Structural Analysis of Carbon Dioxide Emissions in Japan

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https://doi.org/10.15017/1500489

出版情報：九州大学, 2014, 博士（経済学）, 課程博士
バージョン：

Structural Analysis of Carbon Dioxide Emissions in Japan

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of

Ph.D. in Economics

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Chapter 1 Introduction

1.1 Global Environmental Issues

The global warming is a major problem for society that requires urgent solution. The mean global temperature is rising due to the release and long-term accumulation in the atmosphere of excessive amounts of carbon dioxide (CO_2), methane (CH_4), and other substances that have a greenhouse effect (greenhouse gases: GHG). This increase in temperature causes a variety of extremely diverse problems, including destruction of ecosystems, changes in ecosystem distribution, rising sea levels associated with melting icebergs, abnormal weather such as torrential rain, health risks such as heatstroke, increased risk of infectious diseases due to stimulation of disease vectors, and changes in patterns of human behavior. For example, Courchamp *et al*. (2014) estimated that the global mean sea level will go up to two meters by 2100, and there are concerns that if this kind of worst-case scenario progresses, small islands and other land on earth will be lost and, if there are species that will go extinct in those places, biodiversity will greatly diminish. Moreover, if global warming continues excessively, it is predicted that the annual cycle of extent of pathogen contagion will more than double, and it is feared that the risk of malaria and other infectious diseases that pose a serious danger to humans will increase worldwide (Altizer *et al*., 2013).

The mean temperature on earth is determined by the balance between incoming solar energy from the sun and dissipation of heat energy from the earth into space. CO_2 in the atmosphere acts on the heat energy escaping from the earth into space and traps it at the earth's surface. The global warming mechanism now agreed on by most researchers explains that, if excess CO_2 continues to accumulate in the atmosphere, the energy supply–demand balance that determines the mean temperature on earth will collapse and global warming will accelerate (Houghton, 1992).

Since the start of the Industrial Revolution in Great Britain in the mid-eighteenth century, coal, oil, and other fossil fuels have been burned in large amounts as a source of power for vehicles and heavy industrial machinery. As a result, large amounts of GHG have been released into the atmosphere, and these gases remain in the atmosphere for long periods of time. The concentration of GHG in the atmosphere changed greatly around the time of the Industrial Revolution, and it is considered extremely likely that the problem of global warming facing our society today stems from human activity, including the excessive consumption of fossil fuels (Houghton *et al*., 1992; Bernstein *et al*., 2007; Canadell *et al*., 2007; Halsnæs *et al*., 2007; Rogner *et al*., 2007; UNEP, 2010). This is because the release of GHG into the atmosphere destroys the above-mentioned balance of heat energy at the earth's surface. Halsnæs *et al*. (2007) has reported that the highest figures for mean temperature over the past several thousand years of the earth's history have been recorded in the last few decades, and there is a 90% or more probability that this recent warming is of human origin.

The Intergovernmental Panel on Climate Change (IPCC) published the IPCC Working Group III Fifth Assessment Report in 2014 (IPCC, 2014), which is a report summarizing the current situation surrounding the issue of global warming in today's society. The report evaluates recent changes in global warming, factors causing global warming, sustainable development, energy consumption, emissions from industry, and emissions from consumption, as well as outlining future countermeasures.

With regard to global GHG emissions since 1970, a particularly high proportion of these emissions over the past forty years has been accounted for by CO_2, and this proportion hovers at 70% or above (IPCC, 2014). Worldwide CO_2 emissions reached 49.5 Gt per year in 2010. CO_2

emissions have continued to increase since 1970, and the rate of increase has been especially rapid during the past decade, which has seen a mean annual increase of 2.2% (Figure 1.1). Comparing the Fourth Assessment Report published in 2007 and the Fifth Assessment Report published in 2014, there has been little change in the emission levels of developed countries over the past ten years, but the emission levels of developing countries have changed enormously. China, in particular, became the world's largest emitter of CO_2 in 2007, and a shift in the industrial structure in developing countries like China towards the manufacturing sector is considered to be a contributory factor in the increase in CO_2 emitted by developing countries (IPCC, 2014).

