Key Sectors and Linkages in the Complex Global Supply Chain Network

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Key Sectors and Linkages

in the Complex Global Supply Chain Network

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Contents

Chapter 1: Introduction

1.1. Research background

1.1.1. Global warming and greenhouse gas emissions associated with human activity

Human-induced global warming has been reached 1°C above the global average temperature in pre-industrial levels (IPCC, 2018). In addition, since 1970 the global average temperature has been rising rapidly. The greenhouse gas (GHG) causing global warming, has been concentrated since 2000 about 20 ppm per decade, which is up to 10 times faster than any sustained rise in CO_2 during the past 800,000 years (IPCC, 2018). Global warming causes climate change such as abnormal weather, rising sea levels, threat to biodiversity and risk of human health and food crisis. Thus, United Nations held Stockholm Conference and Earth Summits and discussed "sustainable development", and Kyoto Protocol was adopted at the third session of the Conference of the Parties (COP 3).

In the Kyoto Protocol, developed countries committed themselves to binding targets for GHG emissions, CO_2, methane (CH_4), nitrous oxide (N_2O), Hydrofluorocarbons (HFCs), Perfluorocarbons (PFCs), and Sulphur hexafluoride (SF_6). In the Paris Agreement ratified in December 2015, not only developed countries but developing countries commit themselves to binding targets for GHG emissions and "2-degree temperature target".

1.1.2. Global supply-chain complexity and emission responsibility

Although developed countries such as those included in the Kyoto Protocol Annex I have been striving to reduce territorial CO_2 emissions, the emissions arising from international trade have been rapidly increasing in countries with lax environmental regulations with the expansion of trade and the international fragmentation of production (Peters *et al.*, 2011). Peters *et al.* (2011) demonstrated that CO_2 emissions associated with international trade have increased from 4.3 Gt in 1990 to 7.8 Gt in 2008.

With this background, the Paris Agreement at the 21st Conference of the Parties of the UNFCCC extended emission regulations to developing countries that are *not* included in Annex I (UNFCCC, 2015). In reducing the global CO_2 emissions, developed countries need to consider consumption-based emissions (i.e., emissions arising from domestic final demand) and emission transfers (i.e., emissions produced overseas arising from domestic demand) (e.g., Wiedmann, 2009) and effective cooperation between developed and developing countries is crucial in reducing CO_2 emissions through supply-chain engagement (e.g., Kagawa *et al.*, 2015).

Many studies on the calculation of consumption-based emissions and emission transfers have been done by using Multi-Regional Input-Output (MRIO) Analysis (e.g., Peters *et al.*, 2011; Du *et al.*, 2011). To apply the results of these studies to policy making, policy makers need to focus on high-priority key stakeholders within the global supply-chain (Karstensen *et al.*, 2013). Identifying the key sectors in supply-chain networks is important to advance negotiations for climate mitigation, as it can help inform policy makers about issues such as the transfer of greener technologies.

Identifying key sectors is nontrivial because of the complexity of the global supply-chain network. Methodologies for identifying key sectors and the paths of supply-chains, such as Power and Sensitivity of dispersion (Rasmussen, 1956; Hirschman, 1958; Hazari, 1970; Nagashima *et al.*, 2017; Nakano *et al.*, 2017), Structural Path Analysis and Structural Decomposition Analysis, have been proposed (Lenzen, 2003; Peters and Hertwich, 2005; Wood and Lenzen, 2009; Oshita, 2012). However, analyzing global supply-chains using these methods is not easy due to the large computation time (e.g., Kagawa *et al.*, 2015).

In particular, in recent decades, it can be said that the automotive industry supply-chain network is complex and global. A large part of the value chains associated with the automotive industry in developed countries such as Germany, has been shifted overseas and thus automotive supply-chains have contributed to the world economy (Pavlinek *et al.*, 2011; Timmer *et al.*, 2015; Los *et al.*, 2015). Thus, it can be said that the automotive industry supply-chain network is complex and global. The manufacture of transport equipment uses more indirect energy and emits CO_2 to produce chemical products, metal products, and electricity across its supply-chain than directly onsite (see Figure 1-1).

Los *et al.* (2015) reported that 34% of the total value added in the supply-chain of transport equipment in Germany moved overseas; on the other hand, the fraction of CO_2 emissions in the supply-chain of transport equipment in Germany that moved overseas is 67% (Tokito, 2018). The shift from conventional gasoline-powered cars to the next generation of more fuel-efficient vehicles, such as hybrid, electric and hydrogen vehicles, will reduce CO_2 emissions from the driving phase. On the other hand, this shift will increase CO_2 emissions in the production phase (TOYOTA, 2015). Therefore, detecting key 'upstream' sectors and decreasing their manufacturing emissions is crucial for reducing global CO_2 emissions. To the best of our knowledge, there are few studies analyzing the life-cycle of CO_2 emissions that focus on global automotive supply-chains.

The novelty in this thesis comprises the following two points. First, I discussed the conventional key sector methods and clustering method in the relevant global supply-chain analysis. Second, I identified key sectors, clusters and supply-chain paths for effective reduction in CO_2 emission from the supply-chain of transport equipment.

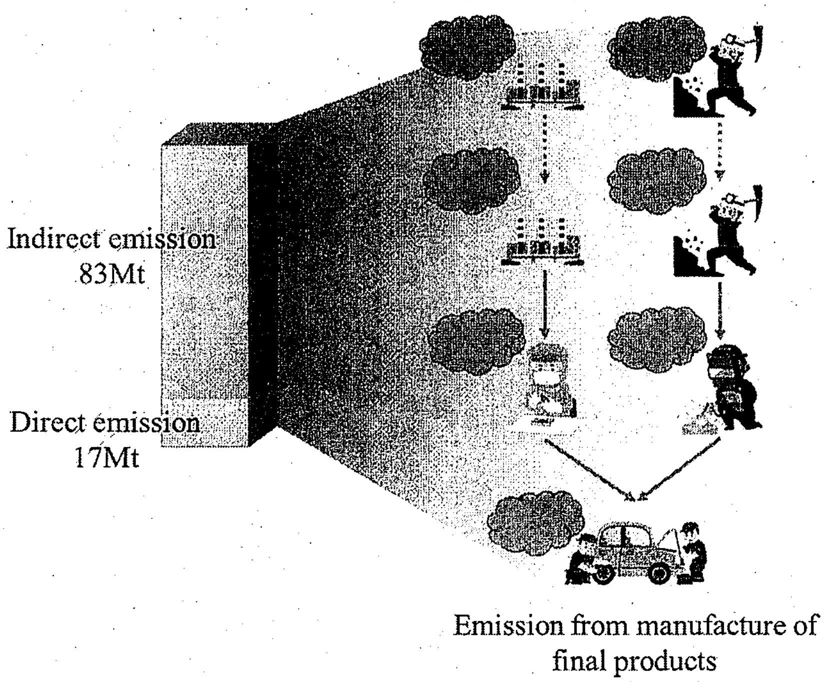

Figure 1-1 CO_2 emissions from global supply-chain of Japanese transport equipment

1.2. Structure of this thesis

This Ph.D. thesis comprises 5 chapters (Figure 1-2). Chapter 2 is a comprehensive literature review focusing on Life Cycle Assessment and Environmentally Extended Input-Output Analysis, related structural analyses, as well as augmented input-output models and industrial cluster analysis. The research objectives and the significance of addressing those objectives are also delineated in this chapter.

Chapter 3 focused on two analysis frameworks of hypothetical extraction method (HEM) and betweenness analysis to identify environmentally important sectors and transactions in supply chain complexity. This chapter derived an analytic expression for the relationship between hypothetical extraction analysis and betweenness centrality analysis. Second, using two widely used multi-regional input-output databases, Eora (Lenzen *et al.,* 2012, 2013) and WIOD (Dietzenbacher *et al.,* 2013; Timmer *et al.*, 2015), this chapter also analyzed how different the "important" sectors detected by two similar approaches, hypothetical extraction analysis and betweenness centrality analysis, are.

Chapter 4 combined the input-output clustering analysis, node betweenness centrality analysis and hypothetical extraction method, and identified critical sectors belonging to important emission clusters with stronger linkages in the global supply chain networks associated with final demand of transport equipment in Japan. Clustering analysis can divide the groups constructing the strong connecting supply chain with large emissions from the global supply chain network, and structural path betweenness represents how much CO_2 emissions from the supply chain paths a sector has in global supply chain network. This chapter applied the combined method to the EORA database which covers 189 countries and focused on the whole global supply chain networks in detail.

Chapter 5 summarizes the analysis results obtained from Chapters 3 and 4, and presents the conclusions of this dissertation.

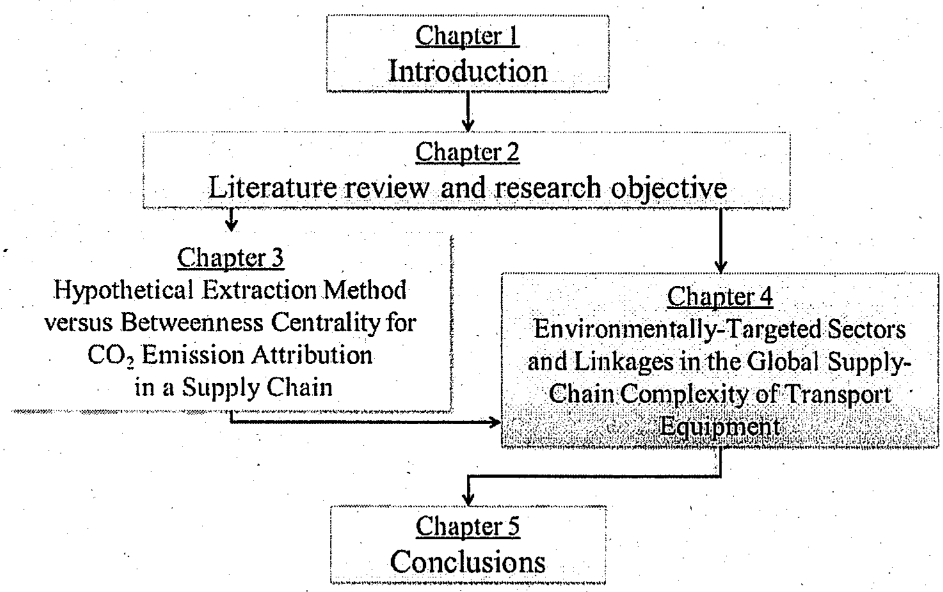

Figure 1-2. Structure of this thesis

Chapter 2: Literature Review

2.1. Life Cycle Assessment and Environmentally Extended Input-Output Analysis

When considering the reduction in global CO_2 emission through the global environmental cooperation, policy maker should focus on not only industries and countries that emit a lot of CO_2 but large consumer industries and countries. Recently, it has been more important to assess total environmental impact of economic activities. Life Cycle Assessment (LCA) has been the standard in the environmental management of most companies in industries as Corporate Social Responsibility (CSR). LCA assesses the environmental impact such as GHG emission and resource use of each stage of life cycle of products, i.e. from mining of materials and processing phase to consumption and disposal.

LCA approach consists of two approaches, process-based approach and input-output approach. When using process-based approach, analyst has to decide 'system boundary', which is the limit of production process that analyst assess. Thus, process-based approach tends to underestimate emissions from production-processing phase (Lenzen, 2001; Raynolds *et al.*, 2000). A combination of process-based and input-output approach is called hybrid LCA. Hybrid LCA has been developed as a compromise to correct for the system boundary problem of process-based approach while taking advantage of its process specificity. Process-based LCA is used to assess the consumption, using and disposal phase because it provides detailed information. On the other hand, input-output approach (Duchin, 1992; Leontief, 1970, 1936; Miller and Blair, 2009) is used to assess the emission of mining of materials and production-processing phase. This is because input-output approach can obtain total emission of supply-chain of a product without decision of system boundary (Acquaye *et al.*, 2011; Lenzen, 2006a; Li *et al.*, 2019; Sato, 2014; Yang *et al.*, 2017).

Increasing globalization and demand of resources which are very unevenly distributed around the world makes global supply-chain more complicated, and that makes it difficult to understand the relationship between producing country and consumption country (Kagawa *et al.*, 2015; Zhang *et al.*, 2017). Main subjects of global environmentally-extended input-output analysis is grasping emission transfer due to the globalization and outsourcing of production to overseas. Global environmentally-extended input-output analysis often adopted two perspectives; *production-based accounting,* which attributes environmental burdens to emitting (producing) countries, and *consumption-based accounting,* which attributes environmental burdens to the consumers who finally avail of those goods (Barrett *et al.*, 2013; Gallego and Lenzen, 2005; Lenzen *et al.*, 2007; Lenzen and Murray, 2010, 2003; Miller and Blair, 2009; Murray and Lenzen, 2001). Adopting these two emission-perspectives, Lenzen *et al.* (2007) discussed emission responsibility between producer and consumer.

When assessing consumption-based emission of products in high-resolution classification level, combining bilateral trade data and domestic input-output data (e.g., Global Link Input-Output model) has been used (Hondo *et al.*, 1998; Liu *et al.*, 2017; Nakano *et al.*, 2009; Nansai *et al.*, 2012, 2009; Peters, 2008; Su *et al.*, 2013; Su and Ang, 2016, 2014, 2013). On the other hand, a lot of previous studies used Multi-Regional Input-

Output model (e.g., Tukker and Dietzenbacher, 2013). Sectors in MRIO are aggregated (Lenzen, 2011; Lenzen *et al.*, 2010; Steen-Olsen *et al.*, 2014) but MRIO model enable us to discuss environmental relationship between developed countries and developing countries spatially. Previous studies analyzed using various environmental-burden data including carbon dioxide (CO_2) (Kanemoto *et al.*, 2014, 2012; Karstensen *et al.*, 2013; Lenzen, 2016; Peters *et al.*, 2011; Peters *et al.*, 2011; Peters, 2008; Peters *et al.*, 2007; Su and Ang, 2014, 2011; Weber and Matthews, 2008, 2007; Wiedmann, 2009; Wiedmann *et al.*, 2010, 2007, 2006), air pollution (López *et al.*, 2013; Moran and Kanemoto, 2016; Nagashima, 2018a; Nagashima *et al.*, 2017; Wang and Song, 2019; Zhang *et al.*, 2017), metal (Nakajima *et al.*, 2011; Nakamura *et al.*, 2007; Nansai *et al.*, 2017, 2014; Tokito *et al.*, 2016) and biodiversity (Moran and Kanemoto, 2017). For example, Moran and Kanemoto (2017) visualized the threat to biodiversity all over the world induced by final demand in United States spatially using Eora database (Lenzen *et al.*, 2013, 2012) covered 189 regions. Besides, various multi-regional input-output database such as WIOD (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015), EXIOBASE (Stadler *et al.*, 2018; Tukker *et al.*, 2013), freely available data, are constructed, and global environmental impact are analyzed using these database.

2.2 Structural Analysis

2.2.1 Key sector analysis

High responsible countries from two emission perspectives, production-based emitters that directly generate large environmental burden and consumption-based emitters that indirectly drive large environmental burden through the supply-chain, can be interpreted as both ends of supply-chain path. At the start point of supply-chain path, large emitting country should be given technological assistance, while at the end point of supply-chain path, large consuming country should inform demand-side measures influencing the choice of final users, such as imposing consumption tax (Liang *et al.*, 2016b). However, not only both ends of supply-chain, producer and consumer, but also intermediate transmission sectors have a large influence on a whole emission. Thus, policy makers in the emission-responsible countries need to focus on a whole supply-chain and detect high-priority key stakeholders within the input-output structure in global supply-chain (Wiebe, 2018). Identifying the key sectors in supply-chain networks is important to advance negotiations for climate mitigation, as it can help inform policy makers about issues such as the transfer of greener technologies. However, identifying key sectors is nontrivial because of the complexity of the global supply-chain.

As the methodologies for identifying key sectors and the paths of supply-chains, with the underlying idea that sectors with strong linkages are in the position to induce the outputs expansion of other sectors, the linkage indicators as measuring interdependencies of sectors have been becoming a common tool. As key sector analysis using IOA, estimation of the *"power of dispersion"* and *"sensitivity of dispersion"* has been suggested (Rasmussen, 1956; Hirschman, 1958; Hazari, 1970; Nagashima *et al.*, 2017; Nakano *et al.*, 2017). These indicators defined the summation of row- or column-vector of Inter-industry transactions matrix as the linkage between sectors (Chenery and Watanabe, 1958; Hazari, 1970). The power of dispersion reflects the *backward linkage* effect, which indicates how much the sector's production induce other sector's production.

While, the sensitivity of dispersion reflects the *forward linkage* effect, how much the sector's production is triggered. These two indicators are used to apply in the field of environmental analysis and detected key sectors for climate mitigation (Lenzen, 2003; Nagashima *et al.*, 2017; Nakano *et al.*, 2017). The forward and backward linkage was defined using another concept, "hypothetical extraction method (HEM)". Hypothetical extraction method (Lahr and Dietzenbacher, 2001; Meller and Marfan, 1981; Miller and Blair, 2009) is to quantify how much the total output of an economy would decrease if a particular sector were removed from that economy. The hypothetical extraction method can be developed to assess the influence of both backward and forward linkage, *"total linkage"*, for a sector (Ali, 2015; Cella, 1984; Dietzenbacher *et al.*, 1993; Dietzenbacher and Lahr, 2013; Meller and Marfan, 1981; Song *et al.*, 2006; Temurshoev, 2010) unlike power and sensitivity of dispersion. There are various methods for detecting the key sector by analyzing changes in the input structure (Casler and Hadlock, 1997; Guilhoto *et al.*, 2005, 1999; Sherman and Morrison, 1950; Sonis *et al.*, 2003, 2000; Wiebe, 2018).

2.2.2 Graph theoretic approach

For understanding a whole input-output structure, inter-industry transactions matrix can be interpreted as an adjacency matrix showing supply chain complexity of industries. Graph theoretic concepts have been widely used to highlight and visualize the important transactions in the supply chain complexity (Rosenblatt, 1957). Qualitative Input-Output Analysis (QIOA) has been proposed to visualize the relation between industrial sectors (Aroche Reyes and Muñiz, 2018; Ghosh and Roy, 1998; Holub and Schnabl, 1985; Kagawa *et al.* 2009; de Mesnard 1995; Titze *et al.,* 2011; Weber and Schnabl, 1998). In addition, key sector analysis using the centrality indicator (Freeman, 1977, 1978) from social network analysis (Friedkin and Johnsen, 1990; Du *et al*., 2017; Amador and Cabral, 2016; Blöchl *et al*., 2011; Brachert *et al*., 2016; Cerina *et al*., 2015; Chen *et al*., 2018; de Mesnard, 1995; Duan and Jiang, 2018; Muñiz, 2013; Muñiz *et al*., 2008; Kagawa *et al*., 2009; Kilkenny and Nalbarte, 1999; McNerney *et al*., 2013; McNerney and Kryazhimskiy, 2009; Wang *et al*., 2017b, 2017a) and has been applied to model the intermediate goods flow network.

