Boosting Economic Competitiveness:
The Industrial Clusters in Input-Output Networks

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Key words

Network analysis, industrial cluster, global supply chain, multi production layer

1. Introduction

As the globalization of world economy progresses, regional industrial 'clusters' have played an important role on global supply chains. Porter (1998) suggested an importance of forming regional industrial 'clusters' and pointed out that it is an indispensable source to promote regional competitiveness, innovation, and growth. Countries facing the deindustrialization and the decline of local industries aim to enhance the national competitiveness by improving business environment through forming the industrial clusters. The countries have to identify economically-important industries to promote the territorial and extensive industrial clusters.

Network analysis in the context of graph theory has been important tools and applied to various socioeconomic networks in the field of economics and business administrations (Granovetter, 1985; Burt, 1992). There exist many previous studies using the concept of graph theoretic clusters defined as "the highly interconnected subgraphs". The cluster coefficient is the most basic social network metric that represents how much cohesive subgraph exists in the whole network. Burt (1992, 2004), for example, clarified that higher cluster coefficient prevented introduction of new knowledge and skills. In addition, Durlauf and Fafchamps (2005), and Centola (2010) showed that the high cluster coefficient was more important than the proximity of the paths in the networks in terms of promoting information and knowledge diffusion. Todo *et al*. (2017) applied cluster coefficient to global corporate supply chain networks and analyzed the characteristics of Japanese firms in that global supply chains.

The graph theory has been applied to the field of input-output analysis since 1950s (Rosenblatt, 1957; Holub and Schnabl, 1985; Ghosh and Roy, 1998; Weber and Schnabl, 1998; Brachert *et al*., 2016; Muniz *et al*., 2008; Brachert *et al*., 2016; Chen *et al.,* 2017; Du *et al*., 2017). The industries and transaction between two industries corresponds to the nodes and edges, respectively. Input-output table (IOT) is expressed as matrix representing the supply chain networks that connect economic activity and consumption considering the production of intermediate products, and recently we can easily handle the supply chains at global level thanks to the development of global multi-regional input-output database (e.g., Eora, WIOD, EXIOBASE). Cerina *et al*. (2015) employed cluster coefficient to global input-output network (intermediate transaction matrix) and compared the changes in the cluster coefficient between international and intra-national industries of countries over twenty years. In addition, Amador and Cabral (2017) applied to value-added network (Leontief model) and showed that the industrial goods sector knit more closely network than service sectors. The higher cluster coefficient in the economic network has been considered as the important factor of knowledge and skill diffusion and growth, and a lot of studies have improved cluster coefficient according to their applications. These studies analyzed changes in clustering structure and spillover effects of inter-firms or inter-industry networks.

On the other hand, some studies identified the relatively interconnected industrial groups as the cluster (industrial accumulation) and analyzed the economic propagation by these industrial clusters. Czamanski (1974), and Feser and Bergman (2000) identified the clusters using the similarity of input structures. Oosterhaven *et al*. (2001) detected the industrial clusters and its core industries by cutting the networks just focusing on the inter-industrial linkages that exceeded the threshold set by authors. The calculation of clustering using threshold that has arbitrary and hierarchical clustering using greedy algorithm becomes huge and it is not appropriate to use these methods for MRIO networks that have an enormous number of industries (or nodes) (Lancichinetti *et al*., 2009). Therefore, Kagawa *et al*. (2013a, 2013b) newly developed clustering method in the input-output networks applying Normalized cut (Shi and Malik, 2000; Zhang and Jordan, 2008). This method can be easily calculated using spectral of graph and more time-saving than conventional clustering methods, and applied to various studies (Kagawa *et al.,* 2013a, 2013b, 2015; Okamoto, 2015; Tokito *et al*., 2016; Tokito, 2017; Rifki *et al*., 2017). Input-output analysis is the powerful tool as for tracking the propagation of productions in the global supply chains, and previous studies applying clustering analysis to input-output tables have integrated the multiple hierarchical supply chain network into single hierarchy for ease of handling (See Figure 1).

[INSERT FIGURE 1 ABOUT HERE]

However, there are possibilities that any two industries have strong connection and extracted as core industries within same cluster although these two industries actually do not have direct connection. This can occur in the case that there are industries that have strong connection between two industries. For example, the direct linkage between material and wholesale industry is relatively weak. However, in the integrated graph (e.g., Leontief inverse matrix), this linkage becomes strong due to the existence of intermediate industries (See Figure 2). In addition, the clustering method using N-cut used in Kagawa *et al*. (2013a, 2013b) and non-hierarchical clustering using K-means are top down “cutting” method. Thus, “the rest of many industries” in the networks that have relatively weak linkages can be detected as the industrial cluster and recognized as one of the most important cluster because the aggregation of total output of within-cluster industries becomes large even if total output of each industry is tiny. Although Kanemoto *et al*. (2018) modified N-cut based clustering that considered direct and indirect transaction separately (former problem), latter problem regarding the rest of many industries is not solved.

