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Identification of Knowledge Bases: The Case of the Czech Republic

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This paper deals with the concept of differentiated knowledge bases, an area related to the study of the regional innovation systems. The concept explores the ways in which knowledge is involved in innovation processes and knowledge flows within and between organisations. Some limitation of this concept can be the fact that there is no clear method for identification of knowledge bases in regions. The aim of this paper is to propose appropriate indicators and methodology to empirically identify the knowledge base of a region. The second aim of this paper is to use this methodology for the identification of knowledge bases in the Czech regions. The methods used for the classification include the point method and cluster analysis. Based on the combination of these methods, the Czech regions are classified into four groups – those with a prevailing analytical, synthetic, analytical-synthetic, and synthetic-analytical knowledge base. The Capital City of Prague, the South Bohemian Region, and the South Moravian Region were among the ones with an analytical base. A synthetic knowledge base was identified in the Liberec Region, the Zlin Region, and the Vysocina Region. One of the two transitional types was found in the remaining regions. In real-life practice the findings can be applied, above all, to the implementation of regional innovation policies, which should always respect the characteristics of the given region.

Keywords: *Knowledge Base, Innovation; Research and Development, Regional Innovation System, Czech Republic, Point Method, Cluster Analysis.*

Introduction

Creation, adoption and transfer of innovation are generally considered the main processes affecting the present and mainly the future competitiveness of regions (Viturka, 2014). However, individual regions differ considerably in their ability to generate innovation as a source of their development. On a theoretical level, the territorial significance of innovation is dealt with by national and regional innovation systems. Concepts of national and regional innovation systems also serve as an analytical framework creating an empirical base for innovation policy creation (Doloreux & Parto, 2005). Innovation systems were first studied at the national level, with the regional level having been added later (Laranja *et al.*, 2008). The key idea behind this systemic approach is that in a company, innovation and technological change do not take place separately. Rather, innovation also depends on the interaction with other entities (innovative companies, knowledge institutions, intermediaries, capital providers, etc.), as well as on the environment in which the company operates. Interactions among individuals, firms and institutions produce the transmission of knowledge in the form of knowledge spillovers (Rodriguez, 2014). In other words, in regional innovation systems, geographical (spatial) proximity facilitates the creation, acquisition, collection and use of knowledge thanks to the existence of both formal and informal relations and networks linking the participants involved in the innovation processes. A close distance between the participants also ensures that they share a similar cultural and social understanding (Doloreux, 2002). The cognitive, organizational and social proximities play important role for innovative knowledge sharing too (Strambach & Klement, 2012).

The character of knowledge available in company/ industry/region for the implementation of innovations is studied by the concept of differentiated knowledge bases. Before we go on to present the concept, some of its key terms need to be explained. B. A. Lundvall is a recognized author who connects the innovation system concepts with the importance of knowledge (e.g. Lundvall, 1994, 2010). Lundvall distinguishes between codified knowledge and tacit knowledge. The codified knowledge can be written down or recorded and in this way it can be available to other people. On the contrary, the tacit knowledge can only be obtained through our own experience. The tacit knowledge represents a source of competitive advantage because it is fixed to a specific region and locality and it is non-transferable. Lundvall and Johnson (1994) differentiate among four types of knowledge: know-what, know-why, know-how and know-who. Whilst knowledge know-what and know-why can be spread through literature, training or databases, knowledge know-how and know-who can be obtained only by personal practical experience (Jensen et al., 2007). Let us add, for the sake of completeness, that the linear model of innovation (also referred to as the "STI model" – Science, Technology and Innovation) represents innovations taking place while the individual phases (basic research, applied research, production preparation, production, and market placement) follow each other in a chronological order. On the other hand, the interactive model of innovation (the "DUI model" – Doing, Using and Interacting) assumes that innovation is a result of an interactive process between the participants of the innovation system, and that the individual phases of the innovation process do not necessarily have to take place in the given order; some can even take place simultaneously (Jensen *et al.*, 2007; Blazek *et al.*, 2011; etc.).

This article deals with the differentiated knowledge bases concept which is closely related to the concept of regional innovation systems and which works on above-mentioned theoretical findings. The knowledge bases concept enables to conceptualize industry-specific differences in the geography of innovation by referring to the nature of knowledge that underlies innovation activities and to knowledge flows within and between organisations (Martin, 2013). The concept is also useful for better and more efficient designing of regional innovation policy (Manniche, 2012; Strambach & Klement, 2012; Dahlstrom & James, 2012; Isaksen & Nilsson, 2012).

Within the context of the knowledge base theory, the aim of this paper is to propose appropriate indicators and methodology in order to empirically identify the knowledge base of a region. These indicators will subsequently be used as the basis to reach our second objective, which is to identify knowledge bases in the Czech regions. Knowledge base types can be inferred from the high values of selected indicators, using various methods. The point method proves to be especially useful for ranking the regions based on a cumulative score. The cluster analysis allows to aggregate regions with similar characteristics. The combination of these methods enables to create the typology of knowledge bases of Czech regions.

