Detecting Energy Clusters from the Automobile Supply Chain: Spectral Clustering Approach

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ABSTRACT

This paper proposes a new method that identifies energy-intensive industrial clusters from product supply chains quantitatively by combining structural path analysis and spectral clustering analysis. The analysis of automobiles has engendered the discovery of numerous clusters joining the upstream and downstream sectors together such as a cluster that consists primarily of three sectors—electrical equipment for internal combustion engines (#244), internal combustion engines for motor vehicles and parts (#250), and motor vehicle parts and accessories (#251)—which reveals a composition of sectors that differs considerably from the current Japan Standard Industrial Classification. This paper also proposes the "within-cluster effect" as a new indicator of energy intensity inside the industrial clusters identified from the automobile supply chain and presents quantitative analyses of the importance of industrial clusters in terms of the environment.

1. Introduction

According to the database of sectoral carbon dioxide emissions provided by the National Institute for Environmental Studies of Japan (NIES)[1], the total of carbon dioxide emissions emitted directly through production activities of firms, increased by 27 million tons-C during the period from 1990 to 2000. Consequently, the total emissions increased by 9.5% during those ten years. In these circumstances, energy-intensive sectors such as electricity, iron and steel, cement, and transportation have received attention as target sectors for the simple reason that total emissions at a domestic level can be reduced efficiently by promoting energy-saving technologies of these sectors.

In implementing sector-wise environmental and energy policies, it is crucial not only to clarify the concept and definition of sectors (e.g., firms, industries, or commodities) but also to decide their priority levels based on reliable environmental inventories such as CO_2 intensities and energy intensities. In these respects, the environmental input–output analyses are useful not only for estimating commodity-wise and industry-wise environmental inventories, but also for identifying the environmentally important key sectors using economic statistics that are calculable from the backward and forward inter-industry linkage effects obtained from column and row sums of the direct and indirect intermediate input coefficient matrix (see Rasmussen, 1956; Hirschman, 1958; Bharadwaj, 1966; Hazari, 1970; Lenzen, 2003).

A recent interesting discussion is that not only net multipliers developed by Oosterhaven and Stelder (2002) can be used to avoid double counting of the total impact of an industry

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[1] See http://www-cger.nies.go.jp/publication/D031/eng/table/embodied/f_embodied.htm, visited at September 18, 2009.

which results from multiplying a certain input–output multiplier by the industrial *output* but also, as Dietzenbacher (2005) discovered, that net multipliers yield a relevant key sector indicator obtained by dividing the total backward linkage effect of industry *j* by the total forward linkage effect of industry *j* (see eq. (3) of Dietzenbacher (2005)). For a recent empirical contribution, Lenzen (2003) identified environmentally important paths, linkages, and key sectors in the Australian economy using weighted and unweighted coefficients of variation derived from backward and forward inter-industry linkage effects. In addition, an alternative key sector approach is to use both in-degrees and out-degrees obtained from column and row sums of the adjacency matrix represented as a {0, 1}-matrix, where 1 denotes an influential inter-industry transaction larger than (or greater than) a certain threshold value, otherwise 0 (see e.g., Ghosh and Roy, 1998; Kagawa et al., 2009 for graph-theoretic analyzes and part II of Lahr and Dietzenbacher (2001) for the theoretical remarks and its applications of the qualitative input–output analysis using the adjacency matrix).

Although sector-wise analyses such as key sector analysis described above indicate key sectors that pollute environment through energy consumption induced by production of energy and materials needed for the production in the sector in question, they are naturally limited to policy implications within a sector rather than between sectors. We also think that it is important to give some incentive to cooperate between different sectors and to attain the same goal of reducing the total environmental burden associated with supply chains from upstream sectors to downstream sectors. Especially, to save energy and reduce environmental burdens efficiently, it is very effective to identify energy-intensive industrial clusters objectively from the supply chains of goods and services in question and provide that information to the public. Thereby, not only are the respective levels of social responsibility of a particular industrial cluster and industries within the cluster in question revealed and ranked, the importance of reducing environmental burdens through cooperation among

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different sectors within the relevant cluster can be emphasized.

In the field of regional studies, many contributions have been put forth in attempts to identify regional and industrial clusters and complexities (see Streit, 1969; Roepke et al., 1974; Czamanski and Ablas, 1979; Feser and Bergman, 2000; Oosterhaven et al., 2001, Feser et al., 2005; Kelton et al., 2008). Their studies normally calculated the relevant four correlation coefficients representing the following similarities between two industries: (1) Industries u and v have similar input purchasing patterns, (2) Industries u and v have similar output selling patterns, (3) The buying pattern of industry u is similar to the selling pattern of industry v, (4) The buying pattern of industry v is similar to the selling pattern of industry u and identified the industrial clusters by application of the similarity matrices to principal component factor analysis (e.g., varimax method and promax method). The bottom-up type cluster methods based on economic distances (e.g. technological similarity) are called *polythetic* methods. In a relevant remark, Oosterhaven (2001, p.811) reported that:

"*The use of the phrase 'relatively closely* [relative similarity]*' indicates that the drawing of the border of any cluster,…, will always involve a certain arbitrariness.*"

It is noteworthy that determining the number of clusters is regarded as a most difficult problem in the field of discrete mathematics (see, e.g. von Luxburg, 2007).

As described herein, we demonstrate that a popular heuristic approach—the Spectral Clustering Approach—is extremely useful for addressing the industrial cluster problem (see section 1.1 of Spielman and Teng (2007) for the short history and Chung (1997) for the related mathematical properties). In fact, although many applied studies have been made in the field of parallel computing (e.g., Hendrickson and Leland, 1995) and image segmentation (Shi and

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Malik, 2000), apparently very few studies have been undertaken in an attempt to detect the industrial clusters using the spectral clustering theory in the field of applied economics. In a related study, Aroche-Reyes (2003) definitively introduced a "network cut criterion" to draw the border of any cluster and identified a tree of the fundamental production structure for Mexico using input–output tables. However, Aroche-Reyes (2003) did not use the spectral graph approach but instead used Prim's algorithm to detect the spanning tree of the Mexico economy. An important feature of the spectral clustering theory is that the border of any cluster can be drawn based on a criterion (cut value, normalized cut value, etc.) (see von Luxburg, 2007; von Luxburg et al., 2008). Consequently, the spectral clustering theory is called a *monothetic* method. The well-known triangulation methods of input–output matrix also belong to a family of the monothetic methods because they depend largely on a criterion of maximizing the degree of linearity and check the relevance of the matrix triangulation (see Simpson and Tsukui, 1965; Fukui, 1986; Howe, 1991; Dietzenbacher, 1996). We understand that both spectral clustering (graph partitioning) and block triangulation from the input–output theory belong to a family.

This study employs the latter, the spectral clustering method, and attempts to identify the energy-intensive clusters by minimizing the normalized cut value consisting of the energy consumption of the sectors within the cluster in question as the denominator and the energy consumption induced by the economic linkage among the clusters as the numerator (i.e. energy cut value). More specifically, applying the 2000 environmental input–output database to the spectral clustering method, we attempted to detect the environmentally important clusters from the supply chain of the automobile sector as a case study, which plays a crucial role in the Japanese economy. Subsequently, we argued that peculiar features of the energy intensive clusters of the Japanese auto sector and policy present implications of saving energy effectively through cooperation among different sectors within the clusters.

This paper is organized as follows: Section 2 reconciles structural path analysis with spectral clustering analysis, Section 3 describes the data sources and Section 4 presents the empirical results obtained by application of the 2000 environmental input–output table of Japan to the spectral clustering analysis and discusses the relevance of the energy-intensive clusters from the automobile supply chain in 2000 and presents quantitative analyses of the importance of the industrial clusters of auto industry in terms of the environment by using the proposed new indicator "within-cluster effect" showing energy intensity inside the industrial clusters. Section 5 explains about the nested structure of detected energy-intensive clusters and Section 6 explains the related policy implications. Finally, Section 7 concludes the paper.

2. Reconciling structural path analysis with spectral clustering

A starting point is that we define the input coefficient matrix as $\mathbf{A} = \left(a_{ij} \right)$ $(i, j = 1, \ldots n)$ representing a million yen's worth of intermediate input of commodity i per million yen of output of commodity j, where n refers to the number of commodities (see e.g., chapter 2 of Miller and Blair, 2009). If the consumption (unit: gigajoule, GJ in SI) of energy resource k directly required for a unit of output of commodity j is defined as the direct energy intensity matrix, $\mathbf{E} = \left(e_{kj} \right)$, then the total direct energy consumption for a unit of output of commodity j is obtainable as the direct energy intensity vector $\tilde{\mathbf{E}} = \mathbf{sE}$, where $\mathbf{s}$ is the summation row vector in which all the elements are unity. Furthermore, we define a diagonal matrix in which each element of $\tilde{\mathbf{E}} = \left(\tilde{e}_j \right)$ is diagonalized as $\mathrm{diag}(\tilde{\mathbf{E}})$. As sectoral energy consumption $\mathbf{C} = \left(C_i \right)$ that is directly and indirectly attributable to automobile production is provided by the following equation.

$$C = \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{X}_{auto} = \mathrm{diag}(\tilde{\mathbf{E}})(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}_{auto}$$
$$= \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{F}_{auto} + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\mathbf{F}_{auto} + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}^2\mathbf{F}_{auto} + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}^3\mathbf{F}_{auto} + \cdots$$

Here $\mathbf{X}_{auto} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}_{auto}$, $\mathbf{I}$ is the identity matrix with appropriate order and $\mathbf{F}_{auto}$ is the

domestic final demand vector in which only the element associated with only automobile

sector has a figure; all other elements are zero.[2] The energy intensity for the production of the

intermediate goods and services flowing from sector i to sector j can be estimated as the (i,

j)-element of the matrix $\mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}$. On the other hand, because the productions of the

intermediate goods and services necessary to produce the domestic final demand (in a million

yen's worth) of, for instance, automobiles are calculable as $\mathbf{A}\mathbf{F}_{auto}$, the energy consumption

(unit: GJ) necessary to produce commodity i purchased for the production of commodity j

directly required for producing the domestic final demand of automobiles can be estimated as

the (i, j)-element of $\mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\,\mathrm{diag}(\mathbf{A}\mathbf{F}_{auto})$, where $\mathrm{diag}(\mathbf{A}\mathbf{F}_{auto})$ represents the diagonal

matrix whose diagonal elements are products of intermediate goods and services induced

directly by the final demand for automobile. Noting that this economy produces automobiles

and intermediate goods and services that are directly demanded for producing the automobiles

and that the economy consumes energy to produce them at downstream stages, the energy

consumption (unit: GJ) necessary to produce commodity i purchased for the production of

commodity j directly and indirectly for producing the domestic final demand of automobiles,

$\mathbf{Q} = (Q_{ij})$ $(i, j = 1, \cdots, n)$, can be finally estimated as

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[2] The matrix $(\mathbf{I} - \mathbf{A})^{-1} = \mathbf{B} = (b_{ij})$ is well known as the Leontief inverse matrix showing the direct and indirect input of commodity i required for the final demand of commodity j (see e.g., chapter 2 of Miller and Blair, 2009).

$$\mathbf{Q} = \mathrm{diag}(\tilde{\mathbf{E}})\mathrm{diag}(\mathbf{F}_{auto}) + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\mathrm{diag}(\mathbf{F}_{auto})$$
$$+ \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\mathrm{diag}(\mathbf{AF}_{auto}) + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\mathrm{diag}(\mathbf{A}^2\mathbf{F}_{auto}) + \cdots \quad , \tag{1}$$

where the first term on the right-hand side of eq. (1) represents the matrix in which the

diagonal element associated with only automobile sector records the energy consumption

required at automobile plants and the other diagonal and off-diagonal elements are zero. The

second term represents the matrix in which the ith row element of the column associated with

automobile sector records the energy consumption necessary to produce an intermediate good

or service i required for producing automobiles and the other matrix elements are zero.[3]

Summing up higher order terms results in an increase in the non-zero elements. In other words,

the inclusion of higher order terms increases the number of sectors participating in

inter-industrial networks.

The matrix $\mathbf{Q} = Q_{ij}\left(i,j = 1,\cdots,n\right)$ in eq. (1) can be regarded as a weighted directed

graph showing the flow from an upstream sector i to a downstream sector j. A graph

$G = (V, A)$ can be reasonably derived from $\mathbf{Q}$ such that the set of vertices is $V = \{1,\ldots,n\}$,

the set of arcs (or directed edges) is $A = \{(i, j) \mid Q_{ij} > 0\}$, and the weight assigned to edge

(i, j) is Q_{ij}. The weight of the flow is the energy consumption necessary to produce

commodity i upstream purchased for the production of commodity j downstream. It is

important that *more direct energy consumption* required for automobile production be

considered and that a major upstream sector i with high-induced energy consumption C_i

associated with automobile production participates in the inter-industrial network. This makes

it easier to discuss the features of the inter-industrial network and detected industrial clusters

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[3] This study uses the same name for both the industrial sector and commodity sector for the industries producing the commodity concerned as the primary product. For instance, the automobile industry produces automobiles as its primary product. It is therefore called the automobile industry.

from the point of view of technological linkages. This study therefore defines the adjacency matrix by summing up the lower order terms shown in the right-hand side of equation (1) such that major high-ranking sectors with high-induced energy consumption participate in inter-industrial networks.