[INSERT FIGURE 2 ABOUT HERE]

This study defines an industrial cluster that takes into account the hierarchical supply chain network structures and proposes the method to detect the core industries in the industrial clusters. Here, we apply the cluster coefficient to input-output framework and introduce the new concept “I-O clusterness” after the idea of Liang *et al*. (2016), Hanaka *et al.* (2017). They followed the betweenness centrality (Freeman, 1977) in the graph theory and applied it to input-output network using structural path analysis (SPA) (Defourny and Thorbecke, 1984; Treloar, 1997; Lenzen, 2003; Suh, 2004; Peters and Hertwitch, 2006; Wood and Lenzen, 2009; Oshita, 2012; Nagashima *et al*., 2017, Nagashima, 2018). I-O clusterness of industry i in this study is defined as the total value-added through the supply chains that include sub-supply chains consisting of industry i and any two connected industries in the same region (countries) as the industry i. The degree of I-O clusterness in this study can be interpreted as the degree of backward and forward linkage effect of three industries and three transactions that construct the cluster in the global supply chains. The higher I-O clusterness represents the higher power and sensitivity of dispersion of industrial cluster in the global supply chains. We used the EXIOBASE and calculated the I-O clusterness scores with a focus of the industries in Japan, United States and China, the top three countries regarding GDP. Relevant economic policies for enhancing domestic industrial clusters and incorporating this high-clusterness industry into global supply chain boost domestic economy through the linkage in industrial clusters.

The remainder of this paper is organized as follows: Sections 2 and 3 explain the methodology and data used here, Section 4 present the results, and Section 5 presents the discussion and conclusions.

2. Methodology

2.1. Leontief model and Multi-Regional Input-Output model

An intermediate input from industry *i* in country *r* to industry *j* in country *s* is defined as $Z_{ij}^{rs}\left(i, j = 1,...,M;\ r, s = 1,...,N\right)$. The final demand of country *s* from industry *i* in country *r* is defined as $F_i^{rs}\left(i = 1,...,M;\ r, s = 1,...,N\right)$. Thus, the total output of industry *i* in country *r* is defined as $x_i^r = \sum_{s=1}^{N}\sum_{j=1}^{M} Z_{ij}^{rs} + \sum_{s=1}^{N} F_i^{rs}$. If intermediate input coefficients $a_{ij}^{rs} = Z_{ij}^{rs} / x_j^s$ are defined, the multi-regional input-output (MRIO) model can be formulated as

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \tag{1}$$

where $\mathbf{x} = \left(x_j^s\right)$, $\mathbf{A} = \left(a_{ij}^{rs}\right)$, and $\mathbf{f} = \left(\sum_{s=1}^{N} F^{rs}\right)$. The MRIO model, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{Lf}$, can show the full extent of the final demand that directly and indirectly generates the industrial output. Here, $\mathbf{I}$ is the identity matrix, and the Leontief inverse, $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \cdots$ is the direct and indirect requirement matrix.

2.2. I-O clusterness

In the graph theory, "cluster" is defined as 3-clique, which is the minimum complete subgraph. An input-output network often is almost complete graph whose all nodes connects mutually. Thus, a lot of previous studies sorted out weaker linkage or used weighted cluster coefficient, but the both methods cannot consider supply chain path and spillover.

In this study, we defined "I-O cluster" as three consecutive transaction between three industries, and we defined the "I-O clusterness" associated with a sector i as the total production of value added from the all supply chain paths passing through the triangle paths by the sectors (i, j, k) that belong to a same group as $i \rightarrow j \rightarrow k \rightarrow i$ (figure 3). From this definition, our cluster c_{ijk} composed of central sector i and the other sectors j, k can be interpreted as the betweenness-based method (Liang *et al.*, 2016; Hanaka *et al.*, 2017) associated with a consecutive paths (i, j), (j, k), (k, i). Thus, using eq. (2), we can formulate eq. (5) as follows:

$$c_{ijk} = \sum_{s=1}^{N}\sum_{t=1}^{N}\sum_{r=1}^{\infty} p_r^{ijk} \times w(s, l_1, l_2, \ldots, l_r, t) \tag{5}$$

[INSERT FIGURE 3 ABOUT HERE]

here p_r^{ijk} is the number of that the consecutive transactions (i, j), (j, k) and (k, i) appears in all supply chain paths from start sector *s* and passing through *r* sectors $(l_1, l_2, \ldots, l_r)$ to reach end sector *t*. In this study, we focused on $i \neq j, k$ and $i, j, k \in$ G, in which G is a set of industries in a region. Here, sector j and k can be a same industry to consider bi-directional linkage between sector i and the sector. The notation w indicates the weight of the supply chain path from sector *s* to sector *t* passing through r sectors $(l_1, l_2, \ldots, l_r)$. w is calculated as

$$w(s, t | l_1, l_2, \ldots, l_r) = v_s a_{sl_1} a_{l_1 l_2} \cdots a_{l_r t} f_t$$

where v_s is the *s* th element of the value added coefficient vector $\mathbf{v}$, and f_t is the *t* th element of the final demand vector **f**. a_{sl} is the (s, l) th element of the input coefficient matrix $\mathbf{A}$.

