Analyzing spatial distribution of knowledge-intensive industries in Hungary at sub-regional level

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In recent years knowledge-intensive industries in production and services have a lead in respect of the development of knowledge-driven economy. They are now the core of growth, with an increasingly high importance especially in less developed countries, like Hungary.

Spatial distribution of knowledge-intensive economic activities shows a certain inequality in Hungary, and determines the formation and existence of 'knowledge poles' described as agglomeration of knowledge-intensive industries in the country. But the fact that these industries and firms 'flock together' and have the same location, does not mean that all firms in the concentration cooperate with each other and have joint actions. It would be necessary to make a differentiation between enterprises in geographical proximity (co-location) and in relational proximity.

Recent study aims to identify only the geographical proximity, the spatial coherence and concentration of knowledge-intensive industries in Hungary at sub-regional level, using the methods and indicators of spatial econometrics and spatial statistics.

1. Introduction

The geographical proximity of economic activities has attracted much attention nowadays. Several theoretical and empirical studies underline the importance of analyzing spatial distribution of economic activities, making a differentiation between the concentration and agglomeration of industries.

Among the industries knowledge-intensive industries (KII) have received much more interest in recent years in the economic analyses, realizing the driving role in the

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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).

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. For this reason recent study also aims to reveal how knowledge-intensive industries distribute across the space in Hungary.

The study is structured into three main chapters. We introduce the relevancy of geographical proximity, and the necessity to distinguish concentration from agglomeration, using various methods and indicators of spatial econometrics and statistics, mainly by the illustration of the model of Ellison-Glaeser and Moran to assess how KIIs distribute across the space. After classifying the knowledge-intensive industries, we introduce our methodology to measure the concentration of firms and agglomeration effects at sub-regional level in Hungary. The last section demonstrates the empirical result about the spatial distribution of KI industries in Hungary, by using a stricted circle of knowledge-intensive industries, than OECD.

2. Geographical proximity: distinguishing between concentration and agglomeration

In the last decades, the process of globalization shed light on the formation of a new spatial organization of the economy, and the key role of geographic proximity also has been proved. Proximity is a critical criterion in firms' choice of where to locate its productive units, and have become key factor in the diffusion and exploitation of knowledge, especially in the context of innovation, cluster development and knowledge spillover. Proximity reduces uncertainty, solves the problem of coordination, facilitates the interactive learning and thus has a positive impact on the economic performance and growth of a region (Krugman 2000). Most regional, national development programs on regional growth emphasize factors like the nearness of high-tech firms and universities, the proximity of experts and researchers or similar sectors. The location pattern of economic activities changes over time and differs also industrially.

The proximity 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 show that KIIs tend to concentrate in geographical space. The spatial clustering is one of the striking features for knowledge-intensive industries (Tödtling, et al. 2006). Because of the growing interest of KKIs, we found it necessary to examine the pattern of geographical proximity of them in Hungary too, and to extend our analysis to see whether there are concentrations and agglomeration effects between KKIs not only within the country, but at a sub-national level.

Geographical proximityis also signified as spatial, local or physical (Knoben–Oerlemans 2006). Geographical or regional sciences traditionally use the notion of proximity, defined as short geographical distance. Distance basically means shortest way between two points, and refers to 'spatial non-identity', - not being in the same place (Nemes Nagy 2009) and measures the amount of physical space between two units (individuals, organizations, towns etc.). Short distance brings the individuals together, favours information transfer and facilitates the exchange of knowledge, especially tacit knowledge. Agents in geographical proximity, benefit from positive externalities (Lengyel–Mozsár 2002). The positive effects may appear in the reductions of transfer and transaction costs, in the number of inputs at lower prices (Lengyel 2001).

Making a closer look to the concept of geographical proximity of economic activities, we see that it is necessary to distinguish between concentration and agglomeration. Even if we examine concentration or agglomeration, both answers the question of how economic activities are distributed across the space and where specific economic activities can be found (at a few locations: a city, a region or a country) (Brakman et al 2009). Both notion deals with the location of specific industrial activities, as the literature of clusters too refers to it (Porter 1990). The literature of 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.

Brakman et al (2009) use the term of agglomeration in a different way. According to them the concentration analyzes the location across the space of industries, while agglomeration describes the location pattern across the space of a much larger part of economic activity, like manufacturing sector. Now we are following the concept introduced by Lafourcade and Mion (2007).

How can we measure spatial distribution of economic activities? 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 γ 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.).

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

e_{ij} is the number of employees in the sector i in territorial unit j

e_j is the number of employees in sector in territorial unit j

E_i is the number of employees in sector i on the national level

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.

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).

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

N_i is the number of enterprises operating in sector i

z_{ik} is the proportion ef 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 in a different way (Table 1).