This study uses the sums of the amounts of energy consumption from sector i to sector j and from sector j to sector i as indicators of the strength of the relation through inter-sectoral energy consumption. For particularly addressing the energy consumption associated with the inter-sectoral transactions, a symmetric matrix $\mathbf{Q}^* = \left(Q_{ij}^*\right)$ $(i, j = 1, \ldots, n)$ with the diagonal element (the energy consumption of the sector itself) set to zero is defined as shown below to examine the non-diagonal elements specifically.

$$Q_{ij}^* = Q_{ij} + Q_{ji} \quad (i \neq j),$$
$$Q_{ij}^* = 0 \quad (i = j).$$

In what follows, we presents the network analysis based on a weighted undirected graph derived from the matrix $\mathbf{Q}^*$. Some notations are introduced before going into details of the analysis. Let $\mathbf{Q}_{CD}$ denote the matrix is in which the elements Q_{ij} $(i \in C, j \in D)$ of $\mathbf{Q}$ for subsets C, D of V are arranged. For instance, when $C = \{1, 3\}$ and $D = \{2, 3, 6\}$, then

$$\mathbf{Q}_{CD} = \begin{bmatrix} Q_{12} & Q_{13} & Q_{16} \\ Q_{32} & Q_{33} & Q_{36} \end{bmatrix},$$

and also $\mathbf{Q} = \mathbf{Q}_{VV}$. Although the sets of row and column indices should be ordered sets rather than proper sets to be more precise, the difference between these two is not necessary and is

therefore not examined. In addition, the sum of all elements of the matrix $\mathbf{Q}_{CD}$ is expressed as

$$\left\|\mathbf{Q}_{CD}\right\| = \sum_{i \in C} \sum_{j \in D} Q_{ij} \; .$$

The same notations for subscripts and the sum of elements are used for $\mathbf{Q}^*$. In some cases, $\mathbf{Q}_{CD}$ is written as $\mathbf{Q}(C, D)$ instead to avoid nested subscripts.

Here we seek to detect energy-intensive industrial sub-networks from the automobile supply chain by partitioning the set of vertices of graph $G = (V, E)$ into two disjoint sets of sectors, C and D, where the graph is derived from the symmetric matrix $\mathbf{Q}^*$ defined above such that the set of vertices is $V = \{1, 2, \cdots, n\}$ and the set of edges is $E = \{(i, j) \mid Q_{ij}^* > 0, i < j\}$. If two sectors in question, u and v respectively belong to sets C and D, then the cut value in the Graph Theory is definable as follows (see e.g., Shi and Malik, 2000)

$$Cut(C, D) = \left\|\mathbf{Q}_{CD}^*\right\| = \sum_{u \in C, v \in D} Q_{uv}^* \; . \tag{2}$$

$Cut(C, D) = Cut(D, C)$ because $\mathbf{Q}^*$ is symmetric. The cut value is understood to be the energy intensiveness of the transactions between two industry groups C and D. To detect the most energy-intensive industrial clusters from the whole supply chain, it is necessary to find the two sets to minimize the energy intensiveness between two industrial groups (i.e. cut value). Consequently, to minimize the cut value is environmentally meaningful. However, as Wu and Leahy (1993) and Shi and Malik (2000) pointed out, one shortcoming of the cut criterion in eq. (2) is that the cut criteria force the cutting of small sets of isolated sectors.

Therefore, following Shi and Malik (2000), the *normalized* cut value is used in this study to avoid that undesirable solution. The normalized cut value can be formulated as

$$Ncut(C,D) = \frac{Cut(C,D)}{\text{vol}(C)} + \frac{Cut(D,C)}{\text{vol}(D)} = \frac{\left\|\mathbf{Q}_{CD}^*\right\|}{\left\|\mathbf{Q}_{CV}^*\right\|} + \frac{\left\|\mathbf{Q}_{DC}^*\right\|}{\left\|\mathbf{Q}_{DV}^*\right\|},$$ (3)

where $\text{vol}(C) = \left\|\mathbf{Q}_{CV}^*\right\|$ and $\text{vol}(D)$ are similarly defined. If the weighted degree of each sector u is defined as $d_u = \sum_{v \in V} Q_{uv}^*$, then eq. (3) can also be reformulated as

$$Ncut(C,D) = \frac{Cut(C,D)}{\sum_{u \in C} d_u} + \frac{Cut(D,C)}{\sum_{v \in D} d_v}.$$ (4)

In eq. (4), the clustering problem is to find the two sets C and D such that not only the cut value (i.e. the numerator) is minimized but also the sizes of both clusters (the denominator) are maximized simultaneously. Our optimization problem is therefore formulated as follows.

$$\left| \begin{array}{ll} \text{minimize} & Ncut(C,D) \\ \text{subject to} & C \cup D = V, C \cap D = \varnothing \end{array} \right.$$ (5)

Here it is well known that this problem is an NP-complete problem. In an influential paper by Shi and Malik (2000), they further transformed eq. (5) into the following equivalent optimization problem.

$$
\left|
\begin{aligned}
&\text{minimize} && \frac{\mathbf{y}^{\mathrm{T}}\left(\mathbf{D}-\mathbf{Q}^{*}\right)\mathbf{y}}{\mathbf{y}^{\mathrm{T}}\mathbf{D}\mathbf{y}} \\
&\text{subject to} && \mathbf{y}^{\mathrm{T}}\mathbf{D}\mathbf{i}=0 \\
& && y_{i}\in\{1,-b\} \quad (i=1,\ldots,n)
\end{aligned}
\right. \tag{6}
$$

Here, the superscript T denotes the transpose of the vector, $\mathbf{y}=(y_{i})$ $(i=1,\cdots,n)$ is the transformed indicator vector, $\mathbf{D}$ is the diagonal matrix whose diagonal elements are weighted degrees d_{u}, $\mathbf{i}$ is the vector of unities, and

$$
b=\sum_{i\in Y}d_{i}\Big/\sum_{i\in V\text{-}Y}d_{i} \quad \text{with} \quad Y=\{i\in V\mid y_{i}=1\}
$$

(see p. 890 of Shi and Malik (2000)). In fact, $\mathbf{D}-\mathbf{Q}^{*}$ is often called the Laplacian matrix and normally denoted by $\mathbf{L}$ in the Graph Theory. It is noteworthy that the optimization problem in eq. (6) is still an NP-complete problem.

The objective function of the optimization problem (6) is the form of the Rayleigh quotient for the generalized eigenvalue problem $\left(\mathbf{D}-\mathbf{Q}^{*}\right)\mathbf{y}=\lambda\mathbf{D}\mathbf{y}$ where λ is the eigenvalue and $\mathbf{y}$ is the corresponding eigenvector (see e.g. Chapter 7 of Bellman (1997) for the Rayleigh quotient). Once the indicator vector $\mathbf{y}$ in eq. (6) is relaxed to take on 'real values', the optimization problem immediately engenders the following problem to find the second smallest eigenvalue and the corresponding eigenvector.

$$
(\text{GEP}(\mathbf{Q}^{*})) \left|
\begin{aligned}
&\text{minimize} && \frac{\mathbf{y}^{\mathrm{T}}\left(\mathbf{D}-\mathbf{Q}^{*}\right)\mathbf{y}}{\mathbf{y}^{\mathrm{T}}\mathbf{D}\mathbf{y}} \\
&\text{subject to} && \mathbf{y}^{\mathrm{T}}\mathbf{D}\mathbf{i}=0 \\
& && y_{i}\in\mathbf{R} \quad (i=1,\ldots,n)
\end{aligned}
\right. \tag{7}
$$

Therein, (GEP($\mathbf{Q}^*$)) refers to the generalized eigenvalue problem using the adjacency matrix $\mathbf{Q}^*$. That the smallest eigenvalue of the generalized eigenvalue problem is 0 and the eigenvector corresponding to the smallest eigenvalue is the unity vector $\mathbf{i}$ is well known: from the definitions of $\mathbf{D}$ and $\mathbf{Q}^*$, we have $(\mathbf{D}-\mathbf{Q}^*)\mathbf{i}=\lambda\mathbf{Di}=\mathbf{0}$ where $\mathbf{0}$ is the null vector.

Defining $\mathbf{w}=\mathbf{D}^{1/2}\mathbf{y}$, eq. (7) can be further transformed as

$$\left|\begin{array}{ll} \text{minimize} & \dfrac{\mathbf{w}^{\mathrm{T}}\mathbf{D}^{-1/2}\left(\mathbf{D}-\mathbf{Q}^*\right)\mathbf{D}^{-1/2}\mathbf{w}}{\mathbf{w}^{\mathrm{T}}\mathbf{w}} \\ \text{subject to} & \mathbf{w}^{\mathrm{T}}\mathbf{D}^{1/2}\mathbf{i}=0 \\ & w_i \in \mathbf{R} \quad (i=1,\ldots,n) \end{array}\right. . \tag{8}$$

The smallest eigenvalue of the normalized Laplacian matrix $\mathbf{D}^{-1/2}\left(\mathbf{D}-\mathbf{Q}^*\right)\mathbf{D}^{-1/2}$ is 0 and the corresponding eigenvector is $\mathbf{D}^{1/2}\mathbf{i}$. Therefore, an optimal solution to the problem in (8) with the orthogonal condition $\mathbf{w}^{\mathrm{T}}\mathbf{D}^{1/2}\mathbf{i}=0$ invariably provides the eigenvector corresponding to the second smallest eigenvalue. The second smallest eigenvalue of the normalized Laplacian matrix is called the Fiedler eigenvalue (see Fiedler, 1973; Chung, 1997); the eigenvector corresponding to the Fiedler eigenvalue is called the Fiedler eigenvector.

Using the matrix elements, eq. (8) can also be rewritten as (see, e.g., pp. 12–13 of Chung (1997))

$$
\begin{array}{|l}
\text{minimize} \quad \dfrac{\displaystyle\sum_{i=1}^{n}\sum_{j=1}^{n}Q_{ij}^{*}\left(\dfrac{w_i}{\sqrt{d_i}}-\dfrac{w_j}{\sqrt{d_j}}\right)^2}{\displaystyle\sum_{i=1}^{n}w_i^2} \\[4ex]
\text{subject to} \quad \displaystyle\sum_{i=1}^{n}w_i\sqrt{d_i}=0 \\[3ex]
\qquad\qquad\quad w_i \in \boldsymbol{R} \quad (i=1,\ldots,n)
\end{array}
\qquad , \qquad (9)
$$

or equivalently,

$$
\begin{array}{|l}
\text{minimize} \quad \dfrac{\displaystyle\sum_{i=1}^{n}\sum_{j=1}^{n}Q_{ij}^{*}\left(y_i-y_j\right)^2}{\displaystyle\sum_{i=1}^{n}d_i y_i^2} \\[4ex]
\text{subject to} \quad \displaystyle\sum_{i=1}^{n}d_i y_i=0 \\[3ex]
\qquad\qquad\quad y_i \in \boldsymbol{R} \quad (i=1,\ldots,n)
\end{array}
\qquad . \qquad (10)
$$

An important feature of eqs. (9) and (10) is that, as Shi and Malik (2000) explained in their paper, the optimization problem forces the elements of the vector $\mathbf{y}=\mathbf{D}^{-1/2}\mathbf{w}$ to take similar values for sectors i and j that induce a large amount of energy by the bilateral transaction and form the energy-intensive transaction. In summary, if industrial sectors are found which have similar indicator vector values ($-b$ or 1 in the original optimization problem), then the industries in question will form an energy-intensive industrial cluster.

Turning to a precise description of our method, set $r=20$ as the prescribed value for the maximum allowable number of sectors in a cluster to control the following recursive two-way cut algorithm. We assume that any sector, say u, is not isolated from the other sectors in V, i.e. $d_u>0$ for every $u \in V$. That is, any sector is assumed to purchase outputs of other sectors or to be purchased by other sectors. It is notable that the graph to be

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analyzed is not necessarily connected. We seek to partition V into clusters that have the same features because we believe that a set with isolated sectors does not deserve to be called a cluster. In the recursive two-way cut algorithm, therefore, we do not partition a graph, or sub-network, any cut of which invariably induces sub-networks with isolated sectors even if the number of sectors in it is larger than the maximum allowable number, r. Then, the computational algorithm is presented as follows.

Step 0. Set $k := 0$, $j := 0$ and $\Omega := \{V\}$.

Step 1. If $\Omega \neq \varnothing$, then set $N := k$ and $\bar{N} = j$ and terminate the algorithm. Otherwise, set

$j := j+1$, choose a set of sectors $V_j \in \Omega$, and set $\Omega := \Omega - \{V_j\}$ and

$\mathbf{Q}^*_{jj} := \mathbf{Q}^*(V_j, V_j)$.

Step 2. If the number of sectors in V_j is smaller than or equal to the prescribed value r, i.e.

if $|V_j| \leq r$, or any cut of V_j invariably induces sub-networks with isolated sectors,

then set $k := k+1$ and $S_k := V_j$, and go to Step 1.