We formulated $c_{ijk}(h_1, h_2)$ as the total value added associated with the supply chain paths that pass through the consecutive transaction $i \rightarrow j \rightarrow k \rightarrow i$ that has an industrial supply chain with h_1 upstream sectors and h_2 downstream sectors based on Liang *et al*. (2016) and Hanaka *et al*. (2017).

$$
\begin{aligned}
c_{ijk}\left(h_1,h_2\right) &= \sum_{1\le l_1,\ldots,l_{h_1}\le N}\ \sum_{1\le m_1,\ldots,m_{h_2}\le N} v_{l_1} a_{l_1 l_2}\cdots a_{l_{h_1} i} a_{ij} a_{jk} a_{ki} a_{i m_1}\cdots a_{m_{h_2-1} m_{h_2}} f_{m_{h_2}} \\
&= a_{ij} a_{jk} a_{ki} \sum_{1\le l_1,\ldots,l_{h_1}\le N}\ \sum_{1\le l_1,\ldots,l_{h_2}\le N} v_{l_1} a_{l_1 l_2}\cdots a_{l_{h_1} i} a_{i m_1}\cdots a_{m_{h_2-1} m_{h_2}} f_{m_{h_2}} \\
&= a_{ij} a_{jk} a_{ki} \sum_{1\le l_1,\ldots,l_{h_1}\le N} v_{l_1} a_{l_1 l_2}\cdots a_{l_{h_1} i} \sum_{1\le l_1,\ldots,l_{h_2}\le N} a_{i m_1}\cdots a_{m_{h_2-1} m_{h_2}} f_{m_{h_2}} \\
&= a_{ij} a_{jk} a_{ki} \left(\mathbf{v}\mathbf{A}^{h_1}\right)_i \left(\mathbf{A}^{h_2}\mathbf{f}\right)_i \\
&= a_{ij} a_{jk} a_{ki} \mathbf{v}\mathbf{A}^{h_1}\mathbf{J}_{ii}\mathbf{A}^{h_2}\mathbf{f}
\end{aligned}
\tag{6}
$$

where $\mathbf{J}_{ij}$ is the $(N \times N)$ matrix whose (i,j)th element is 1 and the other elements are zero. Using eq. (6), eq. (5) can be simplified as follows:

$$
\begin{aligned}
c_{ijk} &= \sum_{h_1=1}^{\infty}\sum_{h_2=1}^{\infty} c_{ijk}\left(h_1, h_2\right) \\
&= \sum_{h_1=1}^{\infty}\sum_{h_2=1}^{\infty} a_{ij}a_{jk}a_{ki}\mathbf{v}\mathbf{A}^{h_1}\mathbf{J}_{ii}\mathbf{A}^{h_2}\mathbf{f} \\
&= a_{ij}a_{jk}a_{ki}\mathbf{v}\left(\sum_{h_1=1}^{\infty}\mathbf{A}^{h_1}\right)\mathbf{J}_{ii}\left(\sum_{h_2=1}^{\infty}\mathbf{A}^{h_2}\right)\mathbf{f} \\
&= a_{ij}a_{jk}a_{ki}\begin{pmatrix} \mathbf{vAJ}_{ii}\mathbf{Af} + \mathbf{vAAJ}_{ii}\mathbf{Af} + \mathbf{vAAAJ}_{ii}\mathbf{Af} + \ldots \\ + \mathbf{vAJ}_{ii}\mathbf{AAf} + \mathbf{vAJ}_{ii}\mathbf{AAAf} + \ldots \end{pmatrix} \\
&= \sum_{s=1}^{N}\sum_{t=1}^{N}\left(v_s a_{si}a_{ij}a_{jk}a_{ki}a_{it}f_t\right) + \sum_{s=1}^{N}\sum_{t=1}^{N}\sum_{u=1}^{N}\left(v_s a_{su}a_{ui}a_{ij}a_{jk}a_{ki}a_{it}f_t\right) + \ldots \\
&\qquad + \sum_{s=1}^{N}\sum_{t=1}^{N}\sum_{u=1}^{N}\left(v_s a_{si}a_{ij}a_{jk}a_{ki}a_{iu}a_{ut}f_t\right) + \ldots \\
&= a_{ij}a_{jk}a_{ki}\mathbf{vTJ}_{ii}\mathbf{Tf}
\end{aligned} \tag{7}
$$

Here, $\mathbf{T}$ is the indirect requirement matrix. Here, $\mathbf{T}$ is obtained with the following equations:

$$
\begin{aligned}
\mathbf{T} &= \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 \cdots \\
&= \mathbf{AL} = \mathbf{L} - \mathbf{I}
\end{aligned}
$$

In addition, using eq. (7), we can reformulate as eq. (8). From this equation, c_{ijk} can be decomposed to the cluster associated with each supply chain from production sector *s* to consumption sector *t*, c_{ijk}^{st}.

$$c_{ijk} = \sum_{s,t=1}^{N} e_s t_{si} a_{ij} a_{jk} a_{ki} t_{it} f_t = \sum_{s,t=1}^{N} c_{ijk}^{st} \tag{8}$$

Finally, using eq. (7) and summing c_{ijk}, we can obtain the I-O clusterness of sector i, C_i as:

$$\begin{aligned} C_i &= \sum_{j,k} c_{ijk} \\ &= \sum_{j,k} a_{ij} a_{jk} a_{ki} \mathbf{eTJ}_{ii} \mathbf{Tf} \end{aligned} \tag{9}$$

Note that I-O clusterness C_i suggested in this study is not actual amount of value added associated with sector *i* but relative intensity because I-O clusterness multi counts value added associated with the supply chains passing through sector *i* which include the triangle transaction $a_{ij}a_{jk}a_{ki}$ multi-times or include multi-patterns triangle paths (for example, the path $e_1 a_{1i} a_{i1} a_{12} a_{2i} a_{i2} a_{23} a_{3i} a_{i4} f_4$ includes the both triangle $a_{i1}a_{12}a_{2i}$ and $a_{i2}a_{23}a_{3i}$, and the path is counted twice). We can interpret this double count as the more triangle paths of sector *i* are included in a supply chain, sector *i* is more important.

