# Do knowledge-intensive enterprises flock together?
# Evidence from Hungary at sub-regional level

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Knowledge-intensive industries as unique types of sectoral innovation systems in production and services have a lead in respect of the development of knowledge-driven economy. Today they are concerned as the core of growth, the source of regional specialization with an increasingly high importance especially in less developed countries, like Hungary.

Spatial distribution of knowledge-intensive industries is unequal in Hungary, which may derive from the proportion of the spatial boundaries of knowledge used in their firms' innovative processes. 'Knowledge poles' described as concentration or even agglomeration of knowledge-intensive economic activities are shaping in Hungary. Knowledge-intensive firms may 'flock together', but it does not mean that all co-location firms operate in agglomeration economies too. It is necessary to make a differentiation between concentration and agglomeration of firms.

Recent study aims to identify the spatial coherence and concentration of knowledge-intensive industries in Hungary at sub-regional (LAU 1) level, using the methods and indicators of spatial econometrics and spatial statistics. The research also tries to give a framework to analyse knowledge-intensive industries as sectoral innovation systems in terms of their knowledge base.

## 1. Introduction

Knowledge-intensive industries (KII) have attracted much attention in recent years in the economic analyses, realizing the driving role in the development of the knowledge-driven economy. Knowledge has become a key source of competitiveness, and main dimension to examine innovation and innovative performance of economic actors, firms and regions, describing the increasing importance of KIIs too (Tödtling et al 2006, Isaksen 2006).

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The specialization of a region is based on many factors, different inputs, economic actors and specific industrial activities which has an effect on their innovativeness. It is widely accepted that innovation differs across sectors (Pavitt 1984, Malerba 2005), and if the purpose is to analyze regions' innovation performance, it is necessary to survey both the location and innovativeness of knowledge-intensive industries separately from traditional industries, because they are very different in their knowledge sources, knowledge base, links and local clustering (Tödtling et al 2006).

It is also known that industries' ability to generate innovation does not depend on how individual actors perform within an industry, but rather on how they interact as participants of a system, a sectoral (in other words: industrial) innovation system. All industry is a heterogeneous set of agents, interactions, inputs, demand, technologies and knowledge, and if we attempt to see the specific characteristics of knowledge-intensive industries, we have to define also the special nature of knowledge base used by KIIs. The notion of sectoral innovations systems is an appropriate tool to give a theoretical framework to answer the questions that why innovation process is the different in KIIs, why KIIs are different from other industries and even how knowledge describes the spatial distribution of industries, especially KIIs.

The detailed insight into the spatial distribution of knowledge-intensive industries is essential for policy makers especially in Hungary with less developed regions to achieve an effective innovation and regional policy at sub-regional, regional and even in national level. Recent study aims to reveal how knowledge-intensive industries in Hungary distribute in the space and where are the knowledge poles in Hungary in case of certain industries, defined as agglomeration of knowledge-intensive economic activities at a sub-regional level.

The paper aims to reveal the spatial distribution of knowledge-intensive industries as sectoral innovation systems, and structured the following way to demonstrate it. The first section tries to answer that why it is interesting to differentiate knowledge-intensive industries from the traditional industries, based on the theoretical background of sectoral innovation system. We introduce the relevancy of knowledge in different industries, which may be the base to explain the geographical proximity of firms. After classifying the knowledge-intensive industries, we introduce the different indexes to measure the concentration of firms and agglomeration effects at sub-regional level in Hungary. The section 3 mainly illustrates the model of Ellison-Glaeser and Moran to asses that how KIIs flock together in Hungary. The last section demonstrates the empirical result about the spatial distribution of the examined KI industries in Hungary.

## 2. Knowledge-intensive industries in focus

The expansion of knowledge-based economy, the ongoing globalization and the pressure that economic actors in regions have to face to develop their innovation capacity grab the attention to analyze knowledge-intensive industries and even more specifically in less developed regions. To examine the special characteristics of KIIs we introduce the concept of sectoral innovation system, and we reveal the importance of knowledge, and industry specific knowledge base in the distribution of industries.

### 2.1. Knowledge-intensive industries as sectoral innovation systems

Firms in different industries innovate differently, have both commonalities and heterogeneities. They may be similar or heterogeneous in the terms of development, the rate of technological change, knowledge-transfer-based linkages, knowledge base, access and adoption of knowledge, organizational structure and institutional factors etc. It is important to take these factors into account when the aim is to classify and analyze knowledge-intensive industries. But there is another, substantial factors what we have to consider as it was shown by the **sectoral innovation system** approach (by Malerba 2005, and in other innovation systems approaches: national and regional innovation system - Freeman 1995, Nelson 1993, Lundvall 1992, Cooke et al. 2007):that innovation has relevant systemic features. Firms don't innovate in isolation, the innovation is an interactive and collective process between firms, where firms have continuous communication and interaction with other actors and institutions, who have an influence on their innovation performance. An innovation system of sector "*is a set of new and established products for specific uses and the set of agents carrying out market and non-market interactions for the creation, production and sale of those products*" (Malerba 2002).

All firms in different industries have to face different drivers or barriers to innovate. Sectoral system of innovation in all industries have a knowledge base, dominate different technological territories, uses inputs and have demand (Malerba 2005). The system is composed of a set of actors who are connected by either market or non-market interactions (or both), and participate in the creation, development and also diffusion of the industrial product.

To differentiate knowledge-intensive industries from traditional ones, there are three dimensions through which we may do a punctual sector specification.

These factors are the building block of a sectoral innovation system (Malerba 2005):

- knowledge and technologies (the specific knowledge base, technologies which characterize the industry)
- actors and networks (individuals like consumers, entrepreneurs, scientists, and organizations like firms and non-firm organizations, e.g. financial institutions, government agencies, universities),
- institutions (formal and informal ones, like norms, routines, practices, rules, laws, standards).

Central building block of a sectoral innovation system is knowledge and the learning process, which firms from various industries continue to be more innovative. It was the evolutionary literature, which drew the attention to a very important observation: industries differ greatly in terms of the knowledge related to innovation and there are more aspects to describe the knowledge effecting the technological environment of firms (Malerba 2002). The distinction of different knowledge characteristics of also explains the location pattern of industries and spatial distribution of firms.

