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Spatial Distribution of Knowledge-Intensive Industries in Hungary

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Abstract Knowledge-intensive industries have attracted a great attention nowadays in researches because of its contribution to the development of knowledge-driven economy. They generate positive effects on the regional economy and have increasingly high importance in less developed regions, like Hungary. The identification of spatial distribution, the geographical co-location of knowledge-intensive economic activities is substantial to define potential leading industrial branches in regions. This paper aims to identify the spatial coherence and concentration of knowledge-intensive industries nationwide in Hungary at subregional level, and presents results using Ellison-Glaeser geographic concentration index and the measure of spatial autocorrelation with Moran index.

Keywords Knowledge-intensive industry · Geographical concentration · Spatial agglomeration · Hungary

JEL Classification C10 · O14 · R12

Introduction

Geographical proximity of economic activities has attracted increasing interest nowadays. Several theoretical and empirical studies underline the role of geographical proximity and the importance to analyze spatial distribution of economic activities and the formation of agglomeration economies. It is proven that agglomeration economies play a significant role in regional economic development,

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regional growth, and influence industrial location choice and the level of productivity of firms.

The expansion of the knowledge-based economy, the ongoing globalization and the pressure on economic actors in every region to develop their innovation capacity draws the attention to the potential hidden in knowledge-intensive industries (KIIs), even more interestingly in transition economies. For this reason, detailed insight into spatial distribution of KIIs is essential for policy makers to achieve effective innovation and regional policies at subregional, regional and even at national level. Due to the growing interest in KIIs, we found it necessary to examine the pattern of their co-location even in Hungary.

The study is structured into three main parts. After exploring the relevancy of geographical proximity and distinguishing spatial concentration from agglomeration, we present our methodology. Measures use various methods and indicators of spatial econometrics and statistics, and rely basically on the model of Ellison-Glaeser and Moran. The last section demonstrates the empirical results on a restricted circle of KIIs.

It is expected that some KIIs are more localized, and it may be attributed to the knowledge-intensity of the industry. If results show a higher spatial concentration of firms in an industry, the relevance of the industry in a particular region should be further underlined by the existence of agglomeration effects too.

Knowledge-Intensive Industries in the Knowledge-Based Economy

Knowledge is a key determinant to boost competitiveness, it is essential for innovation, to increase innovation performance, and to form local milieus and to experience spatial clustering (Malmberg et al. 1996). Knowledge-intensity has become a key explanatory factor for the development of the knowledge-based economy, which describes the increasing importance of knowledge-intensive industries too (Tödtling et al. 2006).

Geographical proximity of knowledge-driven innovative activities has been largely analyzed in empirical studies (Maurel and Sédillot 1999; Alonso-Villar et al. 2004; Barrios et al. 2005; Braunerhjelm and Johansson 2003). There is evidence on knowledge-intensive activities to concentrate geographically, even though the effects of globalization can be felt in all economic activities. One of the reasons, which explains the spatial clustering to be that essential for KIIs (Tödtling et al. 2006) is the phenomenon of knowledge-spillover, which is spatially restricted (Audretsch 1998).

All industries produce and use new knowledge and technology, but some are more knowledge or technology-intensive. KIIs differ from traditional ones particularly due to the different characteristics related to knowledge. In the early study of Pavitt (1984), it already has been pointed out that innovation cannot be constant across sectors, due to the role of knowledge, which varies from sector to sector. Differences between industries are manifested in knowledge links, interactions, types of knowledge and knowledge base. Asheim and Coenen (2005), Tödtling, Lehner and Trippl (2006) distinguish two main types of knowledge bases:

analytical and synthetic knowledge base. The latter is more likely related to traditional industries (e.g. machinery) with low level of R&D, use of existing knowledge elements and the dominancy of practical skills and tacit knowledge. In industries with synthetic knowledge base, knowledge is rather embedded in experiences and used to solve specific customer problems (e.g. ICT).