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). Input-output analysis is the powerful tool as for tracking the propagation of productions in the global supply chains, and the social network analysis is the useful tool to understand a whole complex and huge network easily(Lantner and Carluer, 2004; Liang *et al*., 2016a; Ohno *et al*., 2016; Tsekeris, 2017; Wakeel *et al*., 2017; Wang *et al*., 2016; Z. Wang *et al*., 2017b, 2017a; Xing, 2017; Xing *et al*., 2017; Zhao, 2015). In particular, betweenness centrality (Freeman, 1977, 1978; Freeman *et al*., 1991) is a major indicator for assess the importance of sectors. Betweenness centrality assess the influence a node has over the spread of information through the network. Betweenness centrality is defined as how often the node appear on shortest paths between the other sectors. A high betweenness-sector has large control over information flowing between others. Thus, the concept of betweenness have been widely used in the field of social networks, world trade networks and urban transportation networks (Liang *et al.,* 2016). In the field of environmental extended input-output network, a high betweenness-sector play the important role to control the emission from a whole supply-chain network. The betweenness centrality in network analysis is mostly measured based on binary networks in which the links between nodes are often undirected, unweighted and single hierarchy network. Previous studies applying centrality analysis to input-output tables have integrated the multiple hierarchical supply chain network into single hierarchy for ease of handling (Figure 2-1). However, links in an input-output network are directed and weighted and have processing hierarchy. Therefore, the concept of links (edges) and paths in input-output network are different from social networks (Lazzarini *et al.*, 2008; Liang *et al.*, 2016b). Thus, it requires significant modification of the betweenness indicator corresponding to the input-output "paths".

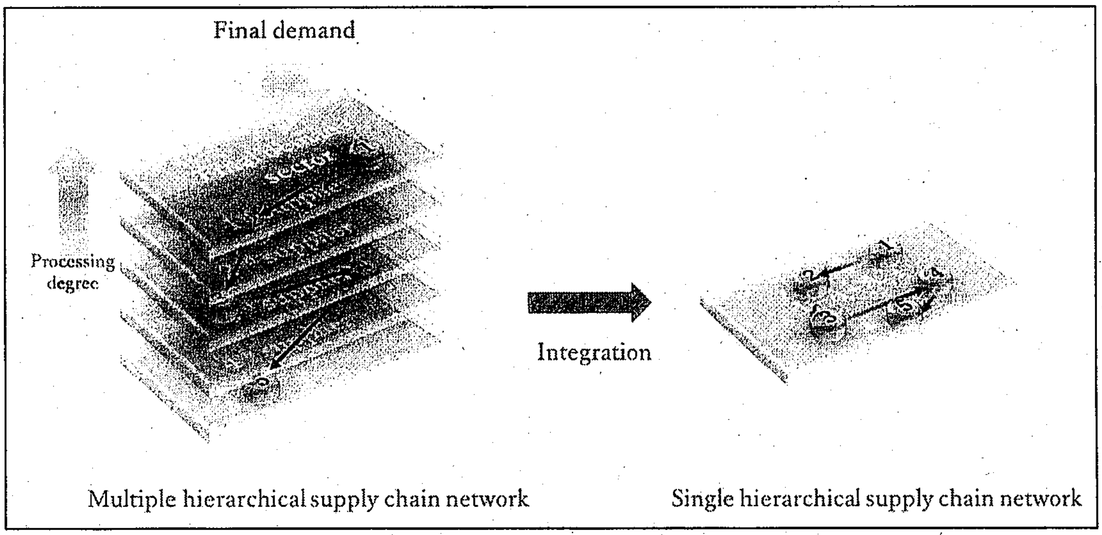

Figure 2-1 Multiple hierarchical network and single hierarchical network

Structural Path Analysis (SPA) (Acquaye *et al.*, 2011; Defourny and Thorbecke, 2006; Lenzen, 2007, 2003; Nagashima, 2018; Nagashima *et al.*, 2017; Oshita, 2012; Peters and Hertwich, 2006; Sonis *et al.*, 2003; Suh, 2004; Treloar *et al.*, 2002; Wood and Lenzen, 2009) has been used to identify important sectors and transactions from the input-output network. Structural path analysis (SPA) can detect important supply-chain paths from complex input-output structures by decomposing Leontief inverse into each "supply-chain paths". SPA has since been used in an environmental extended input-output framework. For example, Nagashima (2017) detected the critical supply-chain paths generating the deceased by PM2.5 in China. SPA defined a supply-chain path as the amount of environmental burden generated by the start point sector (producer) driven by the end point sector producing final products (or consumer) and as a linear chain of sectors in which upstream ones supply downstream ones sequentially. It should be noted that only the start point sector's emissions are counted.

Wood and Lenzen (2009) combined SPA and Structural Decomposition Analysis (SDA)(Lan *et al.*, 2016; Lenzen, 2006b, 2016; Matsumoto *et al.*, 2018; Nagashima, 2018b; Nishijima, 2017; Oshita, 2012; Owen *et al.*, 2014; Peters *et al.*, 2007; Su and Ang, 2016; Tian *et al.*, 2018; H. Wang *et al.*, 2017; Wang and Song, 2019; Wang *et al.*, 2019; Wood *et al.*, 2015), which is the methodology of comparative statics that decomposes the change of emission into some factors, and analyzed the key supply-chain paths in more detail.

Liang *et al.* (2016) suggested betweenness-based method by applying the concept of node betweenness centrality (Freeman, 1977, 1978) into the concept of paths in structural path analysis. Betweenness-based emissions represent both the positional and quantitative importance of a sector in the supply chain network. Hanaka *et al.* (2017) expanded the node betweenness-based emissions to edge betweenness-based emissions and suggested the use of the edge betweenness centrality.

2.3 Cluster analysis

While key sector analysis has been developed, the studies that focus on detecting important sub-network structure from whole network, clustering analysis, has been developed. The clustering method enables us to detect sectors that are large emitters and strongly connected in the supply-chain networks. 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. Previous 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 (1999) 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. However, the computational cost of clustering by using the threshold is quite huge and it is difficult to apply these methods to enormous MRIO networks (Lancichinetti *et al.*, 2009). For this, Kagawa *et al.* (2013a, 2013b) newly developed clustering method in the input-output networks using Normalized cut based on graph theory (Shi and Malik, 2005; Zhang and Jordan, 2008). This method can be easily calculated and more time-saving than conventional clustering methods. Actually, it is applied to various input-output networks and has identified important industrial clusters (Kagawa *et al.*, 2015, 2013a, 2013b; Okamoto, 2015; Rifki *et al.*, 2017; Tokito *et al.*, 2016).

However, Kanemoto *et al.* (2018) pointed out that this clustering method may divide an important transaction to different clusters. For example, it supposes that the direct linkages between material industry, manufacture industry and wholesale industry are relatively strong. However, in the integrated graph defined in (Kagawa *et al.*, 2015, 2013b, 2013a; Rifki *et al.*, 2017), the linkage between manufacture industry and wholesale industry becomes weak due to the emission intensity of manufacture industry. Recently, Kanemoto *et al.* (2018) proposed the fitter clustering method for the input-output networks by modifying it. Although the clustering method proposed in Kanemoto *et al.* (2018) needs too large computation time to apply to Eora database.

2.4 Summary and contribution of the thesis

In the previous studies, the emission responsibility between producing countries and consuming countries has been discussed calculating production-based and consumption-based emission by using global environmental extended input-output analysis. Besides, various key sector analysis has been developed for effective reduction in global environmental burden through the ripple effect on supply-chain.

However, methodologies of detecting key sector, key transaction, paths and clusters in previous studies have computation problem (HEM and SPA) and consistency problem (social network indicator), and they didn't analyze key sectors in a large database like Eora covered 189 countries and regions.

Chapter 3 introduced two analysis frameworks of hypothetical extraction method (HEM) and betweenness analysis to identify environmentally important sectors and transactions in supply chain complexity. Hypothetical extraction method has a computation problem and betweenness analysis has a double-counting problem (Liang *et al.*, 2016). This chapter derived an analytic expression for the relationship between hypothetical extraction analysis and betweenness centrality analysis. Second, using two widely used multi-regional input-output databases, Eora and WIOD, this chapter also analyzed how different the "important" sectors detected by two similar approaches, hypothetical extraction analysis and betweenness centrality analysis, are. In addition, Chapter 3 suggest how to use properly of two methods.

Next, Chapter 4 aimed to identify key sectors and clusters for effective reduction in CO_2 emission from the supply-chain of transport equipment by applying a spectral clustering method and node betweenness centrality analysis to the comprehensive EORA database (Lenzen *et al.*, 2012, 2013). In addition, I analyzed the critical transactions between the clusters detected by using edge hypothetical extraction method. Using the EORA database, which covers 189 countries and regions, enables us to analyze whole supply-chain networks in more detail and detect key sectors and clusters more precisely. From the results of this thesis, I discussed the need for international coordination in the relevant supply-chains.

Chapter 3: Hypothetical Extraction Method versus Betweenness Centrality for CO_2 Emission Attribution in a Supply Chain

3.1. Introduction

The field of Input-Output Analysis (IOA) was developed as the empirical analysis of both the ripple effect induced by changes in the final demand and the interdependencies between different industrial sectors since the 1950s (Chenery and Watanabe, 1958; Leontief, 1936, 1941; Miller and Blair, 2009; Rosenblatt, 1957). Input-output structural analysis allows us to understand complex input-output networks. Previous studies have suggested indicators of key sectors and transactions that affect the whole network environmentally and economically using complex input-output networks (see Table A-1 for the previous relevant researches).

With the underlying idea that sectors with strong linkages are in the position to induce the outputs expansion of other sectors, the linkage indicators as measuring interdependencies of sectors have been becoming a common tool. As key sector analysis using IOA, estimation of the "power of dispersion" and "sensitivity of dispersion" has been suggested (Rasmussen, 1956; Hirschman, 1958; Hazari, 1970; Nagashima *et al.*, 2017; Nakano *et al.*, 2017). These indicators focus on the linkage between sectors. The power of dispersion reflects the backward linkage effect, and the sensitivity of dispersion reflects the forward linkage effect. There are various methods for detecting the key sector by analyzing changes in the input structure (e.g., Casler and Hadlock, 1997; Wiebe, 2018). The hypothetical extraction method (Ali, 2015; Cella, 1984; Dietzenbacher *et al.*, 1993;

Dietzenbacher and Lahr, 2013; Meller and Marfan, 1981; Song *et al.*, 2006; Temurshoev, 2010) is to quantify how much the total output of an economy would decrease if a particular sector were removed from that economy. The hypothetical extraction method can be used to assess the influence of backward and forward linkage for a sector.

Inter-industry transactions matrix can be interpreted as an adjacency matrix showing supply chain complexity of industries. Graph theoretic concepts have been widely used to highlight and visualize the important transactions in the supply chain complexity (Rosenblatt, 1957). Qualitative Input-Output Analysis (QIOA) has been proposed to visualize the relation between industrial sectors (Holub and Schnabl, 1985; Ghosh and Roy, 1998; Weber and Schnabl, 1998)(de Mesnard, 1995; Kagawa *et al.*, 2009; Titze *et al.*, 2011). In addition, key sector analysis using the centrality indicator (Freeman, 1977, 1978) from social network analysis (Friedkin and Johnsen, 1990; Muniz *et al.*, 2008; Kagawa *et al.*, 2009; Brachert *et al.*, 2016; Chen *et al.*, 2017; Du *et al.*, 2017; Duang and Jiang, 2018) and cluster analysis (Kagawa *et al.*, 2015, 2013a, 2013b; Rifki *et al.*, 2017; Tokito, 2018; Tokito *et al.*, 2016) has been applied to model the intermediate goods flow network.

Structural path analysis (Defourny and Thorbecke, 1984; Trelor, 1997; Lenzen, 2003; Suh, 2004; Peters and Hertwitch, 2006; Wood and Lenzen, 2009; Oshita, 2012; Nagashima *et al.*, 2017), betweenness-based emission analysis (Liang *et al.*, 2016) and edge betweenness centrality analysis (Hanaka *et al.*,2017) have been used to identify important sectors and transactions from the I-O network. Structural path analysis is based on economic influence and its transmission throughout the input-output system. Liang *et* *al.* (2016) suggested betweenness-based emission analysis by applying the concept of node betweenness (Freeman, 1977, 1978) into structural path analysis. Betweenness-based emissions represent both the positional and quantitative importance of a sector in the supply chain network. Hanaka *et al.* (2017) expanded the node betweenness-based emissions to edge betweenness-based emissions and suggested the use of the edge betweenness centrality.

Note that both the hypothetical extraction method and betweenness analysis focus on the output from all supply chain paths passing through the sector. However, betweenness centrality is weighted by the number of times the sector appears in the supply chain path. Thus, sectors which have higher betweenness centrality indicators will appear many times in a supply chain. Therefore, as in the policy discussions of Liang *et al.* (2016), Hanaka *et al.* (2017) and Tokito (2018), climate policies for the targeted sector and transaction which have higher betweenness centrality (e.g., reduction in emission intensity) can be implemented effectively using this information to reduce the emissions embedded in the supply chain network.

The novelty in this thesis comprises the following two points. First, I focused on the relationship between the various I-O structural analysis methods mentioned above and in particular, I derived an analytic expression for the relationship between hypothetical extraction analysis (Meller and Marfan, 1981; Cella, 1984; Dietzenbacher, 1993, 2013; Miller and Blair, 2009) and betweenness centrality analysis (Liang *et al.*, 2016; Hanaka *et al.*, 2017; Tokito, 2018). Second, using two widely used databases, Eora (Lenzen *et al.*, 2012, 2013) and WIOD (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015), I analyzed how different the "important" sectors detected by two similar approaches, hypothetical extraction analysis and betweenness centrality analysis, are. When the results of these methods differ greatly, the importance of a sector that is high betweenness sector in the supply chains is ignored. Thus, we can say that betweenness centrality analysis is more appropriate for using the structure of a supply chain network to determine policies to reduce emissions.

The remainder of this Chapter is organized as follows: Sections 3.2 and 3.3 explain the methodology and data used here, Section 3.4 present the results, and Section 3.5 presents the discussion and conclusions.

3.2. Methodology

3.2.1 Leontief model

An intermediate input from industry i to industry j is denoted by $z_{ij}(i, j = 1, \dots, N)$. The final demand for industry i is denoted by $f_i(i = 1, \dots, N)$. Thus, the total output q_i of industry i is defined as $q_i = \sum_{j=1}^{N} z_{ij} + f_i$. If intermediate input coefficients $a_{ij} = z_{ij}/q_j$ are defined, the input coefficient matrix $\mathbf{A} = (a_{ij})$ is constructed as

$$\mathbf{A} = \begin{pmatrix} a_{11} & \cdots & a_{1i} & \cdots & a_{1N} \\ \vdots & \ddots & & & \vdots \\ a_{i1} & & a_{ii} & & a_{iN} \\ \vdots & & & \ddots & \vdots \\ a_{N1} & & a_{Ni} & & a_{NN} \end{pmatrix}$$

$$= \begin{pmatrix} \mathbf{a}_1^c & \cdots & \mathbf{a}_i^c & \cdots & \mathbf{a}_N^c \end{pmatrix}$$

$$= \begin{pmatrix} \mathbf{a}_1^r \\ \vdots \\ \mathbf{a}_i^r \\ \vdots \\ \mathbf{a}_N^r \end{pmatrix}$$

where $\mathbf{a}_i^c$ is the $(N \times 1)$ column vector representing the input coefficient from all sectors to sector i and $\mathbf{a}_i^r$ is the $(1 \times N)$ row vector representing the input coefficient from sector i to all sectors. The first-order indirect economic influence induced by the final demand for industry i is calculated as $\sum_{u=1}^{N} a_{ui} f_i =^t \mathbf{I}\mathbf{a}_i^c f_i$, in which $\mathbf{I}$ is the $(N \times 1)$ column vector whose all elements are 1. Similarly, the second economic influence induced by the final demand of country s from industry i in a country is calculated as $\sum_{v=1}^{N} \sum_{u=1}^{N} a_{vu} a_{ui} f_i = \mathbf{I}\mathbf{A}\mathbf{a}_i^c f_i$. The Leontief model, $x = \mathbf{e}(\mathbf{E} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{eLf}$, can show the full extent of the final demand that directly and indirectly generates the industrial environmental burden x. Here, $\mathbf{e}, \mathbf{E}, \mathbf{f}$ are the emission intensity vector, the identity matrix and final demand vector, respectively, and the Leontief inverse, $\mathbf{L} = (\mathbf{E} - \mathbf{A})^{-1}$ is the direct and indirect requirement matrix. The Leontief inverse involves all ripple effects as

$$x = \mathbf{e}(\mathbf{E}-\mathbf{A})^{-1}\mathbf{f}$$

$$= \mathbf{e}(\mathbf{E}+\mathbf{A}+\mathbf{A}^2+\mathbf{A}^3+\ldots)\mathbf{f}$$

$$= \sum_{i=1}^{N} e_i f_i + \sum_{i=1}^{N}\sum_{j=1}^{N} e_i a_{ij} f_j + \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} e_i a_{ij} a_{jk} f_k + \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} e_i a_{ij} a_{jk} a_{kl} f_l + \ldots$$

(3-1)

where e_i, f_i are the i^{th} element of the emission intensity vector **e** and the final demand vector **f**, respectively, and a_{ij} is the (i, j)th element of the technical coefficient matrix **A**. The Leontief inverse $\mathbf{L} = (l_{ij})$ is constructed as

$$\mathbf{L} = \begin{pmatrix} l_{11} & \cdots & l_{1j} & \cdots & l_{1N} \\ \vdots & \ddots & & & \vdots \\ l_{i1} & & l_{ij} & & l_{iN} \\ \vdots & & & \ddots & \vdots \\ l_{N1} & & l_{Nj} & & l_{NN} \end{pmatrix}$$

$$= \begin{pmatrix} \mathbf{l}_1^c & \cdots & \mathbf{l}_j^c & \cdots & \mathbf{l}_N^c \end{pmatrix}$$

$$= \begin{pmatrix} \mathbf{l}_1^r \\ \vdots \\ \mathbf{l}_i^r \\ \vdots \\ \mathbf{l}_N^r \end{pmatrix}.$$