Step 3. Solve the generalized eigenvalue problem GEP($\mathbf{Q}^*_{jj}$) in (7) and obtain the eigenvector

$\mathbf{y}$ that corresponds to the second smallest eigenvalue.

Step 4. Set $C := \{u | y_u \geq 0\}$, $D := \{v | y_v < 0\}$ and $\Omega := \Omega \cup \{C, D\}$.

Step 5. Go to Step 1.

The computation was done using software (Matlab; The MathWorks Inc.). When the algorithm terminates, we are left with $\bar{N}$ sub-networks and their sets of vertices and associated weight matrices are $V_1, \ldots, V_{\bar{N}}$ and $\mathbf{Q}_{11}, \ldots, \mathbf{Q}_{\bar{N}\bar{N}}$, respectively. In addition, N of the $\bar{N}$ sub-networks are clusters and their sets of vertices are $S_1, \ldots, S_N$. Actually, $S_1, \ldots, S_N$ are exhaustive and mutually exclusive subsets of the set of all the industrial sectors V, i.e. $S_1 \cup \cdots \cup S_N = V$ and $S_i \cap S_k = \varnothing$ $(i, k = 1, \ldots, N; i \neq k)$. Let $p(k)$ denote the index of a sub-network such that it is the k-th cluster is the $p(k)$-th sub-network, i.e. $V_{p(k)} = S_k$. It is noteworthy that a sub-network, say j, has its two "children", h and i such that $V_j = V_h \cup V_i$ and $V_h \cap V_i = \varnothing$ unless it is a cluster.

Therefore, we used the recursive two-way cut algorithm and detected the energy clusters of the Japanese automobile supply chain in 2000. Here let us recall that the matrix $\mathbf{Q} = \left(Q_{ij} \right)$ $(i, j = 1, \cdots, n)$ represents the energy consumption (unit: GJ) that is necessary to produce commodity i purchased for the production of commodity j required for the production of automobiles. Accordingly, this automobile supply chain totally consumes energy of $\|\mathbf{Q}\|$. It is noteworthy that we obtain the relation $\|\mathbf{Q}^*\| = 2\|\mathbf{Q}\|$. The total amount of energy consumption, $\|\mathbf{Q}\|$, can be decomposed as

$$
\begin{aligned}
\|\mathbf{Q}\| = {} & \left\| \mathbf{Q}_{p(1)p(1)} \right\| + \left\| \mathbf{Q}_{p(1)p(2)} \right\| + \cdots + \left\| \mathbf{Q}_{p(1)p(N)} \right\| \\
& + \left\| \mathbf{Q}_{p(2)p(1)} \right\| + \left\| \mathbf{Q}_{p(2)p(2)} \right\| + \cdots + \left\| \mathbf{Q}_{p(2)p(N)} \right\| \\
& + \cdots \\
& + \left\| \mathbf{Q}_{p(N)p(1)} \right\| + \left\| \mathbf{Q}_{p(N)p(2)} \right\| + \cdots + \left\| \mathbf{Q}_{p(N)p(N)} \right\|
\end{aligned}
\tag{11}
$$

where $\mathbf{Q}_{ij} = \mathbf{Q}(V_i, V_j)$. Furthermore, $\left\| \mathbf{Q}_{p(k)p(k)} \right\|$ represents the subtotal of energy induced by the intermediate inputs between the sectors belonging to the k-th cluster. We designate $\left\| \mathbf{Q}_{p(k)p(k)} \right\|$ as a within-cluster effect of cluster k. Using the proposed index, we evaluated the relevance of energy-intensive clusters of the automobile supply chain and the temporal changes in the within-cluster effects during the period of 2000.

3. Data Sources

As described in this paper, we specifically examined the 33 primary and secondary energy resources (Coking coal, Steam coal, lignite and anthracite, Coke, Blast furnace coke, Coke oven gas, BFG consumption, BFG generation, LDG consumption, LDG generation, Crude oil, Fuel oil A, Fuel oils B and C, Kerosene, Diesel oil, Gasoline, Jet fuel, Naphtha, Petroleum-derived hydrocarbon gas, Hydrocarbon oil, Petroleum coke, LPG, Natural gas, LNG, Mains gas, Black liquor, Waste wood, Waste tires, Recycled plastic of packages origin, Nuclear power generation, Hydroelectric and other power generations, Electric power for enterprise use, and On-site power generation). We compiled the energy inputs in calorific units (GJ) necessary for the respective sectoral production processes in monetary units (million yen), which data are obtainable from the Japanese Benchmark Input–Output Table in 2000 producer's prices (393 sectors) (see Nansai et al., 2007, 2009 for more details and Table A1 of the appendix for the sector classification). The primary and secondary energy resources are categorized into 5 energy sectors (see Table A2 of the appendix for the energy sector classification).

From the energy input–output database, the total energy consumption of each sector is calculable by summing up the energy inputs of each sector. The direct total energy intensity of sector j, $\tilde{e}_j$, is obtainable by dividing the total energy consumption by the sectoral production. It is noteworthy that summing up the energy inputs that belong to an energy category in question and dividing the calculated total energy consumption of the energy category by the sectoral production readily yields the direct total energy intensity of each energy category of sector j. Finally, we obtained the (393×393) diagonal matrix with total energy intensities and constructed the adjacency matrix of energy consumptions $\mathbf{Q}$ by substituting the energy

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intensity matrix $\mathrm{diag}(\tilde{\mathbf{E}})$, input coefficient matrix $\mathbf{A}$ from the benchmark input–output table, and the diagonalized matrix for the automobile domestic final demand (i.e., household consumption expenditure of automobile + fixed capital formation of automobile + increase in stock of automobile) $\mathrm{diag}(\mathbf{F}_{auto})$ into the right-hand side of eq. (1).[4]

4. Case study of the Japanese automobile supply chain in 2000

The fundamental idea of the aforementioned sectoral approach is to reduce carbon dioxide emissions by extracting energy-intensive sectors from a supply chain from its upstream to downstream sectors and demanding that such sectors take further energy conservation measures. For example, this means that increased promotion of energy conservation in individual sectors would require further reduction of the power needed for the operation of the production lines of these auto-parts manufacturers. Parts assembly manufacturers, however, have already been making efforts to conserve energy through means such as the implementation of systems to monitor energy consumption in their production process to check their power consumption meticulously at each production line. The current situation, therefore, is that further energy conservation and carbon emission reduction through the efforts of individual parts assembly manufacturers is difficult to achieve.

Under such circumstances, heterogeneous (intersectoral) industry cooperation is expected to facilitate future energy-saving measures and carbon emission reduction. An important question to ask is which sectors need to cooperate mutually to reduce energy consumption and carbon dioxide emissions more effectively. More specifically, *which*

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[4] In Japan, the final demand of automobiles purchased by households is recorded in the household consumption expenditure, while the final demand of automobiles purchased by firms is recorded in the fixed capital formation.

material producers the assembly manufacturers must closely collaborate with is the question that must be answered to advance their effort to conserve energy. One way is to select the sectors subjectively based on knowledge from various experiences and then regard the group of these sectors as a cluster (group), and demand that they strengthen their operational ties for energy saving. This method, however, causes the arbitrary judgment of the analyzer and policy-maker to affect the final decision about the cluster significantly. Avoiding such arbitrary decision-making requires objective methods of some kind.

The new method proposed in Section 2 enables us to objectively detect the energy-intensive clusters from the automobile supply chain. From eq. (1), this study redefines the adjacency matrix, which is shown below as the total up to the quadratic terms so that the 30 high-ranking sectors with a large amount of induced energy consumption by sector will participate in the inter-industrial networks.

$$\mathbf{Q} = \mathrm{diag}(\tilde{\mathbf{E}})\mathrm{diag}(\mathbf{F}_{auto}) + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\mathrm{diag}(\mathbf{F}_{auto}) + \mathrm{diag}(\tilde{\mathbf{E}})\mathbf{A}\mathrm{diag}(\mathbf{A}\mathbf{F}_{auto})$$

It should be noted that the total of the induced energy consumptions (C_i) of these top 30 sectors comprises more than 90% of the sum total $\sum_{i=1}^{n} C_i$ of induced energy consumption.

A cluster can be extracted objectively from a network using the spectral clustering approach formulated in the previous section. More specifically, first, the adjacency matrix $\mathbf{Q}^*$ that expresses the weighted undirected graph is calculated using the adjacency matrix $\mathbf{Q} = (Q_{ij})$ $(i, j = 1, \cdots, n)$ that expresses the weighted directed graph. Then, the solution to the problem GEP($\mathbf{Q}^*$) given by eq. (7), i.e., the second eigenvector $\mathbf{y}$ of the generalized eigenvalue problem $(\mathbf{D} - \mathbf{Q}^*)\mathbf{y} = \lambda\mathbf{Dy}$, is obtained, and the network is divisible into two

highly energy-intensive sub-networks using the signs of the elements of $\mathbf{y}$.

Sorting the elements of the calculated second eigenvector in ascending order yielded the following vectors.

$$\mathbf{y}^* = \begin{array}{r} \#128 \\ \#78 \\ \#73 \\ \#80 \\ \vdots \\ \#263 \\ \#130 \\ \#357 \\ \#378 \\ \#341 \\ \#114 \\ \#274 \\ \#96 \\ \vdots \\ \#232 \\ \#165 \\ \#164 \\ \#163 \end{array} \left[\begin{array}{l} -7.92 \times 10^4 \\ -6.97 \times 10^4 \\ -6.82 \times 10^4 \\ -6.13 \times 10^4 \\ \vdots \\ -3.52 \times 10^8 \\ -2.91 \times 10^8 \\ -1.31 \times 10^8 \\ -2.83 \times 10^9 \\ 2.70 \times 10^7 \\ 3.55 \times 10^7 \\ 4.63 \times 10^7 \\ 5.60 \times 10^7 \\ \vdots \\ 1.09 \times 10^5 \\ 1.13 \times 10^5 \\ 1.60 \times 10^5 \\ 1.60 \times 10^5 \end{array} \right] \begin{array}{l} \\ \\ \\ \\ \Big\} \; \mathrm{sgn}(y_i^*) < 0 \\ \\ \\ \\ \\ \\ \\ \\ \\ \Big\} \; \mathrm{sgn}(y_i^*) > 0 \\ \\ \\ \end{array}$$

where sector numbers corresponding to the elements are added as notations on the left border of the second eigenvectors. By particularly addressing the sign of the elements of this second eigenvector, the entire network is divisible into two sub-networks – one comprising the sectors belonging to the set of $V_2 = \{\#128$ (synthetic fibers), #78 (yarn and fabric dyeing and finishing (processing on commission only)), #73 (fiber yarns), #80 (carpets and floor mats), …, and #378 (other amusement and recreation services)$\}$ and the other composed of the sectors belonging to the set of $V_3 = \{\#341$ (research institutes for natural sciences (private,

non-profit)), #114 (petrochemical aromatic products (except synthetic resin)),…, and #164 (crude steel (electric furnaces), #163 (crude steel (converters))}. If the number of sectors belonging to these sub-networks that have been identified is equal to or smaller than the maximum allowable number of sectors, which is set as $r = 20$ in this study, they are determined as a cluster. The number of sectors belonging to the sets V_2 and V_3, however, exceeds this maximum allowable number of sectors. Therefore, each of the sub-networks formed by the sectors belonging to these sets is divided further into two. In concrete terms, the algorithm is $\Omega = \{V_2, V_3\}$ at this stage. Therefore, one of its elements, i.e. a sub-network that has been detected, is selected. We assume that V_3 has been selected. The adjacency matrix $\mathbf{Q}_{33}^* = \mathbf{Q}^*(V_3, V_3)$ that corresponds to this sub-network is defined and the solution to the problem GEP($\mathbf{Q}_{33}^*$) given by eq. (7) is obtained. Sub-network V_3 is further divided into two sets of industrial sectors, V_4 and V_5, based on the sign of the elements of the solution. Subsequently, we determine whether the number of sectors in each of V_4 and V_5 is greater than the maximum allowable number of sectors. If it does not, the sectors are determined as a cluster and if it does, the sub-networks detected are divided into two again in the same way. These steps are repeated until the calculation is stopped when there is no sub-network which has not been divided into two yet and should be divided because the number of sectors is greater than the maximum allowable number of sectors and further division without producing isolated sectors is possible.

As a result of the analysis, 27 clusters were detected. Although all 27 clusters cannot be described in this article because of space limitations, the results related to the top ten clusters with high "within-cluster effect ($\left\|\mathbf{Q}_{p(k)p(k)}\right\|$)" formulated in the previous section are reported in the following.