Baba, Shichijo and Sedita (2009) classify industries according to three types of industry-specific knowledge base: synthetic, analytical and the combination of synthetic and analytical knowledge base. Industries featured by analytical knowledge base (e.g. the biotechnology, pharmaceuticals), or the combination of analytical and synthetic knowledge base (e.g. engineering, advanced materials, medical devices) use both tacit and codified knowledge where the source of knowledge is not only the generic customer–supplier relation, but the more specific interactions between customers and suppliers, universities and firms. Knowledge-intensive firms apply or combine existing knowledge elements, and create new knowledge. R&D efforts are typically geographically concentrated to generate radical innovation.

Breschi and Malerba (2005) describe innovation as a creative, collective process, in which innovators interact, transfer knowledge and continue knowledge–based communication. In most cases these interactions take place in geographical limits due to the location of actors. Therefore innovation activities are characterized by spatial boundaries of knowledge. Breschi and Malerba (2005) confirm the key role of knowledge in location choice, and provide empirical evidence of the importance of geography for KIIs (Malerba 2004). Knowledge matters, and knowledge-intensity explains the spatial distribution of innovation activities.

International Evidence on Spatial Distribution of Knowledge-Intensive Industries

A number of researchers investigated empirically the spatial distribution of KIIs. Jaffe and his co-authors (1993), Audretsch and Feldman (1996) observed the higher geographic concentration of KIIs in the USA, while evidence on the United Kingdom (Devereux et al. 2004), Belgium, Portugal and Ireland (Barrios et al. 2005) does not underline the high spatial dependence of the KIIs.

Measures on spatial distribution lead mostly to various results due to the different methodologies applied. Studies use typically different spatial and sectoral aggregations and indicator sets. Maurel and Sédillot (1999) analyzed French manufacturing industries on 2 and 4-digit sectoral level, both at regional and subregional level, and proposed a modification for Ellison and Glaeser's concentration index to analyze geographical concentration. They found that the high-tech manufacturing industries are mostly highly localized on subregional level, and this can be observed even at regional level. Comparison with the results of Ellison and Glaeser for the USA did not lead to significant changes and it confirms the importance of technological spillover in geographical concentration.

Alonso-Villar and her co-authors (2004) analyzed manufacturing industries in Spain at 2 digit and 3-digit level. Data were taken between 1993 and 1999, and were provided in two geographical levels, including 17 regional autonomous communities and 50 provinces. Analysis was based on the original Ellison-Glaeser γ index and on the modified γ index from Maurel and Sédillot. Results also point out the high geographical concentration of several high-tech manufacturing industries, and confirm that higher knowledge-intensity implies higher geographical concentration.

The study of Braunerhjelm and Johansson (2003) examines spatial concentration of the Swedish manufacturing and service sector at 2 and 4-digit level. The analysis involves 70 regional areas, and refers to the years 1975 and 1993. Based on the two given periods, the authors also present the change in spatial concentration, but do not find evidence for KIIs to have higher geographical concentration. However, there are more among the knowledge-intensive service, which are spatially concentrated, than among the manufacturing industries.

Similarly to the Swedish case, measures of Alecke and Untiedt (2008) in Germany also do not confirm the correlation between spatial concentration and knowledge-intensity of sectors. They analyzed a wide range of economic activities in districts and regional districts, on 3-digit level, including agricultural activities, industries and services. Alsleben (2005) gave a possible explanation for their results. He employs a duopoly model, and explains that the firms are afraid of poaching their workers, so they often choose to work in different places.

Breschi (1998) carried out an analysis to explore the spatial pattern of innovative activities in Italy based on a data set of patent applications. Data are aggregated on the level of provinces (NUTS 3 level) at 3-digit level, and were collected during the time period from 1987 to 1994 for given 30 technological fields. Results show that innovative and manufacturing activities have a higher level of spatial concentration than population and the innovative activities (the patent applications) are generally more concentrated than the manufacturing industries. Measures for spatial autocorrelation point out that in case of less innovative and spatially less concentrated activities, spatial autocorrelation is positive and significant, meanwhile innovative activities appears as ‘islands’ in few provinces.

