions. Many regions may face today the challenge of revitalizing their industrial structure. Slovakia is also facing the challenge of transforming its industrial district into creative one. Therefore, it is an important question if regions and districts can take up this challenge of strengthening their knowledge bases by themselves. However, there has been no clear evidence about the consequence of specialization in certain knowledge base on regional innovation and economic growth. Thus, it would be worthy to further investigate differentiated knowledge bases in terms of their impact on employment or economic growth.

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