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The Identification of Industrial Clusters in the Chungbuk Region in Korea

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Abstract

This paper aims to identify the spatial concentrations and linkage properties of industrial clusters in the Chungbuk Province region in Korea using a three-step approach, which is composed of the cluster index, Getis-Ord's G_i^* , and qualitative input-output analysis. The results of the study reveal: a) what industrial sectors are concentrated and where they are; b) where the spatially interdependent industries are; and c) how the industrial sectors of the identified clusters in different locations are vertically interconnected. In addition, the degree of strength of the interindustry linkages between industrial clusters are assessed. Based on the findings, some plausible industrial policies are suggested.

Keywords

Identification of industrial clusters; Cluster index; Getis-Ord's G_i^* ; Qualitative input-output analysis; Spatial concentrations

1. INTRODUCTION


In recent years, it is widely believed that industrial clusters play key role in regional economic development. Accordingly, industrial cluster analysis has attracted increasing attention from various areas, including regional science, economic geography, economic development, and business management, and so on. A variety of articles on industrial clusters has proliferated in the last decades, as demonstrated by various attempts in the literature to organize different strands, concepts, and topics of research on industrial clusters (Cruz and Teixeira,

2010; Lazaretti et al., 2014).

Of the various issues of industrial cluster analysis, the identification of industrial clusters in adequate and comprehensive ways has been the focal topic in cluster analysis. However, despite all the theoretical and conceptual understanding of the working mechanisms of industrial clusters, there is still no consensus in the relevant literature on the use of quantitative methods for proper cluster identification (vom Hofe and Bhatta, 2007). Nevertheless, one important strain of cluster identification methodologies has evolved around using input-output tables. The basic idea behind the use of input-output tables is to identify interindustry linkages based on vertical buying-selling relationships, or to group industries according to similarities in the trade patterns. As the cluster concept is rooted in agglomeration theory, input-output based approaches for cluster identification are considered advantageous to capture various forms of backward as well as forward interindustry linkages, which primarily stem from concentrations of interlinked firms.

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World Technopolis Review
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Though widely applied, the input-output table based methods of identifying industrial clusters are not free from criticisms. One major criticism is that because input-output tables are aspatial by design, industrial clusters identified through the input-output based methods fail to provide information on how close firms and related establishments are located to each other (Latham, 1976; Uallachain, 1984). Given the shortcoming of the approaches based on input-output table only, the input-output table based approaches need to be combined with other proper methods by which the spatial dimension of industrial clusters can be explored, with which the information of aspatial industrial linkages as well as spatial agglomerations of firms for industrial clusters can be disclosed.

The aim of this paper is to identify industrial clusters in Chungbuk Province and its adjacent areas, Korea, using a three-step approach to cluster identification, which is composed of the cluster index, Getis-Ord's G_i^* , and qualitative input-output analysis (QIOA). The paper is constructed as follows. In Section 2, the cluster concept and different approaches of cluster identification are overviewed. Section 3 describes the three-step approach to cluster identification as used in this paper. Section 4 presents the results obtained from applying the three-step approach to the study region. Finally, conclusions and implications are offered in Section 5.

2. CLUSTER CONCEPT AND APPROACHES OF CLUSTER IDENTIFICATION

2.1 The cluster Concept

There has been growing interest in industrial cluster-centered economic development in academia and policy areas. As research on the spatial concentration of industrial activities has been attacked from a variety of disciplines, however, there is much confusion concerning the proper conceptualization of a cluster (Karlsson, 2008). Actually, terms such as agglomeration, clusters, new industrial areas, social embeddedness, milieux, and complex are used interchangeably, without proper concern for questions of their operationalization.

In the meantime, Gordon and McCann (2000) provide a comprehensive assessment of various theoretical frameworks in which industrial clusters can be analyzed, thereby certainly obviating the conceptual ambiguity of industrial cluster. They distinguish three analytically distinct models of industrial clustering, each of which evolves in its own logic and discipline.

They are: a) the classical model of pure agglomeration, referring to job matching opportunities and service economies of scale and service, where externalities arise via the local market and local spillovers; b) the industrial complex model, referring to explicit links of sales and purchases between firms leading to reduced transaction costs; and c) the social network model, which focuses on social ties and trust facilitating cooperation and innovation.

The model of pure agglomeration discusses industrial clusters from the perspective of neo-classical economics. This model drives its theoretical foundations from the advantage of localized labor pool (Marshall, 1920), the principles of localization and urbanization economies (Hoover, 1948; Jacobs, 1969; Glaeser et al., 1992; Boschma et al., 2013; Morrissey and Cummins, 2016), or the interplay between localized increasing return to scale and spatial distance transactions costs (Krugman, 1991; 1995; Krugman and Venables, 1995; Venables, 1996; Fujita et al., 2000; Baldwin, 2001; Duranton and Puga, 2004). The cluster ideas of Porter (1998; 2000; 2011), Redman (1994), and Rosenfeld (1995) belong to this category. Geographical proximity among the related firms and institutions, which will facilitate the formation of trade linkages and employment matches, is critical to the efficient working of this system (Gordon and McCann, 2000).

Next, the model of industrial complex emerges from the classical and neo-classical economic tradition. Industrial complexes are characterized by sets of identifiable and stable relations among firms which are in part manifested in their spatial behavior. The trade links between firms represent the patterns of sales and purchases that govern their location behavior. Analysis of the industrial complex focuses on the relationship between spatial transactions costs and geographical distance, as well as the nature of the input-output requirements of the firms in question (Gordon and McCann, 2000). Industrial complexes include clustering groups of firms interlinked through production chains that are aspatial in nature (Czamanski and Ablas, 1979; Feser and Bergman, 2000; Feser et al., 2005) and all the subsequent developments of various spatial counterpart location theory to traditional economic input-output analysis (Isard, 1951; Moses, 1958; Miller and Jensen, 1978). Congregating in industrial complexes, firms locate close to other firms within the particular input-output production and consumption hierarchy of which they are part, and minimize their spatial transactions costs. The industrial complex emerges incrementally through strategic location decisions of a few influential firms and concerted decisions by the

firms in co-location.

Finally, the social network model emerges as a critique of the neo-classical approach to the existence and development of institutions within the new institutionalist perspective (Williamson, 1985; 2000). Viewed from the new institutionalist perspective, the development of organizations is a process of internalization and coordination of transactions with which trust becomes institutionalized within the economic system. The sociological response to the institutionalist approach is the social network model, in which interfirm social interactions are more intensive than their intrafirm counterparts (Gordon and McCann, 2000; Brachert et al., 2011). The relations in the social network model are socially embedded in the sense that they depend on norms, institutions, and sets of assumptions shared among the group of actors and are not simply the outcome of economic decisions. The socially embedded factors promote the firms to engage in developing and reproducing the location-specific networks. Here, co-location is a necessary but not sufficient for sharing the benefits generated from the social network.

A brief examination of the cluster concept above signifies that the types and operational characteristics of clusters condition the appropriate methodologies for identifying industrial clusters. Thus, a priori choice of methodology without due regard paid to the characteristics of cluster in question is hardly justified. Various methods and techniques for cluster identification are next examined.

2.2 Methods for Cluster Identification

Despite considerable progress in clarifying the cluster concept, no generally accepted cluster theory has developed as yet (Martin and Sunley, 2003). This ambiguity also applies to the issue of methodology for industrial cluster identification. As no common approach to cluster identification exist, a variety of methods compete through empirical application for industrial clusters.