Usai and Paci (1999) attempt to investigate the process of spatial agglomeration of 85 innovation and production activities based on data from 1990 to 1991 in 784 groups of municipalities, namely in the Italian Local Labour Systems. Measuring Moran’s index, they confirm strong spatial autocorrelation, which can be experienced even in the third neighboring region. When the relevant territorial unit was a metropolitan region or when the industry was a high-tech industry agglomeration effects were stronger. There is evidence on the existence of cross-border technological spillovers too, however positive and significant spatial autocorrelation can be observed only until the second contiguous area. Beyond this, with the increase of distance, agglomeration effects die out, technological spillover becomes spatially bounded.

Geographical Proximity: Spatial Concentration Versus Agglomeration

Geographical proximity reduces uncertainty, solves the difficulties of coordination, facilitates the interactive learning and thus has a positive impact on the economic performance and growth of regions (Boschma 2005; Kirat and Lung 1999; Torre and Rallet 2005). Most of the regional, national development strategies for regional growth and development emphasize the relevance and proximity of high-technology firms and universities, the closeness of experts, researchers or similar sectors.

Geographical proximity is also signified as spatial, local or physical proximity (Knoben and Oerlemans 2006). Geographical or regional sciences traditionally use the notion of proximity, defined as short geographical distance (Nemes Nagy 2009). Short distance brings individuals together, favours information transfer and facilitates the diffusion and exploitation of knowledge, especially tacit knowledge. Actors in geographical proximity benefit from positive externalities, which reduce transfer and transaction costs (Lengyel 2010).

Whether the subject of analyses is to measure geographic concentration or agglomeration, both are related to the question of how economic activities are distributed across the space and where specific economic activities can be found (Brakman et al. 2009). Both notions deal with the location of specific industrial activities, thus cluster literature use the terms of spatial concentration and agglomeration as synonyms (Porter 1990).

Lafourcade and Mion (2007) recommend to make a differentiation between the two concepts. Spatial concentration refers to firms in an industry clustered in a number of regions, without taking into account whether these regions are close or far from each other (Lafourcade and Mion 2007). Two industries may be equally concentrated even if they are in adjacent or isolated regions. The only important condition in case of concentration is the co-location of firms within one region.

Measurements on agglomeration look for the degree of spatial interdependence among territorial units. Thus the condition of agglomeration economies is the presence of firms of an industry in neighbouring, and not isolated regions. To identify regularities in the spatial pattern, spatial autocorrelation is calculated (Lafourcade and Mion 2007). Spatial autocorrelation occurs when values of a variable observed at nearby locations are more similar to each other than those observed at locations at a greater distance from each other. Positive autocorrelation refers to locations close to each other and with similar values in case of a given variable. On the contrary, negative autocorrelation refers to dissimilar values.

Brakman and his co-authors (2009) use the term of agglomeration from a different perspective. According to them, while geographic concentration refers to the location of firms from a particular industry, agglomeration describes the location pattern of a greater proportion of an economic activity, like the manufacturing sector. Recent analysis follows the concept introduced by Lafourcade and Mion (2007).

Indicator sets to explore the pattern of spatial concentration and the existence of agglomeration effects are different. Measures are usually based on employment or production data to highlight the weight of industries within a region and to analyze spatial distribution. For this reason, recent analysis also built on employment data.

Geographical concentration of industrial activities has been repeatedly studied. To measure geographical concentration index numbers like location quotient (LQ), Herfindahl index, Gini coefficients, Theil index, Ellison-Glaeser index or Ellison-Glaeser γ index can be measured. Recent analysis uses one of the most frequently and easily understandable LQ index (Pearce 1993) and the Ellison-Glaeser's γ index (EG γ) (Ellison and Glaeser 1997).

To measure agglomeration effects, a widely used index is the Moran index, which was introduced by Moran in 1948 (Moran 1950; Lafourcade and Mion 2007). The Moran index is subsequently used in many studies employing spatial autocorrelation. The Moran's I indicates whether the spatial distribution of a currently analyzed data values show any kind of regularity, and used to estimate the strength of the correlation between observations. The Moran's I has one major limitation, namely it provides one statistic and evaluates global spatial autocorrelation. This inspired statisticians to develop local indices to examine clustering on local level by using local spatial autocorrelation. A standard tool to examine the localized version is Luc Anselin's (1995) LISA (Local Indicator of Spatial Association), which is the local equivalent of Moran's I.