(1) Motor vehicle parts and accessories cluster

Figure 1 presents the five clusters from the highest within-cluster effects. The clusters that have the highest within-cluster effect at approximately 20.7 PJ and is the most energy-intensive in the automobile supply chain is the cluster consisting primarily of three sectors including "electrical equipment for internal combustion engines (#244)," "internal combustion engines for motor vehicles and parts (#250)," and "motor vehicle parts and accessories (#251)" as indicated in Fig. 2. Calculation of the degrees of the sectors in this cluster revealed that the degree of "motor vehicle parts and accessories (#251)" was the highest; for this reason, this cluster is named the "motor vehicle parts and accessories cluster" for convenience. The other clusters that were detected were also named similarly. Figure 1 presents consumption by type of energy of the within-cluster effect of this cluster as 9.1 PJ for power consumption and 5.7 PJ for petroleum-based consumption, which comprise approximately 44% and 28%, respectively, of all consumption. These data suggest that the reduction of power consumption and petroleum-based energy in the cluster is the most important issue. Examination of the weight on the edges (i.e. the energy consumption induced by the inter-sectoral transactions) in the graph (the cluster) indicated in Fig. 2 reveals a particularly strong connection of the three major parts assembly manufacturers described earlier with three sectors made up of "cast and forged materials (iron) (#171)," "non-ferrous metal castings and forgings (#182)," and "bolts, nuts, rivets and springs (#188)" in the motor vehicle parts and accessories cluster. According to the information related to the Web site shown by Kinki Forging Cooperative Association (http://www.kintan.jp/forging.html), forged materials are used everywhere on automobiles, as connecting rods, crankshafts, rocker arms, various gears, constant-velocity joints, clutch hubs, and wheels. The development of forged materials therefore constitutes an important key to solving the conflict between the weight reduction of car bodies to improve the fuel-efficiency and hardening of car bodies to ensure collision safety (Osakada, 2009). These estimation results suggest that material development

is important not only to improve fuel efficiency and ensure collision safety on the part of end users through the industrial cooperation between auto-parts manufacturers and forged material manufacturers, but also to reduce energy consumption at the stage of manufacturing forged materials (ferrous and nonferrous) through the development of such materials. In particular, manufacturing of forged materials generally uses not only fuels such as fuel oil and kerosene as heating agents, but a large amount of electric power to operate hammers and forging machines for press (heavy equipment). In addition to the development of forged materials, the manufacturers of forged materials themselves are able to conserve energy of the entire automobile supply chain efficiently by making efforts to reduce the consumption of such energy. The power conservation in the use of forging machinery (heavy equipment) would naturally require cooperation between forged material manufacturers and heavy equipment manufacturers.

[**Insert Figure 1 here**]

[**Insert Figure 2 here**]

(2) Sheet glass and safety glass cluster

Modern cars are lumps of iron and can also be considered lumps of glass. Because of this, it is easily imaginable that a cluster consisting largely of glass manufacturers will be detected. This analysis caused the detection of this cluster as having the second highest within-cluster effect (c.f. Fig. 1). The consumption by type of energy of the within-cluster effect in Fig. 1 reveals that, in particular, the crude oil-based energy and electric power comprise approximately 60% and 31%, respectively, of all consumption in this "sheet glass and safety glass cluster," suggesting that the reduction of these types of energy is the priority

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issue. Figure 3 portrays this cluster's shape, which reveals that the inter-sectoral transactions, among others, from "materials for ceramics (#29)" and "industrial soda chemicals (#108) to "sheet glass and safety glass (#149)" and to "passenger motor cars (#246)," are energy-intensive. Especially, glass manufacturing uses a large amount of fuel oil for melting raw materials such as silica sand and soda ash (Na_2CO_3), which increases crude oil-based energy consumption in the cluster. Glass manufacturing can be expected to reduce its carbon dioxide emissions by substituting natural gas for the fuel oil required in the melting process (Nippon Electric Glass Co., Ltd., 2009). Although tempered glass for automobiles (windshield, windows, etc.) is demanded to offer various features such as shock resistance, safety, insulation, blocking ultraviolet rays, and water repellence, design to reduce to the greatest extent possible the amount of energy-intensive glass used through measures such as weight reduction is needed. The technology for laminated glass (an intermediate membrane is inserted between two sheets of glass) has been developed in recent years, supporting the development of materials that can ensure both weight reduction and safety. It is important that auto-manufacturers adopt such materials with high environmental performance and also that they collaborate closely with glass manufacturers to design glass that meets the market needs.

[**Insert Figure 3 here**]

(3) Motor vehicle bodies cluster

As portrayed in Fig. 1, the cluster with the third highest within-cluster effect was the cluster that had "motor vehicle bodies (#249)" as its downstream sector. This cluster is characterized by the consumption of coal-based energy, which is higher than other clusters. Just as "cast and forged materials (iron)," the development of steel plates, an important material for car bodies, has become increasingly important for reducing the weight of car bodies and ensuring safety. Additionally, Fig. 4 suggests the great importance of reducing the

amount of energy consumed throughout the inter-sectoral transactions from "motor vehicle bodies (#249)" to "hot rolled steel (#165)," "cold-finished steel (#167)," "coated steel (#168)," and "iron and steel shearing and slitting (#172)" in view of the environment. Tanaka and Fujita (2007), for instance, state that the development of high-tensile steel sheets by adopting the thermo-mechanical process technology is necessary for the reduction of car body weight and for improvement of collision safety. However, they fail to mention the degree to which additional energy would be consumed through the use of thermo-mechanical process. If the manufacturing of the new material generates additional energy consumption, then it is important that car body manufacturers and steel plate manufacturers work together and study the extent of fuel efficiency improvement achieved through car body weight reduction and whether the energy reduced by the fuel efficiency improvement exceeds the additional energy generated by the new material manufacturing. Moreover, because car bodies are connected more closely to energy-intensive "coastal and inland water transport (#312)" than other auto-parts, further improvement of logistics is anticipated to help achieve energy conservation.

[**Insert Figure 4 here**]

(4) Other high-ranking clusters

Those clusters with the fourth and fifth highest within-cluster effects were those composed largely of "tires & inner tubes (#142)", and that mostly containing "plastic products (#141)," respectively (see Figs. 5 and 6). These results suggest the continuing importance of energy saving measures in these two sectors. Regarding rubber products, which are important parts of automobiles, increased efforts to reduce energy at the manufacturing stage of rubber products through alliances between auto-parts manufacturers and rubber product manufacturers are demanded. The clusters from the sixth to the tenth highest within-cluster

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effects are provided in the appendix for reference.

[**Insert Figure 5 here**]

[**Insert Figure 6 here**]

5. Nested structure of detected energy-intensive clusters

Section 4 presented results of partitioning the inter-industrial network consisting of 302 sectors after excluding the industrial sectors whose degree is zero from 393 sectors displayed in Table A1 into 27 clusters by applying the method of dividing inter-industrial networks recursively into two sub-networks or clusters based on the normalized cut value. Although the clusters detected were examined individually in Section 4, this section considers mutual relations, i.e. the nested structure of these clusters and sub-networks.

The normalized cut value defined by eq. (3) ranges from 0 to 2 for any graph and its sub-graphs. The 27 clusters presented in the previous section were obtained by dividing the (sub-)networks 26 times, and the minimum value of the corresponding 26 normalized cut values was 1.026, the median is 1.272, and the maximum value is 1.646. These values are substantially larger than the largest normalized cut value (0.04 or 0.08) in the numerical example in the image segmentation presented by Shi and Malik (2000). However, a commonality exists between the image segmentation as a network analysis covered by their analysis and our theme, inter-industrial network analysis, that understanding the clusters' mutual relations as a nested structure is important; as they stated, "it is more appropriate to think of returning a tree structure corresponding to a hierarchical partition instead of a single 'flat' partition (Shi and Malik, 2000, p. 888)." In our analysis, a larger normalized cut value

signifies the greater importance of analyzing the nested structure in addition to the analysis of individual clusters that are detected systematically through the monothetic method presented in Section 2.

Figure 7 depicts the nested structure of sub-networks and clusters obtained by recursively applying the method to partition a (sub-)network into two. Meanwhile, the results of applying the algorithm with $r = 10$ are presented in the figure to present the possibility of further partitioning of the 27 clusters reported in Section 4. The integers in the figure are sequential serial number j of the sub-network (the corresponding set of the industrial sectors is V_j) that is formed in the process of applying the recursive algorithm. The y-coordinate (ordinate) of the point corresponding to each sub-network expresses the number of industrial sectors contained in the sub-network, as indicated in the figure using a logarithmic scale. The solid line in the figure expresses the nested structure of the sub-networks based on recursive division. It shows, for instance, that sub-network 1 was divided into sub-networks 2 and 3 and that sub-network 2 was divided into sub-networks 10 and 11 by application of the algorithm. Furthermore, the division of sub-network 39 into sub-networks 56 and 57 is indicated. Sub-network 39 was not partitioned any more in Section 4 because the number of industrial sectors contained in it is 18, which is less than 20, the maximum allowable number of sectors in a cluster. Therefore, sub-network 39 was reported as a cluster, in which the sector with the highest degree is "motor vehicle parts and accessories (#251)."

The width of each area shaded gray in the figure shows how large the cut value in the recursive algorithm is when a sub-network, say h, is divided into sub-networks i and j, as the ratio of the cut value to the total energy consumption in the inter-industrial network,

which is

$$\frac{Cut(V_i, V_j)}{\|\mathbf{Q}\|} = \frac{\|\mathbf{Q}_{ij}^*\|}{\frac{1}{2}\|\mathbf{Q}^*\|} = \frac{2\|\mathbf{Q}_{ij}^*\|}{\|\mathbf{Q}^*\|} \quad .$$

The three sub-networks h, i, and j have relations of $V_h = V_i \cup V_j$ and

$$\|\mathbf{Q}_{hh}^*\| = \|\mathbf{Q}_{ii}^*\| + \|\mathbf{Q}_{jj}^*\| + \|\mathbf{Q}_{ij}^*\| + \|\mathbf{Q}_{ji}^*\|$$
$$= \|\mathbf{Q}_{ii}^*\| + \|\mathbf{Q}_{jj}^*\| + 2\|\mathbf{Q}_{ij}^*\|$$

among themselves. Now let us regard sub-networks i and j as temporary clusters in the process of the recursive algorithm regardless of the numbers of sectors contained in them. The portions of the within-cluster effect $\|\mathbf{Q}_{hh}^*\|$ of sub-network h that correspond to the within-cluster effects $\|\mathbf{Q}_{ii}^*\|$ and $\|\mathbf{Q}_{jj}^*\|$ of sub-networks i and j are not shaded gray in the figure while the portion that corresponds to energy consumption, $2\|\mathbf{Q}_{ij}^*\|$, not included in either of the within-cluster effects is shaded gray. These amounts of energy are indicated in the figure as the ratio of them to the total energy consumption $\|\mathbf{Q}_{hh}^*\|$. Consequently, by shading the amount not included in the within cluster effects of the sub-networks for each division in the process of recursive algorithm, not only is the hierarchy of the sub-networks expressed with solid lines, but the strength of the relations in terms of the energy consumption between   sub-networks is indicated in the figure. For instance, the cut value when sub-network 1 is divided into sub-networks 2 and 3 is approximately 5.8% of the total consumption (i.e. $2\|\mathbf{Q}_{23}^*\|/\|\mathbf{Q}_{11}^*\| = 0.058$) and the cut value when sub-network 3 is divided into sub-networks 4 and 5 is approximately 45.7% of the total consumption (i.e.

$2\left\|\mathbf{Q}_{45}^{*}\right\|/\left\|\mathbf{Q}_{33}^{*}\right\| = 0.457$).

The most downstream sector in the supply chain expressed by the whole inter-industrial network in the analysis is apparently "passenger motor cars (#246)," and the sub-networks to which the sector belongs are, in order of division based on the recursive algorithm, sub-networks $1 \to 3 \to 5 \to 7 \to 9 \to 14$. Of these five divisions, the cut values of the second one ($3 \to 5$) and the fifth one ($9 \to 14$) are particularly large. The figure implies, therefore, that although close cooperation within sub-network 14 (e.g., between "passenger motor cars (#246)" and "sheet glass and safety glass (#149)") obtained by dividing sub-network 9 is important, collaboration in the entire sub-network 9 (e.g., including "petroleum refinery products (inc. greases) (#138)," which does not belong to sub-network 14) is also highly significant.

Reducing the number of sectors in the clusters by dividing sub-networks is expected to facilitate the communication for the cooperative work among the industrial sectors as the number of alliance partners is reduced. Meanwhile, the communication with a range of partners expanded to the sub-networks before division must be given adequate attention, as noted above. In Fig. 7, some points representing sub-networks before and after the corresponding divisions are on a almost straight vertical line. A typical example is $2 \to 10 \to 58$. These represent the sub-networks surrounding "tires & inner tubes (#142)" or "synthetic rubber (#117)," in which the number of industrial sectors is 77, 17, and 4, respectively. On the other hand, their within-cluster effects are, respectively, 6.9 PJ, 5.7 PJ, and 4.2 PJ. Although the number of industrial sectors is reduced to about one-twentieth in sub-networks 2 to 58, the within-cluster effect declines only to about 60% of the original. Consequently, this is considered a hierarchy of sub-networks in which the importance of

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communication with partners extended to the sub-networks before division is low.   The pair of

sub-networks 25 and 39 is a similar example. The sector of the highest degree in both of these two

sub-networks is "motor vehicle parts and accessories (#251)." The number of industrial sectors

decreases to two thirds from 27 to 18 in the process of dividing sub-network 25 to obtain

sub-network 39 (and sub-network 38). Meanwhile, the within-cluster effect is reduced only to

approximately 80% from 24.5 PJ to 20.7 PJ. Conversely, the part in which the process of

recursive division is drawn as a side-to-side zigzag line is likely to represent a hierarchy in

which the communication with partners extended to the sub-networks before division is

highly demanded.