The following text is divided into four parts. The first part explains the concept of knowledge bases and its theoretical background. It also describes some empirical studies that were aiming at the empirical identification of knowledge bases. The second part focuses on the methods that will be subsequently used for the identification of knowledge bases in Czech regions. It deals with the point method and the cluster analysis. The following chapter applies both methods and based on them it classifies four groups of Czech regions – those with a prevailing analytical, synthetic, analytical-synthetic, and synthetic-analytical knowledge base. The final part summarizes and offers conclusions.

The Differentiated Knowledge Base Concept

The concept of knowledge bases, attributed mainly to B. Asheim and M. Gertler (Asheim & Gertler, 2005; Asheim & Coenen, 2005; etc.), is based on the assumption that the innovation process can take very different forms in different places. The key point of differentiating between knowledge bases is not to explain the competence level (of human capital, for example) or the intensity of R&D (e.g. high- or low-tech). Rather, the idea is to describe the nature of specific (or key) knowledge sources and inputs on which innovation activity is based. (Asheim & Gertler, 2005) This concept is useful to analyse, compare and explan knowledge exchange process across industries in a regional context (Plum & Hassink, 2011; Aslesen & Freel, 2012). According to the prevailing (dominant) knowledge base, it is possible to establish a general typology of economic sectors, clusters as well as regional innovation systems. The following knowledge base types are distinguished: analytical (with a prevalence of natural sciences), synthetic (engineering), and symbolic (creativity, arts). These knowledge bases represent ideal types. In practice, an industry or a region reveals a mix of characteristic features of various knowledge bases. The extent to which a particular base dominates depends on company profile (size, age, owner structure), position of the firm, industry, type of activity (e.g. research and production), scarcity of potential collaborators and so on (Asheim *et al.*, 2011a; Plum & Hassink, 2011).

The difference between an analytical and a synthetic knowledge base was first presented by Laestadius (1998) as an alternative to the OECD's industry classification based on R&D intensity (high-tech vs. low-tech industries). Laestadius aimed at proving that knowledge intensity is more important than R&D intensity. The knowledge base concept was further developed by Asheim and Gertler (see Asheim & Gertler, 2005, etc). They studied the character of innovation in different companies and industries, using knowledge bases to demonstrate wider organizational and geographical implications of various types of knowledge (the way innovation processes are organized, the importance of spatial proximity, etc.). The symbolic knowledge base type was added later in order to account for the growing significance of cultural production (Asheim *et al.*, 2007).

Knowledge bases differ mainly in the nature of undertaken research and development, use of tacit and codified knowledge, employee qualification requirements, entities involved, importance of spatial proximity, or the way of cooperation (see Table 1).

In an analytical knowledge base scientific knowledge is important, and knowledge creation is built on cognitive processes and formal models. Examples of an analytical knowledge base include biotechnology and nanotechnology. In their innovation activities, companies typically cooperate with universities and research institutes. Therefore, the link between business and the research sector is much more important than in the other types of knowledge base (Asheim & Hansen, 2009).

In a synthetic base, knowledge creation is built on the application or novel combination of existing knowledge. This often includes situations when a particular problem arising from the communication with customers or suppliers needs to be dealt with (collaboration of actors in the value chain). Therefore, research is of lesser importance compared to an analytical knowledge base, and if it does take place, it is mainly applied research and development. An example of a synthetic knowledge base is the construction of large investment units, special-purpose machinery, or shipbuilding. (Asheim & Hansen, 2009)

A symbolic knowledge base is typical of industries in which aesthetics, design, or cultural aspects are important. The work involves the creation of new ideas, images or other cultural expressions rather than an actual, physical production process. Creativity, artistic- and aesthetic abilities are important, rather than education or research. The essence of knowledge is to know how, and to know who (i.e. the knowledge of potential collaborators). The cooperation is usually short-term and involves a single project, for example, the making of a film (Asheim & Hansen, 2009). The symbolic knowledge base opens opportunities for studying of non-technological and socio-cultural types of innovations (Manniche, 2012). The aims of this paper are related to the analytical and synthetic knowledge bases, and this is why in the following text we solely focus on these types of knowledge bases.

Knowledge in an analytical knowledge base tends to be codified. However, tacit knowledge is utilized, too. The importance of codified knowledge results from the fact that new knowledge can be acquired through written documents, e.g. research reports or patent documents. The knowledge is applied in the form of brand new products or processes, and there are more radical innovations compared to the other knowledge bases. In a synthetic base, new knowledge emerges from testing, experiments, computer simulations, or practical work. Although knowledge tends to be at least partly codified, tacit knowledge plays a more important role there. Know-how, craft and/or practical skills are required. A typical result of the innovation process is an incremental innovation (Asheim *et al.*, 2011a; Asheim *et al.*, 2011b).