Knowledge has different degrees of **accessibility** (Malerba – Orsenigo 2000). Firms are aspired to gain new knowledge that may be internal or external to the industry. The greater accessibility of knowledge decreases the concentration of an industry.

Industries may face different **opportunity** conditions according to knowledge, which is reflected by the "*likelihood of innovating for any given amount of money invested in search*" (Breschi – Malerba 2005).

Knowledge may be **cumulative**, which refers to the degree by which the production of a new knowledge builds upon current knowledge (Malerba – Orsenigo 2000). It may have three sources, the learning processes and dynamic increasing returns at the technology level, the organizational capabilities and the feedbacks from the market. The knowledge is cumulating in various levels: technological, firms, sectoral and local level. If the cumulativeness takes place at a local level, it may happen because the firms' technological competencies and innovative capabilities located in a specific geographical area. The high cumulativeness is generally associated with low appropriability conditions and spatially localized knowledge spillovers (Breschi – Malerba 2005).

The **appropriability** conditions are the possibilities to protect innovation from imitation. The level of appropriability may be high with successful solutions to protect the innovation, and low which characterized by widespread knowledge externalities, knowledge spillovers (Malerba

– Orsenigo 2000). Firms from different industries do not use the same means to protect their innovations. The solutions range from patents to secrecy, continuous innovation etc.

The different dimensions of knowledge are fundamental factors to characterize the knowledge and learning environment (so called technological regime – see Breschi – Orsenigo 2000) in which firms operate. Nelson and Winter (1982) showed that the technological environment of firms is described by the opportunity and appropriability conditions, have a major effect on the intensity of innovation and the industrial concentration. This concept was further developed by Malerba and Orsenigo in 1990's, who defined the learning environment by the combination of four fundamental factors.

Besides the opportunity, appropriability conditions and the cumulativeness of the knowledge, there is a forth factor, the nature of the relevant **knowledge base**, which forms the firms' learning environment and firms knowledge absorptive capacity (Breschi – Malerba 2005). The knowledge in the industry's knowledge base may be generic or specific with well defined application domains, characterized by the degree of tacitness, where knowledge is tacit and local or codified and easily transferable, the degree of complexity (concerning to the variety of competencies needed for innovative activities) and the degree of interdependence by examining whether knowledge is easily identifiable or embedded in a larger system.

The dimensions of knowledge allow us to make a differentiation between traditional and knowledge-intensive industries. Industries seem to differ in knowledge links, interactions, types of knowledge of relevance and knowledge base. Tödtling, Lehner and Trippl (2006) showed some evidence according to the knowledge base of industries and distinguished two main types of knowledge base: the analytical and synthetic knowledge base. The latter one is more likely concerned to the traditional industries (like machinery) with low level of R+D, application of existing knowledge and dominancy of practical skills, and tacit knowledge. In this industries the knowledge is rather embedded in experiences, and used to solve specific problem of the customers. Comparing to this, the analytical knowledge base is typical to those knowledge-intensive industries, like ICT. Beside the relevance of tacit knowledge, firms focus on to codify their knowledge in the form of different studies, patent descriptions etc.

Baba et al (2009) built an analytical framework to attempt to classify the different industries according to their prevalent knowledge base and specification of innovation process (Table 1).

***Table 1.*** Industry specific knowledge base for innovation

| **Main features** | **Types of knowledge base** | | |
|---|---|---|---|
| | **Synthetic (A)** | **Analytical (B)** | **Synthetic and analytical (C)** |
| **Nature of innovation** | application or novel combination of existing knowledge | creation of new knowledge | A+B |
| **Prevalent type of knowledge** | technical knowledge | scientific knowledge | A+B |
| **Open search strategies for innovation** | based on client-supplier interactions | rooted in university-industry collaborations | A+B |
| **Innovation type** | mainly incremental | mainly radical | A+B |
| **Dominant knowledge** | dominance of tacit (know-how, craft, practical skills) | dominance of codified knowledge (patents, publications) | A+B |
| **Typical industrial settings** | engineering-based (plant engineering, shipbuilding) | science-based (biotechnology, pharmaceuticals) | hybrid (advanced materials, medical devices) |

*Source*: own construction based on Baba et al (2007)

Concerning to the analytical and synthetic way of classification of knowledge base, knowledge-intensive industries are clearly different from the traditional ones. Industries featured by analytical knowledge base, or the combination of analytical and synthetic knowledge base use both tacit and codified knowledge, where the source of knowledge not only the generic customer-supplier relations, but the more specific interaction between customer and suppliers, universities and firms. Knowledge intensive firms operate in a more intensive and interactive knowledge and technological environment in terms of the creation of new knowledge, the rate of product and process innovation (of a radical nature). R+D effort in this industries typically concentrated on the generation of radical innovation.

The literature of sectoral innovation systems and technological regimes in recent years described a relatively new phenomenon (Breschi – Malerba 2005): the knowledge and learning environment in which firms operate (the technological regime) is connected to different geographical levels. It was shown that innovators of a certain industry are geographically concentrated when there are conditions of high opportunity, high appropriability and high cumulativeness. In this case the relevant source of scientific and technological knowledge is in a specific location, or knowledge base is characterized by tacitness, complexity and systemic features. Innovators are geographically dispersed when there are low conditions in all dimensions, or the knowledge base is relatively simple.

It was also proved that firms have to face certain proportion (global or local) of knowledge spatial boundaries (Breschi – Malerba 2005). The innovation is a creative, collective process, where innovators, actors interact with each other, transfer knowledge and have a knowledge –based communication. In most of the cases these interactions take place within certain borders of geographical areas because of the location of the actors. For this reason the innovation process of firms characterized by spatial boundaries of knowledge.

Knowledge spatial boundaries of innovative activities have a local nature, if the knowledge base is tacit, complex, embedded in a larger system and the knowledge is associated with not generic, but systemic suppliers or users. In this case the geographical proximity of the actors has an increasingly important role in the innovation process. In other cases, when the knowledge base is more simple, codified and the sources of new knowledge are the generic suppliers and users, geographical proximity is unnecessary, and the knowledge spatial boundaries tend to have national, international or global nature.

The research and the detailed empirical studies done by Malerba and Orsenigo proved that even if we do no not take the geographical dimensions of sectoral innovation system approach into consideration for the first sight (only rather the relational proximity), it is underlined to analyze firms and actors of a sectoral system in geographical proximity too. Knowledge has a key role in determining the dynamics and localization of different kind of industries. The concept of knowledge spatial boundaries gives us a good tool to watch regions' innovation performance through the eyes of the innovation performance of industries.