Many researches have been done in predicting global GHG emissions, and the results conclude that emissions will continue to increase in the future unless drastic environmental measures are taken to counter global warming (Green, 1992; Stott *et al*., 2002; Smith *et al*., 2007; Allen *et al*., 2009; Meinshausen *et al*., 2009; Neill *et al*., 2010; Blok *et al*., 2012; Booth *et al*., 2012; IPCC, 2014). For example, according to IPCC (2014), if particularly drastic measures are not taken against global warming, the amount of CO_2 in the world's atmosphere will reach around 100 Gt-CO_2eq by 2100, and this is equivalent to approximately 1.5 times the emissions that would occur if measures against global warming were taken. Moreover, Booth *et al*. (2012) suggest that the increase and accumulation of CO_2 emissions in the atmosphere will bring about an increase in the current mean temperature of up to 5.7 degrees. The reduction of future greenhouse gases must be urgently addressed to mitigate the enormous risks that could be brought about by global warming.

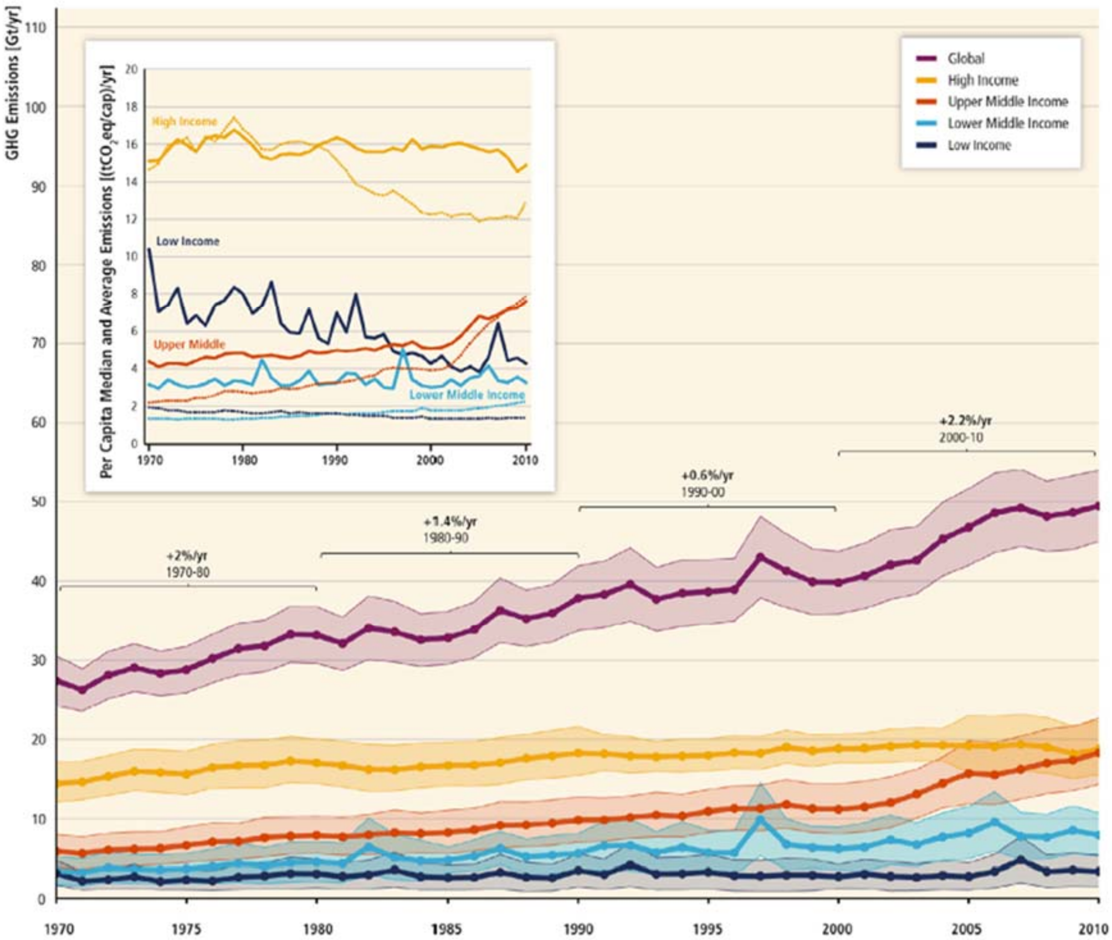

Figure 1.1 Change in GHG emissions between 1970 and 2010 according to global economic level