3. Data

In this study, we used the EXIOBASE 3 MRIO table in 2011 covering 163 industrial sectors, which is publicly available at https://www.exiobase.eu/ (Tukker *et al.*, 2013; Wood *et al.*, 2015). As the case study, we detected the large clusters and calculated the IO-clusterness associated with 163 industries in United States, China and Japan, the top 3 countries in GDP, in the global supply chain network. Finally, we analyzed which industries lead domestic supply chain to global supply chain.

4. Results

Applying the EXIOBASE for the year of 2011 to a new cluster analysis suggested in this study, we detected the higher I-O clusterness sectors and larger clusters. The large I-O cluster is the high power and sensitivity of dispersion of industrial cluster in the global supply chains, and the higher I-O clusterness represents the sector lead the large clusters. This means that the high I-O clusterness sectors are highly competitive in global supply chain and boost the GDP through the spillover to domestic industries from the global final demand.

First, we calculated the clusterness scores with a focus of the Japanese industries in the global supply-chain networks (see table 1). The result shows that the highest clusterness scores are "Re-processing of secondary steel into new steel", followed by "Other business activities", "Computer" and "Financial intermediation, except insurance and pension funding" in 2011. It indicates the Japanese steel industries played a central role in forming larger clusters in the global supply-chains. Figure 4 shows the top 30 clusters of Japanese industries in the global supply-chain networks. We visualized the 90 edges between the sectors constructing top 30 clusters which consist of 3 sectors each, and the sectors constructing the top clusters can be overlapped. Thus, it should be noted that some edges overlapped. In addition, 2 of 3 sectors constructing a cluster can be a same industry, and note that 1 of 3 edges constructing a cluster can be “self-loop,” which is the paths connecting sectors to itself. From figure 4, we can see that the highest I-O clusterness sector, “Re-processing of secondary steel into new steel” constructed the “steel cluster” with “Manufacture of basic iron and steel and of ferro-alloys and first products thereof.” Whereas, “Other business activities”, “Financial intermediation, except insurance and pension funding” and “Publishing, printing and reproduction of recorded media” constructed the clusters that consist of various industries.

[INSERT TABLE 1 ABOUT HERE]

[INSERT FIGURE 4 ABOUT HERE]

Table. 2 shows the top 20 sectors for IO-clusterness of industries in United States in the global supply-chain networks. The highest I-O clusterness scores are “Other business activities”, “Manufacture of fabricated metal products, except machinery and equipment” and “Financial intermediation, except insurance and pension funding” in 2011. Figure 5 shows the top 30 clusters of industries in United States. “Other business activities” and “Financial intermediation, except insurance and pension funding” constructed the clusters that consist of various industries similar to case of Japan.

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 5 ABOUT HERE]

Finally, we represent the result of IO-clusterness of Chinese industries in the global supply-chain networks (Table 3). The highest I-O clusterness scores are “Other business activities”, “Financial intermediation, except insurance and pension funding” and “Computer.” Figure 6 shows the top 30 clusters of Chinese industries. Unlike Japan and United States, “Manufacture of machinery and equipment n.e.c.” and “Manufacture of basic iron and steel and of ferro-alloys and first products thereof”, the secondary industries, constructed the larger clusters in 2011.

[INSERT TABLE 3 ABOUT HERE]

[INSERT FIGURE 6 ABOUT HERE]

5. Discussion and conclusions

In this study, we developed the “cluster coefficient” in graph theory into I-O clusterness to assess the importance of a sector and cluster in supply chains and detected the important sectors and clusters in Japan, United States and China. Among the larger clusters identified in this study, the large cluster for Japan and United States comprises third sectors but for China comprises secondary sectors. The higher I-O clusterness sectors are the important sectors for not only economic spillover but sharing new knowledge and innovation. In the case of Japan, "Other business activities" and "Financial intermediation, except insurance and pension funding" construct clusters across the industries. We propose the government policy boost the economic development through the reduction in transaction cost, investment for R&D and improvement of competitiveness in the important clusters. In addition, this study not only developed the "cluster coefficient" and suggested a new framework of "clustering method" but also enabled to identify the core sectors constructing some important clusters. Using the regional input-output table at a country, the framework suggested in this paper should provide useful information for economic development.