In order for a technique of cluster identification to be considered appropriate, it should reveal the characteristics of cluster operation and the patterns of linkage among spatially clustered businesses. Broadly speaking, diverse techniques for cluster identification are classified into bottom-up vs. top-down approaches (Sternberg and Litzenberger, 2004; Brachert et al., 2011). Bottom-up approaches use highly qualitative methods such as export survey, regional workshops, or social network analysis. The qualitative techniques are suitable for identifying the socially embedded interactions between firms

and related institutions. The operational features of many interfirm social interactions in clusters are so elusive that it is difficult to detect them with quantitative methods. In this sense, given Gordon and McCann's (2000) classification of clusters, it can be said that the qualitative techniques are appropriate for identifying industrial clusters in the form of social network models.

On the other hand, top-down approaches use selective types of geographically disaggregated data to identify spatial clustering of firms localized in the same area. When the sources of economic benefits accruing to firms within the local area involve a localized pool of specialized labor, the increased local provision of non-traded inputs, and the maximum flow of information and ideas, geographical proximity and co-location of firms can measure these sources of economic benefits prevailing in industrial clusters. These kinds of economic benefits are just the principal forces that promote the development of pure agglomeration. Several simple indices designed to estimate the degrees of industrial concentration in local areas well fit for identifying the model of pure agglomeration, which is one of Gordon and McCann's (2000) three types of industrial cluster. The simple indices include the Gini coefficient, the Herfindal index or concentration rate, the location quotients, the cluster index, and the Ellison-Glaeser index.

However, these simple indices are not adequate as an instrument of capturing the sectoral or spatial interdependence between industrial conglomerations. Some statistical indices of spatial autocorrelation are appropriate for measuring inter-cluster or inter-agglomeration dependence. The statistics such as local Moran's I or Getis-Ord's G and G_i^* are most frequently used to estimate the spatial dependence between the geographically isolated groups of industrial concentration. These statistical indices are suitable for determining whether the spatial interdependence exists between the concentrations of firms located in different locations. This means that the statistics of spatial autocorrelation are proper to identify the spatial linkages between discrete agglomerations, whether pure agglomerations or industrial complexes, at the regional level.

The simple indices examined above are deficient in identifying the interindustry linkages within or between industrial clusters (Feser et al., 2005; Brachert et al., 2011). This point signifies some plausible techniques with which vertical industrial linkages, which are considered the most important dimension of industrial clusters, can be documented. Various input-output based techniques offer a promising instrument

for exploring the vertical linkages of industrial clusters (Dietzenbacher et al., 2005; Dietzenbacher and Romero, 2007; Morrissey and Cummins, 2016). Then, they can be a tool of investigating the structure of value chains and the location patterns of interconnected industrial sectors. In this respect, the input-output based techniques might offer a proper method for identifying two types of industrial clusters, i.e. the classical model of pure agglomeration and the industrial complex model.

A most common method based on the input-output model is principal component factor analysis (Ullachain, 1984; Feser and Bergman, 2000; Feser et al., 2005; Midmore et al., 2006). In principal component factor analysis, the measures of direct and indirect linkages calculated from interindustry trade data are treated as variables to present the relative strength of a given industry and a derived factor (Oosterhaven et al., 2001). As different industries are grouped into one cluster according to the similarity of intermediate trade structure, the highest-loading industries are regarded as members of an industrial cluster. Because of its focus on the entire value chains, this method is of limited relevance when regional specialization occurs along certain parts of these templates (Brachert et al., 2011).

Q factor analysis is another input-output based technique to assess the nature of interrelationships among inter-cluster units or firms. It identifies sectoral forward and backward linkage clusters in input-output systems, thereby gleaning insights into common attributes among the groups (Athiyaman and Parkan, 2008; Sonis et al., 2008). The central point of this method is to interpret the structural chains of highest dimension as the most significant input-output industrial clusters and to visualize economic complexity through the process of structural economic complication.

On the other hand, Hill and Brennan (2000) applies an input-output based discriminant analysis for identifying interindustry linkages in industrial clusters. The method is to identify the driver industries which encourage the region's economy and its competitive advantage. The industrial linkages that the driver industries establish with supplier and customer industries are detected based on the information from a region-specific input-output model.

The focus of the variants of input-output technique examined above is on measuring vertical linkages between different industries but not on detecting their intensities. With these techniques, the assessment of the intensities of interindustry linkages is indirect. In contrast, QIOA, which has been first

developed by Schnabl (1994), is an input-output based method with which the intensities of vertical industrial linkages are directly estimated. A merit of QIOA is its ability to transform the quantitative interindustry trades to binary qualitative linkages, i.e. significant or non-significant (Titze et al., 2011). As QIOA constitutes a key component of the three-step approach of this paper, its details are addressed in the next section.

As examined so far, each technique of cluster identification has its own merit with which a specific attribute of a specific type of industrial cluster can be investigated. Then, a combination of some stand-alone techniques can provide a complementary for approaches to cluster identification.

3. A THREE-STEP APPROACH FOR IDENTIFYING INDUSTRIAL CLUSTERS

The individual stand-alone methods of identifying industrial clusters are themselves prone to identify parts of the attributes of industrial clusters. A more comprehensive approach has then a significant merit for identifying the multiple dimensions of industrial clusters. Keeping along this idea, this paper employs a three-step approach, which is formed by the combination of three separate methods, i.e. the cluster index (CI), Getis-Ord's G_i^* , and QIOA. It is noted that these three component techniques are highly quantitative-oriented. This means that the three-step approach of this paper implicitly targets for identifying the clusters of pure agglomeration and/or industrial complex. Detailed explanations of these three component methods follow.

3.1 The Cluster Index

By correlating relative industrial density, relative industrial stock, and relative sizes of firms, the cluster index, CI, of Sternberg and Litzenberger (2004) measures the strengths of concentration of industries. Then, the CI is composed of three variables: the relative industrial density, the relative industrial stock, and the relative firm sizes. According to the CI, the condition for industrial concentrations to be industrial clusters is that they should not be dominated by just a handful of firms. This means that industrial density relative to industrial stock should not be very high, but just above their averages (Brachert et al., 2011).

The cluster index for industry i in region r , CI_{ir} , is expressed as:

$$(1) CI_{ir} = ID_{ir} \times IS_{ir} \times \frac{1}{SB_{ir}} = \frac{(e_{ir}/\sum_r e_{ir})(b_{ir}/\sum_r b_{ir})}{(p_r/\sum_r p_r)(a_r/\sum_r a_r)}$$

where *ID*, *IS*, and *SB* represent relative industrial density, relative industrial stock, and relative sizes of businesses, respectively; *e* denotes employment; *b* denotes the number of establishments; *p* means the number of residents; and *a* denotes the size of the subregion.

Eq. (1) indicates that the CI is proportional to the number of people employed, the number of establishments, whereas is reciprocal of the areal sizes and the number of inhabitants. Then, it can be claimed that if the magnitude of the CI is greater than 1.0 for a specific industry and a subregion, the relevant industry is concentrated and specialized in the relevant subregion. It is evident from eq. (1) that the CI does not offer any information about the vertical dimension of industrial linkages.