Analytical and synthetic knowledge bases also differ in the role of geographical proximity, which is more significant for the latter. An analytical knowledge base allows cooperation over greater distances, also thanks to the use of codified knowledge. Analytical bases tend to follow the linear model of innovation (the STI model), whereas in synthetic knowledge bases the interactive (DUI) model of innovation prevails. (Asheim *et al.,* 2011a).

Table 1

Differentiated Knowledge Bases: a Typology

	Analytical (science based)	Synthetic (engineering based)	Symbolic (arts based)
Rationale for knowledge creation	Developing new knowledge about natural systems by applying scientific laws; know why	Applying or combining existing knowledge in new ways; know how	Creating meaning, desire, aesthetic qualities, affect, intangibles, symbols, images; know who
Development and use of knowledge	Scientific knowledge, models, deductive	Problem solving, custom production, inductive	Creative process
Research types	Basic and applied	Applied	
Actors involved	Collaboration within and between research units	Interactive learning with customers and suppliers	Experimentation in studios, project teams
Knowledge types	Strong codified knowledge content, higly abstract, universal	Partially codified knowledge, strong tacit component, more context specific	Importance of interpretation, creativity, cultural knowledge, sign values; implies strong context specificity
Dominant type of innovation process	STI mode	DUI mode	
Importance of spatial proximity	Meaning relatively constant between places	Meaning varies substantially between places	Meaning higly variable between place, class and gender
Main type of cooperation	Mid-term or short-term	Long-term	Short-term
Outcome	Drug development	Mechanical engineering	Cultural production, design, brands

Source: Asheim & Gertler (2005), Asheim et al. (2007), Asheim & Hansen (2009), Asheim et al. (2011a),; authors' *own modification*

The knowledge base concept was originally applied in its pure form. Later it has been argued that combinations of different knowledge bases might enhance the innovation performance of firms (Todtling & Grillitsch, 2015) and that regional innovation system rarely rely on interactions within one single knowledge base (Manniche, 2012). The combinations of knowledge bases (called also combinatorial knowledge) are often a source of the more radical innovations (Asheim *et al.,* 2015).

The concept of knowledge bases has been used in several empirical studies. The best way how to empirically identify the types of knowledge bases is under a wide research discussion. The second problem shared by all empirical studies is the lack of relevant statistical data. Attempts to identify the prevailing base in various industries were made by Asheim & Coenen (2005), Moodysson *et al.* (2008) and others. The authors' typical point of departure was an analysis of scientific publications and patents in companies and organizations (analyses based on keywords and references to other sources, as well as on identification of subjects cooperating within patenting and publishing). A definition of knowledge bases at the regional level was attempted by Asheim & Hansen (2009), who utilized official occupation-related statistics classified using the Swedish occupation code nomenclature (International Standard Classification of Occupations – ISCO). They classified the individual occupations as being part of either analytical, synthetic or symbolic knowledge base. This, however, provided no information about the industries in which the people were employed. Therefore, this data should ideally be interconnected with the NACE classification of economic activities. Martin (2012) tried to identify the knowledge base of the Swedish regions too. He used occupation data reflecting the tasks and duties undertaken by the local workforce, in association with a location quotient analysis. Other authors investigated the knowledge bases in selected fields (industries) within particular regions. Plum & Hassink (2011) compared knowledge networking in two case studies from Germany (biotechnology industry in Aachen – the analytical knowledge base, and automotive industry in Saxony – the synthetic knowledge base). Their research was based on standardized interviews with managers and other experts. Martin (2013) investigated several regional industries located in different parts of Europe and he focused on companies' relations to other organizations. Some of the empirical studies were not aimed at identification and characterization of knowledge bases but they were aimed at some specific aspects of knowledge bases. Aslesen & Freel (2012) explored open innovation and Herstad *et al.* (2014) explored international innovation collaboration in different knowledge bases. Some recent studies pay its attention to combining of knowledge bases. We can name studies concentrating on ICT sector in Austria (Todtling & Grillitsch, 2015), on Austrian automotive supplier industry (Grillitsch & Trippl, 2014) or on seven sectors in the European regions (Strambach & Klement, 2011).

The existing literature on knowledge bases is largely grounded on in-depth case studies, but lesser effort has been done to operationalize the concept in a more systematic manner (Martin, 2012). As the above-mentioned empirical studies showed, it is necessary to search for other and better ways to define knowledge bases in regions.