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Figures

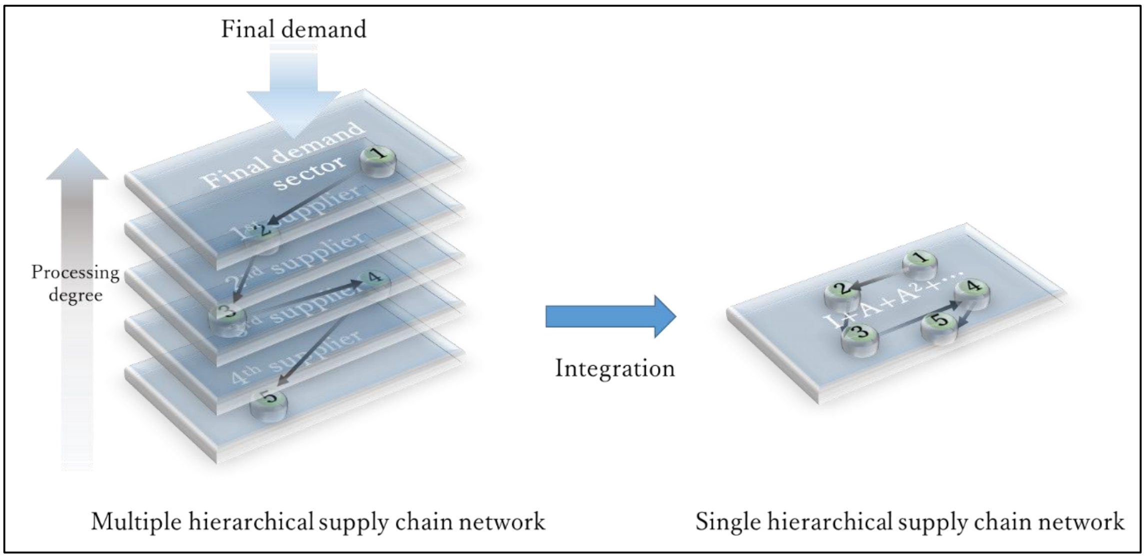

Figure 1. Multiple hierarchical network and single hierarchical network

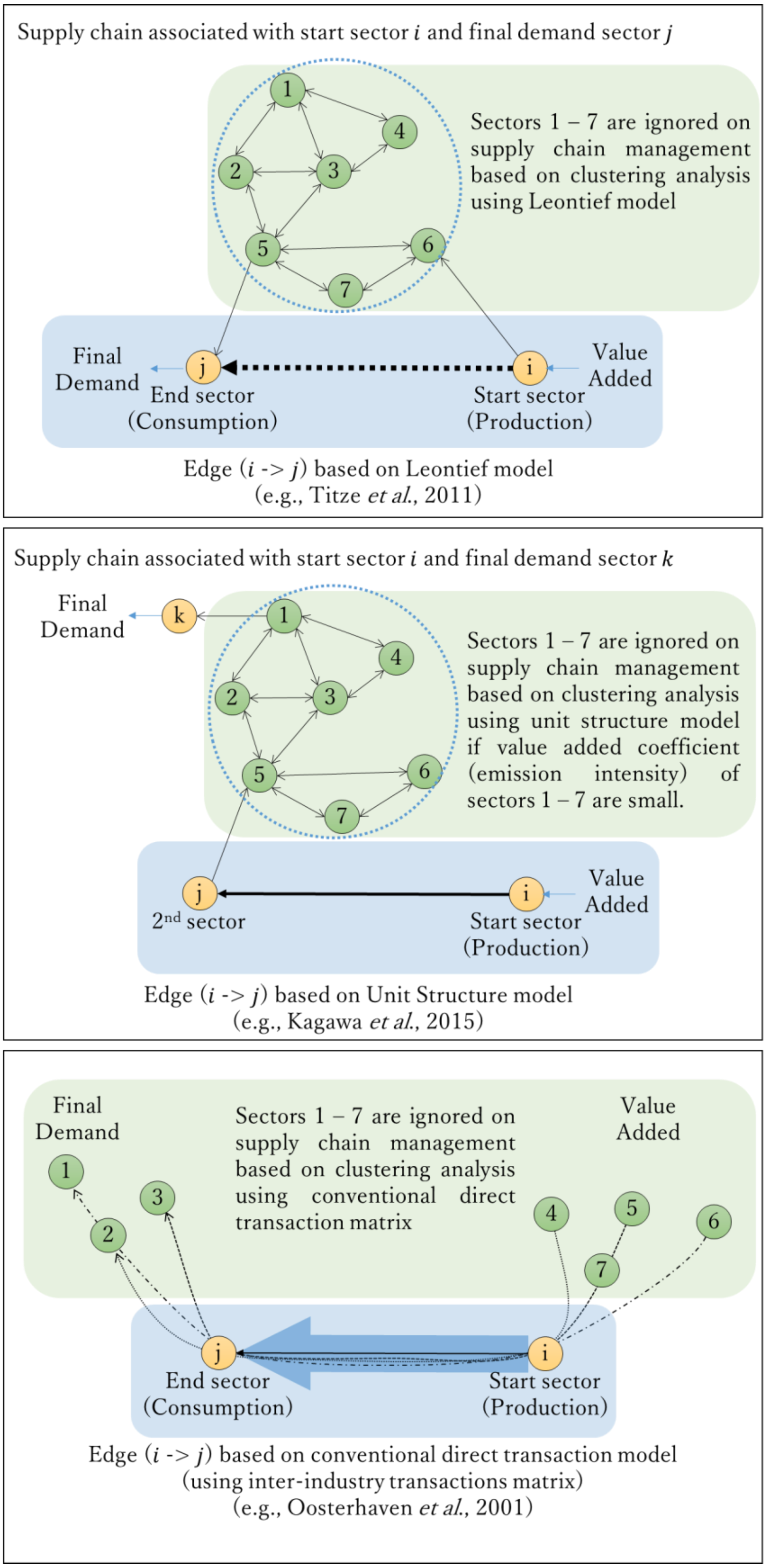

Figure 2. Major 3 I-O network models

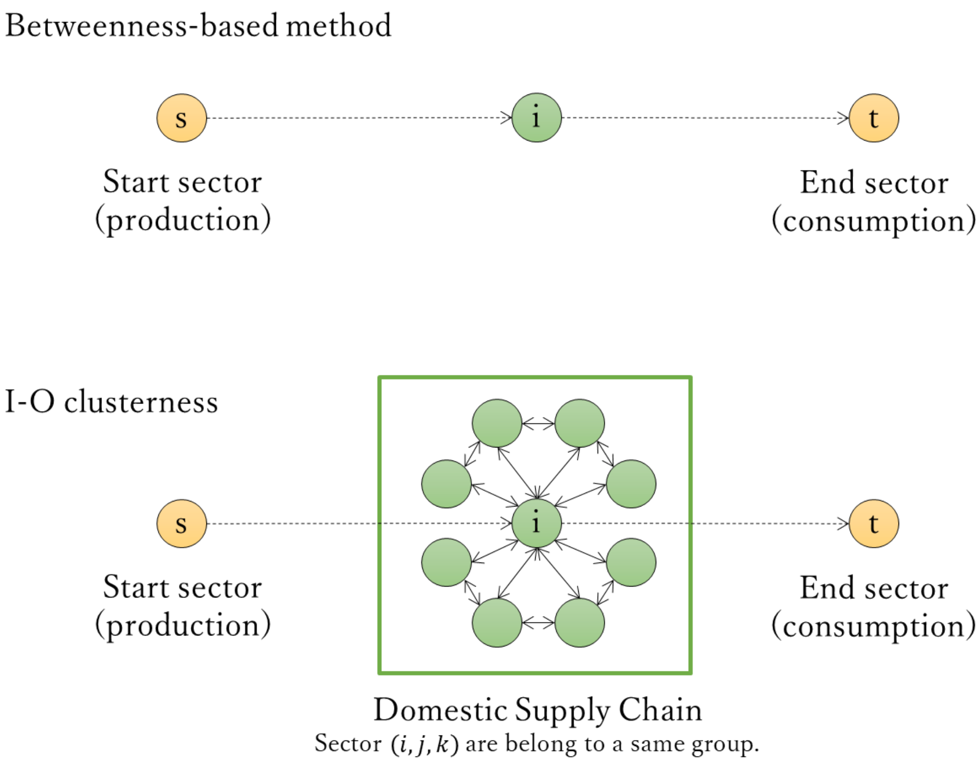