Methodology

Recent empirical study focuses on KIIs with the aim to explore how they distribute across the space in Hungary, at a subregional (LAU 1) level. Spatial distribution has been calculated for the number of employees and the number of firms and their sites in case of all KIIs. Economic activities are identified according to NACE Rev. 2. on 2-digit level, and classified following the methodology of Eurostat (2009).

The broad definition of KIIs describes KIIS both as leading producers and users/consumers of high-technology products and activities, industries, which employ highly qualified labour to exploit the knowledge of innovative outcomes and new technological solutions (OECD 2001). According to the current aggregation, there are high and medium-high-technology manufacturing industries and knowledge-intensive services (KIS) (Eurostat 2009). The circle of KIS is divided to knowledge-intensive market and financial services. The classification also makes distinction between high-tech KISs and other KISs. The latter refers to less KIIs, which only exploit the knowledge produced by other economic activities and qualified labour force.

The current industrial classification system is not the most appropriate mechanism for describing a set of common business activities, due to the grouping of a very wide range of economic activities. However to make measures, collect and more importantly to compare statistical data it is an adequate and widely used classification. Due to this limitation, this paper restricts the classification of KIIs, and focuses on the more knowledge-intensive activities, by excluding the other KISs.

The dataset is provided by the Hungarian Central Statistical Office (HCSO). The HCSO gives a detailed dataset of plants by the Company-Code-Register (in Hungarian: Cég-Kód-Tár) in every quarter. This study is based on data from the third quarter of 2009. The data collection started from the level of settlements, with further aggregation to the level of local administrative units (LAU 1). The study takes all the 174 subregions in Hungary into consideration. Employment data derives from the Territorial Statistical Yearbook 2008 (HCSO 2009).

Measures are taken from two perspectives: when data on the capital is included and when data on Budapest is excluded. This reveals the distortions in the results for two reasons (Lukovics 2008). Firstly, Budapest has a central and dominant social and economic power in Hungary, and many institutions with national importance are concentrated in the capital. Secondly, Budapest is included in all territorial divisions and considered separately as one unit, whether it is municipal (LAU 2), subregional (LAU 1) or county level (NUTS 3).

Results

To reveal how KIIs flock together and to investigate their empirical properties on geographical concentration and spatial agglomeration the Ellison-Glaeser's γ index and Moran index was calculated. Based on the values of EG γ index, a classification of KIIs was made with the following categories: an industry can be spatially sparse, weakly concentrated, moderately concentrated, or strongly concentrated.

In the case of the Moran index it is impossible to determine the autocorrelation level of the spatial distribution of industries based on values only. To determine this, the distribution is estimated and defined by using actual concentration values, with the help of the Monte Carlo method. The Geoda 0.9.5. software developed by Luc Anselin is suitable to make these calculations. As a result, it is possible to determine the spatial distribution of given KIIs with a preliminary defined significance level: with strongly negative, with negative, with no autocorrelation, with positive and with strongly positive autocorrelation.

Mixed picture emerges from the results (Tables 1, 2). There are large differences between the industries. In case of high and medium-high-tech manufacturing industries, a more complex and varied picture has resulted, either the data on the capital is included or excluded. A closer look to the data however reveals that knowledge-intensive services are generally more spatially concentrated.