3.2.2. Hypothetical extraction method

(1) Sector hypothetical extraction method

Using this hypothetical extraction method, we can calculate the impact arising from both the forward and backward direct linkage of a sector. In this Chapter, I calculate the environmental impact of the case that a specific sector i is extracted from the economy. The environmental sector extraction impact x^i can be calculated as follows:

$$x^i = x - \bar{x}^i \tag{3-2}$$

where, x is the total emission from the economy that all sectors exist in, and $\bar{x}^i$ is the total emission from the economy that a specific sector i is extracted from. $\bar{x}^i$ can be obtained using the "extracted" input coefficient matrix $\bar{\mathbf{A}}^i$ as

$$\begin{aligned} \bar{x}^i &= \mathbf{e}\left\{\left(\mathbf{E} - \bar{\mathbf{A}}^i\right)^{-1} - \mathbf{J}_{ii}\right\}\mathbf{f} \\ &= \mathbf{e}\bar{\mathbf{L}}^i\mathbf{f} - e_i f_i \end{aligned}$$

In which, $\bar{x}^i$ is the total emission from the supply chain paths not passing through sector i, and $\mathbf{J}_{uv}$ is the matrix whose (u, v)th element is 1 and the other elements are zero. An element of $\bar{\mathbf{A}}^i = \left(\bar{a}^i_{uv}\right)$ is as:

$$\bar{a}^i_{uv} = \begin{cases} a_{uv} & u \neq i \wedge v \neq i \\ 0 & u = i \vee v = i \end{cases}$$

From the following equation (3-3), the environmental sector extraction impact x^i

can be interpreted as the total emissions associated with the supply chain paths passing through sector i.

$$
\begin{aligned}
x^{i} &= x - \bar{x}^{i} \\
&= \mathbf{eLf} - \left(\mathbf{e}\overline{\mathbf{L}}^{i}\mathbf{f} - e_i f_i\right) \\
&= \mathbf{e}\left(\mathbf{L} - \overline{\mathbf{L}}^{i}\right)\mathbf{f} + e_i f_i \qquad \text{(3-3)} \\
&= \mathbf{e}\left\{\left(\mathbf{E} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \dots\right) - \left(\mathbf{E} + \overline{\mathbf{A}}^{i} + \left(\overline{\mathbf{A}}^{i}\right)^2 + \left(\overline{\mathbf{A}}^{i}\right)^3 + \dots\right)\right\}\mathbf{f} + e_i f_i \\
&= e_i f_i + \sum_{u=1}^{N}\sum_{v=1}^{N}\left(e_u a_{uv} f_v - e_u \bar{a}_{uv}^{i} f_v\right) + \sum_{u=1}^{N}\sum_{v=1}^{N}\sum_{w=1}^{N}\left(e_u a_{uv} a_{vw} f_w - e_u \bar{a}_{uv}^{i} \bar{a}_{vw}^{i} f_w\right) + \dots
\end{aligned}
$$

(2) Edge hypothetical extraction method

Focusing on the direct linkage from sector i to sector j ($i \neq j$), the environmental impact of the case that a specific transaction from sector i to sector j is extracted from the economy also can be calculated. The total impact of extracting the transaction from sector i to sector j, x^{ij} can be obtained alike sector extraction impact as follows:

$$
\begin{aligned}
x^{ij} &= x - \bar{x}^{ij} \\
&= \mathbf{eLf} - \mathbf{e\bar{L}}^{ij}\mathbf{f} \\
&= \mathbf{e}\left(\mathbf{L} - \mathbf{\bar{L}}^{ij}\right)\mathbf{f} \\
&= \sum_{u=1}^{N}\sum_{v=1}^{N}\left(e_u a_{uv} f_v - e_u \bar{a}_{uv}^{ij} f_v\right) + \sum_{u=1}^{N}\sum_{v=1}^{N}\sum_{w=1}^{N}\left(e_u a_{uv} a_{vw} f_w - e_u \bar{a}_{uv}^{ij} \bar{a}_{vw}^{ij} f_w\right) + \ldots\ldots
\end{aligned}
\tag{3-4}
$$

here $\bar{\mathbf{A}}^{ij} = \left(\bar{a}_{uv}^{ij}\right)$ is the input coefficient matrix where the (i, j)th element is zero, and $\bar{\mathbf{L}}^{ij}$ is the "extracted" Leontief inverse calculated by using the "extracted" input coefficient $\bar{\mathbf{A}}^{ij}$. From this equation, the extraction impact of transaction from sector i to sector j, x^{ij} can be understood as the total emission from the supply chains that exclude the supply chain paths not passing through the transaction from sector i to sector j, and can be interpreted as the total emissions associated with the supply chain paths passing through the transaction from sector i to sector j.

3.2.3 Betweenness centrality

(1) Node betweenness centrality

Liang *et al.* (2016) proposed the input-output node betweenness centrality, which is a measure of the betweenness of a specific sector that considers the production tiers in the supply chains. Sectors with higher betweenness centrality transmit larger amounts of CO_2 emissions throughout the supply chains. Using an input-output table, Liang *et al.* (2016) defined b_i as the input-output node betweenness centrality of a specific sector i as follows:

$$b_i = \sum_{s=1}^{n}\sum_{t=1}^{n}\sum_{r=1}^{\infty}\left(q_r \times w\left(s,t \middle| k_1, k_2, \ldots, k_r\right)\right). \tag{3-5}$$

Here, s and t are the start and end sectors of a supply chain path, respectively, q_r is the number of times that sector i appears in the supply chain path, w indicates the weight of the supply chain path starting from sector s and passing through r sectors (k_1, k_2, ..., k_r) to reach end sector t, and w is calculated as

$$w\left(s,t \middle| k_1, k_2, \ldots, k_r\right) = e_s a_{sk_1} a_{k_1k_2} \cdots a_{k_rt} f_t$$

Notice that a particular supply chain path passing through the same sector multiple times increases the sector betweenness. In other words, this definition allows the double-counting of the weight of the same supply chain path based on the number of times that sector i appears in this supply chain path.

Liang *et al.* (2016) formulated $b_i(l_1, l_2)$ as the total emissions associated with the supply chain paths that pass through sector i that has an industrial supply chain with l_1 upstream sectors and l_2 downstream sectors.

$$
\begin{aligned}
b_i(l_1,l_2) &= \sum_{1\le k_1,\dots,k_{l_1}\le n}\ \sum_{1\le j_1,\dots,j_{l_2}\le n}\left(e_{k_1}a_{k_1k_2}\cdots a_{k_{l_1}i}a_{ij_1}\cdots a_{j_{l_2-1}j_{l_2}}f_{j_{l_2}}\right) \\
&= \sum_{1\le k_1,\dots,k_{l_1}\le n}\left(e_{k_1}a_{k_1k_2}\cdots a_{k_{l_1}i}\sum_{1\le j_1,\dots,j_{l_2}\le n}\left(a_{ij_1}\cdots a_{j_{l_2-1}j_{l_2}}f_{j_{l_2}}\right)\right) \\
&= \left(\sum_{1\le k_1,\dots,k_{l_1}\le n}\left(e_{k_1}a_{k_1k_2}\cdots a_{k_{l_1}i}\right)\right)\left(\sum_{1\le j_1,\dots,j_{l_2}\le n}\left(a_{ij_1}\cdots a_{j_{l_2-1}j_{l_2}}f_{j_{l_2}}\right)\right) \\
&= \left(\mathbf{eA}^{l_1}\right)_i\left(\mathbf{A}^{l_2}\mathbf{f}\right)_i \\
&= \mathbf{eA}^{l_1}\mathbf{J}_{ii}\mathbf{A}^{l_2}\mathbf{f}
\end{aligned}
\tag{3-6}
$$

Here, $(\mathbf{eA}^{l_1})_i$ and $(\mathbf{A}^{l_2}\mathbf{f})_i$ are the i^{th} element of the vector $\mathbf{eA}^{l_1}$ and $\mathbf{A}^{l_2}\mathbf{f}$, respectively. Using eq. (3-6), eq. (3-5) can be simplified as follows:

$$
\begin{aligned}
b_i &= \sum_{l_1=1}^{\infty}\sum_{l_2=1}^{\infty}b_i(l_1,l_2) \\
&= \sum_{l_1=1}^{\infty}\sum_{l_2=1}^{\infty}\left(\mathbf{eA}^{l_1}\mathbf{J}_{ii}\mathbf{A}^{l_2}\mathbf{f}\right) \\
&= \mathbf{eAJ}_{ii}\mathbf{Af}+\mathbf{eAAJ}_{ii}\mathbf{Af}+\mathbf{eAAAJ}_{ii}\mathbf{Af}+\dots \\
&\qquad +\mathbf{eAJ}_{ii}\mathbf{AAf}+\mathbf{eAJ}_{ii}\mathbf{AAAf}+\dots \\
&= \sum_{u=1}^{N}\sum_{v=1}^{N}\left(e_u a_{ui}a_{iv}f_v\right)+\sum_{u=1}^{N}\sum_{v=1}^{N}\sum_{w=1}^{N}\left(e_u a_{uv}a_{vi}a_{iw}f_w\right)+\dots \\
&= \mathbf{eTJ}_{ii}\mathbf{Tf} = \mathbf{et}_i^c\mathbf{t}_i^r\mathbf{f}
\end{aligned}
\tag{3-7}
$$

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

$$
\begin{aligned}
\mathbf{T} &= \mathbf{AL} \\
&= \mathbf{A} + \mathbf{A}^2 + \cdots \\
&= \mathbf{L} - \mathbf{E} \\
&= \{t_{uv}\}
\end{aligned}
$$

T is constructed as:

$$
\mathbf{T} = \begin{pmatrix} t_{11} & \cdots & t_{1j} & \cdots & t_{1N} \\ \vdots & \ddots & & & \vdots \\ t_{i1} & & t_{ij} & & t_{iN} \\ \vdots & & & \ddots & \vdots \\ t_{N1} & & t_{Nj} & & t_{NN} \end{pmatrix}
$$

$$
= \begin{pmatrix} \mathbf{t}_1^c & \cdots & \mathbf{t}_j^c & \cdots & \mathbf{t}_N^c \end{pmatrix}
$$

$$
= \begin{pmatrix} \mathbf{t}_1^r \\ \vdots \\ \mathbf{t}_i^r \\ \vdots \\ \mathbf{t}_N^r \end{pmatrix}
$$

It should be noted that the betweenness centrality in Liang *et al.* (2016) does not count the direct emission from sector *i*, $e_i f_i$ and the emission from the 1st supplier *i* triggered by final demand of sector *j*, $e_i a_{ij} f_j$, respectively.

In this Chapter, for comparison of the hypothetical extraction method and input-output betweenness centrality, I reformulated b_i as the environmental input-output node betweenness centrality of a specific sector i as follows:

$$b_i = \sum_{s=1}^{n}\sum_{t=1}^{n}\sum_{r=0}^{\infty}\left(q_r \times w\left(s,t \middle| k_1,k_2,\dots,k_r\right)\right) \tag{3-8}$$

where $w\left(s,t \middle| k_1,k_2,\dots,k_r\right) = e_s a_{sk_1} a_{k_1k_2} \cdots a_{k_r t} f_t$. Note that r can be 0 in eq. (3-8). It means that the betweenness centrality used in this Chapter counted the direct emission from sector i from final demand of sector i. Thus, eq. (3-8) can be reformulated as

$$\begin{aligned} b_i &= \sum_{l_1=0}^{\infty}\sum_{l_2=0}^{\infty} b_i(l_1,l_2) \\ &= \sum_{l_1=0}^{\infty}\sum_{l_2=0}^{\infty}\left(\mathbf{e}\mathbf{A}^{l_1}\mathbf{J}_{ii}\mathbf{A}^{l_2}\mathbf{f}\right) \\ &= e_i f_i + \sum_{u=1}^{N}\left(e_u a_{ui} f_i\right) + \sum_{u=1}^{N}\sum_{v=1}^{N}\left(e_u a_{ui} a_{iv} f_v\right) + \sum_{u=1}^{N}\sum_{v=1}^{N}\sum_{w=1}^{N}\left(e_u a_{uv} a_{vi} a_{iw} f_w\right) + \dots \\ &= \mathbf{eLJ}_{ii}\mathbf{Lf} = \mathbf{e}\mathbf{l}_i^c \mathbf{l}_i^r \mathbf{f} \end{aligned} \tag{3-9}$$

(2) Edge betweenness centrality

Hanaka *et al.* (2017) proposed input-output edge betweenness centrality, which is a measure of the betweenness of transactions in the supply chains. Transactions with higher betweenness centrality transmit larger amounts of CO_2 emissions throughout the supply chains. Reformulating the methodology of Liang *et al.* (2016), Hanaka *et al.* (2017)

defined b_{ij} as the input-output node betweenness centrality of a specific transaction from sector i to sector j ($i \neq j$) with a simple equation (see Hanaka *et al.*, 2017):

$$\begin{aligned} b_{ij} &= a_{ij}\mathbf{eLJ}_{ij}\mathbf{Lf} \\ &= \mathbf{el}_i^c a_{ij} \mathbf{l}_j^r \mathbf{f} \end{aligned} \tag{3-10}$$

3.2.4. Differences between hypothetical extraction methods and betweenness centralities.

In this Chapter, I address the question on what is the difference between the two methods that have a similar concept, the extraction impact x^i and x^{ij} and betweenness centrality b_i and b_{ij}. From the equation A6 and A9, b_i and b_{ij} are described by using x^i and x^{ij} respectively as follows (See Appendix):

$$b_i = (1 + t_{ii})x^i \tag{3-11}$$

$$b_{ij} = (1 + a_{ij} l_{ji})x^{ij} \tag{3-12}$$

From equation (3-11) and (3-12), we can see that the value of the betweenness centrality is always higher than the value of the extraction impact. Figure 3-1 shows the difference between the sector hypothetical extraction method and node betweenness centrality. We can see that x^i and x^j are same but b_i and b_j are distinctly different. The value of betweenness centrality is weighted according to number of times that a sector appears in the supply chain path. From the perspective of betweenness centrality, a sector appearing more times in a supply chain is more important than sectors appearing fewer times for t_{ii} and $a_{ij}l_{ji}$ in the node betweenness and edge betweenness centrality, respectively. Hypothetical extraction method ignored the number of times that a sector appears in the supply chain path. From the perspective of policy implication, technical improvement in a sector appearing more times in supply chain are more effective than sectors appearing less times. When the results of these methods differ greatly, the number of appearing the sector in the supply chain is large, and the sector plays an important role in the supply chain.

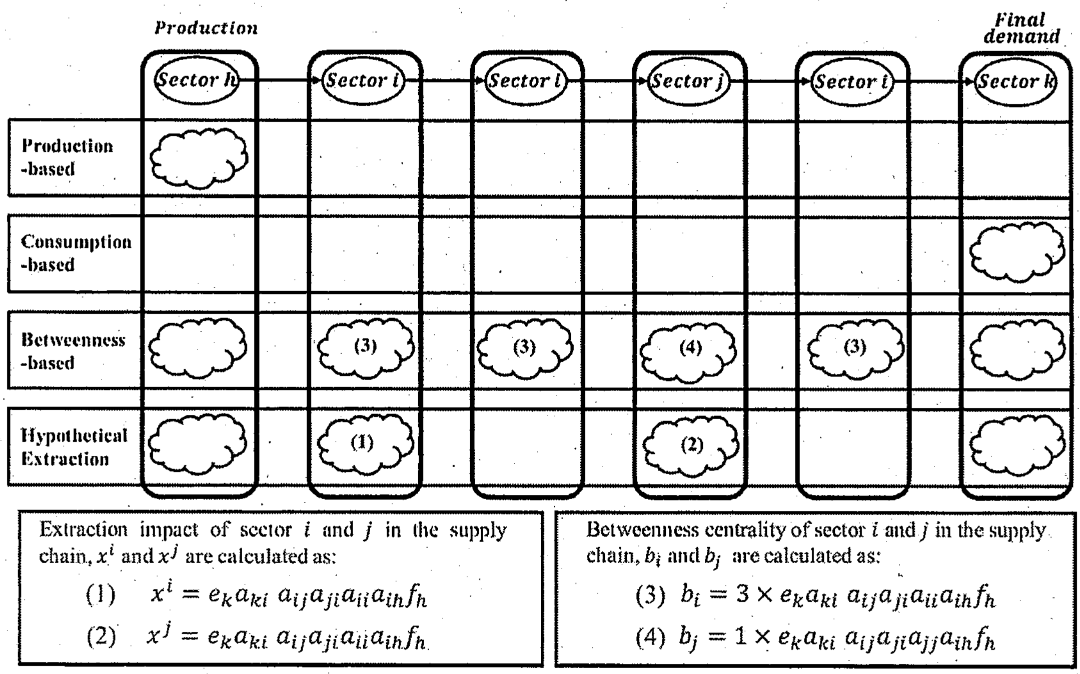

Figure 3-1 Difference between the major emission accountings of production-based, consumption-based, betweenness-based and hypothetical extraction methods.

Suppose that there is an input-output table for three sectors as in Table 3-1. I assume that the emission coefficients are 1 in this example to analyze how differences in the input structure result in differences in the obtained indicators. From the above methods, the input coefficient matrix and the Leontief inverse are defined as in Table 3-2 and 3-3.

Table 3-1 Input-Output table for three sectors

		Industry 1	Industry 2	Industry 3		Final Demand		Total Output
Industry 1	**Z**	50	30	25	**f**	20	**X**	125
Industry 2		20	65	20		30		135
Industry 3		40	30	70		45		185
Value Added		15	10	70				
Total Output		125	135	185				

Table 3-2 Input coefficient matrix

	Industry 1	Industry 2	Industry 3
Industry 1	0.4	0.222	0.135
Industry 2	0.16	0.481	0.108
Industry 3	0.32	0.222	0.378

Table 3-3 Leontief inverse

	Industry 1	Industry 2	Industry 3
Industry 1	2.446	1.379	0.772
Industry 2	1.099	2.704	0.709
Industry 3	1.652	1.676	2.259

The extraction impact and the betweenness centrality of the industries x^i and b_i can be obtained from the equation (3-4) and (3-9), respectively.

Table 3-4 Results of hypothetical extraction method and betweenness centrality

	Rank x^i	x^i	Rank b_i	b_i	t_{ii}	$t_{ii}x^i$
Industry 1	3	265.60	3	649.62	1.45	384.02
Industry 2	2	287.56	1	777.42	1.70	489.87
Industry 3	1	306.24	2	691.90	1.26	385.66

From these two results, we can see that the value and the rank differ depending on the size of t_{ii}. For example, industry 3, which has the highest extraction impact, has a lower betweenness centrality than industry 2. In graph theory, the edges connecting sectors to itself are called "self-loops." If the self-loop is bigger, that means the diagonal element of input coefficient matrix a_{ii} is bigger, the proportion of transaction from sector i to sector i is higher, and the number of supply chains that sector i appears multiple times is bigger. This is mean that t_{ii} which is the total supply chain paths from start sector i to end sector i is bigger. The betweenness centrality emphasizes that the self-loops of sectors are important components of IO networks (Liang *et al.*, 2016).