Table 1. Classification of KIIs based on Herfindahl index

	Range of sectoral concentration	**Value of** H*
Sector	highly fragmented	H* < 0,01
	fragmented sector	0,01 < H* < 0,1
	weak sectoral concentration	0,1 < H* < 0,18
	strong sectoral concentration	0,18 < H*

Source: own construction

The Ellison-Glaeser concentration index (G_i) is similar to the Gini coefficient measuring disparity. The index compares the spatial distributions 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,

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 γ_i index** (EG γ) appeared 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).

When $I > \frac{-1}{M-1}$, the spatial autocorrelation is positive.

When $I = \frac{-1}{M-1}$, there is no autocorrelation.

When $I < \frac{-1}{M-1}$, the spatial autocorrelation is negative.

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).

Measuring the spatial concentration of economic activities, it is necessary to be conscious about examining absolute or relative concentration. The value of LQ counted based on si/xi quotient, while both Moran's and Ellison-Glaeser γ index are calculated in the basis of si-xi values. LQ measures the concentration along the regions' own employment level, that is why it is relative, the latter ones refers to the absolute flow of national employment. It is recommended to use both in surveys.

3. Methodology

To investigate how knowledge-intensive industries as catalysts in regional development distribute across the space, the first step is to punctuate the circle of 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 on 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

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

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).

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.

4. Evidence from Hungary: concentration and agglomeration at sub-regional level

To answer how knowledge-intensive industries 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 four categories (Table 3.).

Table 3. Classification of KIIs based on Ellison-Glaeser's γ index

	Range of concentration	**Value of γ**
Sector	spatially sparse	$\gamma < 0$
	weakly concentrated	$0 \leq \gamma < 0{,}02$
	moderately concentrated	$0{,}02 \leq \gamma < 0{,}05$
	strongly concentrated	$0{,}05 \leq \gamma$

Source: own construction

In the case of Moran's I based on the sub-regional values in Hungary, the quotient $I = \frac{-1}{M-1}$ is equeal to 0,0058.

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, the range of concentration of a given KII with a preliminary defined significance level, by the categorization of industries into five groups (Table 4.).

Table 4. Classification of KIIs based on Moran's I

	Range of concentration	Value of I	Value of p
Sector	strongly negative autocorrelation	I < –0,0058	p < 0,005
	weak negative autocorrelation	I < –0,0058	0,05 < p< 0,1
	no autocorrelation		0,1 < p
	weak positive autocorrelation	–0,0058<I	0,05 < p< 0,1
	strongly positive autocorrelation	–0,0058<I	p < 0,05

Source: own construction

The results show that in case of high and medium high-tech manufacturing industries and knowledge-intensive industries, we got a very mixed picture concerning to the concentration and agglomeration of the industries, either including or excluding the data on Budapest (Table 5 and Table 6).

Table 5. Concentration and agglomeration of KKIs including data on Budapest

Concentration	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

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

Examining the spatial concentration of KIIs by Ellison-Glaeser's γ index, none of the industries would be in sparse if we include data on Budapest too (see the punctual data in Annex 1.). 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 (51). If we exclude the data on Budapest in measuring the concentration, we get a very different result. Most of the industries from both high and medium-high-tech sectors and KI services are moderately or weakly concentrated; the plant choice depends on the choice of other firms in the industry in a low or medium level.

Table 6. Concentration and agglomeration of KKIs 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		

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

Even if we take into or leave out of consideration the data on Budapest, the results for Moran's I show that there are many industries, where there is no autocorrelation. In other words significantly no agglomeration effects can be observed (see punctual data in Annex 2.) in case of many industries. 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).

Important to take a boundary into account during the use of Moran index. It may be possible that the high values occur because of the concentration of the industry in adjacent subregions with high population, or the existence of adjacent subregions that, however, have especially low employment in the sector and are 'empty'.

Analyzing not the spatial, but sectoral concentration of KIIs by Herfindahl index, we get a less heterogeneous picture (see Annex 3.). Even if we include or exclude data on Budapest, the industries are shown to be fragmented or weakly concentrated, the industry structure consists of rather small and medium sized firms (in the number of employment). The industry of manufacturing basic pharmaceutical products and pharmaceutical preparations appears as a great exception with the strong sectoral concentration. The pharmaceutical industry is strongly concentrated across the space and sector in Budapest.

It is very hard to make a generalization according to the spatial distribution of knowledge-intensive industries. Because of this reason to have a detailed picture of an industry, to grab the special characteristics, we have to make the analysis industry by industry.

6. Conclusion

Recent study aimed to make the initial steps to map the spatial distribution of knowledge-intensive industries in Hungary, to prove whether it is underlined to make further steps to see not only the geographical proximity aspects of the KIIs, but the relational proximity.

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 γ 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 industry. 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's I) the knowledge-intensive industries seem to be more divided. This result is not surprising, since concentration measures the effect of forces having narrower range, while agglomeration 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 how knowledge-intensive industries distribute across the space in Hungary, it is worthy to analyze all KIIs separately, by taking into account all the special characteristics of industries (location of input, customers, competitors etc.)

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Annex 1.