Within the context of the differentiated knowledge base theory, this paper aims at finding suitable and, at the same time, available indicators that would best represent the general characteristics of regional knowledge bases. These indicators will subsequently be used for the establishment of a typology of knowledge bases of the Czech regions. We assume that in the Czech Republic, the symbolic knowledge base forms a minority and does not prevail in any of the country's regions. It corresponds also to approaches used in the previous empirical studies.

Methods

In the following text, knowledge bases in Czech regions will be assessed and a respective typology will be established. Assuming that the symbolic knowledge base cannot be identified in any of the 14 Czech regions, our selection of indicators only allows for analytical and synthetic base characteristics. At the same time, in accordance with the works cited, it is evident that the availability of indicators is limited to a considerable extent. This surely imposes certain limits on the use of the most suitable indicators; but despite this fact, relevant indicators can still be found to identify both knowledge base types.

All of the indicators were recalculated to allow mutual comparison of regions at the indicator level. To that end, the indicator values are given as a percentage. Indicators concerning R&D and student numbers were taken from the databases of the Czech Statistical Office (CZSO, 2013), and then recalculated. Indicators concerning the representation of industries in regions are from the Albertina database (Bisnode, 2014). The selection comprises companies with 10 or more employees and operating mainly in the given industry. The selected industries were related to the respective knowledge bases in accordance with previous empirical studies and theoretical findings. All data refers to the end of 2012, the last year for which all proposed indicators are available.

The following seven indicators were chosen to describe analytical knowledge bases in the Czech regions:

- the ratio between R&D expenditure in natural sciences and the overall R&D expenditure (E-NS);
- the ratio between basic research expenditure and the overall R&D expenditure (E-BR);
- the ratio between the number of natural science R&D workplaces and the overall number of R&D workplaces (W-NS);
- the ratio between the number of natural researchers and the overall number of researchers (R-NS);
- the ratio between the number of natural science students and the overall number of students (S-NS);
- the ratio between the number of companies dealing with the manufacture of chemicals and chemical products, and the overall number of companies in the manufacturing industry (CHEM);
- the ratio between the number of companies dealing with the manufacture of basic pharmaceutical products and pharmaceutical preparations, and the overall number of companies in the manufacturing industry (PHA).

The following eight indicators were chosen to describe synthetic knowledge bases in the Czech regions:

- the ratio between R&D expenditure in technical sciences and the overall R&D expenditure (E-TS);
- the ratio between expenditure on applied- and experimental research, and the overall R&D expenditure (E-AR);
- the ratio between the number of technical science R&D workplaces and the overall number of R&D workplaces (W-TS);
- the ratio between the number of technical researchers and the overall number of researchers (R-TS);
- the ratio between the number of technical students and the overall number of students (S-TS);
- the ratio between the number of companies dealing with the manufacture of electrical equipment, and the overall number of companies in the manufacturing industry (ELE);
- the ratio between the number of companies dealing with the manufacture of machinery and equipment, and the overall number of companies in the manufacturing industry (MACH);
- the ratio between the number of companies dealing with the manufacture of motor vehicles, trailers and semi-trailers, and the overall number of companies in the manufacturing industry (MOT).

Considering our objectives and the character of the indicators, the point method appears to be useful for our assessment. However, should an indicator (or more indicators) show significantly different values, the results produced by the point method can become greatly affected. Therefore, it makes sense to combine this method with cluster analysis.

The point method is based on identifying a region that reaches a maximum or a minimum value for the analysed indicator. The minimum value is relevant when indicator drop is considered positive (the lower the value the better); the maximum value is relevant otherwise. An increase in indicator value is progressive, which is typical of most indicators used in region analysis.

The point value of the given indicator is calculated as follows:

- in case of a maximum, the following equation is used: $B_{ij} = \frac{x_{ij}}{x_{i\,max}}$,
- in case of a minimum, the following equation is used: $B_{ij} = \frac{x_{i\,min}}{x_{ij}}$,

where B_{ij} is the point value of the i-th indicator for the j-th region, x_{ij} is the value of the i-th indicator for the j-th region, $x_{i\,max}$ represents the maximum value of the i-th indicator, and $x_{i\,min}$ is the minimum value of the i-th indicator.

The region with the maximum (minimum) indicator value is assigned a particular number of points (100 in the calculations used here), the other regions are rated according to their actual indicator value (0–100). The main advantage of this method is that we can establish integrated indicators, i.e. take a group of indicators and put it into a single characteristic, a dimensionless number (Melecky & Skokan, 2011). As far as the indicators used in this paper are concerned, more is always better.