## 2.2. Classifying knowledge-intensive industries

All industries produce and use new knowledge and technology, but some are more knowledge or technology-intensive. There is a need to distinguish traditional and knowledge-intensive industries as for example comparably more R&D intensive sectors (as it was described earlier for instance by the OECD, in its traditional sector classification as the principal ranking criteria). Today a broad definition of KKIs is used, describing them both as leading producers and users/consumers of high-technology products and activities. KKIs also include those economic actors who are employing highly qualified labour to exploit the knowledge of technology innovations and new technological solutions (OECD 2001).

To continue to make a differentiation between only high and low-tech industries (as the OECD did in the 1980s) also was not sufficient, it was necessary to specify the circle of KKIs concerning different inputs, characteristics and technology intensity. According to the aggregation primarily defined by the OECD, - based in the technological standard of sectors - there are **high-technology manufacturing** (NACE Rev. 2. at 2 digit level: 21, 26), **medium-high-technology manufacturing** industrial sectors (20, 27, 28, 29, 30) and **knowledge-intensive services** (KIS) (50, 51, 58-66, 69-75, 78, 80, 84-88, 90-93) (Eurostat 2009).

***Table 2***. Knowledge-intensive industries (in a limited sense)

| NACE Rev. 2. codes 2 digit level | **Sectors** |
|---|---|
| **High-technology manufacturing industries** | **21** Manufacture of basic pharmaceutical products and pharmaceutical preparations<br>**26** Manufacture of computer, electronic and optical products |
| **Medium-high-technology manufacturing industries** | **20** Manufacture of chemicals and chemical products<br>**27** Manufacture of electrical equipment<br>**28** Manufacture of machinery and equipment n.e.c.<br>**29** Manufacture of motor vehicles, trailers and semi-trailers<br>**30** Manufacture of other transport equipment |
| **Knowledge-intensive services (KIS)** | **50** Water transport<br>**51** Air transport<br>**59** Motion picture, video and television programme production, sound recording and music publishing activities<br>**60** Programming and broadcasting activities<br>**61** Telecommunications<br>**62** Computer programming, consultancy and related activities<br>**63** Information service activities<br>**64** Financial service activities, except insurance and pension funding<br>**65** Insurance, reinsurance and pension funding, except compulsory social security<br>**66** Activities auxiliary to financial services and insurance activities<br>**69** Legal and accounting activities<br>**70** Activities of head offices; management consultancy activities<br>**71** Architectural and engineering activities; technical testing and analysis<br>**72** Scientific research and development<br>**73** Advertising and market research<br>**74** Other professional, scientific and technical activities<br>**78** Employment activities<br>**80** Security and investigation activities |

*Source*: own construction based on Eurostat (2009)

The circle of KIS is broken up to knowledge-intensive **market services** (50-51, 69-70-71, 73-74, 78-80) and knowledge-intensive **financial services** (64-65-66), and the classification also makes distinction between **high-tech KISs** (59-60-61-62-63 and 72) and **other KISs** (58, 75, 84-85-86-87-88, 90-91-92-93). The latter refers to less knowledge-intensive industries, only exploiting the knowledge of other economic activities and qualified labour force.

The current industrial classification system (the NACE codes) is not the most appropriate mechanism for describing a set of common business activities (even in traditional or knowledge-intensive industries) but to make some measurements, collect and more importantly to compare statistical data it is an adequate grouping for us.

Recent analysis concentrate on the more knowledge-intensive industries, and uses a stricter classification of KKIs (Table 2.), excluding the activities in the category of other knowledge-intensive services.

## 3. Concentration vs. agglomeration of economic activities

In the last decades the intensity of the global competition revealed the increasing importance of geographical proximity of economic activities and actors indicating the formation of new type of spatial organizations in the economy. The key role of geographic proximity has been proved in the diffusion and exploitation of knowledge, especially in the context of innovation, knowledge spillover, cluster formation and development. The location pattern of economic activities changes over time and differs also industrially.

The distribution of innovative activities has been largely analyzed in empirical studies, and there is a large effort nowadays to survey and promote knowledge-intensive industries as key points to develop knowledge-driven economy. There are also evidences about knowledge-intensive firms and activities, which shows that KIIs tend to concentrate in geographical space, because the spatial clustering is one of the striking features for these industries (Tödtling, et al. 2006). Because of the growing interest of KKIs, we found it necessary to examine the pattern of geographical concentration of them in Hungary too, and to extend our analysis to see whether there are agglomeration effects in KKIs not only within the country, but on a sub-national.

Making a closer look to the concept of geographical proximity of economic activities, the uneven distribution of activities may appear in two different ways: concentration or agglomeration. The literature of clusters (Porter 1990), cluster formation use the terms of concentration and agglomeration as a synonym, but as Lafourcade and Mion (2007) made it clear, it is recommended to differentiate between the two concepts.

**Concentration** characterizes enterprises of an industry clustered in a number of regions, without taking into consideration whether the regions are close or far from each other (Lafourcade and Mion 2007). Two industries may be equally concentrated, without considering the fact that they are in adjacent or isolated regions. We may examine gathering of enterprises independently of the distance between to territorial units, but not within one territorial unit. The only important concept in case of concentration is the co-location of enterprises within one region.

In case of **agglomeration** the degree of spatial interdependence matters (which hence spatial autocorrelation) among the geographical units (Lafourcade and Mion 2007). The condition of agglomeration is the presence of enterprises of an industry in not isolated, neighbouring regions. Precisely spatial autocorrelation occurs when values of a variable observed at nearby locations are more similar than those observed at locations more distant from each other.

### 3.1. Tools to measure spatial distribution of economic activities

The concentration facilitates the enterprises to operate in the same interactive learning environment, and thus has a positive impact on the economic performance and growth of a region (Krugman 2000). Most territorial development programs on regional growth emphasize factors like the concentration of high-tech firms and universities, the geographical proximity of experts and researchers or similar sectors.

To assess the geographical distribution of industrial activities and characterize the pattern of concentration or/and the effects of agglomeration, the base indicators and indexes is differentiated. To highlight the weight of industries and to draw up their spatial distribution, typically employment or production is measured. In most cases the degree of clustering expressed in the number of employment, that is the reason why we also refer to employment in the different measurements.