Spatial concentration of KIIs based on Ellison-Glaeser γ index

NACE Rev.2. code - 2.digit level	Concentration (γ) Including Budapest		Concentration (γ) Excluding Budapest	
High and medium-high technology manufacturing industries				
21	0,397211702	strong	-0,00924689	sparse
30	0,057321824		-0,000648195	
20	0,047376372	moderate	0,037646438	moderate
29	0,023784445		0,016579719	weak
27	0,017842927	weak	0,023746586	moderate
28	0,009139748		0,001394074	weak
26	0,00886653		0,011893145	
Knowledge-intensive services (KIS)				
65	0,564989731	strong	-0,031070437	sparse
60	0,386385543		-0,09016134	
64	0,348789484		0,000115094	weak
63	0,325754426		0,005747401	
59	0,309629571		0,012810261	
62	0,273270792		0,010184067	
58	0,210400376		0,01257621	
72	0,209307189		0,018530845	
73	0,188824362		0,00450545	
70	0,184152114		0,007663509	
78	0,180887074		0,010556616	
61	0,166778862		0,236086515	strong
66	0,132310902		0,002982978	weak
80	0,101641217		0,004223516	
71	0,097711242		0,004143611	
69	0,08771691		0,002418967	
74	0,058901634		0,003962334	
51	0,013982946	weak	0,465084133	strong
50	0,010676786		0,008908536	weak

Source: own calculations

Annex 2.

Agglomeration of KIIs based on Moran's I

NACE Rev.2. code - 2.digit level	Agglomeration Including Budapest			Agglomeration Excluding Budapest		
High and medium-high technology manufacturing industries						
	Moran I	**p value**	**Autocorrelation**	**Moran I**	**p value**	**Autocorrelation**
30	0,0943	0,0247	strong	-0,0299	0,248	no
29	0,034	0,1455	no	0,0403	0,1271	no
27	0,0045	0,3124	no	0,0047	0,3079	no
26	-0,0092	0,5356	no	-0,0077	0,5611	no
28	-0,0157	0,4397	no	-0,0267	0,3431	no
21	-0,0112	0,2138	no	0,0044	0,1612	no
20	-0,0361	0,0734	weak	-0,0323	0,065	weak
Knowledge-intensive services (KIS)						
80	0,048	0,0021	strong	0,0947	0,0275	strong
71	0,01	0,0074	strong	0,0695	0,0596	weak
74	0,0361	0,0105	strong	0,1615	0,0029	strong
62	0,0079	0,0194	strong	0,1982	0,0024	strong
70	0,0116	0,0306	strong	0,152	0,0045	strong
61	0,0645	0,0332	strong	-0,0113	0,1864	no
51	0,0191	0,0338	strong	-0,012	0,1847	no
59	0,0022	0,0675	weak	0,2451	0,0006	strong
50	0,0059	0,1439	no	0,0152	0,099	weak
69	-0,0054	0,5809	no	-0,0103	0,5204	no
66	-0,0075	0,3269	no	0,0351	0,1725	no
58	-0,012	0,1781	no	0,004	0,2297	no
63	-0,0103	0,1704	no	0,1457	0,0047	strong
73	-0,0124	0,1192	no	-0,004	0,6244	no
72	-0,017	0,0355	strong	0,023	0,214	no
78	-0,034	0,0038	strong	0,0151	0,2283	no
65	-0,0274	0,0022	strong	-0,0084	0,472	no
64	-0,0312	0,0019	strong	-0,007	0,4941	no
60	-0,0277	0,0017	strong	0,0025	0,3704	no

Source: own calculations

Annex 3.

Sectoral concentration of KIIs based on Herfindahl index

NACE Rev.2. code - 2.digit level	Concentration (H*) Including Budapest		Concentration (H*) Including Budapest	
High and medium-high technology manufacturing industries				
20	0,06349982	fragmented	0,114795879	weak
21	0,192432348	strong	0,254399027	strong
26	0,028426893	fragmented	0,035730352	fragmented
27	0,021298712		0,026526099	
28	0,018010692		0,010659703	
29	0,029466381		0,030715665	
30	0,064503324		0,093347176	
Knowledge-intensive services (KIS)				
50	0,128735039	weak	0,272236933	strong
51	0,421977256	strong	0,269428511	
58	0,007876188	fragmented	0,027791346	fragmented
59	0,005066166		0,010289758	
60	0,092142189		0,093309524	
61	0,125907713	weak	0,132078665	weak
62	0,004964106	fragmented	0,006027226	fragmented
63	0,016093696		0,006312974	
64	0,041967419		0,0059129	
65	0,176921325	weak	0,294197796	strong
66	0,003816952	fragmented	0,001404524	fragmented
69	0,00156534		0,002201033	
70	0,002200507		0,007186776	
71	0,0010397		0,000705575	
72	0,021842112		0,009898588	
73	0,002932853		0,011967289	
74	0,002777243		0,003969547	
78	0,029153016		0,024701889	
80	0,007281959		0,008648654	

Source: own calculations