The analysis of spatial concentration shows that none of the industries would be in sparse, if data on Budapest is included. This might let us presume that the location choice of firms is at least slightly dependent on the location choice of other firms in the same industry. Only the sectors of manufacture of basic pharmaceutical products and pharmaceutical preparations (21) and the manufacture of other transport equipment (30) from the high and medium-high-technology manufacturing industries are strongly concentrated at a subregional level, if data on Budapest is

Table 1 Spatial concentration and agglomeration of KIIs including data on Budapest

Concentration	Spatial autocorrelation				
	Strong negative	Weak negative	None	Weak positive	Strong positive
Strong	60,64,65,72,78		**21**,58,63,66, 69,73	59	**30**,61,62,70,71,74,80
Medium		**20**	**29**		
Weak			**26**,**27**,**28**,50		51
Sparse					

High and medium-high technology manufacturing industries are in bold

Table 2 Spatial concentration and agglomeration of KIIs excluding data on Budapest

Concentration	Spatial autocorrelation				
	Strong negative	Weak negative	None	Weak positive	Strong positive
Strong			51,61		
Medium			**20**,**27**		
Weak			**26**,**28**,**29**,58,64, 66,69,72,73,78	50,71	59,62,63,70, 74,80
Sparse			**21**,**30**,60,65		

High and medium-high technology manufacturing industries are in bold

included. Furthermore this tendency may be drawn up in the case of almost all KISs. Not surprisingly, the resource-driven sectors of water transport (50) and air transport (51) are exceptions. If Budapest is excluded from the analysis, the results are different. In most of the industries the level of spatial concentration is medium or weak.

Whether data on Budapest is included or not, empirical evidence on spatial agglomeration underline that there are many industries where there is no autocorrelation. The Moran index indicates a very strong spatial autocorrelation mainly in case of KISs, with or without data on Budapest, but in a different range.

It is difficult to draw a general conclusion considering the spatial distribution of KIIs in Hungary at subregional level. For this reason it is useful to make a separate analysis for each of the industries. This analysis highlights the specific characteristics of one example of each subgroup of KIIs.

Due to the need for Herfindahl index to count Ellison-Glaeser's γ index, the values of sectoral concentration are also given and demonstrated in the following cases. The results for the Herfindahl index may refer to an industry fragmented in many firms with low numbers of employees or to an industry that consists of some bigger firms. Based on the index industries are marked as: highly fragmented, fragmented industry, industry with weak or strong industry concentration.

To illustrate the spatial concentration and agglomeration for the chosen cases, maps are constructed based on the results for the LQ and local Moran index. For each location the values of LISA allow the computation of similarity with neighbours, and also test its significance. Five scenarios may occur: locations with high values with similar neighbours: (known as hot-spots), with low values with similar neighbours (cold spots), with high values with low-value neighbours (potential spatial outliers), with low values with high-value neighbours (potential spatial outliers) and with no significant local autocorrelation.

Manufacture of Basic Pharmaceutical Products and Pharmaceutical Preparations

The case of manufacture of basic pharmaceutical products and pharmaceutical preparations (21) demonstrates the tendency to spatial concentration and agglomeration of high-tech manufacturing industries. If data on Budapest is taken into

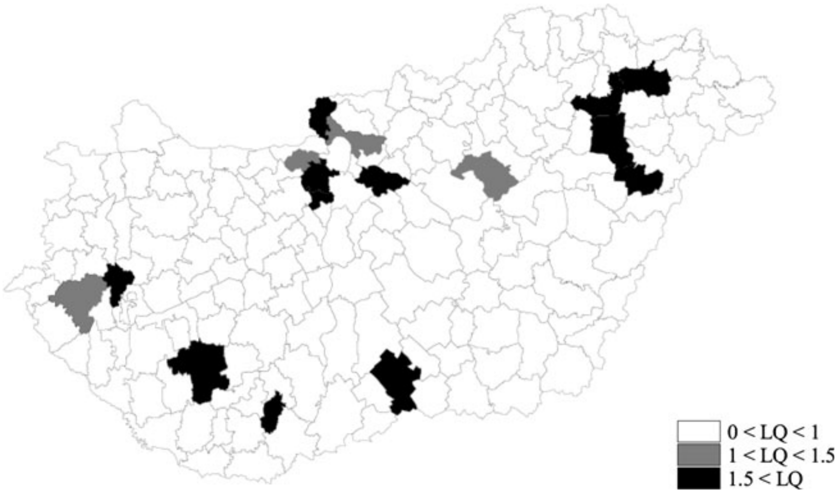

Fig. 1 Distribution of LQ values (excluding Budapest)

account, the industry is strongly concentrated in the space, fragmented and no agglomeration effects can be observed among the neighbouring subregions. If data on Budapest is excluded, the industry does not show spatial concentration in any of the subregions in the countryside. There are no agglomeration economies forming. Firms are located in dispersion and the sectoral concentration is weak.