6. Policy implication

When further reduction of carbon dioxide and other greenhouse gases is necessary to

achieve the goals of the Kyoto Protocol, in May 2008, the Japanese government amended the

Law Concerning the Rational Use of Energy. Before the amendment, individual factories and

offices were necessary to report on their own the amount of their annual energy use (in terms

of crude oil) to the government and be named a designated energy management factory. After

the amendment, however, companies responsible for the entire supply chain concerning their

businesses including factories, offices, and other establishments must report to the

government the mount of energy consumed in the entire supply chain. In other words,

companies must emphasize the energy conservation of a factory alone, but throughout the

entire product lifecycle including material procurement, material processing, parts

manufacturing, finished product manufacturing, and business and sales activities. Evidently,

the government and companies must decide on the targets in the complex product lifecycle

objectively in an effort to reduce energy consumption in the most effective manner using

limited resources. Energy-intensive industrial clusters are identifiable from the entire product supply chains or economic systems using the method of detecting energy clusters proposed in this study. In addition, priorities of the energy saving measures can be determined by measuring the within cluster effect in the clusters. This allows the proposal and implementation of effective energy policy for each cluster.

7. Conclusion

This study has developed a new method of quantitatively identifying energy-intensive industrial clusters from product supply chains by combining structural path analysis and spectral clustering analysis. Detection of industrial clusters from the automobile supply chain using the environmental input–output table of year 2000 caused the discovery of several clusters in which the upstream to downstream sectors are joined together—e.g., from "materials for ceramics (#29)" and "industrial soda chemicals (#108)" to "sheet glass and safety glass (#149)" and then to "passenger motor cars (#246)"—which revealed a composition of sectors that differs significantly from the current Japan Standard Industrial Classification.

The study also proposed the "within-cluster effect" as an indicator of the energy intensity in the industrial clusters identified from the passenger car supply chain and quantitatively analyzed the importance of industrial clusters in terms of the environment. The result of the analysis indicates the cluster with three sectors including "electrical equipment for internal combustion engines (#244)," "internal combustion engines for motor vehicles and parts (#250)," and "motor vehicle parts and accessories (#251)" as the most energy-intensive cluster in the automobile supply chain. The consumption by type of energy of the

within-cluster effect of this cluster reveals extremely high levels of electric power consumption and petroleum-based energy consumption comprising approximately 44% and 28%, respectively, of all energy consumption, suggesting that the most important issue is to reduce the electric power consumption and petroleum-based energy in the clusters. Because this demonstrates, measurement of the within-cluster effect allows the quantitative argument of industrial clusters that should be prioritized in energy-saving measures in the supply chain of the product concerned. This is also capable of specifying the types of energy in industrial clusters that must be reduced.

The Law Concerning the Rational Use of Energy amended in 2008 expanded the range of businesses necessary to control their energy consumption for the purpose of reducing greenhouse gases, encouraging the effective use of fuel resources, and reducing the increased burden on the national economy caused by increased energy prices. The law also encourages energy-saving projects that are jointly pursued by companies from different industries. The responsibility of energy use must be borne not only with the sector concerned but also parties doing business with the sector. For this reason, the identification of policy units that allow efficient joint energy-saving projects becomes an important issue. The new method proposed in this study enables the identification of important and specific policy units in view of energy intensity. The analysis of industrial clusters from product supply chains other than that of automobiles and the analysis of industrial clusters of scarce resources such as precious metals other than energy resources should also be addressed in future studies.

References

Aroche-Reyes, F., 2003. A qualitative input–output method to find basic economic structures, *Papers in Regional Science*, 82, 581–590.

Bellman, R., 1997. *Introduction to matrix analysis*, Society for Industrial and Applied Mathematics, Philadelphia.

Bharadwaj, K.R., 1966. A note on structural interdependence and the concept of a key sector, *Kyklos*, 19, 315–319.

Chung, F.R.K., 1997. Spectral Graph Theory, American Mathematical Society, Providence.

Czamanski, S., Ablas, L.A. 1979. Identification of industrial clusters and complexes: a comparison of methods and findings, *Urban Studies*, 16, 61–80.

Dietzenbacher, E., 1996. An algorithm for finding block-triangular forms, *Applied Mathematics and Computation*, 76, 161–171.

Dietzenbacher, E., 2005. More on multipliers, *Journal of Regional Science*, 45, 421–426.

Feser, E.J., Bergman, E.M., 2000. National industry cluster templates: a framework for applied regional cluster analysis, *Regional Studies*, 34, 1–19.

Feser, E., Sweeney, S., Renski, H., 2005. A descriptive analysis of discrete U.S. industrial complexes, *Journal of Regional Science*, 45, 395–419.

Fiedler, M., 1973. Algebraic connectivity of graphs, *Czechoslovak Mathematical Journal*, 23, 298–305.

Fukui, Y., 1986. A more powerful method for triangularizing input–output matrices and the similarity of production structures, *Econometrica*, 54, 1425–1433.

Ghosh, S., Roy, J., 1998. Qualitative input–output analysis of the Indian economic structure, *Economic Systems Research*, 10, 263–274.

Hazari, B., 1970. Empirical identification of key-sectors in the Indian economy, *Review of Economics and Statistics*, 52, 301–305.

Hendrickson, B., Leland, R., 1995. An improved spectral graph partitioning algorithm for mapping parallel computations, *SIAM Journal on Scientific Computing*, 16, 452–469.

Hirschman, A.O., 1958. The strategy of economic development, Yale University Press, New Haven, CT, USA.

Howe, E.C., 1991. A more powerful method for triangularizing input–output matrices: a comment, *Econometrica*, 59, 521–523.

Kagawa, S., Inamura, H., 2001. A structural decomposition of energy consumption based on a hybrid rectangular input–output framework: Japan's case, *Economic Systems Research*, 13, 339–363.

Kagawa, S., Kudoh, Y., Nansai, K., Tasaki, T., 2008. The economic and environmental consequences of automobile lifetime extension and fuel economy improvement: Japan's case, *Economic Systems Research*, 20, 3–28.

Kagawa, S., Oshita, Y., Nansai, K., Suh, S., 2009. How has dematerialization contributed to reducing oil price pressure?: a qualitative input–output analysis for the Japanese economy during 1990–2000, *Environmental Science & Technology*, 43, 245–252.

Kelton, C.L., Pasquale, M.K., Rebelein, R.P., 2008. Using the North American industry classification system (NAICS) to identify national industry cluster templates for applied regional analysis, *Regional Studies*, 42, 305–321.

Lahr, M.L., Dietzenbacher, E., 2001. *Input–output analysis: frontiers and extensions*, Palgrave, Basingstoke.

Lenzen, M., 2003. Environmentally important paths, linkages and key sectors in the Australian economy, *Structural Change and Economic Dynamics*, 14, 1–34.

Miller, R.E., Blair, R.E., 2009. *Input–output analysis: foundations and extensions*, Cambridge University Press, Cambridge.

Nansai, K., Kagawa, S., Suh, S., Inaba, R., Moriguchi, Y., 2007. Simple indicator to identify the environmental soundness of growth of consumption and technology: "eco-velocity of

Hendrickson, B., Leland, R., 1995. An improved spectral graph partitioning algorithm for mapping parallel computations, *SIAM Journal on Scientific Computing*, 16, 452–469.

Hirschman, A.O., 1958. The strategy of economic development, Yale University Press, New Haven, CT, USA.

Howe, E.C., 1991. A more powerful method for triangularizing input–output matrices: a comment, *Econometrica*, 59, 521–523.

Kagawa, S., Inamura, H., 2001. A structural decomposition of energy consumption based on a hybrid rectangular input–output framework: Japan's case, *Economic Systems Research*, 13, 339–363.

Kagawa, S., Kudoh, Y., Nansai, K., Tasaki, T., 2008. The economic and environmental consequences of automobile lifetime extension and fuel economy improvement: Japan's case, *Economic Systems Research*, 20, 3–28.

Kagawa, S., Oshita, Y., Nansai, K., Suh, S., 2009. How has dematerialization contributed to reducing oil price pressure?: a qualitative input–output analysis for the Japanese economy during 1990–2000, *Environmental Science & Technology*, 43, 245–252.

Kelton, C.L., Pasquale, M.K., Rebelein, R.P., 2008. Using the North American industry classification system (NAICS) to identify national industry cluster templates for applied regional analysis, *Regional Studies*, 42, 305–321.

Lahr, M.L., Dietzenbacher, E., 2001. *Input–output analysis: frontiers and extensions*, Palgrave, Basingstoke.

Lenzen, M., 2003. Environmentally important paths, linkages and key sectors in the Australian economy, *Structural Change and Economic Dynamics*, 14, 1–34.

Miller, R.E., Blair, R.E., 2009. *Input–output analysis: foundations and extensions*, Cambridge University Press, Cambridge.

Nansai, K., Kagawa, S., Suh, S., Inaba, R., Moriguchi, Y., 2007. Simple indicator to identify the environmental soundness of growth of consumption and technology: "eco-velocity of
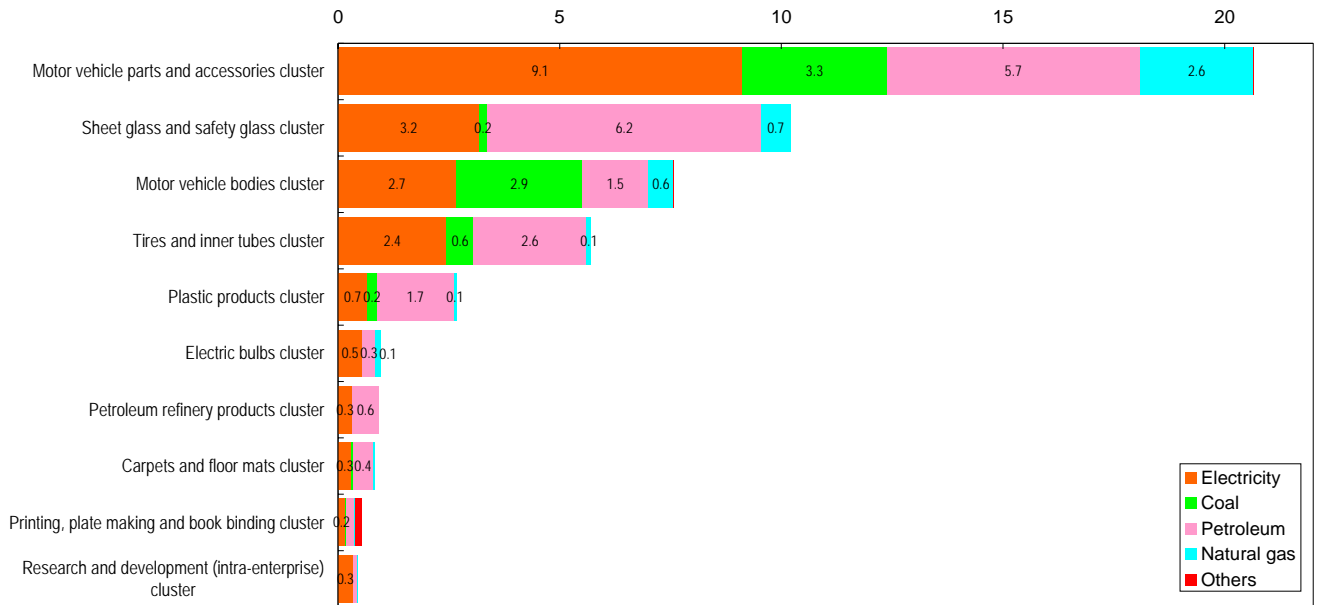
consumption", *Environmental Science & Technology*, 41, 1465–1472.

Nansai, K., Kagawa, S., Suh, S., Fujii, M., Inaba, R., Hashimoto, S., 2009. Material and energy dependence of services and its implications for climate change, *Environmental Science & Technology*, 43, 4241–4246.

Nippon Electric Glass Co., Ltd. (2009) Reduction in CO_2 emissions associated with energy consumptions in Glass manufacturing sector, http://www.meti.go.jp/committee/materials2/downloadfiles/g90527a05j.pdf, last visited on February 2, 2010. (in Japanese)

Takasugi, N. et al., 2009. Nippon Steel Monthly (July), 2–4. (in Japanese)

Tanaka, Y., Fujita, S., 2007. Forecast of the manufacturing technology of high strength steel sheets for lightweight automobile bodies, *JFE Technical Report*, 16, 1–5. (in Japanese)

Oosterhaven, J., Eding, G.J., Stelder D., 2001. Clusters, linkages and regional spillovers: methodology and policy implications for the two Dutch main ports and the rural north, *Regional Studies*, 35 809–822.

Oosterhaven, J., Stelder, D., 2002. Net multipliers avoid exaggerating impacts: with a bi-regional illustration for the Dutch transportation sector, *Journal of Regional Science*, 42, 533–543.

Osakada, K., 2009. The strategy of forging, *Sokeizai*, 50, 68–72. (in Japanese)

Rasmussen, P.N., 1956. *Studies in intersectoral relations*. North-Holland, Amsterdam, Netherlands.