Apart from the point method, cluster analysis, too, represents a way to arrive at a typology of knowledge bases. The resulting cluster of regions represents internal (within-cluster) homogeneity and external (between-cluster) heterogeneity. Regions in a specific cluster share many characteristics, but are different from regions not belonging to the cluster (Melecky & Stanickova, 2014; Koziak *et al.*, 2014). Cluster analysis is an important tool for the study of the spatial homogeneity of data sets (Kraft, 2012). At the same time, the point method helps provide a suitable input, as it converts indicator values to unified, dimensionless point scores that can be used in cluster analysis. The analysis presented in this paper employs hierarchical clustering with an agglomerative approach, in particular: the most commonly used (Meloun & Militky, 2011) hierarchical Ward's method with Euclidean distances.

Ward's method is based on the optimization of cluster homogeneity by the criterion of minimize the increase in the error sum-of-squares compared to its average. (Everitt *et al.*, 2011) At each stage, the increment of sum-of-squares of deviations arising from their clustering is calculated for each pair of deviations. Consequently, the clusters with the minimum value of the increment are connected. For the k objects and m characteristics there is a matrix k x m with elements x_{ij}. (Meloun & Militky, 2011) Within-cluster error sum of squares (E) is given by

$$E = \sum_{i=1}^{m}\sum_{j=1}^{k}\left(x_{ij} - \overline{x_j}\right)^2$$

where

$$\overline{x_j} = \frac{1}{k}\sum_{i=1}^{k} x_{ij}$$

The cluster analysis results can be compared with those obtained by the point method, and their mutual synthesis allows arriving at conclusive findings. This way all regions can be evaluated individually for both knowledge base types, that is, despite analysing different indicators. As the final step, the results obtained for both knowledge base types are compared and the resulting base type is determined for each region. Considering the nature of the socio-economic data, it is likely that for some regions it will be impossible to determine an obvious knowledge base type. This is why we will also define two transitional types: analytical-synthetic and synthetic-analytical, according to the prevailing characteristics in the given region.

Results and Discussion: A Typology of Knowledge Bases in Czech Regions

The numerical values of the individual indicators are converted to points, and the region with the best (i.e. highest) indicator value is assigned 100 points. Therefore, for the examination of analytical knowledge base parameters the maximum achievable score is 700 points (however, this is just a theoretical possibility). Table 2 presents all regions already ranked based on the overall score. The top ranker is Prague (two indicators reaching the maximum value of 100 points), with a total score of 612 points and far ahead of the other regions. The span between the next four rankers (Central Bohemian, South Bohemian, South Moravian and Usti Region) is only 21 points; however, the internal structure of the scores is very different. It is these NUTS3 regions that best reveal the features of an analytical knowledge base. Three other regions exceed the average score, which is 378 points. On the other hand, the regions of Pilsen, Zlin, Karlovy Vary, Liberec and Vysocina scored the lowest number of points. It appears that in these regions no analytical knowledge base can be identified.

Table 2

Knowledge Base Typology – Analytical Base – Point Method

Code	Region	E-NS	E-BR	W-NS	R-NS	S-NS	CHEM	PHA	Total
CZ010	Prague	100	99	100	81	79	63	90	612
CZ020	Central Bohemian	46	29	93	51	70	78	100	468
CZ031	South Bohemian	70	100	85	80	63	30	28	457
CZ064	South Moravian	67	79	85	45	68	34	74	453
CZ042	Usti	59	20	77	100	77	100	14	447
CZ052	Hradec Kralove	53	25	71	53	100	39	81	420
CZ071	Olomouc	67	52	76	68	83	27	28	401
CZ053	Pardubice	47	44	67	69	92	51	15	384
CZ080	Moravian-Silesian	31	64	63	38	75	45	47	363
CZ032	Pilsen	42	40	69	53	68	20	0	292
CZ072	Zlin	20	19	52	23	70	58	32	274
CZ041	Karlovy Vary	33	5	75	63	65	24	0	264
CZ051	Liberec	22	29	55	24	74	22	19	245
CZ063	Vysocina	15	20	56	27	63	37	0	217

Source: authors

For the examination of synthetic knowledge base parameters the maximum achievable score is 800 points (again, this is just a theoretical possibility). Table 3 shows the Liberec Region as the top ranker (three indicators reaching the maximum value of 100 points), with a total score of 711 points and far ahead of the other regions. The span between the regions that occupy the 2nd to 7th place is only 39 points; it is the first seven rankers that potentially draw on a synthetic knowledge base. What is also worth noting is that eight out of nine maximum indicator values pertain to the first three NUTS3 regions in the list. Eight regions exceed the average score, which is 572 points. The regions South Moravian, Usti, Olomouc, South Bohemian, and the Capital City of Prague scored the lowest number of points, which largely corresponds with previous results.