(Source: IPCC (2014))

1.2 Economic Activity and the Global Warming

As mentioned above, the problem of global warming that we face today is considered to result from excessive discharge of greenhouse gases due to our massive consumption of fossil fuels since the Industrial Revolution. In modern society, the consumption of fossil fuels is an essential element that supports economic activity in all areas; for example, as a heat source in thermal power stations, a heat source for blast furnaces in steelworks, and gasoline in cars and trucks. This also indicates that economic activity and the global warming are closely related.

The environmental Kuznets curve (EKC) is widely known as a curve showing the relationship between economic level and environmental pollution (Carson, 2010). The EKC is an inverted-U curve that shows the relationship between environmental pollution and economic development in accordance with the IPAT method (I: Impact; P: Population; A: Affluence; T: Technology) in which environmental impact is determined according to population, affluence, and technology (Rothman, 1998; Chertow, 2000; Levinson, 2002; Pfaff *et al*., 2004; Carson, 2010). If the EKC holds true, after reaching a certain point, environmental pollution lessens with economic development and a depletion curve is obtained. However, studies predicting future CO_2 emissions in China (mentioned earlier as a developing country in which industrialization is progressing) show that the EKC depletion curve had not been reached by 2010 and it will not materialize unless drastic political measures are introduced (Auffhammer *et al*., 2008). Therefore, global CO_2 emissions are expected to continue to increase as industrialization advances and economies grow in developing countries throughout the world.

In the context of industrial structure, as industrialization advances in developing countries, the economies of developed countries shift to service economies. It was thought that as a shift to a service economy progressed, domestic CO_2 emissions would decrease due to the structural change from CO_2 emissions-intensive manufacturing industries to CO_2 emissions-extensive service industries. However, recent researches indicate that domestic CO_2 emissions actually increase because the industries supplying intermediate goods to the service industry become bloated indirectly (Suh, 2006; Oliver-Solà *et al*., 2007; Nansai *et al*., 2009; Fourcroy *et al*., 2012; Martínez, 2013).

The factors for increasing CO_2 emissions include a variety of social and economic factors, such as changing population, changing economic structure, changing consumption, changing technology, and changing land use. For example, from 2007 to 2008, worldwide economic decline was precipitated by the bankruptcy of Lehman Brothers, and at the same time, many countries saw a decrease in CO_2 emissions from industry during that period only. The mechanism behind the influence of these factors on changes in CO_2 emissions is extremely complicated, and the need for more research from a macro-perspective has been identified (IPCC, 2014).

When considering this mechanism, it is important to analyze the effect of industry/business activities on the environment from a micro-perspective. Increasing awareness of the problem of global warming has led to progress in the establishment of international standards for environmental management. The system for certifying that a company is conducting its business activities in an environmentally conscious way has been improved and expanded, as exemplified by the ISO 14001 series[1]. In Japan, over 20,000 organizations have acquired the ISO 14001 certification. This is an

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[1] See website below for details of the ISO 14000 series:
http://www.iso.org/iso/iso14000.

indication that each organization is being managed with concern for the environment. Environmental analysis of the industries/businesses that form the core of economic activity in the nation as a whole is also very important. In particular, Life Cycle Assessment (LCA) is being discussed as a practical task that industries/businesses should address, and it is regarded as important within the above-mentioned standard as well.