The geographical concentration of industries has been repeatedly studied by the literature (Ellison – Glaeser 1997, Lafourcade – Mion 2007), and to measure the extent to which the enterprises of an industry is geographically concentrated, we may follow more approaches, like location quotient, Herfindahl index, Gini coefficients, Theil index, Ellison-Glaeser index or Ellison-Glaeser $\gamma$ index.

One of the most frequently and easily understandable indices is the **location quotient** (LQ), which measures the under or overrepresentation of a certain economic activity in a given region compared to the whole of the national economy (Pearce 1993, p. 336.).

$$LQ_{ij} = \frac{e_{ij}/E_i}{e_j/E} = \frac{s_{ij}}{x_j}$$, where

$e_{ij}$ is the number of employees in the sector *i* in territorial unit *j*; the $e_j$ is the number of employees in sector in territorial unit *j*, the $E_i$ is the number of employees in sector *i* on the national level and $E$ is the number of national employees in the certain sector.

This means that $s_{ij}$ shows the proportion of the employees of the sector *i* in territorial unit *j*, while $x_j$ representing the proportion of the employees of the sector work in the territorial unit *j*. As a rule, if the value of LQ is more than 1, it indicates a relative concentration of the activity in the area, compared to the region as a whole. The European Cluster Observatory in cluster mapping determines a stricter value limit equal to 2.

Another approach used to calculate the degree of concentration is the **Herfindahl index**, also known as Herfindahl-Hirschman index (H), which measures not the spatial, but the sectoral concentration, exploring the distribution in the number of enterprises operating in the same field of economic activity (Ellison–Glaeser 1997).

$$H_i = \sum_{k=1}^{N_i} z_{ik}^2$$, where

$N_i$ is the number of enterprises operating in sector *i* and $z_{ik}$ is the proportion of employees per enterprise *k* in sector *i*. The comparison of different sectors based on the value of Herfindahl index can only be managed if the number of employees is the sectors is equal. That is why it is worthy to use its normalized value (H*):

$$H^* = \frac{H - 1/N}{1 - 1/N}$$

The Herfindahl index ranges between 0 and 1. The low value of H* (close to zero) refers to the industry fragmented to many enterprises small in the number of employees. If the industry consists of some bigger enterprises, it is concentrated, and the index reaches its maximum value of 1. Based on Herfindahl index sectors can be marked as the following: highly fragmented sector (H* < 0,01), fragmented sector (0,01 < H* < 0,1), weak sectoral concentration in the sector (0,1 < H* < 0,18) and strong sectoral concentration in the sector (0,18 < H*).

The Ellison-Glaeser concentration index ($G_i$ ) is similar to the Gini coefficient measuring disparity. The index compares the spatial distribution of employment in sector *i* to the original spatial distribution of employment (Ellison–Glaeser 1997).

$$G_i = \frac{\sum_{j=1}^{M} \left(s_{ij} - x_j\right)^2}{1 - \sum_{j=1}^{M} x_j^2}, \text{ where}$$

M is the number of territorial units within the examined territorial unit, and $x_j$ and $s_{ij}$ are values defined together with the LQ index. If the value of $G_i$ is low, around zero, the spatial distribution of sectoral employment is similar to the original spatial distribution of employment, while to value close to one refers to a high degree of concentration in the sector.

A modified indicator, the **Ellsion-Glaeser's** $\gamma_i$ **index** (EG γ) appaeared in the 1990s by Ellison – Glaeser by the combination of the important index numbers, the Herfindahl index ($H_i$) and the Ellison-Glaeser concentration index ($G_i$ ).

$$\gamma_i = \frac{G_i - H_i}{1 - H_i}$$

To measure the agglomeration effects, a widely used index is the **Moran index**, which was introduced by Moran (in 1948). Moran index is subsequently used in many studies employing spatial autocorrelation. The Moran's I indicates whether the spatial distribution of a currently analysed data values show any kind of regularity, and used to estimate the strength of the correlation between observations.

If our date are the territorial values of the location quotient $\left(LQ = \frac{s_i}{x_i}\right)$ or some other numerical value indicating concentration like $s_i - x_i$, that results in the spatial auto-correlation coefficient of concentration values.

$$I = \frac{M}{\sum_{i=1}^{M}\sum_{j=1}^{M} w_{ij}} \frac{\sum_{i=1}^{M}\sum_{j=1}^{M} (s_i\text{-}x_i) w_{ij} (s_j\text{-}x_j)}{\sum_{i=1}^{M} (s_i\text{-}x_i)^2}, \text{ where}$$

*M* is the number of territorial units within the examined territorial unit; $w_{ij}$ : element *j* of row *i* of the adjacency matrix. The values of Moran's I range from +1 meaning strong positive spatial autocorrelation (indicate a tendency toward clustering), to 0 (zero) meaning a random pattern to -1 referring strong but negative spatial autocorrelation (indicate a tendency toward dispersion/uniform). (In other words Moran's index's value is 1 if territorial units *i* and *j* are adjacent, otherwise it is 0).

Usually the proximity matrix (as we will use it in our case it is a sub-regional proximity matrix) is 0 (zero) everywhere except for the location i and j taking the value ( $w_{ij}$ ) 1 (where the territorial units have shared border area).

The Moran's I has one major limitations, namely it tends the average local variations in the strength of spatial autocorrelation. This inspired the statisticians to develop local indices to examine the local level of spatial autocorrelation. A standard tool to examine the localized version of autocorrelation is Luc Anselin's (1995) **LISA** (Local Indicator of Spatial Association), which is the local equivalent of Moran's I.

$$I_i = M \frac{(s_i - x_i)\sum_{j=1}^{M} w_{ij}(s_j - x_j)}{\sum_{j=1}^{M}(s_j - x_j)^2}$$

For each location the values of LISA allow for the computation of its similarity with its neighbours and also test its significance. All together five scenarios may occur:

- location with high values with similar neighbours (both $(s_i - x_i)$ and $I_i$ is positive): high-high (known as hot-spots)
- location with low values with similar neighbours (both $(s_i - x_i)$ and $I_i$ is negative): low-low (cold spots)
- location with high values with low-value neighbours ( $(s_i - x_i)$ is posittive, $I_i$ is negative): high-low (potential spatial outliers)
- location with low values with high-value neighbours ( $(s_i - x_i)$ is negative, $I_i$ is positive): low-high (potential spatial outliers)
- locations with no significant local autocorrelation.