Table 3

Knowledge Base Typology – Synthetic Base – Point Method

Code	Region	R-TS	R-AR	W-TS	R-TS	S-TS	ELE	MACH	MAT	Total
CZ051	Liberec	100	90	96	100	79	48	99	100	711
CZ041	Karlovy Vary	95	100	99	74	48	100	67	73	657
CZ072	Zlin	96	94	100	92	100	48	85	40	655
CZ063	Vysocina	99	94	88	99	71	50	86	58	646
CZ020	Central Bohemian	83	89	72	87	45	59	89	99	623
CZ080	Moravian-Silesian	89	74	96	70	97	57	75	64	623
CZ032	Pilsen	83	85	83	52	85	83	82	65	618
CZ053	Pardubice	81	83	85	59	67	57	92	65	589
CZ052	Hradec Kralove	58	92	76	45	53	75	81	61	541
CZ064	South Moravian	55	67	76	50	73	70	82	33	506
CZ042	Usti	60	94	74	39	62	70	50	55	503
CZ071	Olomouc	29	79	72	30	74	60	100	31	476
CZ031	South Bohemian	54	58	66	17	59	57	84	63	459
CZ010	Prague	35	59	55	33	37	90	69	31	408

Source: authors

In order to determine the prevailing knowledge base type in a particular region, the point method results need to be examined further, using cluster analysis. The analysis will help establish clusters of similar regions and, in combination with the point score, identify the type of the knowledge base.

The cluster analysis for data concerning analytical knowledge bases results in defining five clusters, that is, groups of similar regions (see Figure 1). The first group comprises Prague, the South Bohemian, the South Moravian and the Moravian-Silesian Region. The second group comprises Central Bohemian and the Hradec Kralove Region. Five of these six regions (Moravian-Silesian excluded) appear at the top of the point method ranking, so it is evident that the analytical knowledge base features are really important in these regions. The Usti Region represents a separate unit. Its position is surely interesting, also considering the very good point score the region has achieved. For the remaining regions forming the fourth and fifth clusters no analytical knowledge base was identified in the context of the point method analysis stated above.

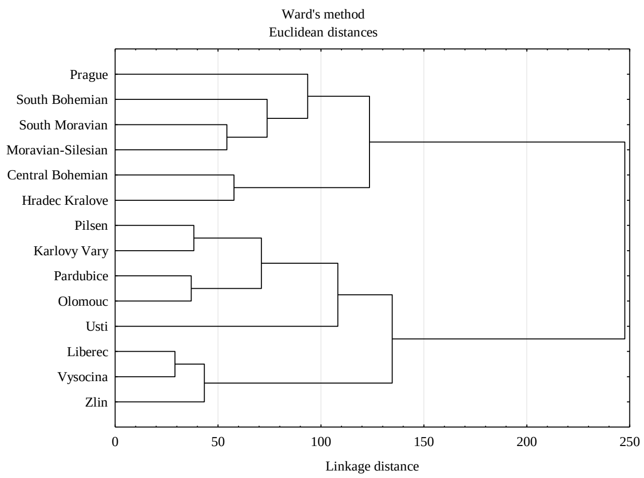

Figure 1. Dendrogram with the analytical knowledge base

Source: authors (using the Statistica 12 software)

The cluster analysis for data concerning synthetic knowledge bases results in defining four clusters (see Figure 2). The first cluster comprises the Liberec and Central Bohemian Regions. Therefore, the Central Bohemian Region appears to share similarities with the region with the highest point score (cluster analysis corrects the above-discussed narrow span of rankings). The second group comprises the Vysocina and the Zlin Region. In all of these regions the existence of a synthetic knowledge base can be assumed. The third group comprises the regions of Pilsen, Pardubice, Moravian-Silesian and Karlovy Vary. The fourth and final cluster includes Prague, South Bohemian, South Moravian, Olomouc, Usti and Hradec Kralove. In the case of these six regions, taking into account the point method results as well, a synthetic knowledge base is unlikely to be found in these regions.

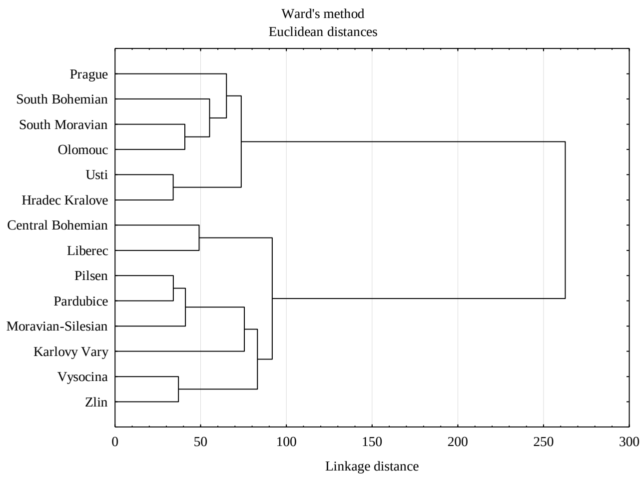

Figure 2. Dendrogram with the synthetic knowledge base

Source: authors (using the Statistica 12 software)