Results for the spatial concentration show similar tendency if data on Budapest is included or excluded. Measures for LQ clearly confirm that the pharmaceutical industry is relatively very highly geographically concentrated in Budapest (LQ = 7.43). Relatively high concentration can be observed only in few other subregions on the countryside (with an LQ value around 1.5) (Fig. 1).

The location pattern of the industry is influenced by the firms' size (Lafourcade and Mion 2007, Alecke and Untiedt 2008). The industry in Hungary consists of a few large and many smaller companies. Without Budapest the industry is characterized only by a few large companies in the countryside.

The industry is strongly concentrated in the space, but without any attracting effect that may occur between neighbouring subregions. The values of the local Moran index show only one subregion where the pharmaceutical sector has a hot spot (Fig. 2). In many subregions the locations have no significant local autocorrelation.

Manufacture of Motor Vehicles, Trailers and Semi-Trailers

The manufacturing industry of motor vehicles, trailers and semi-trailers is one of the medium-high tech industries (29). Taking Budapest into account, the industry shows the following patterns: moderately concentrated in the space, with no autocorrelation, and fragmented to smaller firms. If data on Budapest is excluded the industry becomes weakly concentrated, without observing any regularities among the

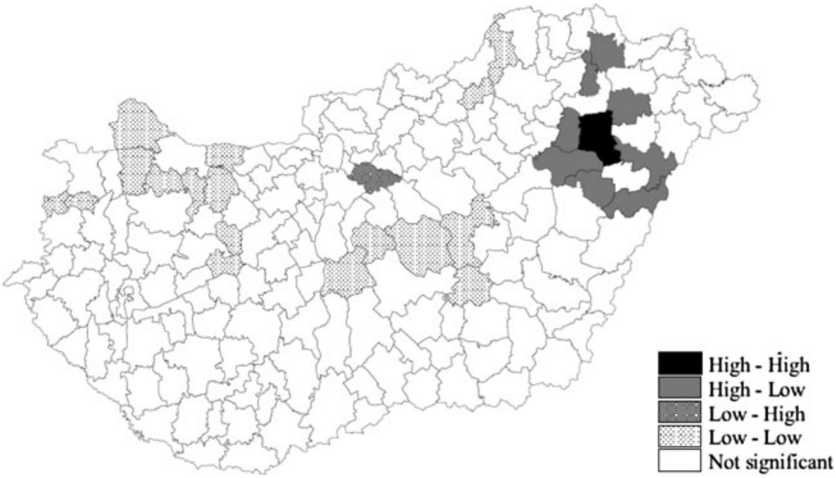

Fig. 2 Subregions according to LISA (excluding Budapest)

subregions. The industry is fragmented even without the data on Budapest. The industry is present in the capital with a relatively low number of firms.

Including the values on Budapest does not cause any distortion. The industry shows a relatively high concentration (with LQ < 1.5) mainly in the Northern-Western subregions of the country (Fig. 3). The clustering of motor vehicle manufacturing activities is repeatedly examined and confirmed in empirical studies in Hungary. Empirical evidence given by Breschi and Malerba (2005) also characterized the automotive industry as a generally geographically concentrated industry with the relevance and need of local knowledge-transfer.