Figure 3. Betweenness-based analysis and I-O clusterness

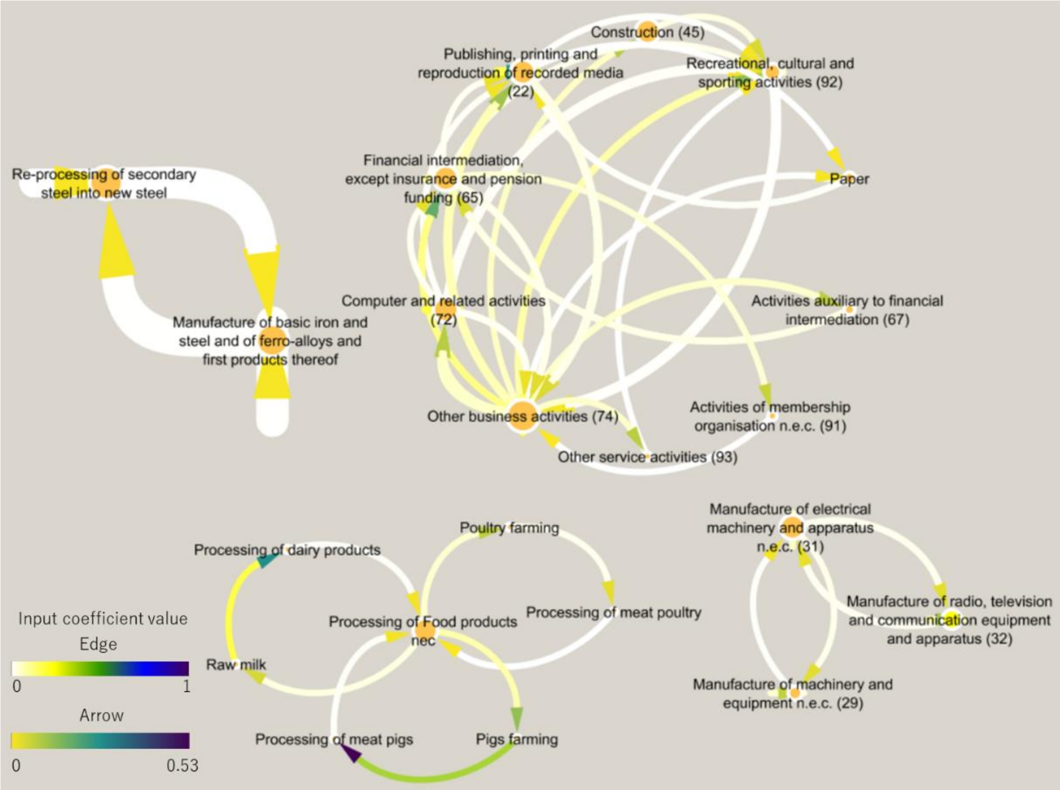

Figure 4. Top 30 clusters of Japanese industries in the global supply-chain networks. The width of edges indicates the size of cluster constructed, and the