An LCA estimates the environmental impact of each stage of a product's life cycle considered 'from the cradle to the grave', i.e. from mining of materials, to the production line, consumption, and disposal. In Japan, most companies in industries such as chemicals and construction estimate their CO_2 emissions, etc. in accordance with the LCA approach. Furthermore, estimates of CO_2 emissions, etc. based on the LCA approach are gradually becoming established in CSR (Corporate Social Responsibility) reports. LCAs have been enthusiastically addressed in recent years, however LCA system boundary problem has not been solved so far.

Thus, both a macro-perspective analysis of the industrial structure and a micro-perspective analysis focusing on the LCAs of each industry/business are essential in analyzing today's global environmental issues. The relationship between economic activity and global warming cannot be easily explained; rather, it must be understood by conducting more comprehensive analyses that include industry characteristics and the initiatives of actual industries.

1.3 Structure of this Thesis

This Ph.D. thesis comprises six chapters (Figure 1.2). Chapter 2 conducts a review of relevant existing articles, identifies the contributions and problems of the existing research, and describes the significance and objectives of the present study. Chapter 3 focuses on the Japanese economy during 1990 to 2005, and decomposed changes in CO_2 emissions associated with detailed industrial activities into five contributing factors, technical effects, industrial composition effects, economic scale effects, import scale effects, and import composition effects. This chapter argues that these effects were instrumental in allowing Japan to attain its emissions-reduction target under the Kyoto Protocol. Chapter 4 focuses on LCAs in industry, and proposes a method for determining objective system boundaries using industrial cluster analysis to resolve problems concerning the arbitrariness of system boundary determination in conventional LCAs. This chapter also objectively determines critical system boundaries for LCA in five major industries that have acquired large numbers of ISO 14001 certifications (non-residential construction (non-wooden), residential construction (wooden), bolts/nuts/rivets and springs, wholesale, and consumer electrical appliances), by analyzing the supply chains and detecting CO_2 emission-intensive industry systems (industry clusters). This chapter finally concludes that industry clusters identified in this study should be considered in critical LCA system boundaries. Chapter 5 develops a method for statistically evaluating the instability of system boundary setting based on multiple cluster analyses, and conducts an empirical analysis with a focus on the automobile LCA. This chapter concludes that the process LCA practitioners should consider the CO_2 intensive industrial clusters identified by using the clustering method and evaluate the bias of life-cycle CO_2 emissions resulting from the stability analysis developed in this study. Finally, Chapter 6 summarizes the results obtained from Chapters 3 to 5, and presents the conclusions of this dissertation.