Roepke, H., Adams, D., Wiseman, R., 1974. A new approach to the identification of industrial complexes using input–output data, *Journal of Regional Science*, 14, 15–29.

Shi, J., Malik, J., 2000. Normalized cuts and image segmentation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22, 888–905.

Simpson, D., Tsukui, J. 1965. The fundamental structure of input–output tables: an international comparison, *Review of Economics and Statistics*, 47, 434–446.

Spielman, D.A., Teng, S., 2007. Spectral partitioning works: Planar graphs and finite element meshes, *Linear Algebra and its Application*, 421, 284–305.

Streit, M.E., 1969. Spatial association and economic linkages between industries, *Journal of Regional Science*, 9, 177–188.

von Luxburg, U., 2007. A tutorial on spectral clustering, *Statistics and Computing*, 17, 4, 395–416.

von Luxburg, U., Belkin, M., Bousquet, O., 2008. Consistency of spectral clustering, *The Annals of Statistics*, 36, 555–586.

Weber, C., Schnabl, H., 1998. Environmentally important inter-sectoral flows: insights from main contributions identification and minimal flow analysis, *Economic Systems Research*, 10, 337–356.

Wu, Z., Leahy, R., 1993. An optimal graph theoretic approach to data clustering: theory and its application to image segmentation, *Transactions on Pattern Analysis and Machine Intelligence*, 15, 1101–1113.
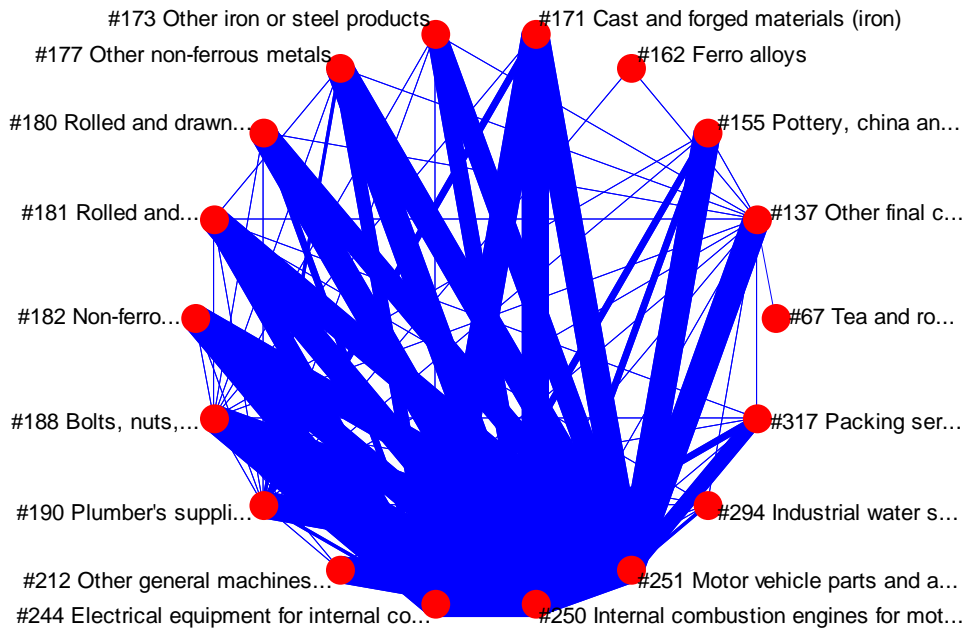
Acknowledgments

Figure 1. Within cluster effects of the energy intensive clusters

from the automobile supply chain of Japan (unit: PJ).

Figure 2. Motor vehicle parts and accessories cluster with the largest within-cluster effect.
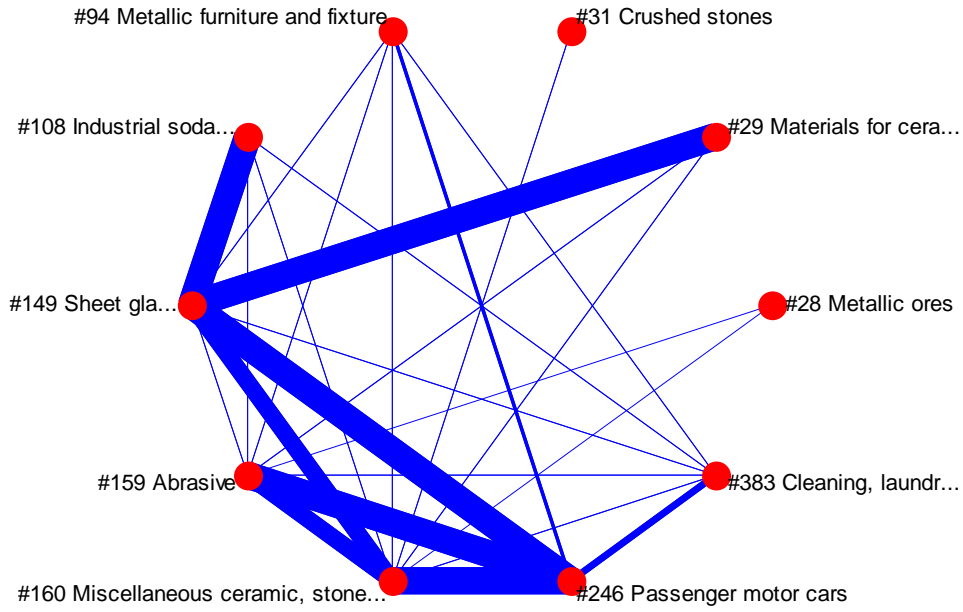
Figure 3. Sheet glass and safety glass cluster with the second largest within-cluster effect.
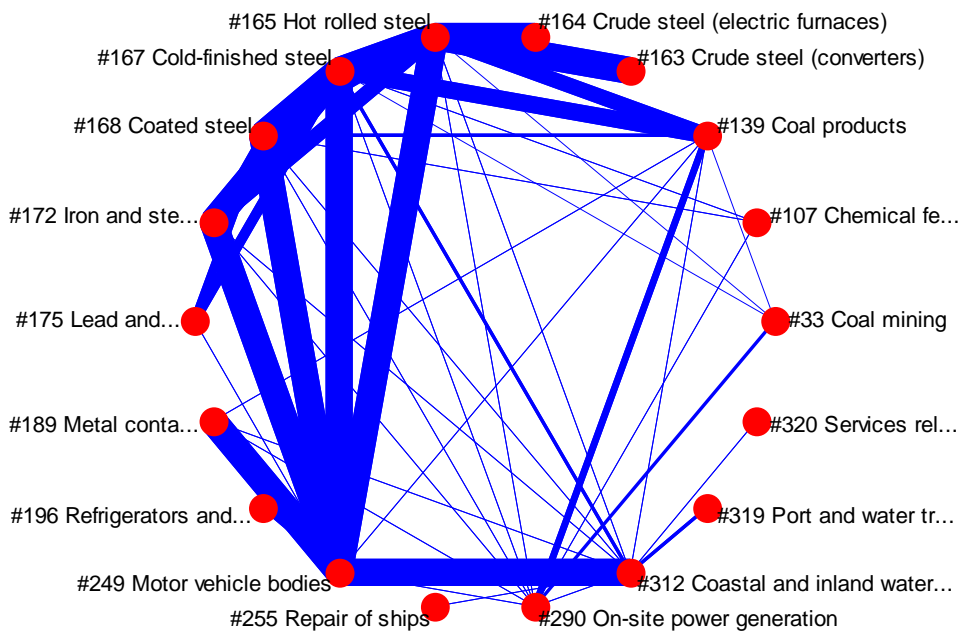
Figure 4. Motor vehicle bodies cluster with the third largest within-cluster effect.
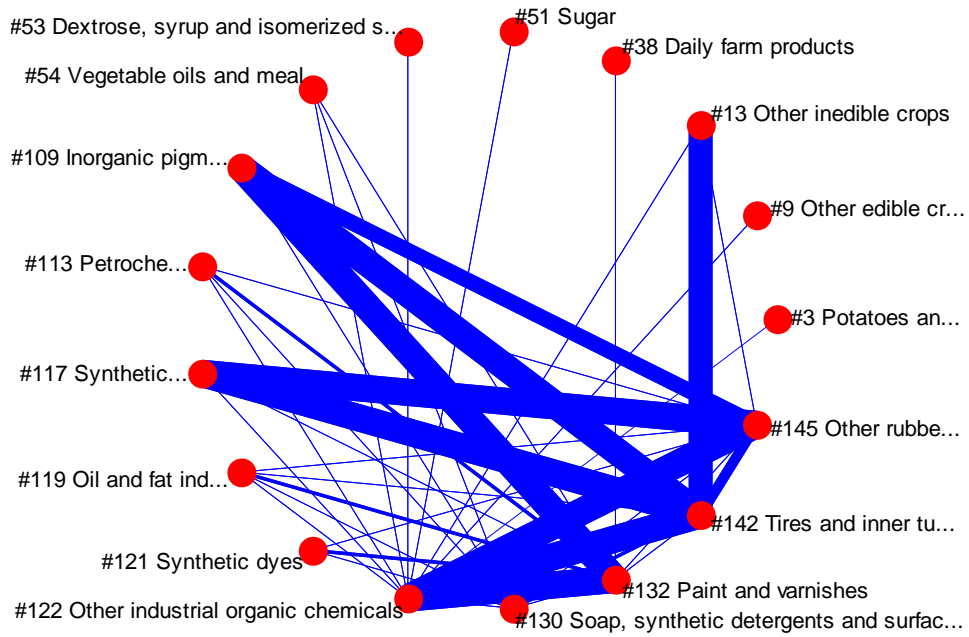
Figure 5. Tires and inner tubes cluster with the fourth largest within-cluster effect.
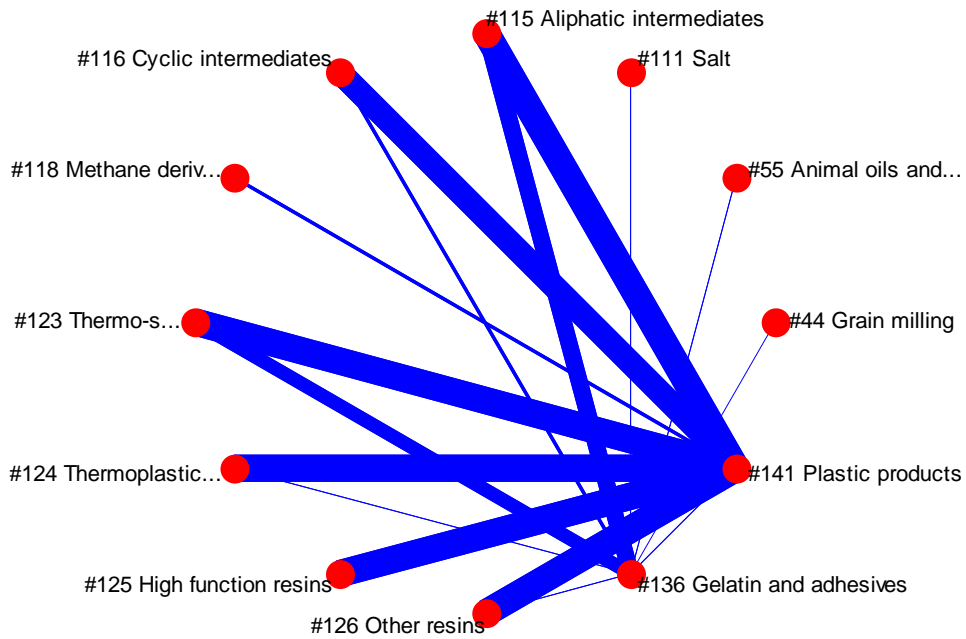
Figure 6. Plastic products cluster with the fifth largest within-cluster effect.