3.2 The Getis-Ord's *Gi** Statistic

As mentioned earlier, one of the most crucial elements that constitute the concept of industrial clusters is the horizontal and vertical interindustry linkages between different industrial clusters. Spatial autocorrelation statistics such as Moran's *I* and Getis-Ord's *Gi** can be used to measure this element of the cluster concept (Feser et al., 2005; Carroll et al., 2008). The measures of spatial autocorrelation ensure to identify places of hot spot in the spatial distribution of sole industries or whole value chains (Brachert et al., 2011). In this paper, the Getis-Ord's *Gi** statistic (Ord and Getis, 1995) is selected to determine the spatial interdependence of economic activities across administrative boundaries.

Given a particular industrial sector, Getis-Ord's *Gi** for region *i* (*i*=1, 2, ..., *n*) calculated by the following equation:

$$(2) Gi^* = \frac{\sum_{j \neq i} w_{ij} x_j - W_i \bar{x}}{s \sqrt{\frac{n S_{ii} W_i^2}{n-1}}}$$

for all regions *j*, where *x* is the number of employment; *w_{ij}* is a spatial weight that defines neighboring regions *j* to region *i*; *W_i* is the sum of spatial weights *w_{ij}*; $\bar{x} = \sum_j x_j / (n-1)$; $S_{ii} = \sum_j w_{ij}^2$; and $s^2 = \{ \sum_j x_j^2 / (n-1) \} - (\bar{x})^2$. Because the *Gi** statistic is expressed in terms of standard deviations from the mean, it can be understood as z scores along the probability density function of normal distribution after a Bonferroni-type correction (Ord and Getis, 1995; Feser et al., 2005; Brachert et al., 2011).

In calculating the Getis-Ord's *Gi** statistic, one critical issue is to determine the spatial weights matrix. Although there is no consensus in the related literature on the ways of defining the elements of the spatial weights matrix, two methods are rather frequently used. One common practice is to use binary code systems under which the immediate neighboring regions inclusive to the region itself are defined as adjacency, i.e. coded one, while non-neighboring regions are assumed not to interact, i.e. coded zero. The other way is to use the reciprocals of the distances between the region centroids as spatial weights (Frizado et al., 2009). In this paper, the latter practice is applied.

3.3 Qualitative Input-Output Analysis

In general, QIOA is recognized as a technique to transform the quantitative interindustry trades of input-output tables into qualitative information. Specifically, the aim of this analysis is to change the flows of goods between industrial sectors into binary relationships, i.e. significant or trivial. Then, the critical issue in practicing QIOA is to establish the criteria with which the interindustry flows of goods are filtered into important or unimportant ones.

In many applications of QIOA for industrial cluster identification, the method of minimal flow analysis (MFA) is used to determine the filter level (Schnabl, 1994; Schnabl et al., 1999; Brachert et al., 2011; Titze et al., 2011). The starting point of the MFA method is the following relationship between the matrix of intermediate trades and the vector of sectoral outputs in the Leontief model:

$$(3) Z = A \langle x \rangle$$

where *Z* is the transaction matrix; *A* denotes the matrix of input coefficients; and $\langle x \rangle$ represents the diagonal matrix of the output vector *x*.

The output vector in the standard Leontief model is expressed as:

$$(4) x = (I-A)^{-1}y = (I+A+A^2+A^3+\dots)y = y + Ay + A^2y + A^3y + \dots$$

where *y* represents the vector of final demands. Substituting eq. (4) into eq. (3) yields:

$$(5) Z = A \langle x \rangle = A \langle y \rangle + A \langle Ay \rangle + A \langle A^2y \rangle + A \langle A^3y \rangle + \dots$$

Then, the transaction matrix Z is considered to be made up of multiple layers, $Z_0, Z_1, Z_2, Z_3, \dots$, in the form of intermediary flow matrices of different orders. That is:

$$(6) Z_0 = A \langle y \rangle, Z_1 = A \langle A y \rangle, Z_2 = A \langle A^2 y \rangle, Z_3 = A \langle A^3 y \rangle, \dots$$

The next step is to convert each matrix layer in eq. (6) to a corresponding adjacency matrix $W^k (k=0, 1, 2, 3, \dots)$ using a given filter value F . The filtering is implemented based on the following equation:

$$(7) w_{ij} = \begin{cases} 1, & \text{if } z_{ij}^k > F \\ 0, & \text{otherwise} \end{cases}$$

where $W^k = [w_{ij}]$ and $Z_k = [z_{ij}]$, respectively.

The last step is to obtain a dependency matrix D and a connectivity matrix H from the adjacency matrices as shown in the following two equations:

$$(8) D = \# \{W(1) + W(2) + W(3) + \dots\}$$

and

$$(9) H = D + D' + D$$

where $W(i) = W^{i-1} W(i-1)$ for $i=1, 2, 3, \dots$, and $W(0) = I$. It is noted that the matrix summation in eq. (8) and the multiplication of $W(i) = W^{i-1} W(i-1)$ should be done in Boolean fashion, whereas the summation in eq. (9) is performed following usual algebraic rules. Each entry of the dependency matrix d_{ij} equals 1 if and only if there exist direct and indirect flows from sector i to sector j , which are greater than or equal to a given filter value, F (Schnabl, 1994; Hioki et al., 2009). On the other hand, the set of elements h_{ij} of the connectivity matrix H takes one of four values, i.e. 0, 1, 2, or 3. These elements reflect the characteristics of industrial linkages between sectors i and j in the following way:

- 0: No linkage between sectors i and j exists;
- 1: A weak link between sectors i and j ;
- 2: A Unidirectional relation between sectors i and j ; and
- 3: A bilateral relation between sectors i and j .

The unidirectional and bilateral relations are of particular importance when detecting industrial cluster templates for the relevant region. In the meantime, as revealed apparently from eq. (7), the values of elements h_{ij} are dependent upon

the chosen filter value F .

In MFA, the filter value is not fixed in advance but determined endogenously through the iterative scanning process. MFA usually uses the information maximization principle to determine the optimal filter value. Based on the concept of entropy (Shannon and Weaver, 1949; Hill, 1973; Li and Guo, 2002), the optimal filter value F is calculated by maximizing the entropy of the connectivity matrix H . Mathematically, entropy E is expressed as:

$$(10) E = -\sum_i \sum_j p_{ij} \cdot \log p_{ij}$$

where p_{ij} represents the probability of the occurrence of one of the four states for h_{ij} . Applied to input-output tables, the entropy index E refers to the degree of randomness in the choice of input coefficients, as reflected by the skewness of a distribution. Therefore, the entropy E is maximized when the probability of occurrence of a state is equal for all states, i.e. 0, 1, 2, or 3 in this case. Starting with a filter value F_s with the maximum number of bilateral relations, F is augmented by equal steps up to a filter value F_L at which the last bilateral value breaks off. Then, the optimal filter value F is the one that maximizes the entropy measure E at a discrete step in the interval between F_s and F_L .

In this paper, the MFA procedure is iterated 50 times for 50 equidistant filter levels. This iterative process generates 50 corresponding H matrices, from which we can choose the one with the highest entropy, say, the one with maximum information. Then, the finally chosen H matrix with maximum information is used to identify the interindustry linkages of industrial clusters.