Once a significance level is set, values can also be plotted on a map to display the specific locations of hot spots and potential outliers.

## 4. Methodology to measure how knowledge-intensive industries flock together

The literature of sectoral innovation systems (and technological regimes) provides evidences about how industries differ according to specific knowledge characteristics and knowledge base. The large theoretical and empirical work done by Franco Malerba gives a framework to analyze the innovation performance of industries through which it is also possible to estimate the potential for development in case of base regions, where the certain industries are located. To investigate later that what are the most relevant knowledge-intensive industries as catalysts in the regions, the first step is to map the spatial distribution of knowledge-intensive industries.

Recent empirical work focuses on knowledge-intensive industries in a limited sense, with the aim to study their spatial pattern in Hungary, at a sub-regional (LAU 1) level. To investigate the tendency of knowledge-intensive economic activities for concentration and aggregation, the computation of spatial distribution relies on the dataset containing data on the number of employees and the number of plants in the different KIIs, based on their main economic activity specialization (according to NACE Rev. 2. up to 2 digit level). We classified the knowledge-intensive firms based on the OECD's classification (mentioned above).

The Hungarian Central Statistical Office (HCSO) in every quarter gives a detailed dataset of plants by the Company-Code-Register (in Hungarian: Cég-Kód-tár), recently using the dataset 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). In Hungary all together there are 174 sub-regions, so we used the 174 subregions as territorial units. The employment data on the level of sub-regional territorial units derives from the Territorial Statistical Yearbook 2008, published by HCSO.

There is one in the research is the lack of exact company data on employees, which would have been necessary to compute each index number to avoid any distortion in our measurements. The Company-Code-Register provides only staff categories, the exact data on employees of firms were not available, and so we had to estimate them. Firstly we presumed that the numbers of employees in one staff categories are distributed evenly (Ellison – Glaeser 1997). When we computed the Herfindahl index, we substituted each staff figure with the square average of the values within its own staff category, while in the case of calculating potential total staff number; we substituted each staff figure with the arithmetic mean of the values within its own staff category.

To define the spatial concentration (EG γ) and agglomeration (Moran's I) we made two different cases for each knowledge-intensive industry: one where the data on the capital, Budapest is included, one where it is excluded. It is necessary to make this differentiation to avoid distortion because of two reasons. Firstly Budapest has a dominant social and economic power, and many institutions (with national importance) are concentrated in the capital. Secondly, Budapest is included in all territorial divisions, whether local, sub-regional or county level as one unit, although the number of the inhabitants represent approximately 17% of Hungary's population.

**5. Do knowledge-intensive industries flock together in Hungary?**

To answer how knowledge-intensive industries flock together, how do they concentrate geographically or form agglomeration economies, we counted the value of Ellison-Glaeser's γ index and Moran index.

The value of the Ellison-Glaeser's γ index may range from -1 to 1. If it is negative, it shows the sparseness of the sector. Compare to this, if it is positive it refers to certain proportion of concentration. Based on the value of Ellison-Glaeser's γ index, we made a classification of knowledge-intensive industries, with the following categories.

- The sector is spatially sparse if $\gamma < 0$.
- The sector is weakly concentrated if $0 \leq \gamma < 0{,}02$.
- The sector is moderately concentrated if $0{,}02 \leq \gamma < 0{,}05$.
- The sector is strongly concentrated if $0{,}05 \leq \gamma$.

In the case of Moran's I, it is possible to determine the level of autocorrelation of the industries' spatial distribution based on values only. To determine this, the distribution was defined by using the actual concentration values, with the help of Monte carlo method. The Geoda 0.9.5. software is suitable to make this calculations. As a result it is possible to determine the spatial distribution of a given KII with a preliminary defined significance level: with strongly negative autocorrelation, with negative autocorrelation, with no autocorrelation, with positive autocorrelation and with strongly positive autocorrelation.

In case of the high and medium high-tech manufacturing industries and knowledge-intensive industries, we got a mixed picture concerning to the concentration and agglomeration of the industries, either including or excluding the data on Budapest (Table 3 and Table 4).

***Table 3.*** Concentration and agglomeration of KKIs including data on Budapest

| Concentraration | 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 | | | | | |

**Spatial autocorrelation**

***Table 4.*** Concentration and agglomeration of KKIs excluding data on Budapest

| Concentraration | 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 | | |

**Spatial autocorrelation**

Note: High and medium-high technology manufacturing industries are in bold.
Source: own calculations

According to the results, examining the concentration of KIIs by Ellison-Glaeser's γ index, none of the industries would be in sparse if we include data on Budapest too. It means that the choice of plant location of firms operating in a sector is at least slightly depend on other firms' choice of the plant 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 in Hungary at a sub-regional level including data on Budapest. Furthermore this tendency may be drawn up in the case of almost all knowledge-intensive services, not surprisingly except for the sectors of water (50) and air transport. If we exclude the data on Budapest in measuring the concentration, we get very different results. Most of the industries from both high and medium-high-tech sectors and KI services, the concentration is medium or weak, the plant choice depends on the choice of other firms in the industry in a low or medium level.

If we leave out of consideration that we do or do not have data from Budapest, the values of Moran index shows that there are many industries, where there is no autocorrelation, no agglomeration effects can be observed. Moran index indicate a very strong spatial autocorrelation mainly in case of knowledge-intensive services, even with or without data on Budapest (but in a different range).

It is very hard to make a generalization about the spatial distribution of knowledge-intensive industries. That is why now we attempt to grab the special characteristics of three industries, namely: the sectors of manufacture of basic pharmaceutical products and pharmaceutical preparations ( NACE 21), the sector of manufacture of motor vehicles, trailers and semi trailers (NACE 29) and the sector of computer programming, consultancy and related activities (NACE 62).

**5.1. Manufacture of basic pharmaceutical products and pharmaceutical preparations (21)**

The sector according to NACE Rev. 2. includes the manufacture of basic pharmaceutical products and pharmaceutical preparations, and also the manufacture of medicinal chemical and botanical products.