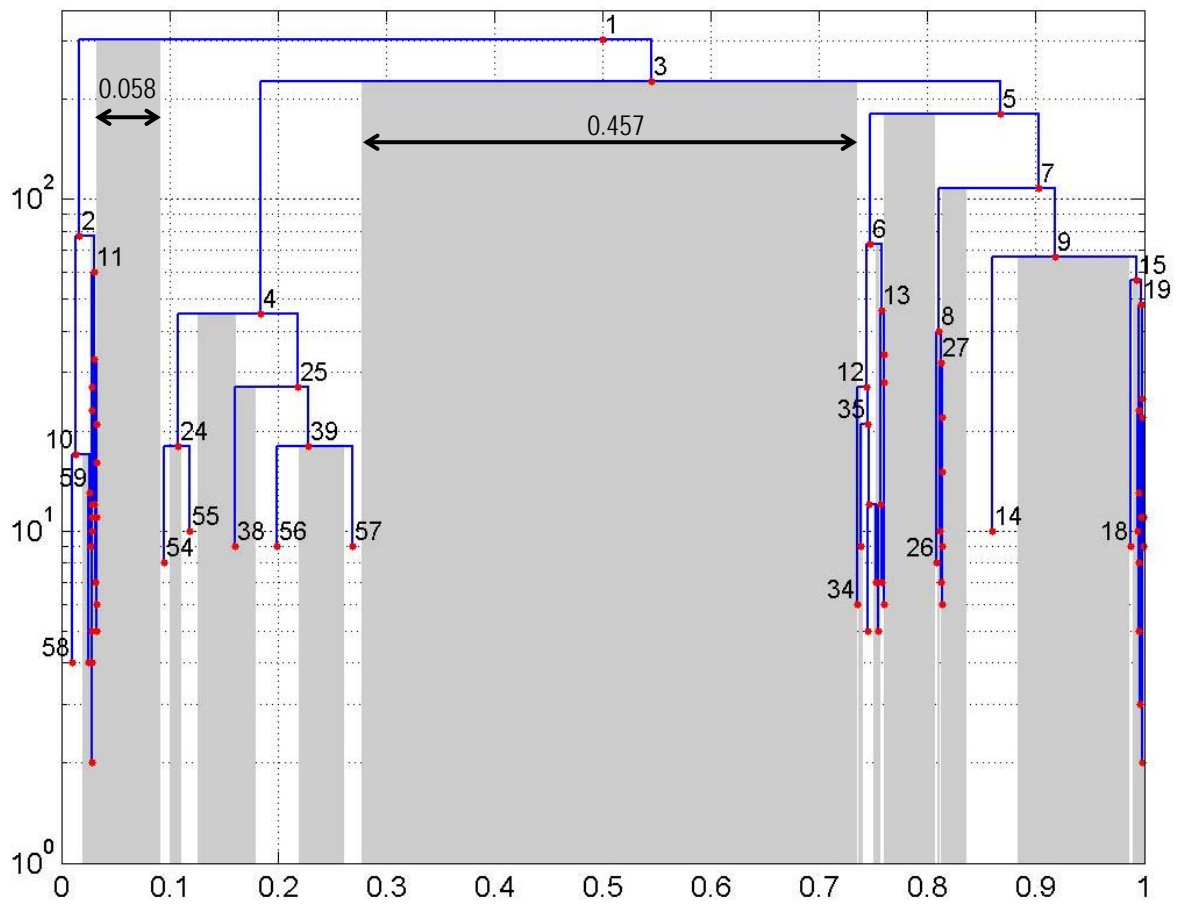**Figure 7**. Nested structure of detecting energy-intensive clusters.

Appendix

Table A1. Sector classification

No.	Sector name	No.	Sector name
1.	Rice	36.	Processed meat products
2.	Wheat, barley, and the like	37.	Bottled or canned meat products
3.	Potatoes and sweet potatoes	38.	Daily farm products
4.	Pulses	39.	Frozen fish and shellfish
5.	Vegetables	40.	Salted, dried or smoked seafood
6.	Fruits	41.	Bottled or canned seafood
7.	Sugar crops	42.	Fish paste
8.	Crops for beverages	43.	Other processed seafood
9.	Other edible crops	44.	Grain milling
10.	Crops for feed and forage	45.	Flour and other grain milled products
11.	Seeds and seedlings	46.	Noodles
12.	Flowers and plants	47.	Bread
13.	Other inedible crops	48.	Confectionery
14.	Daily cattle farming	49.	Bottled or canned vegetables and fruits
15.	Hen eggs	50.	Preserved agricultural foodstuffs (other than bottled or
16.	Fowl and broilers	51.	Sugar
17.	Hogs	52.	Starch
18.	Beef cattle	53.	Dextrose, syrup, and isomerized sugar
19.	Other livestock	54.	Vegetable oils and meal
20.	Veterinary service	55.	Animal oils and fats
21.	Agricultural services (except veterinary service)	56.	Condiments and seasonings
22.	Silviculture	57.	Prepared frozen foods
23.	Logs	58.	Retort foods
24.	Special forest products (inc. hunting)	59.	Dishes, sushi, and lunch boxes
25.	Marine fisheries	60.	School lunch (public)**
26.	Marine culture	61.	School lunch (private)*
27.	Inland water fisheries and culture	62.	Other foods
28.	Metallic ores	63.	Refined sake
29.	Materials for ceramics	64.	Beer
30.	Gravel and quarrying	65.	Whiskey and brandy
31.	Crushed stones	66.	Other liquors
32.	Other non-metallic ores	67.	Tea and roasted coffee
33.	Coal mining	68.	Soft drinks
34.	Crude petroleum and natural gas	69.	Manufactured ice
35.	Slaughtering and meat processing	70.	Feed

No.	Sector name	No.	Sector name
71.	Organic fertilizers, n.e.c.	106.	Publishing
72.	Tobacco	107.	Chemical fertilizer
73.	Fiber yarns	108.	Industrial soda chemicals
74.	Cotton and staple fiber fabrics (inc. fabrics of synthetic	109.	Inorganic pigment
75.	Silk and artificial silk fabrics (inc. fabrics of synthetic	110.	Compressed gas and liquefied gas
76.	Woolen fabrics, hemp fabrics, and other fabrics	111.	Salt
77.	Knitting fabrics	112.	Other industrial inorganic chemicals
78.	Yarn and fabric dyeing and finishing (processing on	113.	Petrochemical basic products
79.	Ropes and nets	114.	Petrochemical aromatic products (except synthetic resin)
80.	Carpets and floor mats	115.	Aliphatic intermediates
81.	Fabricated textiles for medical use	116.	Cyclic intermediates
82.	Other fabricated textile products	117.	Synthetic rubber
83.	Woven fabric apparel	118.	Methane derivatives
84.	Knitted apparel	119.	Oil and fat industrial chemicals
85.	Other wearing apparel and clothing accessories	120.	Plasticizers
86.	Bedding	121.	Synthetic dyes
87.	Other ready-made textile products	122.	Other industrial organic chemicals
88.	Timber	123.	Thermo-setting resins
89.	Plywood	124.	Thermoplastics resins
90.	Wooden chips	125.	High function resins
91.	Other wooden products	126.	Other resins
92.	Wooden furniture and fixtures	127.	Rayon and acetate
93.	Wooden fixtures	128.	Synthetic fibers
94.	Metallic furniture and fixture	129.	Medicaments
95.	Pulp	130.	Soap, synthetic detergents, and surface active agents
96.	Paper	131.	Cosmetics, toilet preparations, and dentifrices
97.	Paperboard	132.	Paint and varnishes
98.	Corrugated cardboard	133.	Printing ink
99.	Coated paper and building (construction) paper	134.	Photographic sensitive materials
100.	Corrugated cardboard boxes	135.	Agricultural chemicals
101.	Other paper containers	136.	Gelatin and adhesives
102.	Paper textiles for medical use	137.	Other final chemical products
103.	Other pulp, paper, and processed paper products	138.	Petroleum refinery products (inc. greases)
104.	Newspapers	139.	Coal products
105.	Printing, plate making and book binding	140.	Paving materials

No.	Sector name		No.	Sector name
141.	Plastic products		176.	Aluminum (inc. regenerated aluminum)
142.	Tires and inner tubes		177.	Other non-ferrous metals
143.	Rubber footwear		178.	Electric wires and cables
144.	Plastic footwear		179.	Optical fiber cables
145.	Other rubber products		180.	Rolled and drawn copper and copper alloys
146.	Leather footwear		181.	Rolled and drawn aluminum
147.	Leather and fur skins		182.	Non-ferrous metal castings and forgings
148.	Miscellaneous leather products		183.	Nuclear fuels
149.	Sheet glass and safety glass		184.	Other non-ferrous metal products
150.	Glass fiber and glass fiber products, n.e.c.		185.	Metal products for construction
151.	Other glass products		186.	Metal products for architecture
152.	Cement		187.	Gas and oil appliances and heating and cooking apparatus
153.	Ready mixed concrete		188.	Bolts, nuts, rivets and springs
154.	Cement products		189.	Metal containers, fabricated plate and sheet metal
155.	Pottery, china, and earthenware		190.	Plumber's supplies, powder metallurgy products and tools
156.	Clay refractories		191.	Other metal products
157.	Other structural clay products		192.	Boilers
158.	Carbon and graphite products		193.	Turbines
159.	Abrasive		194.	Engines
160.	Miscellaneous ceramic, stone and clay products		195.	Conveyors
161.	Pig iron		196.	Refrigerators and air conditioning apparatus
162.	Ferro alloys		197.	Pumps and compressors
163.	Crude steel (converters)		198.	Machinists' precision tools
164.	Crude steel (electric furnaces)		199.	Other general industrial machinery and equipment
165.	Hot rolled steel		200.	Machinery and equipment for construction and mining
166.	Steel pipes and tubes		201.	Chemical machinery
167.	Cold-finished steel		202.	Industrial robots
168.	Coated steel		203.	Metal machine tools
169.	Cast and forged steel		204.	Metal processing machinery
170.	Cast iron pipes and tubes		205.	Machinery for agricultural use
171.	Cast and forged materials (iron)		206.	Textile machinery
172.	Iron and steel shearing and slitting		207.	Food processing machinery
173.	Other iron or steel products		208.	Semiconductor making equipment
174.	Copper		209.	Other special machinery for industrial use
175.	Lead and zinc (inc. regenerated lead)		210.	Metal molds

No.	Sector name	No.	Sector name
211.	Bearings	246.	Passenger motor cars
212.	Other general machines and parts	247.	Trucks, buses, and other cars
213.	Copy machine	248.	Two-wheel motor vehicles
214.	Other office machines	249.	Motor vehicle bodies
215.	Machinery for service industry	250.	Internal combustion engines for motor vehicles and parts
216.	Electric audio equipment	251.	Motor vehicle parts and accessories
217.	Radio and television sets	252.	Steel ships
218.	Video recording and playback equipment	253.	Ships (except steel ships)
219.	Household air-conditioners	254.	Internal combustion engines for vessels
220.	Household electric appliances (except air-conditioners)	255.	Repair of ships
221.	Personal Computers	256.	Rolling stock
222.	Electronic computing equipment (except personal	257.	Repair of rolling stock
223.	Electronic computing equipment (accessory equipment)	258.	Aircraft
224.	Wired communication equipment	259.	Repair of aircraft
225.	Cellular phones	260.	Bicycles
226.	Radio communication equipment (except cellular phones)	261.	Other transport equipment
227.	Other communication equipment	262.	Camera
228.	Applied electronic equipment	263.	Other photographic and optical instruments
229.	Electric measuring instruments	264.	Watches and clocks
230.	Semiconductor devices	265.	Professional and scientific instruments
231.	Integrated circuits	266.	Analytical instruments, testing machines, measuring
232.	Electron tubes	267.	Medical instruments
233.	Liquid crystal element	268.	Toys and games
234.	Magnetic tapes and discs	269.	Sporting and athletic goods
235.	Other electronic components	270.	Musical instruments
236.	Rotating electrical equipment	271.	Audio and video records, other information recording
237.	Relay switches and switchboards	272.	Stationary
238.	Transformers and reactors	273.	Jewelry and adornments
239.	Other industrial heavy electrical equipment	274.	"Tatami" (straw matting) and straw products
240.	Electric lighting fixtures and apparatus	275.	Ordnance
241.	Batteries	276.	Miscellaneous manufacturing products
242.	Electric bulbs	277.	Residential construction (wooden)
243.	Wiring devices and supplies	278.	Residential construction (non-wooden)
244.	Electrical equipment for internal combustion engines	279.	Non-residential construction (wooden)
245.	Other electrical devices and parts	280.	Non-residential construction (non-wooden)

No.	Sector name	No.	Sector name
281.	Repair of construction	316.	Storage facility services
282.	Public construction of roads	317.	Packing services
283.	Public construction of rivers, drainages and others	318.	Facility services for road transport
284.	Agricultural public construction	319.	Port and water traffic control**
285.	Railway construction	320.	Services related to water transport
286.	Electric power facilities construction	321.	Airport and air traffic control (public)**
287.	Telecommunication facilities construction	322.	Airport and air traffic control (industrial)
288.	Other civil engineering and construction	323.	Services related to air transport
289.	Electric power for enterprise use	324.	Travel agency and other services related to transport
290.	On-site power generation	325.	Postal service
291.	Gas supply	326.	Telecommunication
292.	Steam and hot water supply	327.	Other services related to communication
293.	Water supply	328.	Public broadcasting
294.	Industrial water supply	329.	Private broadcasting
295.	Sewage disposal**	330.	Cable broadcasting
296.	Waste management services (public)**	331.	Public administration (central)**
297.	Waste management services (private)	332.	Public administration (local)**
298.	Wholesale trade	333.	School education (public)**
299.	Retail trade	334.	School education (private)**
300.	Financial services	335.	Social education (public)**
301.	Life insurance	336.	Social education (private, non-profit)*
302.	Non-life insurance	337.	Other educational and training institutions (public)**
303.	Real estate agencies and managers	338.	Other educational and training institutions (profit-making)
304.	Real estate rental service	339.	Research institutes for natural science (public)**
305.	House rent	340.	Research institutes for cultural and social science
306.	Railway transport (passengers)	341.	Research institutes for natural sciences (private,
307.	Railway transport (freight)	342.	Research institutes for cultural and social science (private,
308.	Bus transport services	343.	Research institutes for natural sciences (profit-making)
309.	Hired car and taxi transport	344.	Research institutes for cultural and social science
310.	Road freight transport	345.	Research and development (intra-enterprise)
311.	Ocean transport	346.	Medical service (public)
312.	Coastal and inland water transport	347.	Medical service (non-profit foundations, etc.)
313.	Harbor transport service	348.	Medical service (medical corporations, etc.)
314.	Air transport	349.	Health and hygiene (public)**
315.	Freight forwarding	350.	Health and hygiene (profit-making)