4. EMPIRICAL APPLICATION AND RESULTS

4.1 Study Region and Data

In this section, the three-step framework explained in the previous section is implemented to identify industrial clusters scattered in the surrounding region of Chungbuk Province, Korea. As this paper uses new processed sets of raw data, it may be helpful to present a simple description of the study region. The study region is located in the central part of the Korean territory, approximately 142 km south of Seoul. The region comprises a total of 23 local jurisdictions, of which 12 jurisdictions are municipalities and counties of Chungbuk

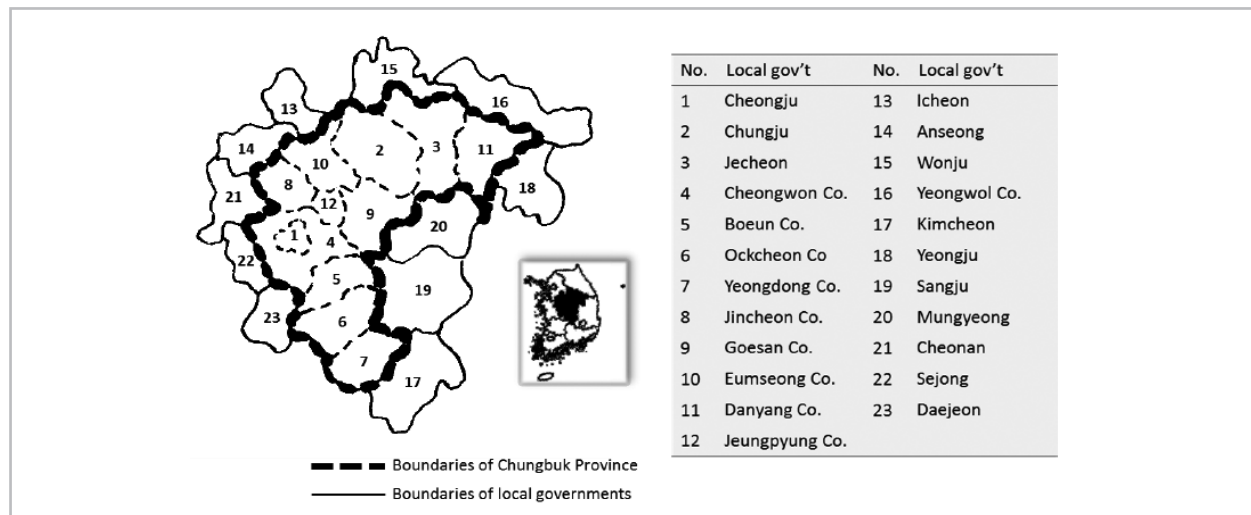


Fig. 1. The map of the study region and the names of local jurisdictions included

Province, while the rest 11 localities are local governments adjacent to and sharing common boundaries with Chungbuk Province. A total of 4,965,013 inhabitants live in the study region as of 2012. This means that the average population size per local government is 215,875 with a standard deviation of 322,171. The largest city in the region is Daejeon with its population of 1,524,583, while the least populous jurisdiction is Danyang County with 31,253 inhabitants. The total area of the study region is 15,906.7 sq km and then, the average area of 23 local jurisdictions is 691.6 sq km with a standard deviation of 282.2 sq km. The average population density of the region is 504 persons per sq km with the highest of 4,346 in Cheongju and the lowest of 36 in Yeongwol County. Fig. 1 presents the location of the study region and the names of local jurisdictions included in the study region.

Two sets of data are prepared to implement the three-step process of cluster identification: one is data on the numbers of employment and business establishments for individual industrial sectors as per each local government, and the other is the national input-output table. The former data set is composed of the information of employment and businesses as of 2012, which are together used to measure the industrial spatial concentrations of industries and the spatial autocorrelation of different concentrations. These data are obtained from the Korean Statistical Information Service (KOSIS) compiled by the central government. In this data set, the industries into which the employment and business data are aggregated are classified into 78 industrial sectors. The 78-sector classification

scheme is adopted to match the industrial classification of the national input-output table used for this research. On the other hand, the latter data set is the 2009 version of Korean input-output table that the Bank of Korea has released in 2012. The 2009 national input-output table includes 78 industrial sectors.

4.2 The Spatial Distribution of Industrial Concentrations

The CI provides information about which industrial sectors are spatially concentrated. In this application, for each local government included in the study region, the CI shown in eq. (1) is calculated to determine the specific industrial sectors of all 78 industrial sectors that can be considered an industrial concentration. The results show that when the calculation of the CI includes the entire industries and all local jurisdictions, the average is 3.2 and the standard deviation is 13.5. When the CI is separately calculated for four broad categories, i.e. the agriculture, forestry, and fishery sector, the mining industry, the manufacturing sector, and the service industry, their averages are 5.12, 13.02, 3.03, and 1.97, respectively.

In identifying the sectors of concentration using the CI, the critical element is to define the threshold value of the CI. Then, if a specific sector's CI value exceeds the defined threshold, that industrial sector is assumed to be spatially concentrated. In this application, the CI values of 19.5 for agriculture, forestry, and fishery, 26.0 for mining, 5.2 for manufacturing, and 9.0 for services are used as thresholds. These threshold values are established as the averages plus one standard deviation for the four individual categories.

Table 1. Spatial distribution of industrial concentrations

| Region | Local jurisdiction | Concentrated industrial sector | Num. of cluster |
|--------------------------------------|--------------------|--|-----------------|
| Chungbuk Province | Cheongju | 12, 16, 17, 18, 21, 29, 42, 43, 44, 45, 52, 55, 56, 57, 58, 59, 62, 63, 64, 65, 67, 68, 70, 71, 72, 74, 75, 76, 77, 78 | 30 |
| | Chungju | 3, 4, 50, 60 | 4 |
| | Jecheon | 4, 6, 7, 22 | 4 |
| | Cheongwon Co. | 11, 13, 19, 20, 28, 30, 32, 42, 43, 49, 60, | 11 |
| | Boeun Co. | 11, 26 | 2 |
| | Ockcheon Co. | 36, 49, 50 | 3 |
| | Yeongdong Co. | 4 | 1 |
| | Jincheon Co. | 9, 11, 13, 23, 24, 25, 27, 28, 29, 30, 32, 33, 35, 37, 38, 39, 40, 41, 48, 49, 50 | 21 |
| | Goesan Co. | 4, 6, 27, 36 | 4 |
| | Eumseong Co. | 9, 10, 14, 16, 20, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 34, 35, 37, 38, 39, 46, 51 | 22 |
| | Danyang Co. | 8, 22, 34, 60 | 4 |
| | Jeungpyung Co. | 12, 31, 33, 43 | 4 |
| Region adjacent to Chungbuk Province | Icheon | 1, 10, 13, 19, 33 | 5 |
| | Anseong | 2, 9, 10, 11, 14, 19, 20, 24, 25, 26, 27, 28, 29, 30, 35, 36, 37, 38, 39, 40, 41, 44, 48, 51 | 24 |
| | Wonju | 46, 50 | 2 |
| | Yeongwol Co. | 7, 8, 34 | 3 |
| | Kimcheon | 15, 25, 26, 44, 45 | 5 |
| | Yeongju | 3, 15, 22 | 3 |
| | Sangju | 22 | 1 |
| | Mungyeong | 3 | 1 |
| | Cheonan | 14, 17, 23, 30, 31, 37, 39, 40, 41, 42, 43, 44, 46, 48, 50 | 15 |
| | Sejong | 27, 35, 38, 49 | 4 |
| | Daejeon | 13, 17, 18, 21, 24, 31, 36, 40, 45, 47, 51, 52, 57, 59, 64, 65, 66, 67, 68, 70, 71, 72, 74, 77 | 24 |
| Total | 23 jurisdictions | | 197 |

Note: The description of the individual industrial sectors is specified in Appendix.