If we taking the data on Budapest into account, we may draw up some special characteristics of the sector, by the followings:

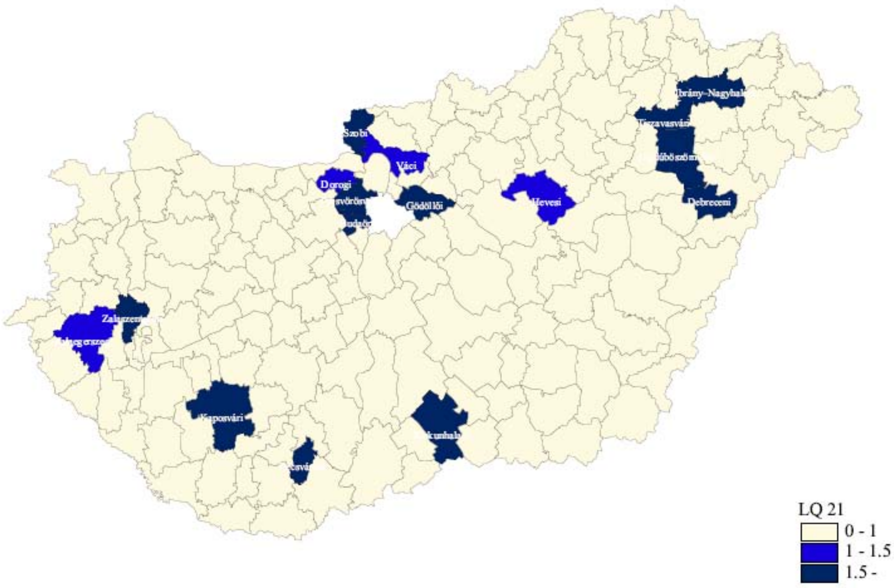
- the sector is strongly concentrated in the space ($\gamma$=0,3972)
- with no autocorrelation (I=-0,0112);
- the sector is fragmented (H*=0,0635)

If we exclude the data on Budapest:

- the sector is spatially sparse ($\gamma$=-0,0092)
- with no autocorrelation (I=0,0044)
- with weak sectoral concentration in the sector (H*=0,1148)

The analysis of the LQ values based on the data on employment; of the different subregions demonstrate that the result in this sector is very similar in both cases, in the case of including and excluding Budapest from the analysis (Figure 1.). The pharmaceutical sector shows a relatively high concentration in Budapest (LQ=7,43) and in other few number of subregions. all around the country.

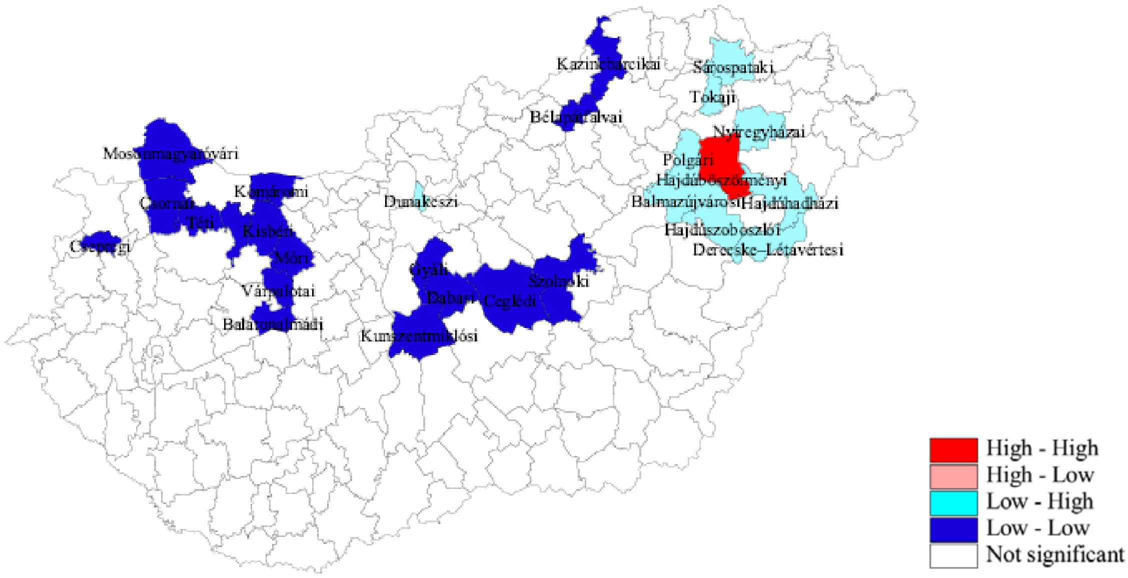
***Figure 1***. Distribution of LQ values in sector 21 (Budapest is exluded)




Source: own construction

The sector is strongly concentrated in the space, but without any attracting effects that may occur between neighbouring subregions. The values of local Moran index, the Lisa shows only one subregion (excluding data on Budapest), where the pharmaceutical sector has a hot spot. In many subregions the locations has no significant local autocorrelation.

***Figure 2***. Classification of subregions according to local Moran index (LISA) concerned to the sector 21 (including Budapest)




Source: own construction

### 5.2. Manufacture of motor vehicles, trailers and semi trailers (29)

The sector includes the manufacture of motor vehicles, of bodies (coachwork) for motor vehicles, manufacture of trailers and semi trailers and also the manufacture of the parts and accessories for motor vehicles.

Including the data on Budapest into account, the sector have the following values:

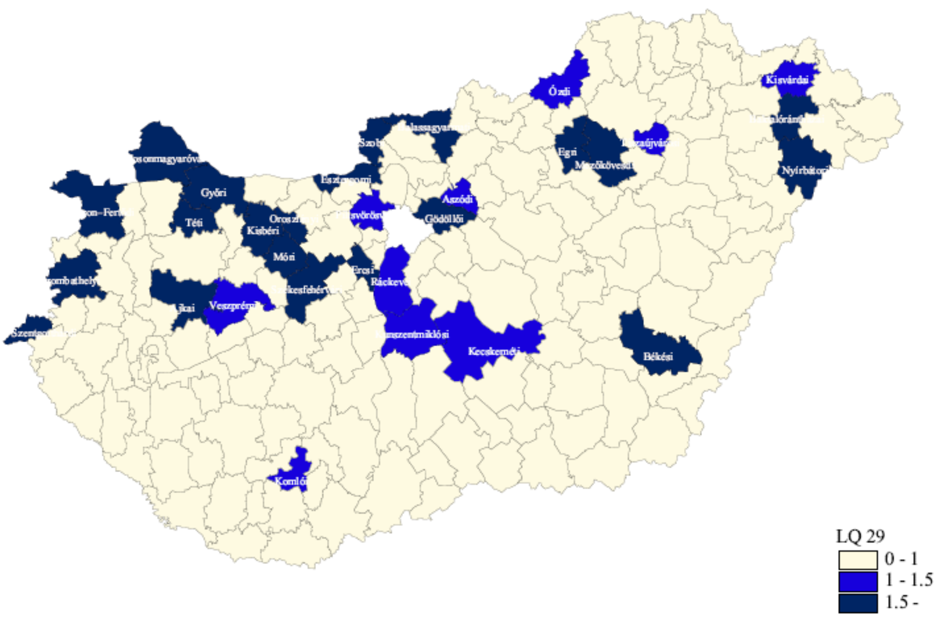
- the sector is moderately concentrated in the space ($\gamma$=0,0238)
- with no autocorrelation (I=0,034);
- the sector is fragmented (H*=0,0295)

If we exclude the data on Budapest:

- the sector is weakly concentrated ($\gamma$=0,0165)
- with no autocorrelation (I=0,0403)
- the sector is fragmented (H*=0,0307)

Taking a closer look to the sector based on the LQ, we may disregard the data on Budapest in the analysis again, but for some other reason comparing to the pharmaceutical sector. The sector does not show a relative concentration in the region of Budapest, it does not represents a major amount of the firms in the sector with a value of LQ equal to 0,2582.

***Figure 3***. Distribution of LQ values in sector 29 (excluding Budapest)

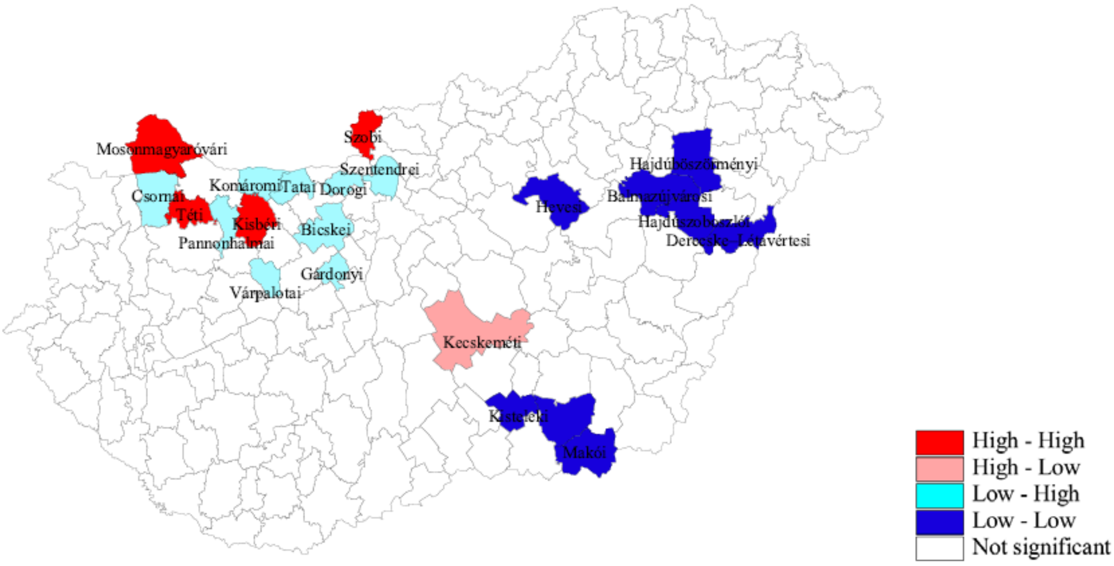



Source: own construction

The values on Budapest do not cause any distortion. The industry shows a relatively high concentration (with LQ<1,5) mainly in the northern-western subregions of the country (Figure 3.). The clustering of manufacturing activities of motor vehicles is widely examined in different empirical studies in Hungary.

The further analyses of this manufacturing industry would show the existence of local knowledge boundaries. The empirical studies done by Breschi and Malerba (2005) also characterized the automotive industry as a generally geographically concentrated industry with local knowledge boundaries.

***Figure 4***. Classification of subregions according to local Moran index (LISA) concerned to the sector 29 (including Budapest)




Source: own construction

Not surprisingly in the case of the manufacturing sector of motor vehicles, the values of LISA reveal the agglomeration effects in four subregions, all from the northern-western part of Hungary. The cold spots, where the neighbouring regions have similarly low values, can be found in Eastern Hungary.

### 5.3. Computer programming, consultancy and related activities (62)

This division includes the activities of providing expertise in the field of information technologies, like writing, modifying, testing and supporting software, planning and designing computer systems that integrate computer hardware, software and communication technologies, on-site management and operation of clients' computer systems and/or data processing facilities, and other professional and technical computer-related activities.

With the data on the capital, the sector can be characterized as the following:

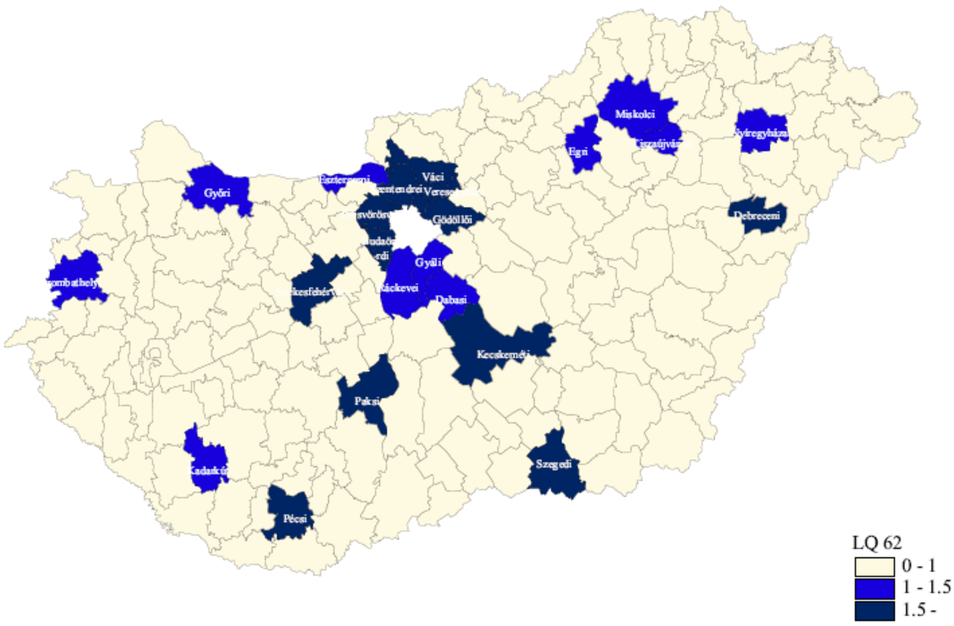
- the sector is strongly concentrated in the space (γ=0,2732)
- with positive strong autocorrelation (I=0,0079);
- the sector is fragmented (H*=0,0049)