color of edges and arrows reflect input coefficient from source sector to target sector. The size of nodes shows I-O clusterness of the sector.

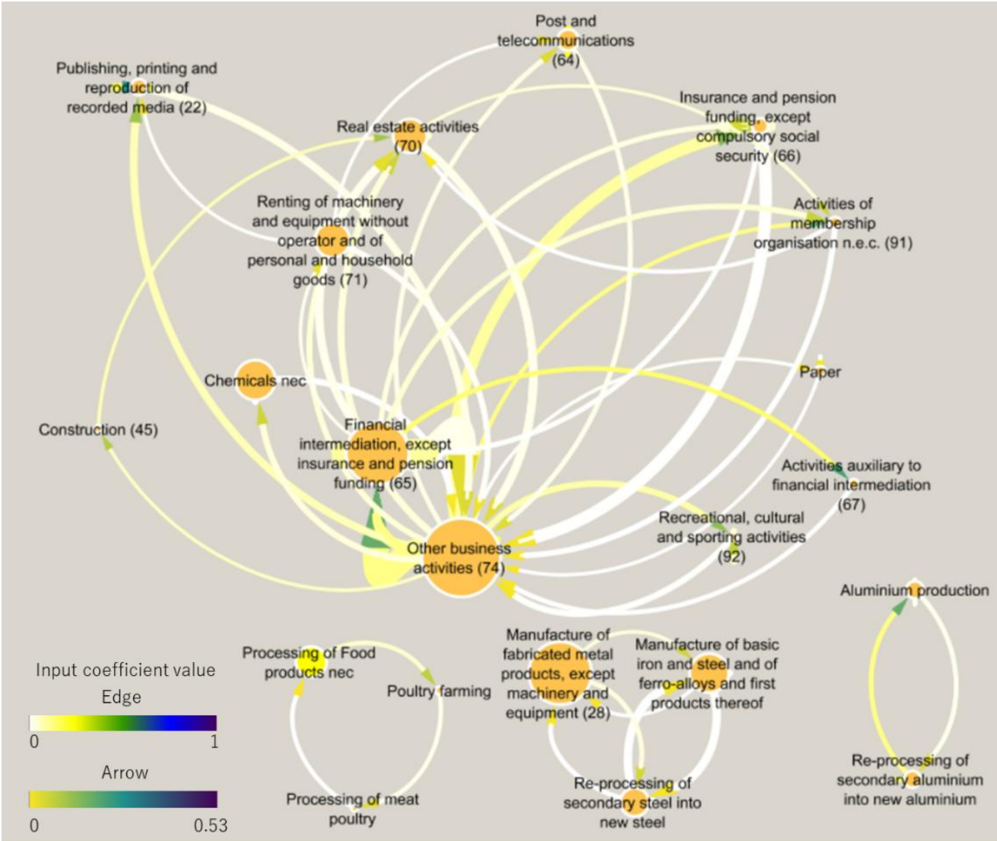

Figure 5. Top 30 clusters of industries in United States in the global supply-chain networks.