When these threshold values are applied, the results show that there exist a total of 197 industrial concentrations in the study region encompassing 23 local jurisdictions. Table 1 presents the distribution of industrial concentrations for individual local governments in the study region. According to the table, Cheongju, the provincial capital of Chungbuk, hosts 30 industrial concentrations, which represent the largest number throughout all 23 local jurisdictions in the study region. This is

followed by Eumseong County, where 22 concentrations are located, and Jincheon County, where 21 industrial clusters are located. Yeongdong County hosts only one industrial concentration, the least across the local governments in Chungbuk Province. On the other hand, of the neighboring local governments of Chungbuk Province, Daejeon and Anseong host the same number of concentrations, i.e. 24 industrial clusters.

One salient feature of the spatial distribution of industrial

Table 2. Spatial distribution of hot spots

| Region | Local jurisdiction | Industrial sector of hot spot | Num. of hot spot |
|--------------------------------------|--------------------|---|------------------|
| Chungbuk Province | Cheongju | 5, 8, 12, 22, 27, 34, 75 | 7 |
| | Cheongwon Co. | 3, 5, 9, 10, 11, 12, 13, 14, 16, 17, 18, 19, 20, 21, 24, 27, 28, 29, 30, 32, 33, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 61, 62, 65, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78 | 62 |
| | Jincheon Co. | 9, 12, 14, 16, 28, 29, 30, 32, 37, 39 | 10 |
| | Eumseong Co. | 23 | 1 |
| | Jeungpyung Co. | 33 | 1 |
| Region adjacent to Chungbuk Province | Cheonan | 9, 28, 29, 30, 35, 49 | 6 |
| | Sejong | 9, 11, 12, 13, 14, 16, 18, 19, 20, 21, 28, 29, 30, 35, 40, 41, 42, 43, 44, 45, 47, 49, 51, 52, 53, 55, 56, 57, 58, 59, 64, 65, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78 | 46 |
| Total | 7 jurisdictions | | 133 |

Note: The description of the individual industrial sectors is specified in Appendix.

concentrations is that industrial clusters located in Cheongju are skewed toward service sectors. Specifically, of the 30 industrial clusters in the city, 19 concentrations are classified as service sectors. This contrasts to the case of Daejeon. That is, although Daejeon is bigger than Cheongju, of a total of 24 concentrations in the city, only 12 clusters are service sectors. Such a high level of service industry clusters in Cheongju is noticeable compared with Cheonan, which is similar in population with Cheongju.

As mentioned earlier, the CI does not provide any information on vertical linkages between industries or spatial interdependence between industrial concentrations located in different jurisdictions. It only presents information about the locations of industrial concentrations, together with potential industrial linkages between the identified concentrated sectors. A glance at the 197 industrial concentrations identified through the CI reveals that they are composed of 72 sectors. Then, it can be said that within a local government’s boundaries, a multitude of potential horizontal linkages may be established between parts of the 72 industrial sectors with which the local jurisdiction’s concentrations are constituted. Yet, the characteristics of individual potential linkages, that is, whether a particular linkage is unimportant, weak, unidirectional, or bilateral, can be identified through QIOA.

4.3 The Spatial Interdependence of Industrial Concentrations

The Getis-Ord’s G_i^* statistic, together with the results of the CI, provides information of the horizontal spatial interdependence of industrial cluster structures (Brachert et al., 2011). This means that Getis-Ord’s G_i^* reveals the locations of concentration in the spatial distributions of industrial clusters in which a particular local jurisdiction and other jurisdictions have similar cluster index values (Carroll et al., 2008).

Using the spatial weights matrix whose elements are equivalent to the reciprocals of the distances between the region centroids, we calculate the Getis-Ord’s G_i^* statistic for each jurisdiction-sector combination. Because the number of industries is 78 and that of local governments in study area is 23, then, a total of 2,794 Getis-Ord’s G_i^* values are computed. If, for a specific industry, certain concentrations had a large G_i^* value, then, this implies that a significant level of spatial autocorrelation exists between the local jurisdictions where the industrial concentrations with large G_i^* values are located. The -distribution: for example, if a region-cluster combination is to be significant at the 5% level, its G_i^* value should be 1.96 or greater. At this level, a total of 133 significant region-cluster combinations, i.e. hot spots, are identified. When the significance level is set at 1%, it appears that the total number of hot spots with the G_i^* value of 2.54 or greater falls to 87.

Table 2 presents the locations of hot spots and their constituent sectors identified at the 5% significance level. According to the table, the 133 hot spots identified at 5% level are spatially dispersed over seven local jurisdictions. This means that

only seven of the 23 local jurisdictions in the study region share the entire hot spots. The distributions of hot spots over the seven local governments are specified as follows: 62 hot spots in Cheongwon County; 46 hot spots in Sejong; 10 hot spots in Jincheon; seven hot spots in Cheongju; six hot spots in Cheonan; and one hot spot in Eumseong County and Jeungpyung County, respectively. No local jurisdictions except these seven local governments harbor hot spots. It is unexpected to find that Daejeon, the biggest city in the study region, accommodates no hot spots. This implausible finding may be due to the city's lack of strong industrial interdependence with the industrial concentrations located in other local jurisdictions, with most interindustry linkages confined within the city's boundaries.¹

The uneven distribution of hot spots as such contrasts to the spatial distribution of industry concentrations that are previously identified from the CI values. As examined earlier, a total of 197 industrial concentrations are spread over all of the 23 local jurisdictions. Hence, it can be said that compared with industrial concentrations, hot spots are more evenly dispersed throughout the local governments in the study region.

On the other hand, it is revealed the 133 hot spots identified are composed of 66 industrial sectors. This means that 67 (=133-66) industrial sectors are duplicated in the component industries of the 133 hot spots. Then, it is implied that a total of 11,542 potential vertical linkages would be established between the 66 sectors across the boundaries of the seven local governments harboring hot spots.² Yet, the characteristics of individual potential vertical linkages, i.e. insignificant, weak, unidirectional, or bilateral, can be identified through the application of QIOA.

4.4 The Interindustry Linkages of Industrial Clusters

The method of QIOA is used to identify significant interindustry linkages established within local jurisdictions or across the boundaries of local governments. In this paper, the sectoral interdependence of the industrial clusters is assessed based on relevant interindustry flows of the 2009 national input-output table. The critical step in implementing QIOA is to determine the optimum filter value F . The optimum filter rate

is decided by MFA, in which a series of iterative procedures are continued until the maximum value of entropy in eq. (10) is found. Table 3 shows the procedure to endogenously determine the optimum filter rate. The MFA process consists of 50 equidistant filter steps, each of which produces the corresponding value of entropy as calculated based on information on the characteristics of the interindustry linkages contained in the connectivity matrix H .

As shown in Table 3, the optimum filter rate is obtained at step 28, with the value of 0.077. At this optimum F value, the level of entropy is 210.7577.³ Based on this filter value, the corresponding connectivity matrix H constructed and, from this matrix, a total of 6,084 interindustry linkages are identified in the 78×78 dimension. Of the 6,084 vertical interindustry linkages, 1,296 linkages appear insignificant (0), 1,621 linkages are weak (1), 1,621 links are unilateral (2), and 1,546 links are bilateral (3).

The 78×78 matrix of H corresponding to the optimum filter value provides the national template. Based on this matrix, we can identify the characteristics of the horizontal linkages between industrial concentrations within local jurisdictions, on the one hand, and the status of the vertical interindustry linkages crossing the local government boundaries, on the other. The former information is obtained by overlapping QIOA with the CI and, while the latter is from the combination of QIOA and Getis-Ord's G_i^* .