If we exclude the data on Budapest:

- the sector is weakly concentrated (γ=0,0102)
- with positive strong autocorrelation (I=0,1982)
- the sector is fragmented (H*=0,0060)

In information technology (IT), this is the sector (NACE 62) which includes all the economic activities that have a major value added compared to other information technology activities. Its spatial distribution shows some interesting result. As it can be seen in other knowledge-intensive services, the sector has a relatively high concentration in Budapest (LQ=3,32). In this case (beside Budapest) there are only four subregions where the value of LQ is above 1. But by disregarding Budapest, we get an interesting picture of the sector. It is cleared out that IT firms flock together mainly in other subregions from the Central-Hungary, and from so called pole cities (most developed cities beside Budapest) in the countryside.

***Figure5***. Distribution of LQ values in sector 62 (excluding Budapest)

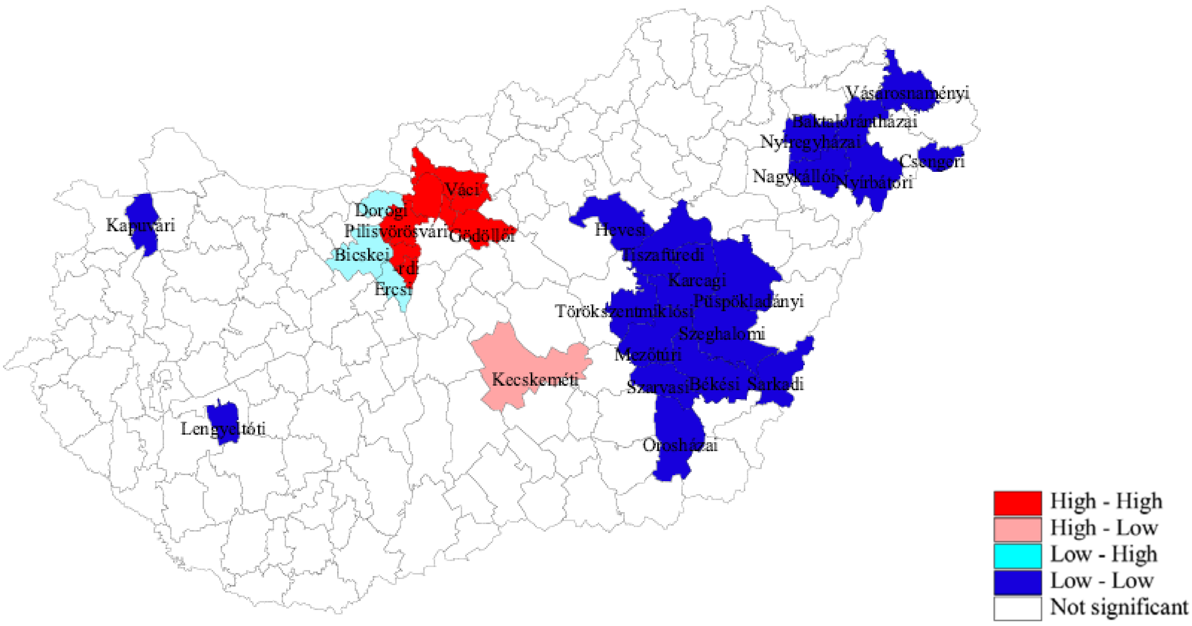



Source: own construction

As other studies show: in software, computer programming industry there are many innovators who are geographically concentrated with both local and global knowledge boundaries (Breschi – Malerba 2005). The case of local knowledge boundaries may be the case in Hungary too.

The local Moran index does not show that the agglomeration effects in the countryside, in the above mentioned pole cities would be significant. The cold spots can be easily identified, mainly again in the eastern part of the country. The hot spots are definitely formed in Budapest and its agglomeration.

***Figure 6***. Classification of subregions according to local Moran index (LISA) concerned to the sector 62 (including Budapest)




Source: own construction

## 6. Conclusion

The theoretical framework of sectoral innovation system showed us, that is reasonable to attempt the geographical proximity of firms in knowledge-intensive industries, by the examination of the knowledge characteristics of different sectors, especially KIIs. After giving a brief introduction of the literature of sectoral innovation systems, and the dimension of knowledge, which influences the innovativeness of the industries, we made the initial steps to map the spatial distribution of KIIs in Hungary, to facilitate to generate further steps to see not only the geographical proximity aspects of the KIIs, but the relational proximity aspects.

Surveying the concentration of knowledge-intensive industries, the sectors display a rather mixed picture in terms of concentration and agglomeration. Based on the index number of spatial concentration (Ellison-Glaeser $\gamma$ index), we can conclude that a few of high and medium-high-tech industries and most of the knowledge-intensive services may be called at least moderately concentrated industries. The high degree of concentration is due to the Budapest region, what causes a continuous distortion in the spatial analysis in Hungary.

However based on the index number of agglomeration (Moran index) the knowledge-intensive industries seem to be more divided. This result is not surprising, since concentration measure the effect of forces having narrower range, while agglomeration also assesses the effect of forces going beyond the borders of the territorial units.

To grab the tendency in spatial distribution of knowledge-intensive industries, it would be better to examine the manufacturing sectors and knowledge-intensive services not together. Furthermore to answer the question that do knowledge-intensive industries flock together in Hungary, it is worthy to analyze all KIIs separately, by taking into account all the special characteristics of industries, which may rooted from their specific knowledge base.

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