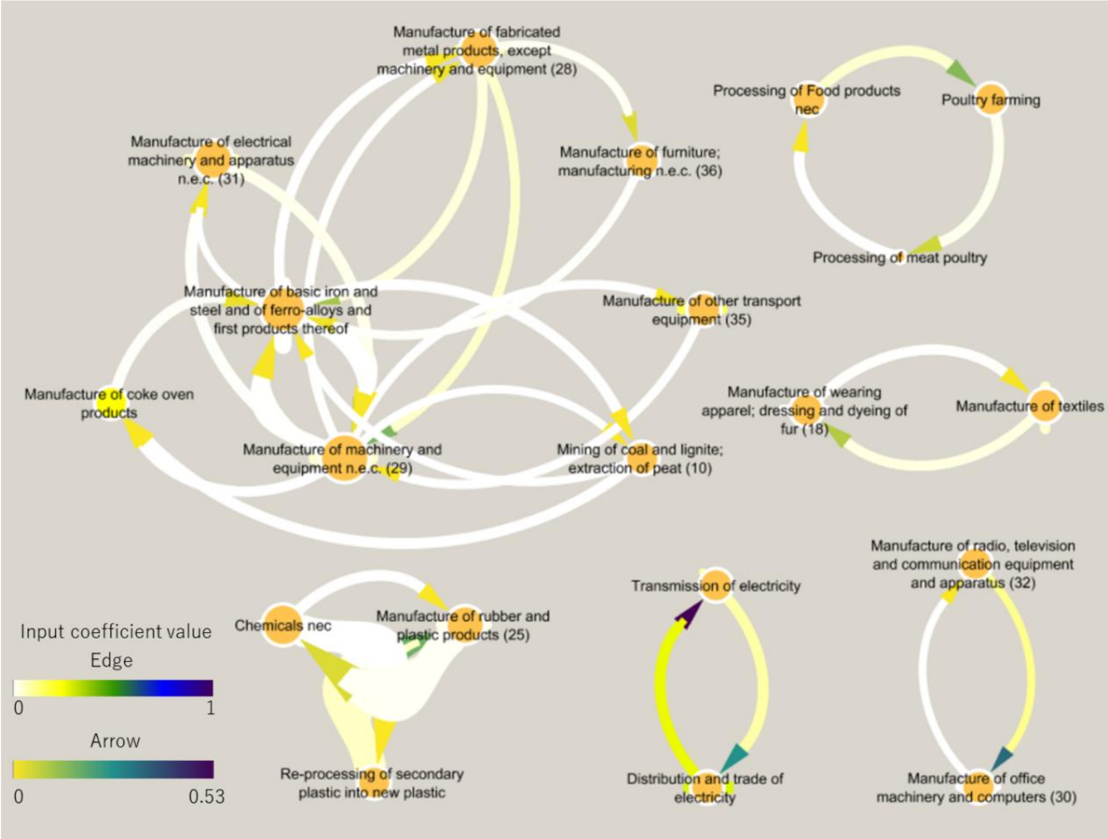

Figure 6. Top 30 clusters of Chinese industries in the global supply-chain networks.

Tables

Table 1. Top 20 sectors for IO-clusterness of Japanese industries in the global supply-chain networks.

Rank	Sector name (Japan)	Clusterness c_i
1	Re-processing of secondary steel into new steel	113324474
2	Other business activities	109228801
3	Manufacture of basic iron and steel and of ferro-alloys and first products thereof	105282621
4	Computer and related activities	18700566
5	Financial intermediation, except insurance and pension funding	17266475
6	Publishing, printing and reproduction of recorded media	14863443
7	Manufacture of electrical machinery and apparatus n.e.c.	12495053
8	Processing of Food products nec	10334761
9	Construction	10114163
10	Manufacture of radio, television and communication equipment and apparatus	7220551
11	Manufacture of fabricated metal products, except machinery and equipment	6727320
12	Public administration and defence; compulsory social security	6570420
13	Chemicals nec	6449715
14	Other land transport	6269201
15	Recreational, cultural and sporting activities	5861701
16	Manufacture of rubber and plastic products	5450964
17	Renting of machinery and equipment without operator and of personal and household goods	4322594
18	Manufacture of machinery and equipment n.e.c.	4054004
19	Paper	3024460
20	Activities auxiliary to financial intermediation	2169077

Table 2. Top 20 sectors for IO-clusterness of industries in United States in the global supply-chain networks.

Rank	Sector name (United States)	Clusterness c_i
1	Other business activities	1053058148
2	Manufacture of fabricated metal products, except machinery and equipment	132466062
3	Financial intermediation, except insurance and pension funding	125755412
4	Chemicals nec	60596061
5	Manufacture of basic iron and steel and of ferro-alloys and first products thereof	59150875
6	Renting of machinery and equipment without operator and of personal and household goods	51542768
7	Real estate activities	49908877
8	Processing of Food products nec	44318669
9	Re-processing of secondary steel into new steel	40377227
10	Post and telecommunications	27358722
11	Aluminium production	20712948
12	Manufacture of rubber and plastic products	19986620
13	Re-processing of secondary aluminium into new aluminium	19736191
14	Publishing, printing and reproduction of recorded media	18562820
15	Insurance and pension funding, except compulsory social security	18037318
16	Computer and related activities	11912309
17	Activities of membership organisation n.e.c.	10150322
18	Research and development	9077167
19	Manufacture of machinery and equipment n.e.c.	8823704
20	Paper	8606229

Table 3. Top 20 sectors for IO-clusterness of Chinese industries in the global supply-chain networks.

Rank	Sector name (China)	Clusterness c_i
1	Other business activities	31801713
2	Financial intermediation, except insurance and pension funding	11212204
3	Computer and related activities	4359184
4	Construction	3778812
5	Supporting and auxiliary transport activities; activities of travel agencies	2205843
6	Processing of Food products nec	1878401
7	Post and telecommunications	1705571
8	Other land transport	1193734
9	Mining of chemical and fertilizer minerals, production of salt, other mining and quarrying n.e.c.	1114590
10	Transmission of electricity	953929
11	Distribution and trade of electricity	654751
12	Real estate activities	544993
13	Quarrying of stone	516866
14	Manufacture of motor vehicles, trailers and semi-trailers	497961
15	Manufacture of rubber and plastic products	443586
16	Plastics, basic	382822
17	Manufacture of other transport equipment	355503
18	Insurance and pension funding, except compulsory social security	345391
19	Renting of machinery and equipment without operator and of personal and household goods	338439
20	Sea and coastal water transport	317641