Putting all the analyses, results and interpretations together, four knowledge base types can be established in the fourteen Czech regions, as already mentioned above. The four types are defined as follows:

- analytical knowledge base – the region is among the top rankers in the analytical base point score assessment and tends to score lower in the synthetic base assessment; it forms clusters with similar regions especially when clustering data characteristic of analytical knowledge bases;
- synthetic knowledge base – the region is among the top rankers in the synthetic base point score assessment and tends to score lower in the analytical base assessment; it

forms clusters with similar regions especially when clustering data characteristic of synthetic knowledge bases;

- analytical-synthetic knowledge base – the region generally scores higher in the analytical base point score assessment; it does not form clusters with the best rankers in the synthetic base point score assessment;
- synthetic-analytical knowledge base – the region generally scores higher in the synthetic base point score assessment; it does not form clusters with the best rankers in the analytical base point score assessment.

The particular knowledge base types as identified in the individual Czech regions are given in Table 4. The regions of Central Bohemian and Olomouc, however, represent a certain problem. The Central Bohemian Region scores well in the point assessment of both knowledge base types, which is further supported by the cluster analysis results. That we identify this region's prevailing knowledge base as synthetic-analytical is the result of similarity with the Liberec Region, which tops the synthetic base characteristics assessment. The Olomouc Region is not a strong performer in any of the assessments, but it appears that the region generally scores higher in the analytical base point score assessment, and it does not form clusters with the best rankers in the synthetic base point score assessment.

Table 4

Knowledge Base Typology

Analytical	Synthetic	Analytical-synthetic	Synthetic-analytical
CZ010 Prague	CZ051 Liberec	CZ042 Usti	CZ020 Central Bohemian
CZ031 South Bohemian	CZ063 Vysocina	CZ052 Hradec Kralove	CZ032 Pilsen
CZ064 South Moravian	CZ072 Zlin	CZ071 Olomouc	CZ041 Karlovy Vary
		CZ080 Moravian-Silesian	CZ053 Pardubice

Source: authors

The resulting typology can also be represented by a cartogram (see Figure 3). Looking at the spatial distribution of the individual types, we cannot unambiguously formulate any dependencies that could possibly be generalized. It seems that the synthetic knowledge base type dominates in the western part of the country (with the exception of the Usti Region), whereas in the eastern – Moravian – regions (with the exception of Zlin) the analytical type prevails.

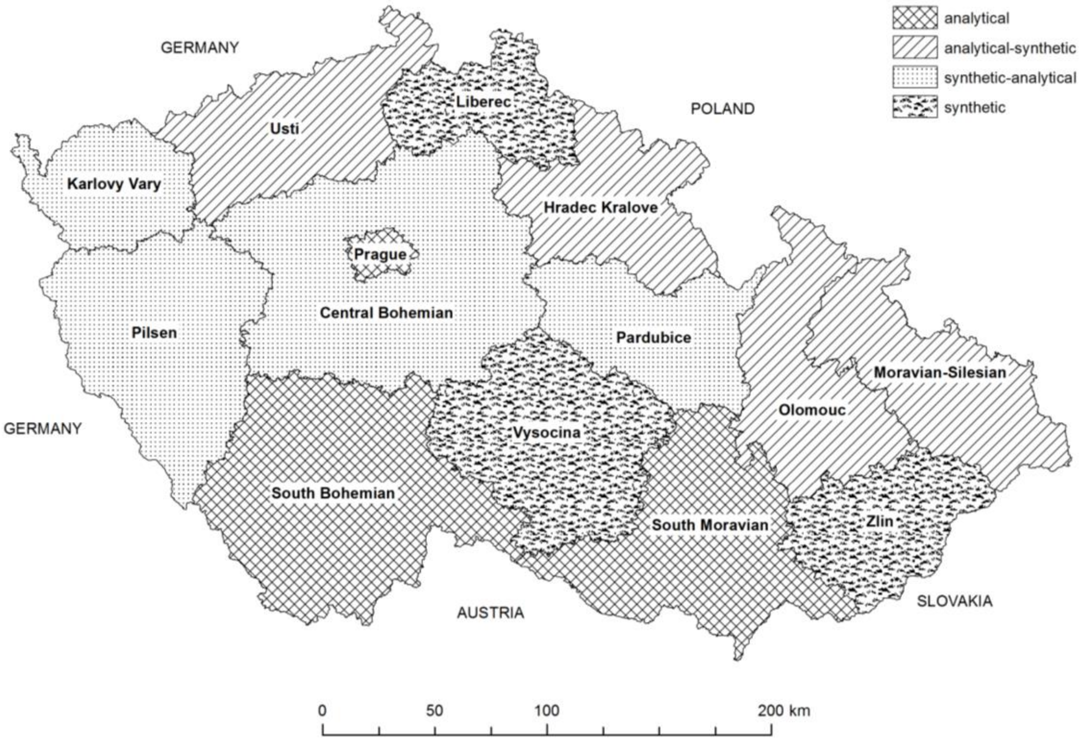

Figure 3. Knowledge Base Typology Of The Czech Regions

Conclusion

The concept of knowledge bases is part of a wider concept of regional innovation systems, dealt with by geographers and regional economists. The concept of knowledge bases focuses on the nature of key knowledge that affects innovation performance and that can be used to establish a general typology of economic sectors, clusters as well as regional innovation systems. There are three types of knowledge base: analytical, synthetic, and symbolic.