3.2.5. Analyzing correlation between hypothetical extraction methods and betweenness centralities

I analyzed the substitution of x^i and b_i, x^{ij} and b_{ij}, and calculated the Spearman rank correlation coefficient to see the consistency of the ranks assigned to different sectors by the hypothetical extraction method and betweenness centrality.

3.3. Data

In this thesis, I used the Eora MRIO table for 2015 covering 26 industrial sectors and 189 regions, which is publicly available at http://www.worldmrio.com/ (Lenzen *et al.*, 2012, 2013) and the WIOD MRIO table for 2008 covering 35 industrial sectors and 40 regions, which is publicly available at http://www.wiod.org/home (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015).

3.4. Results

3.4.1. The result of hypothetical extraction method and betweenness centrality analysis

From WIOD for 2008, the emissions from industries in 41 countries total 25598 Mt CO_2. From the production-based CO_2 emissions obtained from WIOD, the largest emitters were China (5923 Mt CO_2), followed by the United States (4550 Mt CO_2), Russia (1515 Mt CO_2), India (1367 Mt CO_2), and Japan (1021 Mt CO_2). The emissions in these five countries accounts for about 70% of the total emissions.

Some studies have reported the production of trade goods in developing countries has also contributed greatly to the increase in CO_2 emissions in recent decades (e.g., Peters, 2011). In this situation, considering the consumption-based emissions is important when assessing the emission responsibility of developed and developing countries (Wiedmann, 2009; Peters, 2011). The emission responsible countries should reduce the CO_2 emission through the climate policy as technology investment to key sectors.

The hypothetical extraction method can be used for detecting key sectors. Using the hypothetical extraction method, I can calculate the magnitude of the linkage between sectors, and the emissions of the supply chain paths passing through a sector or a transaction.

Applying the sector hypothetical extraction method and the edge hypothetical extraction method outlined in (1) and (2) of Sections 3.2.2 to the WIOD, I calculated two indicators and ranks (Tables 3-5 and 3-6; the results for Eora are shown in Appendix). From Table 3-5, the highest extraction impact sector is Electricity, Gas and Water Supply (CHN)(3250Mt-CO_2).

From Table 3-6, we can also see the Chinese sectors have a large extraction impact. Especially, transaction from the Electricity, Gas and Water Supply (CHN) sector or the transaction to the Construction (CHN) sector affect the total emissions throughout the supply chain network.

Table 3-5 Top 10 sectors by extraction impact: WIOD

	Sector name (WIOD)	x^i (Mt-CO_2)
1	CHN _ Electricity, Gas and Water Supply	3250
2	USA _ Electricity, Gas and Water Supply	2318
3	CHN _ Construction	1973
4	RoW _ Electricity, Gas and Water Supply	1861
5	CHN _ Basic Metals and Fabricated Metal	1737
6	CHN _ Other Non-Metallic Mineral	1219
7	CHN _ Electrical and Optical Equipment	1085
8	CHN _ Chemicals and Chemical Products	1078
9	RoW _ Construction	938
10	RoW _ Mining and Quarrying	878

Table 3-6 Top 10 transactions by extraction impact: WIOD

	Source sector		Target sector	x^{ij} (Mt-CO_2)
1	CHN _ Other Non-Metallic Mineral	→	CHN _ Construction	853
2	CHN _ Electricity, Gas and Water Supply	→	CHN _ Basic Metals and Fabricated Metal	608
3	CHN _ Basic Metals and Fabricated Metal	→	CHN _ Construction	425
4	CHN _ Electricity, Gas and Water Supply	→	CHN _ Chemicals and Chemical Products	417
5	RoW _ Electricity, Gas and Water Supply	→	RoW _ Mining and Quarrying	407
6	CHN _ Basic Metals and Fabricated Metal	→	CHN _ Electrical and Optical Equipment	393
7	CHN _ Electricity, Gas and Water Supply	→	CHN _ Mining and Quarrying	337
8	CHN _ Basic Metals and Fabricated Metal	→	CHN _ Machinery, Nec	306
9	CHN _ Electricity, Gas and Water Supply	→	CHN _ Other Non-Metallic Mineral	235
10	RoW _ Other Non-Metallic Mineral	→	RoW _ Construction	222

Hypothetical extraction method analysis allows us to calculate the CO_2 emissions throughout a sector. In the actual supply chain, however, even if the CO_2 emissions are the same, if a sector appears in a supply chain multiple times, then the sector and the transaction will differ in importance. For climate policy, this perspective has important implications because the technical improvement in a sector that appears in a supply chain many times may reduce the more emission from the supply chain than that in a sector that has same extraction impact and appears in the same supply chain only once (see Figure 3-1). Therefore, I analyze the results of the betweenness centrality in the next paragraph.

Applying the node betweenness centrality and edge betweenness centrality outlined in Sections 3.2.3 to the WIOD, I calculated two indicators and sets of ranks (Tables 3-7 and 3-8, and the results for Eora are shown in Appendix).

From Table 3-7, the sector with the highest node betweenness centrality is also Electricity, Gas and Water Supply (CHN)(4806Mt-CO_2). Similar to the results for the extraction impact, the betweenness centrality of Chinese sectors are highest. In the list of the top 10 sectors, the ranks in Table 3-7 are similar to those in Table 3-5. Focusing on the Basic Metals and Fabricated Metal (CHN) sector, this sector is the 5th highest in extraction impact but 2nd highest in betweenness centrality. Thus, I can say the supply chain paths in this sector appear multiple times, and are induced by global final demand more than the supply chains with the 2nd to 4th highest extraction impact. The betweenness centrality reflects the size of the number of times that the sector appears in the supply chain path. Policy makers should focus on Basic Metals and Fabricated Metal (CHN) sector rather than sectors of 2nd to 4th highest extraction impact.

Then, from Table 3-8, we can see the highest edge betweenness centrality transaction is Other Non-Metallic Mineral (CHN) -> Construction (CHN). Similar to the results for the extraction impact, the betweenness centrality of the transactions between the Chinese sectors are highest. In comparison to Hanaka *et al.* (2017), the size of both the node betweenness and edge betweenness of the Chinese sectors and transactions are induced by Chinese final demand.

Note that the value and rank of the results of the edge betweenness and edge hypothetical extraction method are almost the same. This is apparently attributable to self-loop exclusion resulting in differences in both the value and rank being far smaller than those obtained in the results for the nodes. It may therefore be seen that in the Chinese domestic supply chain, particularly in the input from Electricity, Gas and Water Supply (CHN) and the input to Construction (CHN), not only is the intermediate emission rate high but the number of occurrences of the Transaction is large and is important from a graph theory perspective.

Table 3-7 Top 10 sectors by node betweenness centrality: WIOD

	Sector name (WIOD)	b_i (Mt-CO_2)
1	CHN _ Electricity, Gas and Water Supply	4806
2	CHN _ Basic Metals and Fabricated Metal	2747
3	USA _ Electricity, Gas and Water Supply	2332
4	RoW _ Electricity, Gas and Water Supply	2190
5	CHN _ Construction	1999
6	CHN _ Electrical and Optical Equipment	1567
7	CHN _ Chemicals and Chemical Products	1524
8	CHN _ Other Non-Metallic Mineral	1449
9	RoW _ Mining and Quarrying	1172
10	RoW _ Construction	960

Table 3-8 Top 10 transactions by edge betweenness centrality: WIOD

	Source sector		Target sector	b_{ij} (Mt-CO_2)
1	CHN _ Other Non-Metallic Mineral	→	CHN _ Construction	853
2	CHN _ Electricity, Gas and Water Supply	→	CHN _ Basic Metals and Fabricated Metal	610
3	CHN _ Basic Metals and Fabricated Metal	→	CHN _ Construction	425
4	CHN _ Electricity, Gas and Water Supply	→	CHN _ Chemicals and Chemical Products	419
5	RoW _ Electricity, Gas and Water Supply	→	RoW _ Mining and Quarrying	416
6	CHN _ Basic Metals and Fabricated Metal	→	CHN _ Electrical and Optical Equipment	396
7	CHN _ Electricity, Gas and Water Supply	→	CHN _ Mining and Quarrying	343
8	CHN _ Basic Metals and Fabricated Metal	→	CHN _ Machinery, Nec	312
9	CHN _ Electricity, Gas and Water Supply	→	CHN _ Other Non-Metallic Mineral	235
10	RoW _ Other Non-Metallic Mineral	→	RoW _ Construction	222

3.4.2. Correlation between the sector hypothetical extraction method and node betweenness centrality, and the edge hypothetical extraction method and edge betweenness centrality

Applying the sector hypothetical extraction method and node betweenness centrality outlined in (1) of Sections 3.2.2 and 3.2.3 (see Figs. A-1 and 3-2) and the edge hypothetical extraction method and edge betweenness centrality outlined in (2) of Sections 3.2.2 and 3.2.3 (see Figs. A-2 and 3-3) to the WIOD and Eora datasets, I calculated two correlation coefficients (see Table 3-9). These tables show that both correlation coefficients are positive and significant.

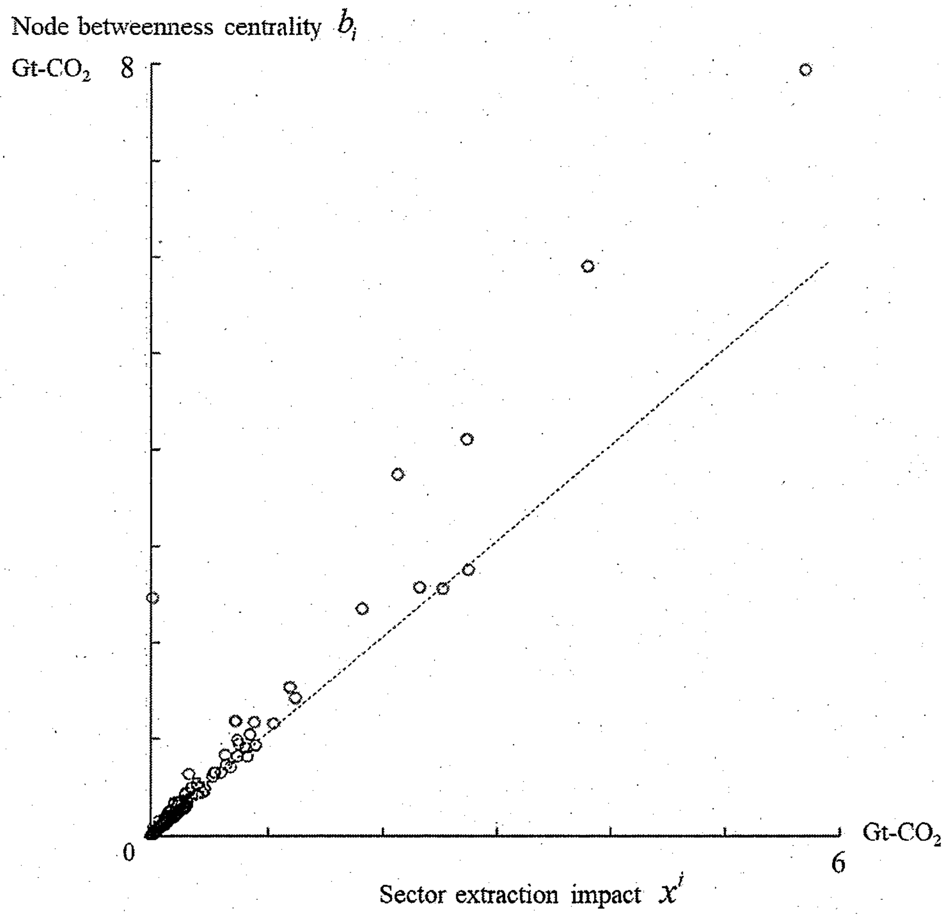

Figure 3-2 Sector extraction impact values versus node betweenness centrality: Eora

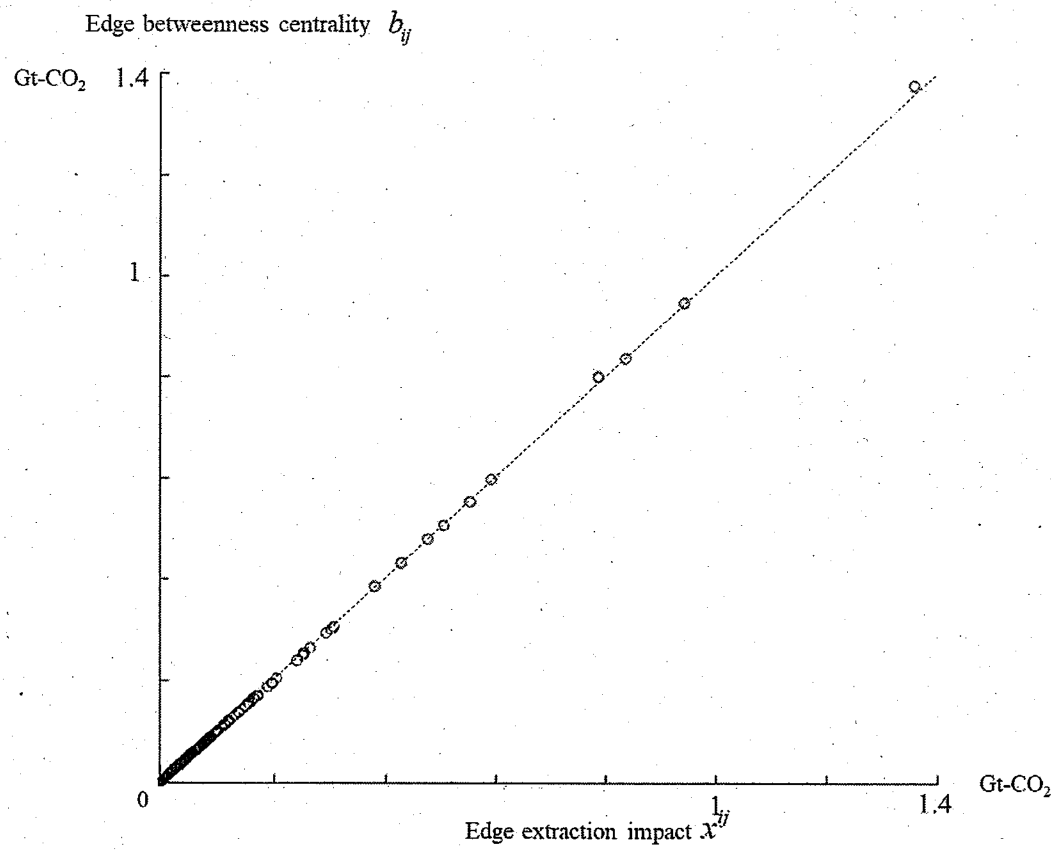

Figure 3-3 Edge extraction impact versus edge betweenness centrality: Eora

Table 3-9 Correlation between the sector hypothetical extraction method and betweenness centrality

	WIOD	Eora
Rank correlation (x^i and b_i)	0.999142	0.999996
Rank correlation (x^{ij} and b_{ij})	0.999998	0.999995

3.5. Discussion and Conclusion

In this thesis, I detected and analyzed the key sectors and transactions in a supply chain by applying the hypothetical extraction method and betweenness centrality to WIOD and Eora. From the results, Electricity, Gas and Water Supply (CHN) was identified as a key sector by both indicators and 12% of the total emissions accompanied the supply chain passing through this sector. On the other hand, Other Non-Metallic Mineral (CHN) -> Construction (CHN) had the highest values for both indicators, and of the CO_2 emissions accompanying the supply chain via Other Non-Metallic Mineral (CHN) and Construction (CHN), these sectors account for 43% and 69%, respectively. Moreover, in the CO_2 emissions via the transactions including Electricity, Gas and Water Supply (CHN), Electricity, Gas and Water Supply (CHN) -> Basic Metals and Fabricated Metal (CHN) is largest, accounting for 18% of the total.

Results from the extraction impact, which is the emissions actually passing through the sector and may be called the sector reduction potential, and the betweenness centrality analysis, which is the value representing the importance of a sector including a weighting based on the number of occurrences, were very similar. Furthermore, the rank correlation of the results for these two indicators is large and positive. The double-counting of transactions did not have a particularly large effect on the results of the edge betweenness, and the results for the two methods were similar.

In the hypothetical extraction method computation, for the calculation of one sector and edge impact, setting the input coefficients and calculating the inverse matrix would take an extremely long time for a large matrix such as the Eora or WIOD datasets. In contrast, computation of the betweenness centrality can be performed using a fixed Leontief inverse matrix and can therefore be accomplished in a very short time. For a large dataset such as WIOD or Eora, an extremely large calculation is necessary and big data can be more readily treated. For analysis of I-O networks that are more global, the computing-volume problem is important. In this Chapter, I showed that the extraction impact can be calculated from the *less computationally-expensive* betweenness centrality obtained using the equations (3-11) and (3-12).

The extraction impacts show the magnitude of influencing outputs of other industries along the supply chains related to transactions of an industry in question, whereas the betweenness centrality shows the importance of networking industries through a node of an industry in question as well as a transaction between the industry in question and another industry. The hypothetical extraction method is widely used to assess inter-industry linkages and the economic importance of industries (e.g., Dietzenbacher *et al.*, 2019). Thus, the both methods have different advantages. Therefore, I propose that researchers firstly use betweenness centrality that is less computationally-expensive and secondly estimate the extraction impacts using equations (3-11) and (3-12) developed in this thesis.

Chapter 4: Environmentally-Targeted Sectors and Linkages in the Global Supply-Chain Complexity of Transport Equipment

4.1. Introduction

Although developed countries such as those included in the Kyoto Protocol Annex I have been striving to reduce territorial CO_2 emissions, the emissions arising from international trade have been rapidly increasing in countries with lax environmental regulations with the expansion of trade and the international fragmentation of production (Peters *et al.*, 2011). Peters *et al.* (2011) demonstrated that CO_2 emissions associated with international trade have increased from 4.3 Gt in 1990 to 7.8 Gt in 2008. With this background, the Paris Agreement at the 21st Conference of the Parties of the UNFCCC extended emission regulations to developing countries that are *not* included in Annex I (UNFCCC, 2015). In reducing the global CO_2 emissions, developed countries need to consider consumption-based emissions (i.e., emissions arising from domestic final demand) and emission transfers (i.e., emissions produced overseas arising from domestic demand) (e.g., Wiedmann, 2009) and effective cooperation between developed and developing countries is crucial in reducing CO_2 emissions through supply-chain engagement (e.g., Kagawa *et al.*, 2015).