No.	Sector name	No.	Sector name
351.	Social insurance (public)**	386.	Public baths
352.	Social insurance (private, non-profit)*	387.	Photographic studios
353.	Social welfare (public)**	388.	Ceremonial occasions
354.	Social welfare (private, non-profit)*	389.	Miscellaneous repairs, n.e.c.
355.	Nursing care (In-home)	390.	Places for private lessons
356.	Nursing care (In-facility)	391.	Other personal services
357.	Private non-profit institutions serving enterprises	392.	Office supplies
358.	Private non-profit institutions serving households, n.e.c.*	393.	Activities not elsewhere classified
359.	Advertising services		
360.	Information services		
361.	News syndicates and private detective agencies		
362.	Goods rental and leasing (except car rental)		
363.	Car rental and leasing		
364.	Repair of motor vehicles		
365.	Repair of machines		
366.	Building maintenance services		
367.	Judicial, financial and accounting services		
368.	Civil engineering and construction services		
369.	Worker dispatching services		
370.	Other business services		
371.	Motion picture and video production, and distribution		
372.	Movie theaters		
373.	Theater and entertainment facilities		
374.	Amusement and recreation facilities		
375.	Stadiums and companies of bicycle, horse, motorcar and motorboat races		
376.	Sport facility service, public gardens and amusement		
377.	Theatrical companies		
378.	Other amusement and recreation services		
379.	General eating and drinking places (except coffee shops)		
380.	Coffee shops		
381.	Eating and drinking places for pleasures		
382.	Hotel and other lodging places		
383.	Cleaning, laundry and dyeing services		
384.	Barber shops		
385.	Beauty shops		

Table A2. Energy sector classification

| No.	Energy sector	No.	Primary and secondary energy resources
1.	Coal-based energy	1.	Coking coal
		2.	Steam coal
		3.	Lignite and anthracite
		4.	Coke
		5.	Blast furnace coke
		6.	Coke oven gas
		7.	BFG consumption
		8.	BFG generation
		9.	LDG consumption
		10.	LDG generation
2.	Petroleum-based energy	11.	Crude oil
		12.	Fuel oil A
		13.	Fuel oils B and C
		14.	Kerosene
		15.	Diesel oil
		16.	Gasoline
		17.	Jet fuel
		18.	Naphtha
		19.	Petroleum-derived hydrocarbon gas
		20.	Hydrocarbon oil
		21.	Petroleum coke
		22.	LPG
3.	Natural gas-based energy	23.	Natural gas
		24.	LNG
		25.	Mains gas
5.	Electricity-based energy	26.	Electric power for enterprise use
		27.	On-site power generation
4.	Other energy	28.	Black liquor
		29.	Waste wood
		30.	Waste tires
		31.	Recycled plastic of packages origin
		32.	Nuclear power generation
		33.	Hydroelectric and other power generations
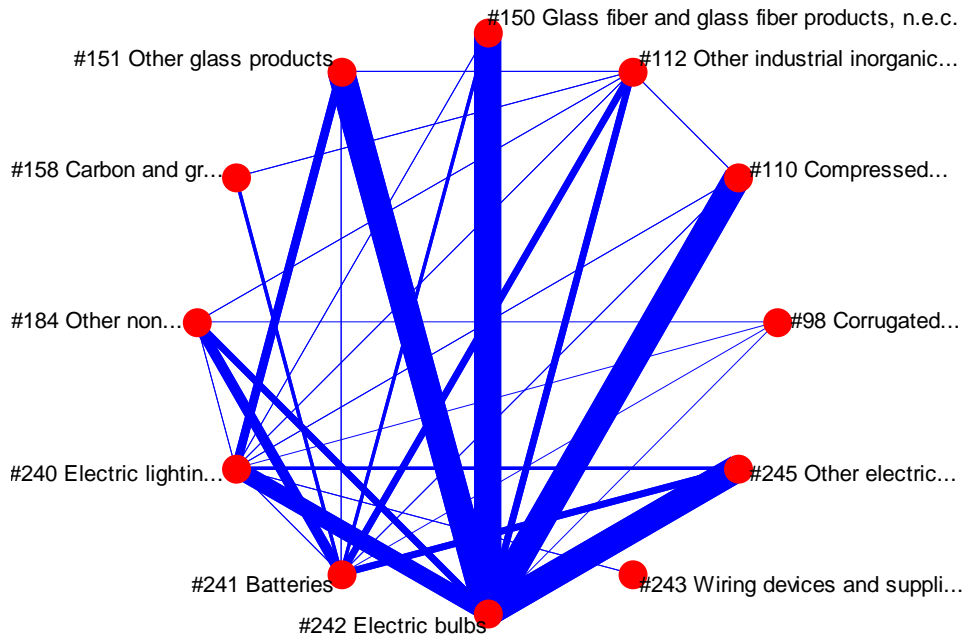
Figure A1. Electric bulbs cluster with the sixth largest within-cluster effect.
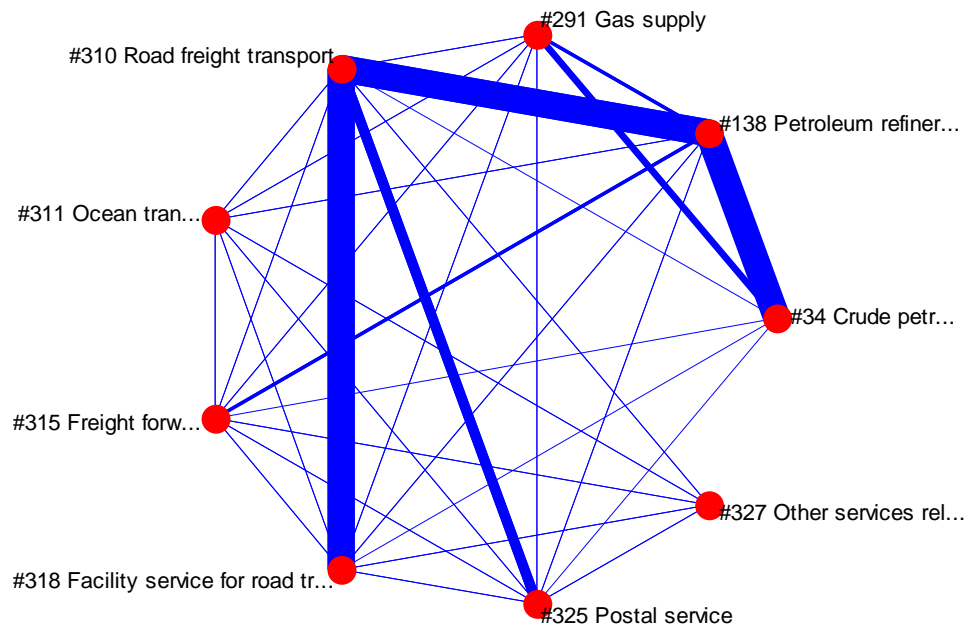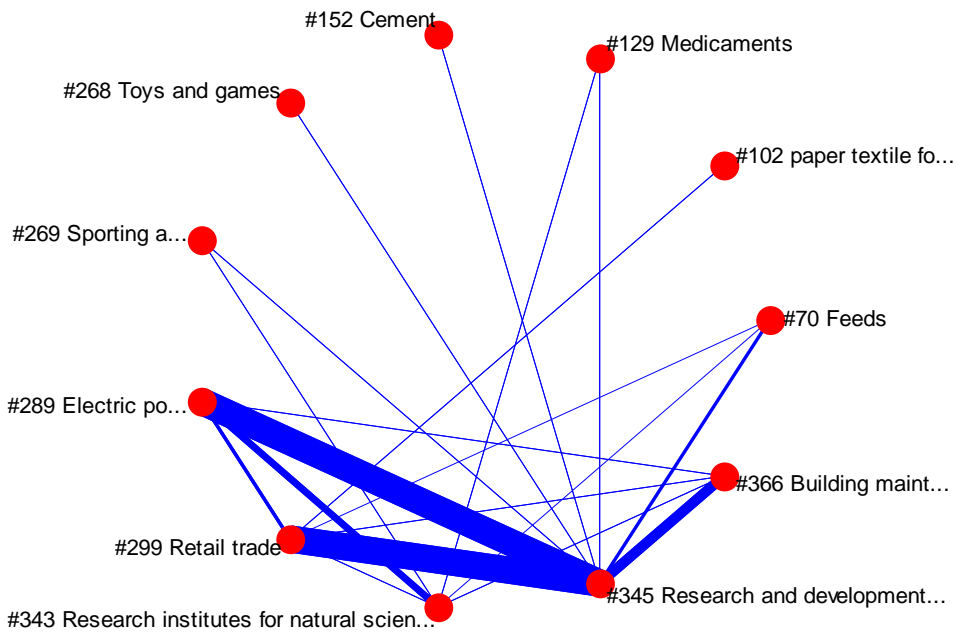

Figure A2. Petroleum refinery products cluster with the seventh largest within-cluster effect.
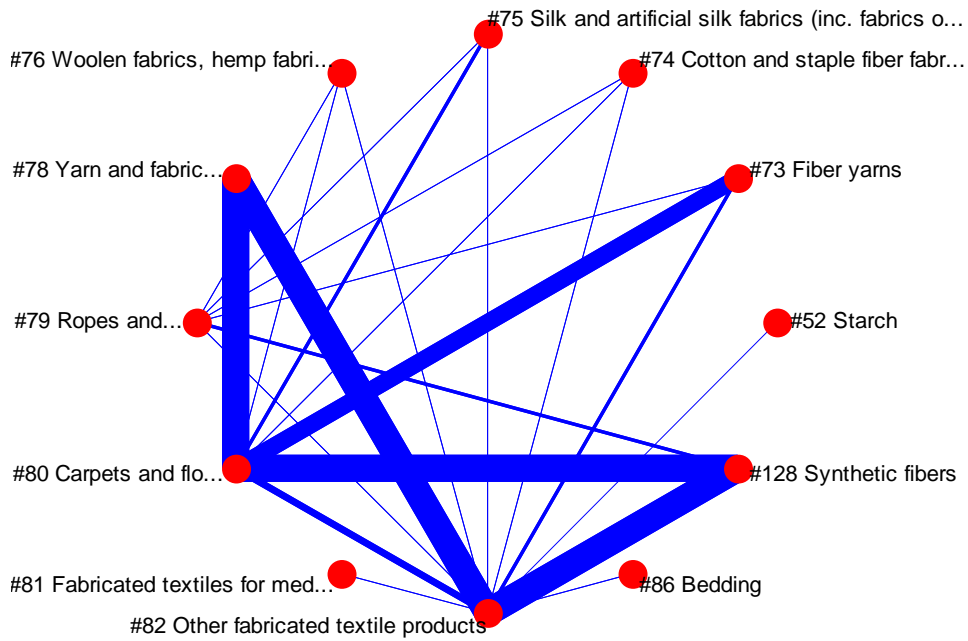
Figure A3. Carpets and floor mats cluster with the eighth largest within-cluster effect.
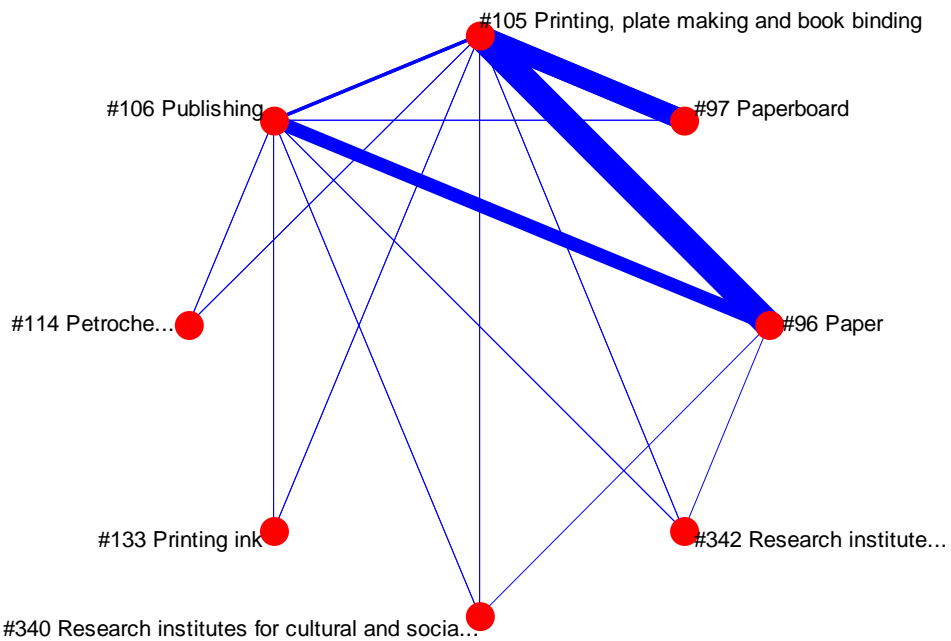
Figure A4. Printing, plate making, and book binding cluster with the ninth largest

within-cluster effect.

Figure A5. Research and development (intra-enterprise) cluster with the tenth largest within-cluster effect.