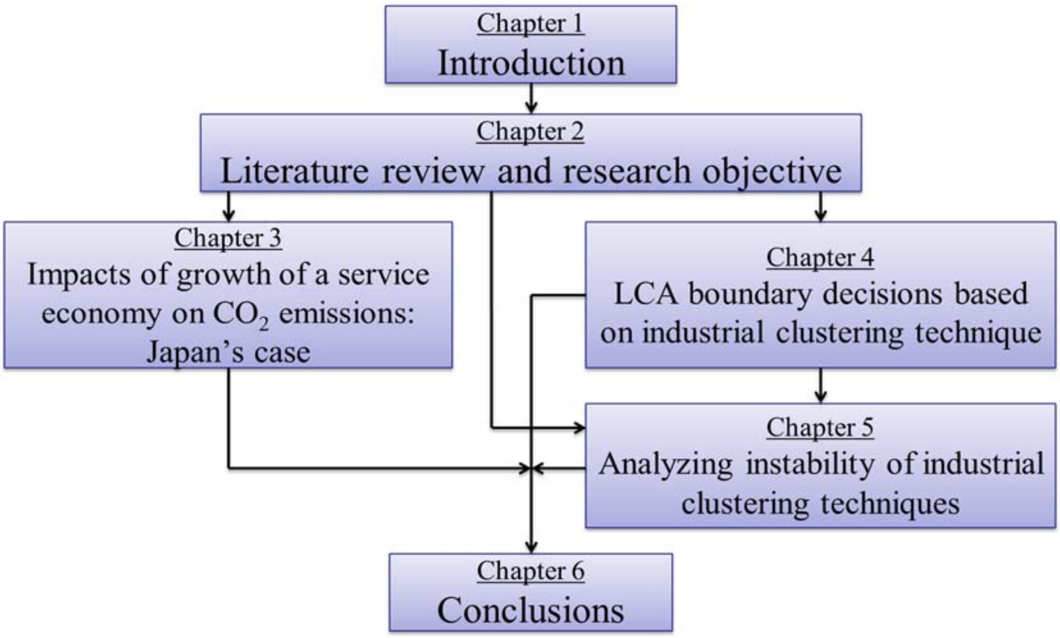

Figure 1.2 Structure of this Thesis

Chapter 2 Literature review and research objective

2.1 Research on Relationship between Environmental Pollution and Economic Growth

Many of the studies that analyze environmental issues from a macroeconomic perspective estimate environmental Kuznets curves (EKC) (mentioned in the previous chapter) showing the relationship between economic growth and environmental pollution. An EKC is an inverted-U curve that shows the relationship between degree of economic growth (e.g. GPD per capita) and amount of environmental pollution (e.g. sulfur dioxide emissions) (Levinson, 2002; Pfaff *et al*., 2004; Carson, 2010). If the EKC holds true, emissions of environmental pollutants increase as economic growth progresses, but decrease with economic growth after a certain economic development level has been reached. Most of the researches investigate the relationship between emissions and economic growth by estimating a regression equation using time-series data on GDP per capita and domestic greenhouse gas emissions (Fodha *et al*., 2010; He *et al*., 2010; Nasir *et al*., 2011; Shahbaz *et al*., 2013).

However, the research conducted thus far into the relationship between emissions and economic growth using regression equations ignores industry characteristics (e.g. fossil fuel consumption by industry, emission factor by industry), and does not take into account the technical factors concerning GHG emissions in industry. The CO_2 emissions generated per unit of combustion of fuels, such as coal, oil, and natural gas are different, and so it is easy to comprehend that the emissions from countries with the same level of GDP will be different if they consume different fossil fuels (Nansai *et al*., 2012).

Changes in industrial structure related to economic growth also have a large effect on CO_2

emissions. There is a large difference in domestic fossil fuel consumption between a country like Japan where the ratio of contribution of the service industry to GDP is high, and a country where the contribution ratio of the manufacturing industry is high, such as China. In China, where it is possible to mine cheap and plentiful coal, more coal is consumed than any other fossil fuel, and it is important to also analyze the effect that differences in fuel use structure associated with the abundance of fossil fuels have on CO_2 emissions.

Estimations of CO_2 emissions that take into account domestic industrial structure include environmental analyses using environmental input–output tables (Lenzen *et al*., 2001; Labandeira *et al*., 2002). Environmental input–output tables for Japan give input–output tables showing the intermediate inputs between approximately 400 industry sectors, and list the CO_2 emission factors (CO_2 emissions per unit of industrial output) corresponding to these industry sectors (Nansai *et al*., 2012). Input–output tables show intermediate flows between industries, with supply and demand for goods/services in a country balanced at the level of each sector, and they are extremely useful data for analyzing industrial structure and economic ripple effects (Streit, 1969; Hazari, 1970; Roepke *et al*., 1974; Czamanski *et al*., 1979; Leontief, 1986; Casler, 1997; Sonis *et al*., 2000; Hoen, 2002; Oosterhaven *et al*., 2002; Aroche-Reyes, 2003; Melitz, 2003; Dietzenbacher, 2005; Institute of Developing Economies, 2006; Wood *et al*., 2006; Miller *et al*., 2009; Suh, 2009; Kagawa, 2011; Alcott, 2012; Dietzenbacher *et al*., 2012; ten Raa *et al*., 2013). By multiplying the intermediate flows of goods/services between industries by industrial emission factors, it is possible to analyze the relationship between industrial structure and CO_2 emissions and conduct an environmental assessment of an entire country (e.g. Leontief, 1970; Leontief *et al*., 1972).