In particular, in recent decades, a large part of the value chains associated with the automotive industry in developed countries such as Germany, has been shifted overseas and thus automotive supply-chains have contributed to the world economy (Pavlinek *et al.*, 2011; Timmer *et al.*, 2015; Los *et al.*, 2015). Thus, it can be said that the automotive industry supply-chain network is complex and global. The manufacture of transport equipment uses more indirect energy to produce chemical products, metal products, and electricity across its supply-chain than directly onsite (Kagawa *et al.*, 2013). Los *et al.* (2015) reported that 34% of the total value added in the supply-chain of transport equipment in Germany moved overseas; on the other hand, the fraction of CO_2 emissions in the supply-chain of transport equipment in Germany that moved overseas is 67% (Tokito, 2018). The shift from conventional gasoline-powered cars to the next generation of more fuel-efficient vehicles, such as hybrid, electric and hydrogen vehicles, will reduce CO_2 emissions from the driving phase. On the other hand, this shift will increase CO_2 emissions in the production phase (TOYOTA, 2015). Therefore, detecting key 'upstream' sectors and decreasing their manufacturing emissions is crucial for reducing global CO_2 emissions. To the best of our knowledge, there are few studies analyzing the life-cycle of CO_2 emissions that focus on global automotive supply-chains. This Chapter focused on the supply-chain associated with final demand for production in the "Transport Equipment" sector.

Many studies on the calculation of consumption-based emissions and emission transfers have been done by using Multi-Regional Input-Output (MRIO) Analysis (e.g., Peters *et al.*, 2011; Du *et al.*, 2011). To apply the results of these studies to policy making, policy makers need to focus on high-priority key stakeholders within the global supply-chain (Karstensen *et al.*, 2013). Identifying the key sectors in supply-chain networks is important to advance negotiations for climate mitigation, as it can help inform policy makers about issues such as the transfer of greener technologies.

Identifying key sectors is nontrivial because of the complexity of the global supply-chain network. Methodologies for identifying key sectors and the paths of supply-chains, such as Structural Path Analysis and Structural Path Decomposition Analysis, have been proposed (Lenzen, 2003; Peters and Hertwich, 2005; Wood and Lenzen, 2009; Oshita, 2012). However, analyzing global supply-chains using these methods is not easy due to the large computation time (e.g., Kagawa *et al.*, 2015).

Studies applying network centrality analysis and clustering analysis to such complex industrial networks have been performed to mechanically elucidate the main characteristics of networks (Amador, 2016) and visualize network structures. Various indicators have been proposed (McNerney, 2009; Zhao, 2015; Amador and Cabral, 2016; Liang *et al.,* 2016; Xing, 2017) to enable the application of methodology originally intended for the analysis of somewhat sparse social networks to supply-chain networks that are nearly complete graphs. In this way McNerney (2009), Zhao (2015), Amador and Cabral (2016) and Xing (2017) have used giant MRIO tables to elucidate global value chain structures.

Kagawa *et al.* (2013a, 2013b, 2015) and Okamoto (2015) identified CO_2 emission-intensive supply-chain groups using cluster analysis to understand the structure of production networks and enable the detection of the key sectors of the global supply-chain network. Their methodology can quickly and consistently identify key sectors and clusters. Kagawa *et al.* (2015) analyzed the World Input-Output Database (WIOD) and identified 4756 significant CO_2 clusters from the global supply-chain network associated with the final demand countries. However, they focused on only the 40 countries and regions covered in the WIOD, and many other countries in Asia and Africa that are still developing were not considered in their supply-chain analysis. In addition, Kagawa *et al.* (2015) did not consider sectors that belong to multiple clusters. Thus, understanding the global supply-chain network in more detail is necessary to suggest climate policy for all CO_2 emitting countries.

The clustering method enables us to detect sectors that are large emitters and strongly connected in the supply-chain networks *but* are not suitable targets for reducing CO_2 emissions because there is little inter-industry linkage, and thus less opportunity for emission reductions from adopting greener technology in such sectors, due to their fewer connections to other sectors.

Liang *et al.* (2016) proposed the concept of input-output node betweenness centrality to identify sectors transmitting large amounts of CO_2 emissions throughout their supply-chains. Applying a policy to sectors with higher betweenness is much more effective across the whole network, because global CO_2 emissions are efficiently reduced through the inter-industry linkages centered around the key sectors with higher betweenness. A combination of the clustering analysis and the structural betweenness analysis can identify the environmentally important clusters including the key sectors with higher betweenness. Hanaka *et al.* (2017) expanded the node betweenness-based emissions to edge betweenness-based emissions and suggested the use of the edge betweenness centrality. The concept of these methods is similar to the hypothetical extraction method (Meller and Marfan, 1981; Cella, 1984; Dietzenbacher, 1993, 2013), which is to quantify how much the total output of an economy would decrease if a particular sector were removed from that economy. The hypothetical extraction method can be used to assess the influence of backward and forward linkage for a sector. However, betweenness centrality is weighted by the number of times the sector appears in the supply-chain path.

This Chapter aimed to identify key sectors and clusters for effective reduction in CO_2 emission from the supply-chain of transport equipment by applying a spectral clustering method and node betweenness centrality analysis to the comprehensive EORA database (Lenzen *et al.*, 2012, 2013). In addition, I analyzed the critical transactions between the clusters detected by using edge hypothetical extraction method. Using the EORA database, which covers 189 countries and regions, enables us to analyze whole supply-chain networks in more detail and detect key sectors and clusters more precisely. From the results of this thesis, I discussed the need for international coordination in the relevant supply-chains.

The remainder of this Chapter is organized as follows: Section 4.2 explains the methodology used here, Sections 4.3 and 4.4 present and discuss the results, and Section 4.5 presents the conclusions.

4.2. Methodology

4.2.1. Unit structure model

In this section, I define adjacency matrices of the CO_2 emissions associated with global commodity flows. An intermediate input from industry i in country r to industry j

in country s is defined as $Z_{ij}^{rs}(i,j=1,\dots,M;r,s=1,\dots,N)$. The final demand from industry i in country r to final consumers in country s is defined as $F_i^{rs}(i=1,\dots,M;r,s=1,\dots,N)$. As a result, the total output of industry i in country r is defined as $x_i^r=\sum_{s=1}^{N}\sum_{j=1}^{M}Z_{ij}+\sum_{s=1}^{N}F_i^{rs}$. If intermediate input coefficients $a_{ij}^{rs}=Z_{ij}^{rs}/x_j^s$ are defined, the widely used MRIO model can be formulated as $\mathbf{x}=\mathbf{A}\mathbf{x}+\mathbf{f}$ in matrix notation (e.g., Kagawa *et al.*, 2015), where $\mathbf{x}=(x_j^s)$, $\mathbf{A}=(a_{ij}^{rs})$ and $\mathbf{f}=(\sum_{s=1}^{N}F_i^{rs})$. The MRIO model, $\mathbf{x}=(\mathbf{E}-\mathbf{A})^{-1}\mathbf{f}=\mathbf{L}\mathbf{f}$, can show the extension of the final demand that directly and indirectly generates the industrial output. Here, $\mathbf{E}$ is the identity matrix, and $\mathbf{L}=(\mathbf{E}-\mathbf{A})^{-1}=(l_{ij}^{rs})$ is the direct and indirect requirement matrix that represents how many units of a product of industry i in country r are needed to produce one unit of a product of industry j in country s. If the industrial CO_2 emission per unit of output of industry i in country r is defined as the vector $\mathbf{e}=(e_i^r)$, then the global CO_2 emission transaction matrix can be represented with the following equation:

$$\mathbf{X}=\hat{\mathbf{e}}\mathbf{L}\,\mathrm{diag}(\mathbf{f}) \tag{4-1}$$

where $\hat{\mathbf{e}}$ is a diagonal matrix whose diagonal elements are the CO_2 emissions per unit of output of industry i in country r.

Ozaki (1980) introduced the unit structure model that represents the economic transactions associated with the final demand for products for a specific industry j in a specific country s. Using this model, I can obtain the induced demand for the products of industry j in country s, described as $\mathbf{x}_j^s=\mathbf{l}_j^s f_j^s$, where $\mathbf{l}_j^s$ represents the direct and indirect requirement for one unit of production of industry j in country s, which is the

$\{(s-1)\times M+j\}$th column vector in $\mathbf{L}$. f_j^s is the final consumption of products of industry j in country s. Consequently, the study presented a new version of the economic network model, $\mathbf{X}_j^s=\mathbf{A}\mathrm{diag}(\mathbf{l}_j^s f_j^s)$, which shows the economic transactions that are triggered by the final demand for industry j in country s.

Using the emission intensity vector, the global CO_2 emissions $\mathbf{X}_j^s=(x_{ij}^{rs})$ induced by the geographical inter-industry deliveries from industry i in country r to industry j in country s and associated with the final demand for a specific industry j in a specific country s can be formulated as follows (Kagawa *et al.*, 2015):

$$\mathbf{X}_j^s=\hat{\mathbf{e}}\mathbf{A}\,\mathrm{diag}\left(\mathbf{l}_j^s f_j^s\right) \tag{4-2}$$

This thesis considered the directed graph of the CO_2 emissions associated with the geographical flow between industry i in country r and industry j in country s. Each sector is defined as a vertex, and the emission transfers between sectors are indicated by arcs weighted by the total emissions.

This Chapter focused on the "Transport Equipment" sector. Over 60% of the global production of transport equipment was attributed to five countries in the EORA database; the United States, China, Germany, Japan and France. This thesis considered Japan and the industry "Transport Equipment".

Following Kagawa *et al.* (2013b) and Tokito *et al.* (2016), I used a cluster analysis method based on nonnegative matrix factorization (NMF). I partitioned the CO_2 emission flow network of international trade $\mathbf{G} = (g_{ij}^{rs})$ into K groups (hereafter K clusters). Here, g_{ij}^{rs} represents the CO_2 emission flow associated with trade volume between sector i in country r and sector j in country s (exports from sector i in country r to sector j in country s + imports from sector j in country s into sector i in country r), and matrix $\mathbf{G}$ is the adjacency matrix, thus $g_{ij}^{rs} = g_{ji}^{sr}$. The diagonal components of $\mathbf{G}$ are zero and I excluded the domestic CO_2 emissions from the network data. I defined the symmetric adjacency matrix $\mathbf{G} = (g_{ij}^{rs})$ from the unit structure matrix $\mathbf{X}_j^s$, as follows:

$$\begin{cases} g_{ij}^{rs} = 0 & (i = j, r = s) \\ g_{ij}^{rs} = x_{ij}^{rs} + x_{ji}^{sr} & (\text{Otherwise}) \end{cases} \tag{4-3}$$

At this point, I defined an index to express the degree to which the K groups are separated from the network as in previous studies (Kagawa *et al.*, 2015; Tokito *et al.*, 2016), the adjacency matrix $\mathbf{G}$ can be applied to the widely used industrial clustering analysis.

4.2.2. Clustering analysis

I defined an index to express the degree to which the K industrial groups are separated from the global supply-chain network as $Cut = \sum_{k=1}^{K} \left(\sum_{i \in V_k, j \in V} g_{ij} - \sum_{i \in V_k, j \in V_k} g_{ij} \right)$, where the value of the index is called the cut value (Wu and Leahy, 1993), and $V = \{1, 2, \ldots, N\}$ represents a set of vertices (corresponding to industrial sectors in this thesis), while V_k is the set of vertices belonging to the k^{th} cluster. Note that the following mathematical relationship holds: $V = \cup_{k=1}^{K} V_k$. By finding the combination of vertices for which the cut value is minimized, I determined the CO_2 clusters that have close international flows.

However, if I divide the network in order to minimize the cut value, there is a tendency to arrive at a cluster with a single vertex (industrial sector) (Shi and Malik, 2000). Therefore, to resolve this limitation, I defined d_i as the degree of vertex i which represents the total number of connections of vertex i estimated by $\sum_j g_{ij}$ and thus can simultaneously try to maximize the aggregate value of the degrees of vertices belonging to a particular cluster, $\sum_{i \in V_k} d_i$. In other words, I can define a normalized cut value (4-4) that includes an additional condition to maximize the total number connections of each cluster, and apply a grouping to minimize this value.

$$
\begin{aligned}
Ncut &= \sum_{k=1}^{K} \frac{\sum_{i \in V_k, j \in V} g_{ij} - \sum_{i \in V_k, j \in V_k} g_{ij}}{\sum_{i \in V_k} d_i} \\
&= \sum_{k=1}^{K} \frac{\mathbf{h}_k^T (\mathbf{D} - \mathbf{G}) \mathbf{h}_k}{\mathbf{h}_k^T \mathbf{D} \mathbf{h}_k}
\end{aligned}
\qquad (4\text{-}4)
$$

Here, $\mathbf{h}$ is the indicator vector associated with cluster k, defined below. The superscript T indicates the transposition.

$$
\mathbf{h}_k = (h_{i,k}) = \begin{cases} 1 & (i \in V_k) \\ 0 & (i \notin V_k) \end{cases}
$$

$\mathbf{D}$ in Eq. (4-4) is the diagonal matrix having degree d_i for the diagonal components.

However, the problem with minimizing Eq. (4-4) is that each vertex needs to be assigned to one of the k clusters. Within the context of computation time, this minimization problem is referred to as an NP-complete problem (Shi and Malik, 2000). By expanding the values obtained for this discrete indicator vector $\mathbf{h}$ over real space, the discrete optimization problem of Eq. (4-4) can be reduced to the NMF problem of Eq. (4-5); see Ding *et al.* (2008, 2013) for details.

$$\underset{\mathbf{H}\geq\mathbf{0}}{\text{Minimize}} \left\| \mathbf{D}^{-\frac{1}{2}}\mathbf{G}\mathbf{D}^{-\frac{1}{2}} - \mathbf{H}\mathbf{H}^T \right\|_F^2 \tag{4-5}$$

Here, $\mathbf{H}$ is a non-negative matrix. If the number of vertices that constitute the network is N and the number of clusters is K, then $\mathbf{H}$ is an $N \times K$ matrix.

$$\mathbf{H} = [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \cdots \quad \mathbf{h}_K]$$

By using the algorithm proposed by Lee and Seung (1999, 2001), I can determine the matrix $\mathbf{H}$ that minimizes the norm of Eq. (4-5). The result is that the i^{th} row vector of matrix $\mathbf{H}$ (h_i) becomes a feature vector of vertex i, and by identifying the vertex points of similar feature vectors as belonging to the same cluster, I can identify the K clusters; this is referred to as the K-means technique (Bolla, 2011).

When identifying clusters using a combination of NMF and the K-means technique, the number of clusters K is arbitrary, thus its value must be decided in advance. The choice of K strongly affects the shape of the cluster structure after partitioning. To assess the quality of the cluster structure, I used the modularity index proposed by Newman and Girvan (2004) and Clauset *et al.* (2004):

$$Q(K)=\sum_{i=1}^{K}\left\{\frac{\sum_{i\in V_k}\sum_{j\in V_k} g_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij}}-\left(\frac{\sum_{i\in V_k}\sum_{j\in V} g_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij}}\right)^{2}\right\} \tag{4-6}$$

The modularity index is accuracy of a clustering result widely used in cluster analysis. The number of clusters is selected to maximize the value of $Q(K)$ in Eq (4-6) (Newman and Girvan, 2004).

4.2.3. Node betweenness centrality

Liang *et al.* (2016) proposed node betweenness centrality, which is a measure of betweenness of a specific sector that considers the production tiers in the supply-chains. Sectors with higher node betweenness centrality transmit larger amounts of CO_2 emissions throughout the supply-chains. Using an input-output table, Liang *et al.* (2016) defined b_i as the node betweenness centrality of a specific sector i, and reformulated it as a simple equation as follows:

$$
\begin{aligned}
b_i &= \sum_{s=1}^{n}\sum_{t=1}^{n}\sum_{r=1}^{\infty}\left(q_r \times w\left(s,t \middle| k_1,k_2,\ldots,k_r\right)\right) \\
&= \mathbf{eTJ}_i\mathbf{Tf}
\end{aligned}
\tag{4-7}
$$

Here, s and t are respectively the start and end sectors of a supply-chain path. q_r is the number of times that sector i appears in the supply-chain paths. w indicates the weight of the supply-chain path starting from sector s and passing through r sectors (k_1, k_2, ..., k_r) to reach end sector t. w is calculated as

$$
w\left(s,t \middle| k_1,k_2,\ldots,k_r\right) = e_s a_{sk_1} a_{k_1k_2} \cdots a_{k_rt} f_t
$$

where e_s is the s^{th} element of the emission intensity vector $\mathbf{e}$, and f_t is the t^{th} element of the final demand vector $\mathbf{f}$. a_{sk} is the (s,k)th element of the technical coefficient matrix $\mathbf{A}$. $\mathbf{T}$ is the indirect requirement matrix, and $\mathbf{J}_i$ is the matrix whose (i,i)th element is 1 and other elements are 0. $\mathbf{T}$ and $\mathbf{J}_i$ are obtained with the following equations:

$$
\mathbf{T} = \mathbf{A} + \mathbf{A}^2 + \cdots
$$

$$
\mathbf{J}_i = \begin{cases} j_{uv} = 1 & \text{if } u = v = i \\ j_{uv} = 0 & \text{otherwise} \end{cases}
$$

For the supply-chain induced by final demand of a sector t for a specific country, I defined the betweenness of sector i as follows:

$$b_{it} = \sum_{s=1}^{n}\sum_{r=1}^{\infty}\left(q_r \times w\left(s,t \middle| k_1, k_2, \ldots, k_r\right)\right). \tag{4-8}$$

Then, I reformulated $b_{it}(l_1, l_2)$ as the total emissions associated with the supply-chain paths of the final demand of sector t that pass through sector i that has an industrial supply-chain with l_1 upstream sectors and $l_2 - 1$ downstream sectors.

$$\begin{aligned} b_{it}(l_1,l_2) &= \left(\mathbf{eA}^{l_1}\right)_i \left\{ \sum_{1\le j_1,\cdots,j_{l_2}\le n} \left(a_{ij_1} a_{j_1 j_2} \cdots a_{j_{l_2-1} j_{l_2}=t} f_t\right) \right\} \\ &= \left(\mathbf{eA}^{l_1}\right)_i \left\{ \sum_{1\le j_1,\cdots,j_{l_2}\le n} \left(a_{ij_1} a_{j_1 j_2} \cdots a_{j_{l_2-1} j_{l_2}=t}\right) \right\} f_t \\ &= \left(\mathbf{eA}^{l_1}\right)_i \left(\mathbf{A}^{l_2}\right)_i \mathbf{f}_t \\ &= \mathbf{eA}^{l_1}\mathbf{J}_i\mathbf{A}^{l_2}\mathbf{f}_t \end{aligned} \tag{4-9}$$