Regarding the former, it is assumed that within local jurisdictions, potential intra-jurisdictional industrial linkages exist between the industrial concentrations, which are identified by the CI analysis. By overlaying these potential linkages on top of the nation template, then, we can identify each potential linkage as unimportant, weak, unidirectional, or bilateral. Taking Cheongju as an example, 30 industrial concentrations are located within the jurisdiction (see Table 1). This means that there exist a total of 900 [=30×30] potential industrial linkages within the city. These potential linkages, when superimposed on the national template, can be broken into 161 unimportant, 222 weak, 222 unidirectional, or 295 bilateral linkages.

On the other hand, regarding the identification of the char-

¹ It might be a result of the dependence of this type of analysis on the spatial frame that partitions the study region. When using administrative boundaries, the portioning is arbitrary and can create this type of results. This problem would not be present if other space partitioning frame such as, for example, a uniform grid system is employed.

² It is assumed that each hot spot in a local jurisdiction has industrial linkages with all individual hot spots in other jurisdictions. Then, the total number of jurisdiction-industry combinations is calculated by the equation: $(7 \times 126) + (62 \times 71) + (10 \times 123) + (1 \times 132) + (1 \times 132) + (6 \times 127) + (46 \times 87) = 11,542$.

³ For improving readability, the entropy values presented in Table 3 are down-scaled. They are scaled by dividing the original values of entropy by the rate of 10.

Table 3. The optimum filter value F and the results of MFA

| Filter step | Filter (F) | Entropy | Status of industrial linkages | | | | |
|-------------|------------|----------|-------------------------------|------|------------|-----------|---------|
| | | | Isolated | Weak | Unilateral | Bilateral | Overall |
| 1 | 0.050 | 205.8428 | 654 | 1405 | 1405 | 2620 | 6084 |
| 2 | 0.051 | 205.7843 | 662 | 1401 | 1401 | 2620 | 6084 |
| 3 | 0.052 | 206.8320 | 716 | 1424 | 1424 | 2520 | 6084 |
| 4 | 0.053 | 207.7166 | 774 | 1445 | 1445 | 2420 | 6084 |
| 5 | 0.054 | 208.6789 | 774 | 1493 | 1493 | 2324 | 6084 |
| • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • |
| 24 | 0.073 | 210.2280 | 1032 | 1547 | 1547 | 1958 | 6084 |
| 25 | 0.074 | 210.4340 | 1099 | 1557 | 1557 | 1871 | 6084 |
| 26 | 0.075 | 210.6743 | 1165 | 1607 | 1607 | 1705 | 6084 |
| 27 | 0.076 | 210.7284 | 1231 | 1614 | 1614 | 1625 | 6084 |
| 28 | 0.077 | 210.7577 | 1296 | 1621 | 1621 | 1546 | 6084 |
| 29 | 0.078 | 210.7154 | 1447 | 1657 | 1657 | 1323 | 6084 |
| 30 | 0.079 | 210.7154 | 1447 | 1657 | 1657 | 1323 | 6084 |
| 31 | 0.080 | 210.7083 | 1519 | 1656 | 1656 | 1253 | 6084 |
| 32 | 0.081 | 210.6520 | 1737 | 1581 | 1581 | 1185 | 6084 |
| • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • |
| 46 | 0.095 | 208.6915 | 2281 | 1468 | 1468 | 867 | 6084 |
| 47 | 0.096 | 208.7916 | 2293 | 1490 | 1490 | 811 | 6084 |
| 48 | 0.097 | 208.5738 | 2329 | 1484 | 1484 | 787 | 6084 |
| 49 | 0.098 | 208.5738 | 2329 | 1484 | 1484 | 787 | 6084 |
| 50 | 0.099 | 202.4940 | 2787 | 1282 | 1282 | 733 | 6084 |

acteristics of the vertical industrial linkages between clusters, potential interindustry linkages are postulated to exist between hot spots in different jurisdictions. The individual hot spots as identified per each jurisdiction by Getis-Ord's *Gi** represent the starting or sinking nodes of the cross-boundary industrial linkages. For example, as shown in Table 2, Cheongju and Jincheon County contain seven hot spots (i.e. sectors 5, 8, 12, 22, 27, 34, and 75) and 10 hot spots (i.e. sectors 9, 12, 14, 16, 28, 29, 30, 32, 37, and 39), respectively. This means that a total of 70 [=7×10] potential links would exist across the ad-

ministrative boundaries of the two jurisdictions.

When these potential linkages are overlaid on the national template, they are broken down into 9 unimportant, 25 weak, 12 unilateral, and 24 bilateral linkages.

4.5 The Characteristics of the IT and the Biotechnology Industrial Clusters

So far, presented is an empirical application of the three-step framework to the identification of industrial clusters in the study region. However, the results demonstrate that as the

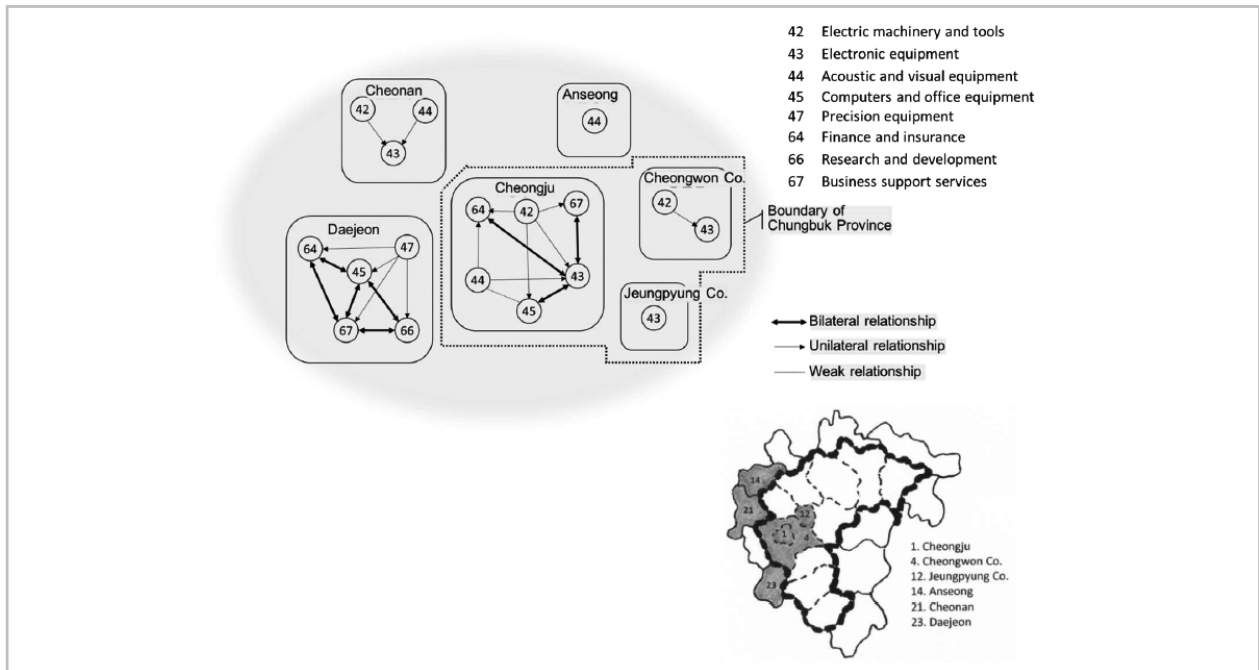


Fig. 2. The structure of IT cluster in the region of Chungbuk Province

number of industrial sectors is substantially large, i.e. 78 sectors, identifying every detail of the characteristics of industrial clusters is unrealistic. To offer clear-cut idea of empirical application, an attempt is hereafter presented to identify in detail two selective industrial clusters: the information technology (IT) cluster and the biotechnology cluster. In fact, nurturing these two industrial clusters has long been the goal of industrial and economic development policy of the provincial government of Chungbuk. They are necessarily considered instrumental of fostering regional economic growth.