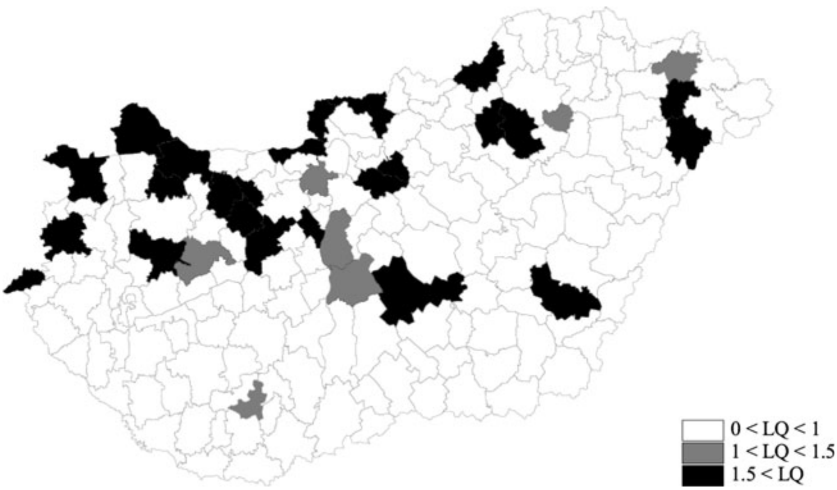

Fig. 3 Distribution of LQ values (including Budapest)

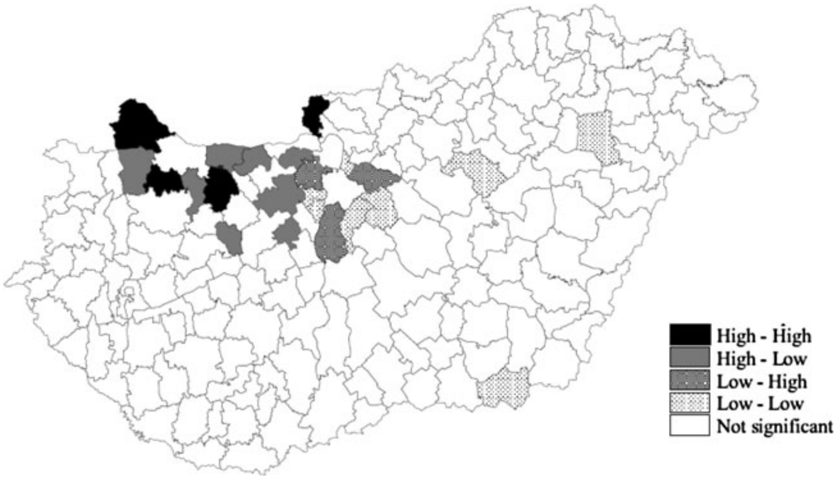

Fig. 4 Subregions according to LISA (including Budapest)

Values for LISA reveal that the manufacturing industry of motor vehicles is not only geographically concentrated in the North-Western part of Hungary (Fig. 4). The industry has hot spots in four subregions, all in the North-Western part. The cold spots, where the neighbouring regions have similarly low values, can be found in Eastern Hungary.

Computer Programming, Consultancy and Related Activities

One example of knowledge-intensive services is the computer programming, consultancy and related activities (62). Including data on the capital, the industry is strongly concentrated in the space, fragmented, with positive strong autocorrelation. If data on Budapest is excluded the industry is weakly concentrated, with positive strong autocorrelation. The industry is fragmented.

Compared to other KISs, the industry has a relatively high concentration in Budapest (LQ = 3.32). Beside Budapest, if data on Budapest is taken into account, there are only four subregions, which have a LQ value higher than one. But by disregarding Budapest it becomes clearly visible that firms also flock together in other subregions. Relatively high concentrated is observed in the so called pole cities (most developed cities in Hungary beside Budapest) on the countryside (Fig. 5).

Observations of Breschi and Malerba (2005) underline that in the software computer programming industry there are many innovators who are geographically concentrated, and have a need for both local and global knowledge flows.

The local Moran index does not reveal agglomeration economies in the countryside, not even in the pole cities. The cold spots can be easily identified, mainly in the eastern part of the country. The hot spots are definitely formed in Budapest and its agglomeration (Fig. 6).