Here, $(\mathbf{A}^{l_1})_i$ and $(\mathbf{A}^{l_2})_i$ are the i^{th} element of the vector $\mathbf{A}^{l_1}$ and i^{th} row vector of the matrix $\mathbf{A}^{l_2}$, respectively, and $\mathbf{f}_t$ is the vector whose t^{th} element is f_t and other elements are 0. The node betweenness centrality of sector i associated with the final demand of sector t is obtained as follows:

$$\begin{aligned} b_{it} &= \sum_{l_1=1}^{\infty}\sum_{l_2=1}^{\infty} b_{it}(l_1,l_2) \\ &= \mathbf{eTJ}_i\mathbf{Tf}_t \end{aligned} \tag{4-10}$$

4.2.5. Edge hypothetical extraction method

Focusing on the direct linkage from sector i to sector j $(i \neq j)$, the environmental impact of the case that a specific transaction from sector i to sector j is extracted from the economy associated with Japanese transport equipment also can be calculated. The total impact of extracting the transaction from sector i to sector j, x_t^{ij} can be obtained edge extraction impact as follows:

$$
\begin{aligned}
x_t^{ij} &= x_t - \bar{x}_t^{ij} \\
&= \mathbf{eLf}_t - \mathbf{e\bar{L}}^{ij}\mathbf{f}_t \\
&= \mathbf{e}\left(\mathbf{L} - \mathbf{\bar{L}}^{ij}\right)\mathbf{f}_t \\
&= \sum_{u=1}^{N}\left(e_u a_{ut} f_t - e_u \bar{a}_{ut}^{ij} f_t\right) + \sum_{u=1}^{N}\sum_{v=1}^{N}\left(e_u a_{uv} a_{vt} f_t - e_u \bar{a}_{uv}^{ij} \bar{a}_{vt}^{ij} f_t\right) + \ldots\ldots
\end{aligned}
$$

here $\bar{\mathbf{A}}^{ij} = \left(\bar{a}_{uv}^{ij}\right)$ is the input coefficient matrix where the (i,j)th element is zero, and $\bar{\mathbf{L}}^{ij}$ is the "extracted" Leontief inverse calculated by using the "extracted" input coefficient $\bar{\mathbf{A}}^{ij}$. From this equation, the extraction impact of transaction from sector i to sector j, x_t^{ij} can be understood as the total emission from the supply-chains associated with Japanese transport equipment that exclude the supply-chain paths not passing through the transaction from sector i to sector j, and can be interpreted as the total emissions associated with the supply-chain paths passing through the transaction from sector i to sector j. From Chapter 3, edge hypothetical extraction impact can be less-computationally-expensive calculated using edge betweenness centrality (Hanaka *et al.*, 2017) as follows:

$$x_t^{ij} = \frac{a_{ij}\mathbf{eLJ}_{ij}\mathbf{Lf}_t}{1 + a_{ij}l_{ji}} \tag{4-11}$$

4.2.6. Combining industrial clustering analysis with betweenness centrality analysis

Using the clustering method defined in Section 4.2.2, I divided the upstream sectors into those with a strong connecting supply-chain with large emissions and those from the global supply-chain network associated with the final demand of the transport equipment industry in Japan.

In addition, using the node betweenness centrality defined in Section 4.2.2, I identified the upstream sectors with high node betweenness centrality, which represents how much CO_2 emission from the supply-chain paths a sector has, from the global supply-chain paths associated with the final demand of the transport equipment industry in Japan.

By only using a clustering analysis, we cannot analyze the importance of a node of a CO_2 emission cluster, and only using the node betweenness centrality, we cannot analyze the role a high-priority node fulfills in its CO_2 emission cluster.

By combining the results of the clustering analysis with those of the node betweenness centrality analysis, we can visualize critical clusters focusing on high betweenness sectors across the whole global supply-chain and suggest supply-chain management to high-priority sectors and clusters.

4.2.7. Combining industrial clustering analysis with hypothetical extraction analysis

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. However, Kanemoto *et al.* (2018) pointed out that this clustering method may divide an important transaction to different clusters. For example, it supposes that the direct linkages between material industry, manufacture industry and wholesale industry are relatively strong. However, in the integrated graph defined in Section 4.2.1 (Kagawa *et al.*, 2015, 2013b, 2013a; Rifki *et al.*, 2017), the linkage between manufacture industry and wholesale industry becomes weak due to the emission intensity of manufacture industry (See Figure 4-1). Recently, Kanemoto *et al.* (2018) proposed the fitter clustering method for the input-output networks by modifying it. Although the clustering method proposed in Kanemoto *et al.* (2018) needs too large computation time to apply to Eora database.

In this thesis, I apply the edge hypothetical extraction method to detect the important transaction

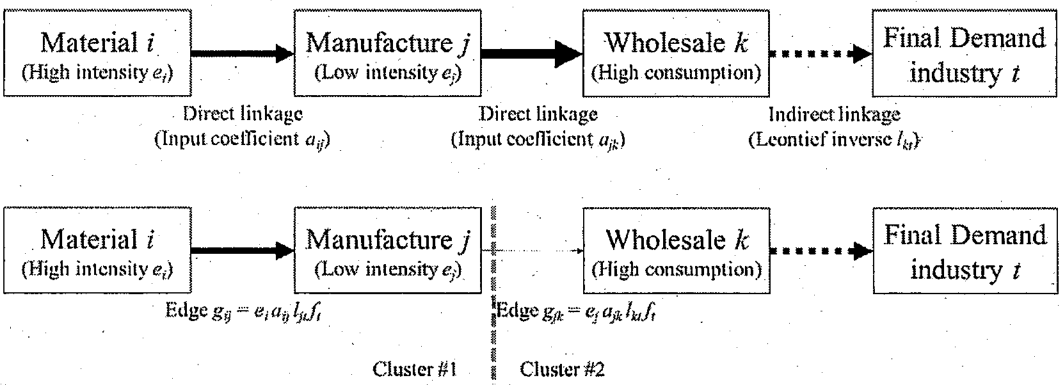

Figure 4-1 Linkages of the adjacency matrix defined by using unit structure model

4.3. Data

In this thesis, I used the EORA MRIO table in 2015 covering 26 industrial sectors, which is publicly available at http://www.worldmrio.com/ (Lenzen *et al.*, 2012, 2013). We can obtain the global CO_2 emissions associated with the final demand for the transport equipment industry ($=j$) in a country (s = Japan) by adding together the elements of the unit structure matrix $\mathbf{X}_j^s$, which is easily obtained by applying the EORA to the unit structure model defined in Eq. (4-2). For the CO_2 emission accounting, I used "CO2 emissions (Gg) from EDGAR Total" including all emission sources (e.g., forest fire).

4.4. Results

4.4.1. Production-based emission induced by Japanese transport equipment and Global emission clustering analysis

Applying the unit structure model outlined in Section 4.2.1 and spectral cluster analysis outlined in Section 4.2.2 to the 2015 EORA database covering 189 countries and regions, I obtained production-based emission induced by Japanese transport equipment through the global supply-chain and identified 17 emission clusters. the Figure 4-2 describes the share by country and cluster of emitted CO_2 in the global supply-chain of Japanese transport equipment in 2015. Tables 4-1 describe the ranking of sectors by country for the emitted CO_2 in the global supply-chain of Japanese transport equipment in 2015. From table 4-1, we can see that in addition to the upstream sectors such as "Mining and Qualifying" and "Electricity, Gas and Water", the intermediate sectors such as "Petroleum, Chemical and Non-Metallic Mineral Products" and "Transport" are larger emitters. In addition, these supply-chains induced large CO_2 emissions in oil-producing or mining countries such as African and Middle Eastern countries.

However, it is difficult to make policies by focusing on the supply-chain structure from only such an emission transfer analysis. In the next section, I identify the key stakeholders for CO_2 emission reduction by combining the clustering results with the node betweenness centrality results defined in the preceding section.

I performed a cluster analysis on the CO_2 emissions of global supply-chain networks associated with the industry of concern in this thesis: transport equipment manufacturing in Japan. It should be noted that the number of emission clusters for Japanese transport equipment was determined by maximizing the modularity index and the maximum modularity index so obtained was 0.2995. Figure 1 shows the network of the 17 detected clusters. The largest cluster in terms of CO_2 emissions induced within its cluster is cluster #4, which comprises 7 sectors, "Petroleum, Chemical and Non-Metallic Mineral Products (JPN)", "Metal Products (JPN)", "Electrical and Machinery (JPN)", Transport Equipment (JPN)", "Electricity, Gas and Water (JPN)", "Transport (JPN)", "Financial Intermediation and Business Activities (JPN)", that emitted large amounts of CO_2. Thus, Cluster #4 comprises the Japanese manufacturing and service sectors. In Japan, these industries should cooperate for reduction in CO_2 emission through the supply-chain of transport equipment. The second largest cluster is cluster #2, which includes 4380 sectors.

The clustering method that is based on Normalized cut is a top down "cutting" method. Thus, this method might detect "the rest of many industries" in the networks that have relatively weak linkages as the industrial cluster and recognize it 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. The third largest cluster consists of the Chinese manufacturing sectors.

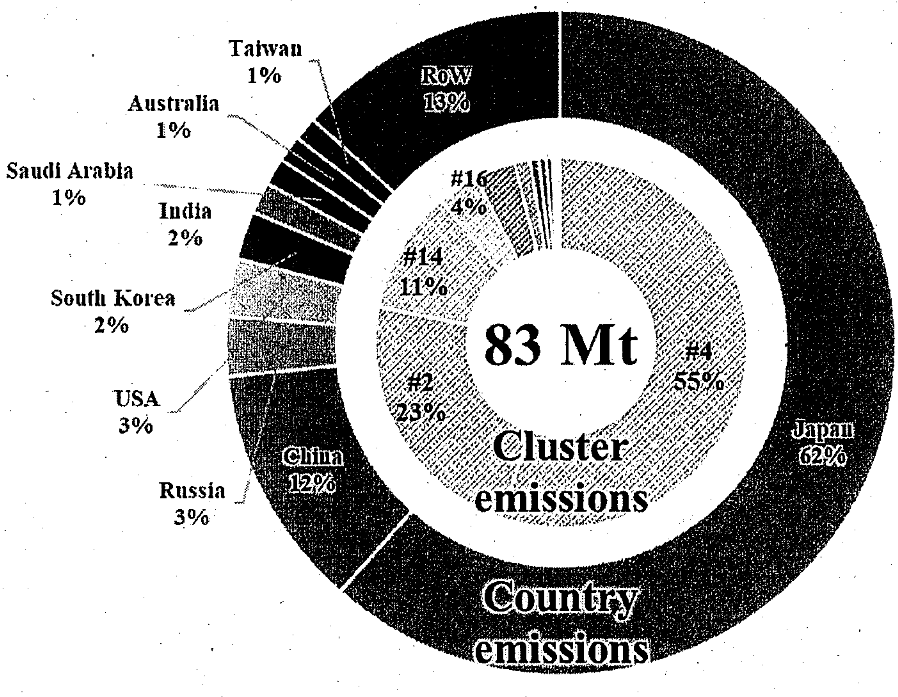

Figure 4-2 The share of which countries and clusters emitted CO_2 in the global supply chain of Japanese transport equipment in 2015

Table 4-1 Ranking of CO_2 emission induced by final demand of Japanese transport equipment

Rank	Code	Sector name	CO_2 (Kt)	Cluster #
1	JPN	Electricity, Gas and Water	45996	4
2	JPN	Petroleum, Chemical and Non-Metallic Mineral Products	35448	4
3	JPN	Transport	34979	4
4	JPN	Transport Equipment	29237	4
5	CHN	Electricity, Gas and Water	9088	14
6	JPN	Electrical and Machinery	8661	4
7	JPN	Metal Products	8226	4
8	CHN	Petroleum, Chemical and Non-Metallic Mineral Products	7968	14
9	KOR	Electricity, Gas and Water	6094	15
10	USA	Transport	4945	2
11	RUS	Electricity, Gas and Water	3633	16
12	IND	Electricity, Gas and Water	3537	1
13	RUS	Mining and Quarrying	3374	16
14	CHN	Metal Products	3242	14
15	CHN	Electrical and Machinery	3010	14
16	CHN	Transport	2988	14
17	USA	Electricity, Gas and Water	2473	2
18	JPN	Finacial Intermediation and Business Activities	1838	4
19	TWN	Electricity, Gas and Water	1525	12
20	ZAF	Electricity, Gas and Water	1455	8
21	JPN	Other Manufacturing	1249	2
22	KOR	Petroleum, Chemical and Non-Metallic Mineral Products	1168	9
23	USA	Petroleum, Chemical and Non-Metallic Mineral Products	1117	2
24	JPN	Mining and Quarrying	1045	2
25	AUS	Electricity, Gas and Water	1036	2
26	JPN	Others	933	2
27	RUS	Petroleum, Chemical and Non-Metallic Mineral Products	887	16
28	SAU	Petroleum, Chemical and Non-Metallic Mineral Products	857	2
29	CHN	Mining and Quarrying	836	14
30	SAU	Electricity, Gas and Water	790	1

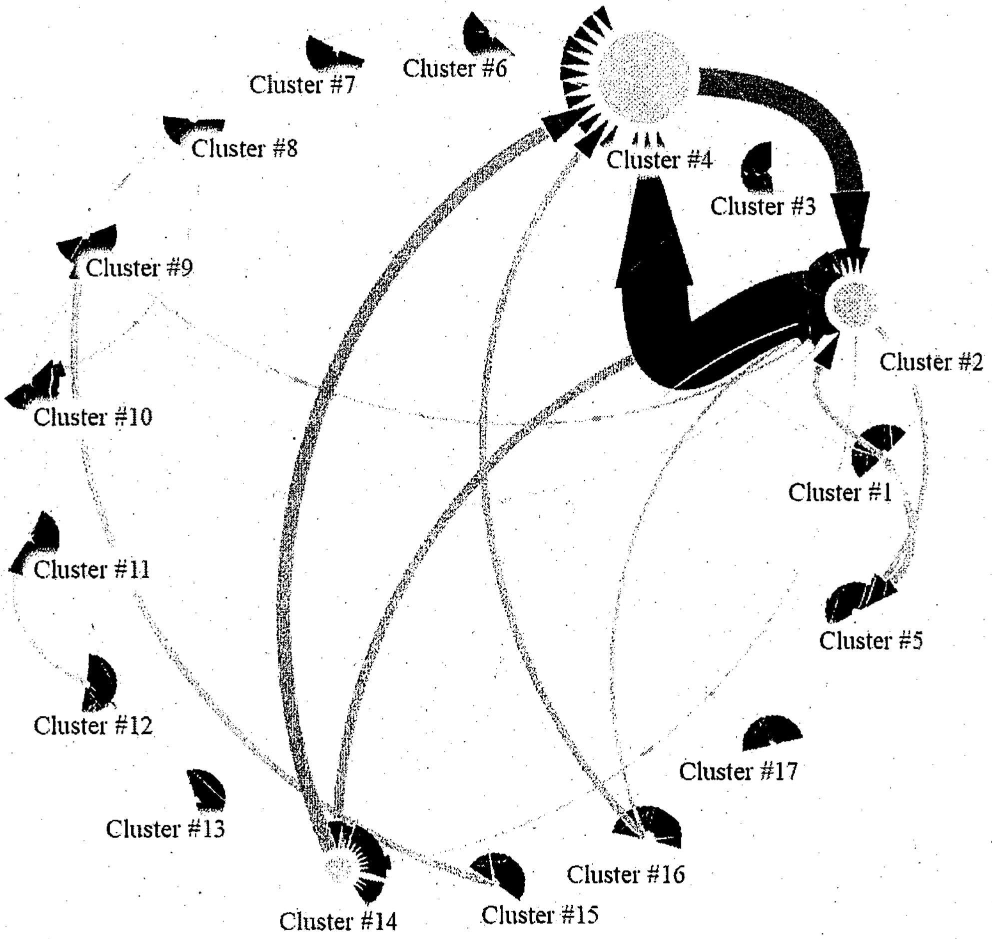

Figure 4-3 CO_2 emission cluster structure in the global supply-chain network associated with final demand of transport equipment in Japan

4.4.2. Node betweenness centrality

I calculated the network betweenness of the sectors in the global supply-chain networks associated with the final demand of transport equipment of each country by using the method formulated in Section 4.2.2 (Table 4-2). From these tables, I observed that sectors with higher betweenness centrality (e.g., "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products", "Electrical and Machinery") tend to belong to larger clusters with higher within emissions (Figure 4-4). Figure 4-4 shows the network structure of top 30 edges with large emission induced by final demand of Japanese transport equipment. The diameter of nodes indicates the node betweenness centrality, and the thickness of the edge indicates the CO_2 emissions associated with trading products from node to node. Conversely, the sectors with the highest emissions such as "Electricity, Gas and Water" do not always show the highest betweenness in the supply-chain network.

Sectors with a higher betweenness may purchase products from many other upstream sectors and sell their products to many downstream sectors. Therefore, production efficiency improvement or supply-chain management in high-priority sectors with higher betweenness is effective for reducing CO_2 emissions through the upstream inter-industry linkages, whereas greener materials and products supplied to those high-priority sectors can contribute to emission reduction through the downstream inter-industry linkages.