First, the IT cluster is not a single-sector industry, but composed of multiple sectors of industry. However, in fact, there is no consensus on the constituent sectors of IT industrial clusters. Despite the lack of unanimity on its definition, the IT industrial cluster is here defined as a combination of eight different industry subsectors from both manufacturing (five sectors) and nonmanufacturing (three sectors). The former includes sectors 42, 43, 44, 45, and 47, while the latter involves sectors 64, 66, and 67.⁴

The calculations of the CI indicate that the eight component sectors of the IT industrial cluster are distributed over six local

jurisdictions, including Cheongju (sectors 42, 43, 44, 45, 64, and 67), Cheongwon County (sectors 42 and 43), Jeungpyung County (sector 43), Cheonan (sectors 42, 43, and 44), Anseong (sector 44), and Daejeon (45, 47, 64, 66, and 67). On the other hand, the results of Getis-Ord's G_i^* identify hot spots per local jurisdiction and thus, present the spatial distributions of the identified hot spots over the six jurisdictions.

Then, the identified industrial concentrations and the identified hot spots can be overlapped to find candidate concentrations with cross-boundary industry linkages. The results of this overlay reveal that of the six local governments, only Cheongwon County has two hot spots duplicated with the industrial concentrations it hosts (i.e. sectors 42 and 43). The remaining five jurisdictions (i.e. Cheongju, Jeungpyung County, Cheonan, Anseong, and Daejeon) have no hot spots with cross-border industry linkages. This means that no vertical interindustry linkages transcend across local borders in the study region. Therefore, it can be said that potential industrial linkages would be confined between the identified industrial concentrations within the local jurisdictional jurisdictions. Then, the identified industrial concentrations are overlaid on

⁴ For the lists of the industrial sectors, see Appendix.

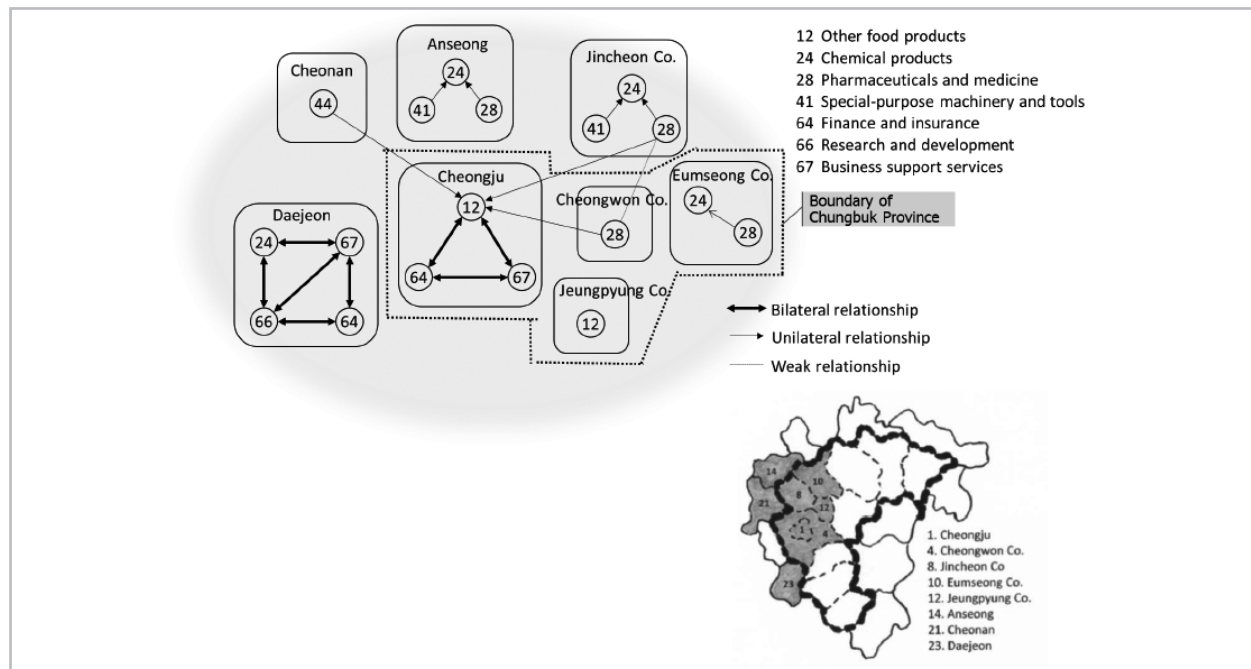


Fig. 3. The structure of biotechnology cluster in the region of Chungbuk Province

the optimal connectivity matrix H to determine the status of the potential individual linkages between the identified industrial concentrations in the six individual local governments. Fig. 2 presents the locations of IT clusters and the characteristics of the interindustry linkages established in the study region.

Next, the biotechnology cluster is analyzed through the same procedures for identifying the IT cluster. The biotechnology cluster is also regarded as composed of a multitude of industry sectors. It is noted, however, that like the IT cluster, no consensus exists on its component subsectors. Despite the absence of agreed definitions, the biotechnology cluster is presumed to encompass seven different industry subsectors: four manufacturing sectors (i.e. 12, 24, 28, and 41) and non-manufacturing sectors (i.e. 64, 66, and 67).⁵

The CI analysis shows that the seven constituent sectors of the biotechnology cluster are spread over eight local governments: sectors 12, 64, and 67 are located in Cheongju; sector 28 in Cheongwon County; sectors 24, 28, and 41 in Jincheon County; sectors 24 and 28 in Eumseong County; sector 12 in Jeungpyung County; sector 41 in Cheonan; sectors 24, 28, and

41 in Anseong; and sector 24, 64, 66, and 67 in Daejeon. On the other hand, the results of Getis-Ord's G_i^* show that of the eight local jurisdictions that contain at least more than one industrial concentrations, six jurisdictions (i.e. Cheongju, Cheongwon County, Jincheon County, Eumseong County, Jeungpyung County, and Cheonan) host one or more hot spots.

Then, by overlapping the identified concentrations with the identified hot spots, we can locate potential industrial concentrations with cross-boundary industry linkages. The results of this overlay indicate that only three local jurisdictions contain hot spots with cross-border industry linkages. Specifically, Cheongju contains sector 12, Cheongwon County has sector 28, and Jincheon hosts sector 28. In contrast, the remaining three jurisdictions (i.e. Eumseong County, Jeungpyung County, and Cheonan) contain no hot spots with inter-jurisdictional linkages.

Then, both the identified industrial concentrations and the identified hot spots with inter-jurisdictional linkages are overlaid on top of the optimal connectivity matrix H . This overlay leads to determination of the characteristics of the

⁵ For the lists of the industrial sectors, see Appendix.

potential intra- and inter-jurisdictional linkages. Fig. 3 presents the locations of biotechnology clusters and the characteristics of the industrial linkages established over the eight local jurisdictions in the study region.