In an analytical knowledge base (science based), scientific knowledge is important and knowledge creation is built on formal models. Both types of research, basic and applied, are relevant and they tend to use codified knowledge. In their innovation activities, companies typically cooperate with universities and research institutes. In a synthetic base (engineering based), knowledge creation is built on the application or novel combination of existing knowledge and applied research plays a more important role than basic research. New innovation often arises from the communication with customers or suppliers and this knowledge base tends to use tacit knowledge. The role of geographical proximity is more significant in this case. A symbolic knowledge base is typical of industries in which aesthetics, design, or cultural aspects are important.

The existing literature on knowledge bases is often based on in-depth case studies of an industry or a particular region. We intended to focus our attention on the identification of knowledge bases at regional level. Similar studies are usually based on analysis of occupational data (ISCO), sometimes on data on classification of economic activities (NACE). Our approach is different from them to some extent. We tried to find appropriate quantitative indicators representing individual knowledge bases that are able to easily describe characteristics of regions in a broader sense. We required them to cover the areas of research activity, character of human resources, and economic activities within the regions.

The objective of this paper is to propose appropriate indicators and methodology in order to empirically identify the knowledge base of a region and to identify knowledge bases in the Czech regions. We assume that none of the Czech regions can demonstrate a significant representation of symbolic base features (characteristics), and this is why we solely focus on the analytical and the synthetic knowledge base.

Considering the nature of the socio-economic data, it has proved practical to also define two transitional knowledge base types: analytical-synthetic and synthetic-analytical. The paper chooses available indicators that best characterize both types of knowledge base. Combining results obtained from point method calculations and cluster analysis, the dominant knowledge base was determined for each region. Regions with an analytical knowledge base include Prague, the South Moravian Region, and the South Bohemian Region. Regions with a prevailing synthetic knowledge base include Zlin, Liberec and Vysocina. For the remaining eight regions, neither of the two elementary knowledge base types could have been unambiguously established. Regions with an analytical-synthetic knowledge base generally score higher in the analytical base point score assessment; they include Usti, Hradec Kralove, Olomouc, and the Moravian-Silesian Region. Conversely, regions with a synthetic-analytical knowledge base tend to achieve a higher score in the synthetic base point score assessment; they include the remaining four Czech regions.

Our analysis confirms the conclusions of similar studies in that further research is necessary to develop methods for the application of this concept. At the level of industries or companies, existing studies focused on a qualitative analysis of collaboration, scientific publications, patents and trademarks. At the regional level it seems appropriate to use statistical data, for example, related to occupations or to various types of economic, research and innovation activity. At the same time, it is a limiting factor of this approach because not all required statistical information is available. Therefore, further research should strive to find methods to overcome this limitation. Future research should also focus on the identification of knowledge bases at international level; in particular, it should identify and compare regional knowledge bases in various countries. Generalization of the procedures applied can be useful for a better concentration of innovation policy in the European Union.

The results of our study can be applied in the preparation and implementation of regional innovation policies. In real-life practice, policies are often implemented through taking over the best practices from high-tech sectors and the best regions. We believe this is not a correct approach, as all regions are unique and have different conditions for the implementation and development of innovations. Regions can differ, for example, in their economic structure, role of research and development, presence of particular knowledge providers, or the degree to which clusters are developed. Therefore, the "one-size-fits-all" approach cannot be applied (Todtling & Trippl, 2005), and regional innovation policy must be differentiated. If policy makers have correct information, they can better target their innovation policies and choose more appropriate tools to support innovation. Our paper and other studies confirm that the knowledge bases concept provides to policy-makers new opportunities for encouraging the development, diffusion and use of economically valuable knowledge (Manniche, 2012). It is necessary to complete and combine local knowledge sourcing with sourcing from higher geographic levels (Todtling & Grillitsch, 2012). In particular, this fact is of high relevance for small open economies, such as the Czech Republic (Kraft & Kraftova, 2012). We would like to emphasize that regional innovation policy cannot be concentrated only to the dominant knowledge base, because all types of knowledge bases are present to some extent in each region and combination of analytical and synthetic knowledge bases leads to more radical innovations and can prevent from the lock-in effect.

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