Table 4-2 Ranking of node betweenness centrality in the global supply-chain induced by final demand of Japanese transport equipment

Rank	Code	Sector name	b_i	Cluster #
1	JPN	Transport Equipment	125171	4
2	JPN	Metal Products	30718	4
3	JPN	Petroleum, Chemical and Non-Metallic Mineral Products	29878	4
4	JPN	Electrical and Machinery	26689	4
5	JPN	Electricity, Gas and Water	21450	4
6	JPN	Transport	11362	4
7	CHN	Electricity, Gas and Water	7440	14
8	CHN	Petroleum, Chemical and Non-Metallic Mineral Products	7124	14
9	JPN	Finacial Intermediation and Business Activities	6465	4
10	CHN	Metal Products	5869	14
11	CHN	Electrical and Machinery	5493	14
12	ROW	Total	3113	5
13	KOR	Petroleum, Chemical and Non-Metallic Mineral Products	3009	9
14	KOR	Metal Products	2704	9
15	JPN	Other Manufacturing	2448	2
16	CHN	Mining and Quarrying	2227	14
17	JPN	Wholesale Trade	2064	2
18	RUS	Mining and Quarrying	1681	16
19	JPN	Wood and Paper	1625	2
20	JPN	Mining and Quarrying	1393	2
21	USA	Petroleum, Chemical and Non-Metallic Mineral Products	1331	2
22	KOR	Electricity, Gas and Water	1327	15
23	CHN	Transport	1287	14
24	JPN	Others	1268	2
25	RUS	Public Administration	1234	2
26	USA	Transport	1123	2
27	IND	Electricity, Gas and Water	1080	1
28	RUS	Metal Products	998	16
29	RUS	Electricity, Gas and Water	985	16
30	KOR	Electrical and Machinery	955	2

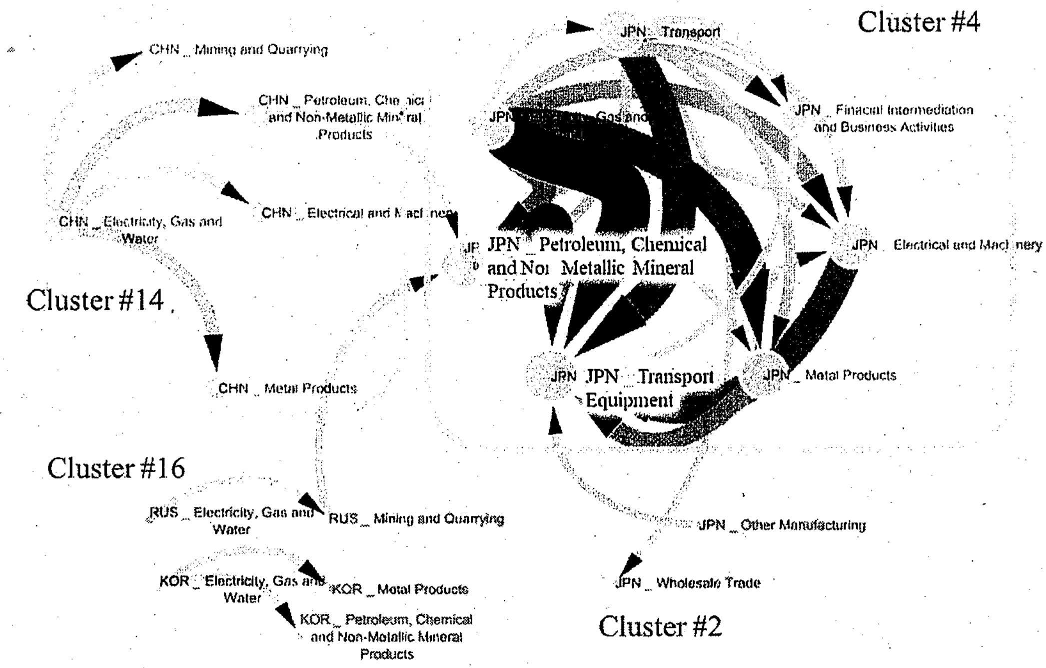

Figure 4-4 Visualization of top 30 edges with large emission induced by final demand of Japanese transport equipment

Note that the size of nodes represents the node betweenness centrality and the color depth and thickness of edges means the amount of CO_2 emission induced by final demand of Japanese transport equipment

4.4.3. Edge hypothetical extraction method

I visualized top 30 edges with large extraction impact in the global supply-chain induced by final demand of Japanese transport equipment (Figure4-5). Figure 4-5 shows the network structure of top 30 edges with large extraction impact induced by final demand of Japanese transport equipment. The diameter of nodes indicates the node betweenness centrality, and the thickness of the edge indicates the edge hypothetical extraction impact. From figure 4-4, the edges from "Electricity, Gas and Water" to other sectors are high-weighted edges. However, from figure 4-5, the edges from "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products", "Electrical and Machinery" to "Transport Equipment" are high-weighted edges. Thus, policy maker should focus on each supply-chain path ("Electricity, Gas and Water" -> "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" or "Electrical and Machinery" -> "Transport equipment") when considering environmental cooperation within the cluster for effective climate mitigation. In addition, comparing with figure 4-4, "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products", "Electrical and Machinery" in cluster #4 are relatively strongly connected with the cluster #14 that is consist of Chinese industries. I can say that not only financially support the relevant emission reduction engagements within the critical emission cluster but an emission reduction engagement or improving environmental technology such as the resource efficiency of "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products", "Electrical and Machinery" in cluster #4 can decrease CO_2 emissions in cluster #14.

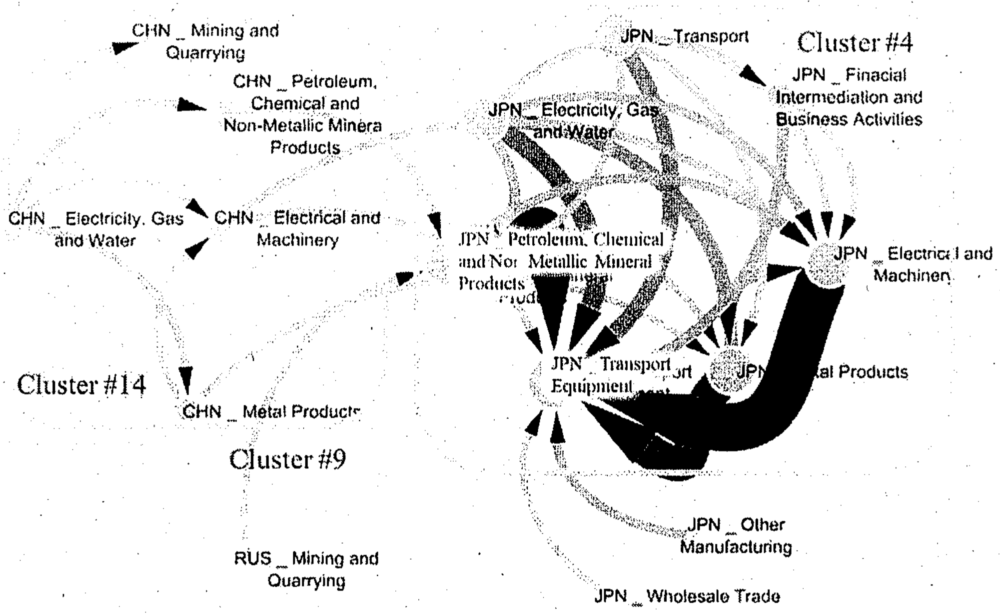

Figure 4-5 Visualization of top 30 edges with large extraction impact induced by final demand of Japanese transport equipment

4.4.4. Discussion

Among the larger clusters identified in this thesis, the largest cluster for Japan comprises domestic sectors with 'higher' betweenness centrality. In the global supply-chain network of transport equipment in Japan, "Metal Products (JPN)", "Petroleum, Chemical and Non-Metallic Mineral Products (JPN)" and "Electrical and Machinery (JPN)" are the sectors with the highest betweenness and these sectors are members of the largest cluster, cluster #4. In addition, these sectors strongly-connected with Chinese sectors with higher betweenness centrality in cluster #14, which is the second largest emission cluster.

Japan should focus on domestic "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" and "Electrical and Machinery" as they have a higher betweenness, and the supply-chain management of these two industries should be done with a focus on the supply-chain paths from upstream "Electricity, Gas and Water (JPN)" to downstream "Transport Equipment". Thus, domestic technological improvements in "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" and "Electrical and Machinery" are more important than the acquisition of greener materials in those two sectors because the high betweenness centrality sectors appear in the global supply-chain associated with Japanese transport equipment more times than the other sectors. In addition, supply-chain paths (Chinese Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" or "Electrical and Machinery" -> Japanese "Metal Products", "Petroleum, Chemieal and Non-Metallic Mineral Products" or "Electrical and Machinery" -> Japanese "Transport equipment") are high weighted-paths. Thus, the acquisition of greener resources and materials of these sectors could contribute to the effective reduction of CO_2 emissions of not only the largest cluster but the China through the global supply-chain associated with the final demand of transport equipment in Japan (Figure 4-6). The Japanese transport equipment industry should positively commit to domestic life-cycle management with a focus on different sectoral characteristics in the global supply-chain networks.

Looking at the role of the transport equipment industry in climate mitigation, Transport equipment should take a leadership role in cross-border environmental cooperation with not only domestic upstream industries but Chinese countries to reduce CO_2 emissions through the backward linkages. A meeting between the German and French Environment Ministries, the world's major automobile nations, was held on 4th September 2017 to promote the swift implementation of the Paris Agreement through environmental cooperation between these two countries (Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety, 2017). The results in this thesis point out the importance of having closer and stronger environmental cooperation between the stakeholder countries. An important suggestion is that stakeholder meetings including key industries identified in this thesis should be held in the near future.

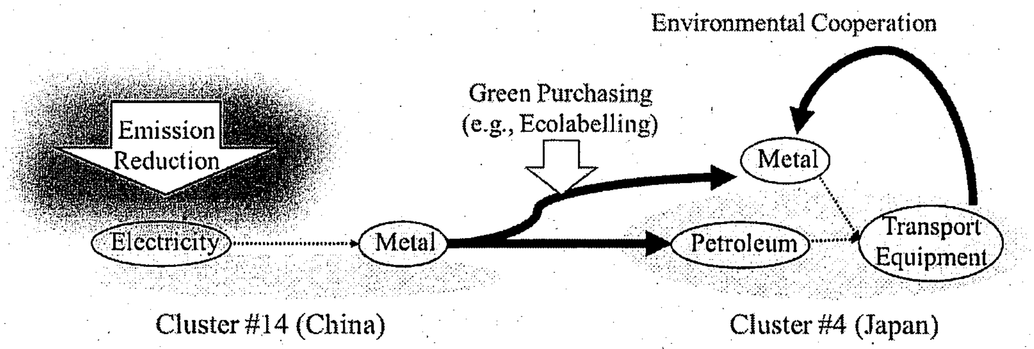

Figure 4-6 Network structure of sectors in cluster #13 induced by final demand of Japanese transport equipment

4.5. Conclusion

This thesis addressed a question on how industries can reduce CO_2 emissions through the global supply-chain engagements. In particular, the automotive industry constructs a dense and complex supply-chain network associated with many upstream industries. As in Kagawa *et al.* (2015), it is difficult to not only identify environmentally-important sectors, supply-chain paths, and clusters for the global supply-chain management but visualize those key supply-chain structures. In this thesis, I proposed the combined approach of clustering analysis, node betweenness centrality analysis and edge hypothetical extraction method. This approach enables the detection of key sectors and clusters and their links within a short computation time from large network databases, which should provide useful information for informing CO_2 mitigation policy from the life-cycle perspective.

In this thesis, I focused on the life-cycle CO_2 emissions associated with the global automotive supply-chains and found that sectors ("Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" and "Electrical and Machinery") with higher betweenness in the supply-chains belong to high-emission clusters. I suggested that cooperation within the high-emission clusters and supply-chain management in high-priority sectors to efficiently reduce the CO_2 emissions associated with the final demand of transport equipment in the producing countries.

Chapter 5: Conclusions

This Ph.D. dissertation reports on the design and execution of comprehensive analyses focusing on Asian supply chain structures to provide the necessary basis for effectively mitigating anthropogenic air pollution from two perspectives: industry and household.

In Chapter 3, I clarified the qualitative and quantitative relationship between hypothetical extraction method and betweenness-based method and showed that the extraction impact can be calculated from the *less computationally-expensive* betweenness centrality obtained using the equations obtained in this chapter. The extraction impacts show the magnitude of influencing outputs of other industries along the supply chains related to transactions of an industry in question, whereas the betweenness centrality shows the importance of networking industries through a node of an industry in question as well as a transaction between the industry in question and another industry. The hypothetical extraction method is widely used to assess inter-industry linkages and the economic importance of industries (e.g., Dietzenbacher *et al.*, 2019). The both methods have different advantages. However, when the results of these methods differ greatly, the importance of a sector that is high betweenness sector in the supply chains is ignored. Thus, I can say that betweenness centrality analysis is more appropriate for using the structure of a supply chain network to determine policies to reduce emissions.

Chapter 4 focused on the life-cycle CO_2 emissions associated with the global transport equipment supply-chains and found that key sectors with higher betweenness in the supply-chains belong to high-emission clusters. I suggested that Japan should focus on domestic "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" and "Electrical and Machinery" as they have a higher betweenness, and the supply-chain management of these two industries should be done with a focus on the supply-chain paths from upstream "Electricity, Gas and Water (JPN)" to downstream "Transport Equipment". Thus, domestic technological improvements in "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" and "Electrical and Machinery" are more important than the acquisition of greener materials in those two sectors because the high betweenness centrality sectors appear in the global supply-chain associated with Japanese transport equipment more times than the other sectors. In addition, supply-chain paths (Chinese Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" or "Electrical and Machinery" -> Japanese "Metal Products", "Petroleum, Chemical and Non-Metallic Mineral Products" or "Electrical and Machinery" -> Japanese "Transport equipment") are high weighted-paths. Thus, the acquisition of greener resources and materials of these sectors could contribute to the effective reduction of CO_2 emissions of not only the largest cluster but the China through the global supply-chain associated with the final demand of transport equipment in Japan. The Japanese transport equipment industry should positively commit to domestic life-cycle management with a focus on different sectoral characteristics in the global supply-chain networks.

This Ph.D. dissertation reveals critical sectors and transactions for mitigating CO_2 emissions from global supply-chain of Japanese transport equipment using cluster method and the two methods, hypothetical extraction method and betweenness-based method.

The combined approach I proposed in this thesis enables the detection of key sectors and clusters and their links within a short computation time from large network databases, which should provide useful information for informing CO_2 mitigation policy from the life-cycle perspective. An important suggestion is that stakeholder meetings including key industries identified in this thesis should be held in the near future.

Appendix

A.1. Differences between extraction methods and betweenness centralities.

First, the input coefficient matrix can be decomposed to the "sector i -extracted" input coefficient matrix $\overline{\mathbf{A}}^i = (\bar{a}^i_{uv})$ and the input coefficient matrix that has the element associated with sector i $\mathbf{A}^i = (a^i_{uv})$ as follows:

$$\mathbf{A} = \overline{\mathbf{A}}^i + \mathbf{A}^i \tag{A-1}$$

Where

$$\bar{a}^i_{uv} = \begin{cases} a_{uv} & u \neq i \wedge v \neq i \\ 0 & u = i \vee v = i \end{cases}$$

$$a^i_{uv} = \begin{cases} a_{uv} & u = i \vee v = i \\ 0 & u \neq i \wedge v \neq i \end{cases}.$$

Here, . $\mathbf{x}$ can be evaluated using eq. (A3-1) as follows:

$$\begin{aligned}\mathbf{x} &= \mathbf{L}\mathbf{f} \\ &= \mathbf{A}\mathbf{x} + \mathbf{f} \\ &= \left(\overline{\mathbf{A}}^{i} + \mathbf{A}^{i}\right)\mathbf{x} + \mathbf{f}\end{aligned}$$

$$\mathbf{x} - \overline{\mathbf{A}}^{i}\mathbf{x} = \mathbf{A}^{i}\mathbf{x} + \mathbf{f}$$

$$\left(\mathbf{E} - \overline{\mathbf{A}}^{i}\right)\mathbf{x} = \mathbf{A}^{i}\mathbf{L}\mathbf{f} + \mathbf{f}$$

$$\mathbf{x} = \left(\mathbf{E} - \overline{\mathbf{A}}^{i}\right)^{-1}\left(\mathbf{A}^{i}\mathbf{L} + \mathbf{E}\right)\mathbf{f}$$

Here, $\left(\mathbf{E} - \overline{\mathbf{A}}^{i}\right)^{-1}$ can be replaced with $\overline{\mathbf{L}}^{i}$ as:

$$\mathbf{x} = \left(\overline{\mathbf{L}}^{i}\mathbf{A}^{i}\mathbf{L} + \overline{\mathbf{L}}^{i}\right)\mathbf{f}$$

Thus, the Leontief inverse can be represented as

$$\mathbf{L} = \left(\overline{\mathbf{L}}^{i}\mathbf{A}^{i}\mathbf{L} + \overline{\mathbf{L}}^{i}\right) \tag{A-2}$$

From eqs. (A-2) and (3-3), the extraction impact of sector i x^{i} can be reformulated as

$$
\begin{aligned}
x^i &= \mathbf{eLf} - \left(\mathbf{e}\overline{\mathbf{L}}^i\mathbf{f} - e_i f_i\right) \\
&= \mathbf{e}\left(\mathbf{L} - \overline{\mathbf{L}}^i\right)\mathbf{f} + e_i f_i \\
&= \mathbf{e}\left(\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{L} + \overline{\mathbf{L}}^i - \overline{\mathbf{L}}^i\right)\mathbf{f} + e_i f_i \\
&= \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + e_i f_i
\end{aligned}
\qquad \text{(A-3)}
$$

Here, the left term in eq. (A-3) can be decomposed as:

$$
\begin{aligned}
\mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} &= \mathbf{e}\left(\overline{\mathbf{L}}^i + \mathbf{J}_{ii} - \mathbf{J}_{ii}\right)\mathbf{A}^i\mathbf{Lf} \\
&= \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\left(\mathbf{E} + \mathbf{J}_{ii} - \mathbf{J}_{ii}\right)\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \left(\mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} - \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf}\right) + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} - \mathbf{e}\left(\overline{\mathbf{L}}^i + \mathbf{J}_{ii} - \mathbf{J}_{ii}\right)\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \left(-\mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf}\right) \\
&\quad + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \left(\mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} - \mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf}\right) - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} \\
&\quad + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \left\{\mathbf{e}\overline{\mathbf{L}}^i\mathbf{A}^i\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf}\right\} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \left\{\mathbf{e}\left(\overline{\mathbf{L}}^i\mathbf{A}^i + \mathbf{J}_{ii}\mathbf{A}^i\mathbf{J}_{ii} - \mathbf{J}_{ii}\mathbf{A}^i\right)\mathbf{Lf}\right\} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \left\{\mathbf{e}\left(\overline{\mathbf{L}}^i\mathbf{A}^i + a_{ii}\mathbf{J}_{ii} - \mathbf{J}_{ii}\mathbf{A}^i\right)\mathbf{Lf}\right\} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf}
\end{aligned}
$$

(A-4)

Here, the i th row elements of $\bar{\mathbf{L}}^i\mathbf{A}^i$ are i th row elements of the input coefficient matrix, and $\mathbf{J}_{ii}\mathbf{A}^i$ is the matrix whose i th row elements are i th row elements of the input coefficient matrix. Thus, eq. (A-4) can be reformulated as:

$$
\begin{aligned}
\text{Eq.}(\text{A4}) &= \left\{\mathbf{e}\left(\bar{\mathbf{L}}^i\mathbf{A}^i + a_{ii}\mathbf{J}_{ii} - \mathbf{J}_{ii}\mathbf{A}^i\right)\mathbf{Lf}\right\} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \left\{\mathbf{e}\left(\bar{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\right)\mathbf{Lf}\right\} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} \\
&= \mathbf{e}\bar{\mathbf{L}}^i\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{Lf} - \mathbf{eJ}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{Lf} \\
&= \mathbf{e}\bar{\mathbf{L}}^i\mathbf{a}_i^c\mathbf{l}_i^r\mathbf{f} + e_i\mathbf{a}_i^r\mathbf{Lf} - e_i a_{ii}\mathbf{l}_i^r\mathbf{f} \\
&= \mathbf{e}\bar{\mathbf{L}}^i\mathbf{a}_i^c\mathbf{l}_i^r\mathbf{f} + e_i\mathbf{t}_i^r\mathbf{f} - e_i a_{ii}\mathbf{l}_i^r\mathbf{f}
\end{aligned}
\tag{A-5}
$$