The results of the analysis of the IT and biotechnology clusters in the study region indicate that in the case of the IT cluster, no vertical linkages between industrial sectors are detected across the different local jurisdictions, while the cross-boundary vertical linkages are significantly weak for the biotechnology cluster. By the way, it is argued that from the cluster perspective, spillover forces, which can be developed within and/or across clusters linked by technology or linkage, influence the performance of clusters in regions (Delgado et al., 2007). In this regard, for promoting cluster development and growth in the study region, the vertical industrial linkages, which are the key source of cluster-level agglomeration effects, should be created or strengthened across local administrative boundaries in the study region.

Given that intra- or inter-cluster interactions are too complicated to be designed from scratch by governments, a preferred policy option is a strategy of cluster-based economic development, which puts emphasis on improving overall business environment conditions. Then, various policy measures can be used to improve the business environment. First, industrial or technology zones can be established to provide the businesses in the region with a clear profile and detailed demands for the business environment. The industrial zones with the preferable business environment would be instrumental to attracting large IT- or biotechnology-related businesses into the region. Then, the new hosting of big companies will contribute to further attracting a number of related businesses that would create new interindustry linkages in the region.

Second, the industrial agglomerations in the study region comprise relative few stages of industrial linkage, lacking the degree of cooperation with complementary services. The low level of integration along the industrial linkage may be due to a large technological gap between regional lead firms and local medium-sized enterprises (SMEs). Then, network brokers and incentives for inter-firm cooperation are required to overcome the lack of strong interindustry linkage. In this case, the role of a multitude of technology-mediating institutions in the region, i.e. universities, local research institutes, and techno-parks, should be emphasized for promoting inter-firm cooperation and knowledge transfer. The strengthened broker role of the technology-mediating institutions

would contribute to intensifying the inter-firm linkages and technology spillovers, extending their spatial scope to the entire region.

Third, skill upgrading policy can strengthen the weaknesses of the interindustry structure of clusters (Ketels and Memedovic, 2008). Given the attribute of a periphery economy of the study region, labor skill and technology would be at the lower level. Organizing cluster-specific working groups with firms and relevant educational organizations in the region to launch skill upgrading programs will be effective for boosting technology progress in the region.

Finally, financial and technical assistance programs targeted for SMEs, which are part of the IT or biotechnology clusters in question, can fix the impaired interindustry relationships. With these assistance programs, the clusters are used as a platform to reach the target groups of SMEs more efficiently, where the existing anchor firms are invited to develop SMEs and create better linkages towards them.

5. CONCLUSIONS

Recently, industrial clusters are increasingly considered a key policy option for promoting regional economic growth and development. The agglomeration benefit spillover- or interindustry linkage-oriented view of clusters offers plausible foundations for defining the cluster concept. Theories of externalities and interindustry interactions put forward that industrial clusters, especially in the types of pure agglomeration or industrial complex, can be understood as spatially concentrated groups of horizontally or vertically interlinked industries and related establishments and thus a multidimensional phenomenon.

In line with the multidimensional propensity of industrial clusters, this paper applies a three-step approach, which is a combination of three stand-alone methods, i.e. the cluster index, Getis-Ord's G_i^* , and qualitative input-output analysis, to identifying empirically the structures of industrial clusters in the Chungbuk Province region and its neighboring areas. The CI identifies geographical locations of 197 industrial concentrations over the 23 local jurisdictions in the study region. On the other hand, the Getis-Ord's G_i^* statistic finds the spatial locations of 133 hot spots, which establish potential linkages with the identified hot spots in different jurisdictions. Then, the industrial concentrations and hot spots identified are

overlaid on top of the results of qualitative input-output analysis. This overlay leads to categorizing the potential intra-jurisdictional as well as border-crossing linkages into insignificant, weak, unilateral, or bilateral.

As the number of industrial sectors are as large as 78, it is too complicated to specify every detail of the structures of industrial clusters in the study region. For a clear-cut idea of empirical application of the three-step framework, the cluster-identifying efforts are focused on the IT cluster and the biotechnology cluster. The results of analysis for these two selective clusters show that as the vertical linkages between industrial subsectors in different localities are scant or weak, both clusters appear in the phase of emerging in the evolution of industrial clusters. It is then emphasized that industrial policy in the region should be focused on establishing and strengthening vertical industrial linkages. Various policy incentives designed to enhance the cluster performance in the region include establishing technology zones, upgrading labor skills, enhancing access to finance and technology infrastructure, mediating the technology transfer and transactions between local enterprises.

The spatial scope of cluster analysis of this paper is limited to the Chungbuk and its adjacent areas. However, interindustry linkages may not be contained within the range of contiguous areas, but stretch to remote regions. In this sense, this paper fails to uncover the area-wide features of industrial cluster extended to remote regions. Then, it constitutes a promising subject of further research to apply the three-step approach of cluster identification to an extended region, possibly to the whole territory of Korea.

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Received November 09, 2017

Revised December 12, 2017

Accepted December 18, 2017

APPENDIX

Description of the industrial sectors

| Code | Sector | Code | Sector | Code | Sector |
|------|--|------|-------------------------------------|------|-----------------------------------|
| 1 | Agriculture | 27 | Manure and agrichemicals | 53 | Electricity |
| 2 | Livestock | 28 | Pharmaceuticals and medicine | 54 | Gas and water supply |
| 3 | Forestry | 29 | Other chemicals | 55 | General construction |
| 4 | Fishing | 30 | Plastic products | 56 | Spatial trade construction |
| 5 | Agriculture and fishery support services | 31 | Rubber products | 57 | Whole and retail trade |
| 6 | Coal, crude petroleum and natural gas | 32 | Glass | 58 | Accommodation and food services |
| 7 | Metal ores | 33 | Ceramic ware and clay products | 59 | Surface transport |
| 8 | Non-metallic minerals | 34 | Cement and concrete products | 60 | Water and air transport |
| 9 | Meat and dairy | 35 | Non-metallic products | 61 | Transportation support services |
| 10 | Manufacture of fishery products | 36 | Cast iron and crude steel | 62 | Communication service |
| 11 | Crop and flour milling | 37 | Basic steel | 63 | Broadcasting |
| 12 | Other food products | 38 | Basic non-metallic products | 64 | Finance and insurance |
| 13 | Beverages | 39 | Metallic products | 65 | Real estate |
| 14 | Feed products | 40 | General-purpose machinery and tools | 66 | Research and development |
| 15 | Tobacco products | 41 | Special-purpose machinery and tools | 67 | Business support services |
| 16 | Textiles | 42 | Electric machinery and tools | 68 | Other business support services |
| 17 | Apparel and clothing | 43 | Electronic equipment | 69 | Public administration and defense |
| 18 | Leather products | 44 | Acoustic and visual equipment | 70 | Education |
| 19 | Wood products | 45 | Computers and office equipment | 71 | Medical and health services |
| 20 | Pulp and paper products | 46 | Electric home appliances | 72 | Social work services |
| 21 | Printing and reproduction | 47 | Precision equipment | 73 | Sanitary services |
| 22 | Coke and coal products | 48 | Motor vehicles | 74 | Publishing and cultural services |
| 23 | Refined petroleum products | 49 | Ships and vessels | 75 | Sports and amusement services |
| 24 | Chemical products | 50 | Other transport equipment | 76 | Membership organizations |
| 25 | Synthetic rubber and resin | 51 | Furniture | 77 | Other services |
| 26 | Synthetic fiber | 52 | Other manufacturing | 78 | Other industries |