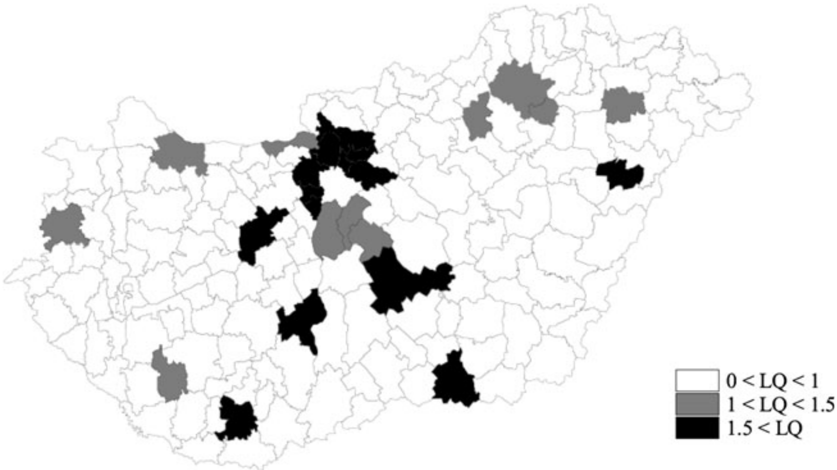

Fig. 5 Distribution of LQ values (excluding Budapest)

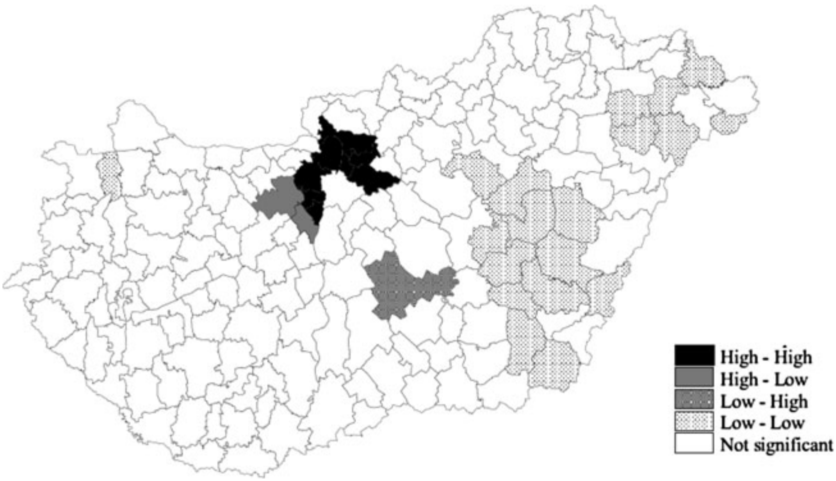

Fig. 6 Subregions according to LISA (including Budapest)

Conclusions

The study is aimed at mapping the spatial distribution of KIIs in Hungary at subregional level, and is meant as the initial step to prove whether it is destined to make further steps to develop and support an industry as a regional leading branch.

The analysis explored the relevance of geographical proximity in KIIs. However, industries display a rather mixed picture in terms of geographical concentration and spatial agglomeration. Based on measures of spatial concentration we can conclude that a few high and medium-high-tech industry and most of the knowledge-intensive services are at least moderately concentrated industries. The high degree of geographical concentration is due to the Budapest region. The city causes continuous distortion in the spatial analysis of industries in Hungary.

However, based on the index number of agglomeration KIIs seem to be more divided. These results are not surprising ones. Geographical concentration measures forces on narrower range, while agglomeration assesses the effect of forces going beyond the borders of the territorial units.

To grab the location pattern of KIIs, and the tendency to agglomerate, it is indispensable to examine the circle of manufacturing economic activities and knowledge-intensive services separately. Furthermore to answer the question of how knowledge-intensive industries distribute across the space in Hungary, it is worthy to analyze all KIIs one by one by taking into account all the special characteristics of industries, like the location of inputs, customers, competitors, the extent of information and knowledge flows and more importantly the characteristics and elements of the knowledge base. It is also highly important to take into account that patterns of spatial distribution are influenced by the social and economic conditions of the region examined and results of analysis depend on the chosen level of territorial unit, where the analysis is done.

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