Using eq. (A-2) and (3-9), the betweenness centrality b_i associated with a sector i can be reformulated as:

$$
\begin{aligned}
b_i &= \mathbf{eLJ}_{ii}\mathbf{Lf} \\
&= \mathbf{e}\left(\bar{\mathbf{L}}^i + \bar{\mathbf{L}}^i\mathbf{A}^i\mathbf{L}\right)\mathbf{J}_{ii}\mathbf{Lf} \\
&= \mathbf{e}\bar{\mathbf{L}}^i\mathbf{J}_{ii}\mathbf{Lf} + \mathbf{e}\bar{\mathbf{L}}^i\mathbf{A}^i\mathbf{LJ}_{ii}\mathbf{Lf}
\end{aligned}
$$

Here, the i th row elements and the i th column elements of $\bar{\mathbf{L}}^i$ are 0 except (i, i)th element, 1. Therefore, $\bar{\mathbf{L}}^i\mathbf{J}_{ii} = \mathbf{J}_{ii}$. Thus, using eq. (A-5), b_i can be represent as:

$$
\begin{aligned}
b_i &= \mathbf{e}\overline{\mathbf{L}}^i \mathbf{J}_{ii}\mathbf{L}\mathbf{f} + \mathbf{e}\overline{\mathbf{L}}^i \mathbf{A}^i \mathbf{L}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} \\
&= \mathbf{e}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} + \mathbf{e}\overline{\mathbf{L}}^i \mathbf{A}^i \mathbf{L}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} \\
&= \mathbf{e}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} + \mathbf{e}\left(\overline{\mathbf{L}}^i \mathbf{A}^i \mathbf{J}_{ii}\mathbf{L} + \mathbf{J}_{ii}\mathbf{A}^i\mathbf{L} - \mathbf{J}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{L}\right)\mathbf{J}_{ii}\mathbf{L}\mathbf{f} \\
&= \mathbf{e}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} + \mathbf{e}\overline{\mathbf{L}}^i \mathbf{A}^i \mathbf{J}_{ii}\mathbf{L}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} + \mathbf{e}\mathbf{J}_{ii}\mathbf{A}^i\mathbf{L}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} \\
&\quad - \mathbf{e}\mathbf{J}_{ii}\mathbf{A}^i\mathbf{J}_{ii}\mathbf{L}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} \\
&= e_i \mathbf{l}_i^r \mathbf{f} + \mathbf{e}\overline{\mathbf{L}}^i \mathbf{a}_i^c l_{ii} \mathbf{l}_i^r \mathbf{f} + \mathbf{e}\mathbf{J}_{ii}\mathbf{T}\mathbf{J}_{ii}\mathbf{L}\mathbf{f} - e_i a_{ii} l_{ii} \mathbf{l}_i^r \mathbf{f} \\
&= e_i \mathbf{l}_i^r \mathbf{f} + l_{ii}\left(\mathbf{e}\overline{\mathbf{L}}^i \mathbf{a}_i^c \mathbf{l}_i^r \mathbf{f} - e_i a_{ii} \mathbf{l}_i^r \mathbf{f}\right) + e_i t_{ii} \mathbf{l}_i^r \mathbf{f} \\
&= \left(1 + t_{ii}\right)\left(\mathbf{e}\overline{\mathbf{L}}^i \mathbf{a}_i^c \mathbf{l}_i^r \mathbf{f} - e_i a_{ii} \mathbf{l}_i^r \mathbf{f}\right) + \left(1 + t_{ii}\right) e_i \mathbf{l}_i^r \mathbf{f} \\
&= \left(1 + t_{ii}\right)\left(\mathbf{e}\overline{\mathbf{L}}^i \mathbf{a}_i^c \mathbf{l}_i^r \mathbf{f} - e_i a_{ii} \mathbf{l}_i^r \mathbf{f}\right) + \left(1 + t_{ii}\right)\left(e_i \mathbf{t}_i^r \mathbf{f} + e_i f_i\right) \\
&= \left(1 + t_{ii}\right)\left(\mathbf{e}\overline{\mathbf{L}}^i \mathbf{a}_i^c \mathbf{l}_i^r \mathbf{f} - e_i a_{ii} \mathbf{l}_i^r \mathbf{f} + e_i \mathbf{t}_i^r \mathbf{f} + e_i f_i\right) \qquad \text{(A-6)} \\
&= \left(1 + t_{ii}\right)\left(\mathbf{e}\overline{\mathbf{L}}^i \mathbf{A}^i \mathbf{L}\mathbf{f} + e_i f_i\right) \\
&= \left(1 + t_{ii}\right) x^i
\end{aligned}
$$

From this equation, in the betweenness centrality analysis, the total emission from supply chains passing through sector i is over calculated for t_{ii}.

Similarly, the edge betweenness centrality b_{ij} can be obtained by the environmental edge extraction impact x^{ij}. First, the input coefficient matrix can be decomposed to the "transaction from sector i to sector j-extracted" input coefficient matrix $\overline{\mathbf{A}}^{ij} = (\bar{a}_{uv}^{ij})$ and the input coefficient matrix whose (i, j)th element is a_{ij} and others are 0, $a_{ij}\mathbf{J}_{ij}$ as follows:

$$\mathbf{A} = \overline{\mathbf{A}}^{ij} + a_{ij}\mathbf{J}_{ij} \tag{A-7}$$

Where

$$\bar{a}_{uv}^{ij} = \begin{cases} a_{uv} & u \neq i \vee v \neq j \\ 0 & u = i \wedge v = j \end{cases}$$

Here, $\mathbf{x}$ can be evaluated using eq. (S3-7) as follows:

$$\begin{aligned} \mathbf{x} &= \mathbf{Lf} \\ &= \mathbf{Ax} + \mathbf{f} \\ &= \left(\overline{\mathbf{A}}^{ij} + a_{ij}\mathbf{J}_{ij}\right)\mathbf{x} + \mathbf{f} \end{aligned}$$

$$\mathbf{x} - \overline{\mathbf{A}}^{ij}\mathbf{x} = a_{ij}\mathbf{J}_{ij}\mathbf{x} + \mathbf{f}$$

$$\left(\mathbf{E} - \overline{\mathbf{A}}^{ij}\right)\mathbf{x} = a_{ij}\mathbf{J}_{ij}\mathbf{Lf} + \mathbf{f}$$

$$\mathbf{x} = \left(\mathbf{E} - \overline{\mathbf{A}}^{ij}\right)^{-1}\left(a_{ij}\mathbf{J}_{ij}\mathbf{L} + \mathbf{E}\right)\mathbf{f}$$

Here, $\left(\mathbf{E}-\bar{\mathbf{A}}^{ij}\right)^{-1}$ can be replaced with $\bar{\mathbf{L}}^{ij}$ as:

$$\mathbf{x}=\left(\bar{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{L}+\bar{\mathbf{L}}^{ij}\right)\mathbf{f}$$

Thus, the Leontief inverse can be represented as $\mathbf{L}=\left(\bar{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{L}+\bar{\mathbf{L}}^{ij}\right)$, and x^{ij} as the environmental extraction impact of a specific transaction between sector i and sector j can be reformulated using equation (3-4) as

$$\begin{aligned}
x^{ij} &= \mathbf{e}\left(\mathbf{L}-\bar{\mathbf{L}}^{ij}\right)\mathbf{f} \\
&= \mathbf{e}\left(\bar{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{L}+\bar{\mathbf{L}}^{ij}-\bar{\mathbf{L}}^{ij}\right)\mathbf{f} \\
&= \mathbf{e}\bar{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{L}\mathbf{f} \\
&= \mathbf{e}\bar{\mathbf{l}}_i^{ij^c}a_{ij}\mathbf{l}_j^r\mathbf{f}
\end{aligned} \tag{A-8}$$

Using eq. (A-8) and (3-10), the edge betweenness centrality b_{ij} associated with a transaction from sector i to sector j can be reformulated as:

$$
\begin{aligned}
b_{ij} &= \mathbf{eL}a_{ij}\mathbf{J}_{ij}\mathbf{Lf} \\
&= \mathbf{e}\left(\overline{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{L} + \overline{\mathbf{L}}^{ij}\right)a_{ij}\mathbf{J}_{ij}\mathbf{Lf} \\
&= \mathbf{e}\overline{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{L}a_{ij}\mathbf{J}_{ij}\mathbf{Lf} + \mathbf{e}\overline{\mathbf{L}}^{ij}a_{ij}\mathbf{J}_{ij}\mathbf{Lf} \qquad \text{(A-9)} \\
&= \mathbf{e}\bar{\mathbf{l}}_i^{ij^c}a_{ij}l_{ji}a_{ij}\mathbf{l}_j^r\mathbf{f} + \mathbf{e}\bar{\mathbf{l}}_i^{ij^c}a_{ij}\mathbf{l}_j^r\mathbf{f} \\
&= \left(1 + a_{ij}l_{ji}\right)\left(\mathbf{e}\bar{\mathbf{l}}_i^{ij^c}a_{ij}\mathbf{l}_j^r\mathbf{f}\right) = \left(1 + a_{ij}l_{ji}\right)x^{ij}
\end{aligned}
$$

From this equation, in the edge betweenness centrality analysis, the total emission from supply chains passing through the transaction from sector i to sector j is over calculated for $a_{ij}l_{ji}$.

Supplementary Tables

Table A-1 Input-output-based key sector analyses.

Proposed Analysis	Methodology	Article
Power of Dispersion and Sensitivity of Despersion	Measuring backward linkage and forward linkage	Rasmussen (1956); Hirschman (1958); Hazari (1970)
Extraction Method	Measuring impact of extracting a sector from economy	Meller and Marfan (1981); Cella (1984); Dietzenbacher (1993)
Stractural Path Analysis	Measuring CO_2 emission through a supply chain path	Defourny and Thorbecke (1984); Lenzen (2002);Nagashima et al. (2017)
Centrality Analysis	Applying indicators of social network analysis	Kagawa et al. (2009); McNerny. (2009); Duang and Jiang (2018)
Clustering Analysis	Deviding and detecting CO2 emission intensive clusters from IO network	Kagawa et al. (2013a, 2013b, 2015); Tokito (2018)
Input-Output Betweenness Centrality	Measuring CO_2 emission through a sector or path	Liang et al. (2016); Hanaka et al. (2017)

Table A-2 Top 10 sectors by extraction impact: Eora

	Sector name (Eora)	x^i (Mt-CO_2)
1	CHN _ Electricity, Gas and Water	5714
2	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	3810
3	CHN _ Construction	2749
4	CHN _ Electrical and Machinery	2747
5	USA _ Electricity, Gas and Water	2533
6	USA _ Transport	2325
7	CHN _ Metal Products	2139
8	IND _ Electricity, Gas and Water	1824
9	CHN _ Transport	1235
10	USA _ Petroleum, Chemical and Non-Metallic Mineral Products	1192

Table A-3 Top 10 transactions by extraction impact: Eora

	Source sector		Target sector	x^{ij} (Mt-CO_2)
1	CHN _ Electricity, Gas and Water	→	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	1360
2	CHN _ Electricity, Gas and Water	→	CHN _ Metal Products	944
3	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	→	CHN _ Construction	837
4	CHN _ Metal Products	→	CHN _ Electrical and Machinery	787
5	IND _ Electricity, Gas and Water	→	IND _ Transport	590
6	CHN _ Metal Products	→	CHN _ Construction	551
7	CHN _ Electricity, Gas and Water	→	CHN _ Electrical and Machinery	504
8	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	→	CHN _ Electrical and Machinery	475
9	CHN _ Electricity, Gas and Water	→	CHN _ Mining and Quarrying	427
10	CHN _ Mining and Quarrying	→	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	379

Table A-4 Top 10 sectors by node betweenness centrality: Eora

	Sector name (Eora)	b_i (Mt-CO_2)
1	CHN _ Electricity, Gas and Water	7957
2	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	5892
3	CHN _ Electrical and Machinery	4111
4	CHN _ Metal Products	3751
5	CHN _ Construction	2764
6	USA _ Transport	2574
7	USA _ Electricity, Gas and Water	2561
8	RUS _ Public Administration	2463
9	IND _ Electricity, Gas and Water	2359
10	USA _ Petroleum, Chemical and Non-Metallic Mineral Products	1546

Table A-5 Top 10 transactions by edge betweenness centrality: Eora

	Source sector		Target sector	b_{ij} (Mt-CO_2)
1	CHN _ Electricity, Gas and Water	→	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	1376
2	CHN _ Electricity, Gas and Water	→	CHN _ Metal Products	949
3	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	→	CHN _ Construction	838
4	CHN _ Metal Products	→	CHN _ Electrical and Machinery	801
5	IND _ Electricity, Gas and Water	→	IND _ Transport	596
6	CHN _ Metal Products	→	CHN _ Construction	552
7	CHN _ Electricity, Gas and Water	→	CHN _ Electrical and Machinery	506
8	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	→	CHN _ Electrical and Machinery	479
9	CHN _ Electricity, Gas and Water	→	CHN _ Mining and Quarrying	433
10	CHN _ Mining and Quarrying	→	CHN _ Petroleum, Chemical and Non-Metallic Mineral Products	386

Supplementary Figures

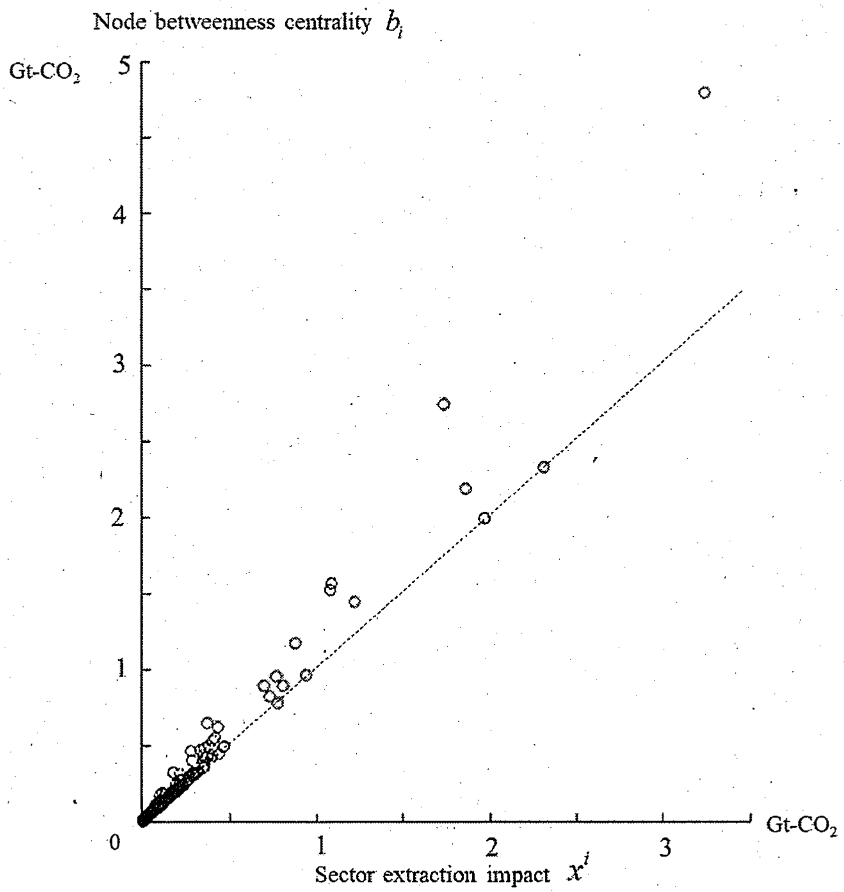

Figure A-1 Sector extraction impact values versus node betweenness centrality: WIOD

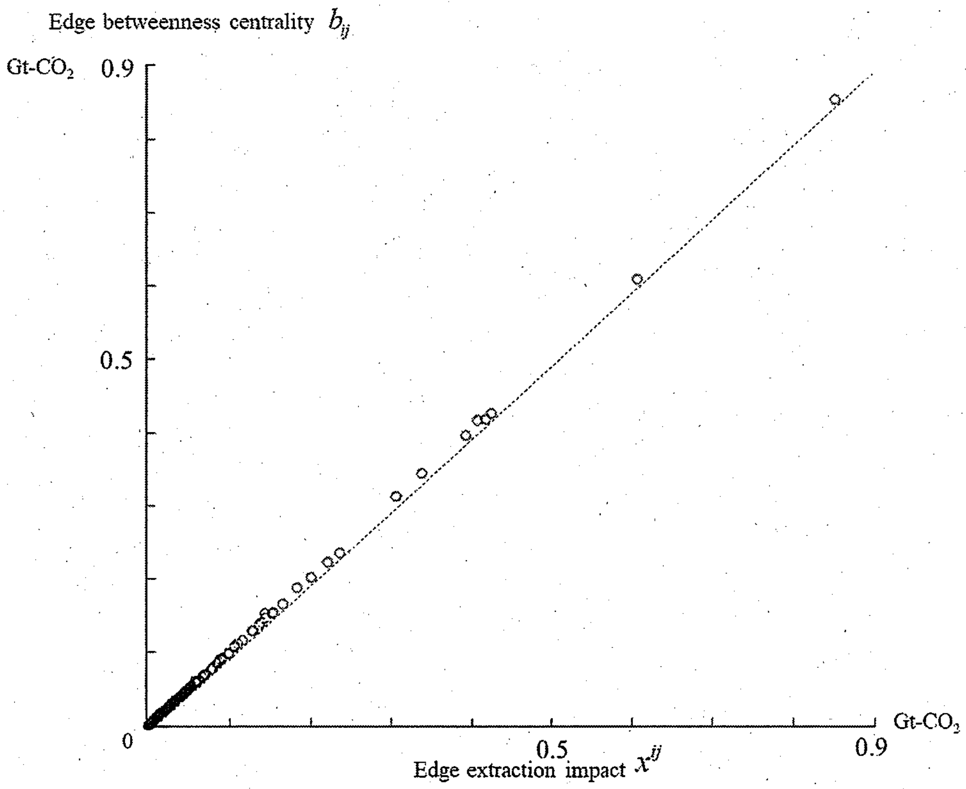

Figure A-2 Edge extraction impact versus edge betweenness centrality: WIOD

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