2.2 Research on Structural Decomposition Analysis

Structural decomposition analysis (SDA) has been developed as a method for analyzing changes in industrial structure. Using this method, it is possible to conduct structural decomposition analysis of changes in economic factors (Dietzenbacher *et al*., 1998, 2000; Ang *et al*., 2003; Hoekstra *et al*., 2003; Ang, 2004; Yabe, 2004; Wood *et al*., 2006; Guan *et al*., 2009; Zhang, 2009; Butnar *et al*., 2011; Edens *et al*., 2011). Many studies have been done in which this technique is applied to environmental issues, and changes in domestic CO_2 emissions are broken down into multiple economic factors (e.g. Ma *et al*., 2008; Okamoto, 2013). For example, by applying SDA to CO_2 emissions from domestic industry, Okamoto (2013) analyzed the changes in CO_2 emissions into five factors: changes in economic scale, changes in industrial structure, changes in emission factors, changes in import scale, and changes in import structure and argued how the structural changes affected global warming.

Structural path analysis (SPA) and structural path decomposition (SPD) are also useful methods of this kind of analysis (Defourny *et al*., 1984; Lenzen, 2003, 2007; Wood *et al*., 2009; Oshita, 2012). For example, Oshita (2012) pointed out that identifying the supply chain paths that greatly influence CO_2 emissions is important in tackling the problem of global warming, and attempts to select key supply chain paths with a large effect on changes in CO_2 emissions associated with final demand. In specific terms, he reveals that the 'electric power industry→wholesale industry→household consumption expenditure' path has a large effect on increase in emissions. These methods are important for a comprehensive understanding of changes in CO_2 emissions associated with worldwide economic activity.

2.3 Research on Consumption-based CO_2 Emissions

While investigating sources of change in CO_2 emissions, many studies have also been done into estimating consumption-based CO_2 emissions in each county. In particular, with the development of environmental input–output database, consumption-based CO_2 emissions at the worldwide level using these environmental input–output tables have also been estimated (Afmad *et al*., 2003; Lenzen *et al*., 2004; Raupach *et al*., 2007; Wiedmann *et al*., 2007; Andrew *et al*., 2009; Hertwich *et al*., 2009; Wiedmann, 2009; Davis *et al*., 2011; Peters *et al*., 2011; Kanemoto *et al*., 2012; Lenzen *et al*., 2012). The method for calculating emissions considered in the Kyoto Protocol follows a so-called 'producer-based' approach, in which CO_2 generated during the production of goods and services is attributed to the region where the fuel was actually combusted and the CO_2 was generated (Bin *et al*., 2005; Guan *et al*., 2008; Davis *et al*., 2011; Peters *et al*., 2011; Brown *et al*., 2012; Kanemoto *et al*., 2012). In contrast, a so-called 'consumer-based' method for estimating emissions has been developed in recent years, and in this method, CO_2 emissions generated in association with production are attributed to the consumer that demanded those goods or services (Huppes *et al*., 2006; Liu *et al*., 2009; Baiocchi *et al*., 2010; Davis *et al*., 2010; Atkinson *et al*., 2011; Caldeira *et al*., 2011; Larsen *et al*., 2011; Peters *et al*., 2011; Sinden *et al*., 2011; Cadarso *et al*., 2012; Barret *et al*., 2013; Feng *et al*., 2013). For example, according to Feng *et al*. (2013), 57% of producer-based CO_2 emissions attributed to China were brought about by the production in China of goods consumed in other Chinese provinces and other countries. Adopting a consumer-based method of estimation makes it possible to discuss the question of where to place the consumers' responsibility for CO_2 emissions. This argument on the consumers' emission responsibility is crucial in environmental agreements between multiple countries (Munksgaard *et al*., 2001; Rodrigues *et al*., 2006; Turner *et al*., 2007; Peters, 2008, 2010; Vringer *et al*., 2010; Droege, 2011).

While above analyses are being carried out to estimate GHG emissions of entire nations, environmental analysis at industry level or company level is also important in proposing environmental measures to reduce GHG emissions. Life Cycle Assessment (LCA) is a technique for evaluating the direct and indirect environmental impact of a product by estimating the emissions generated in each stage from mining of raw materials to use and disposal of the product (Joshi, 1999; Tétreault *et al*., 2013). A very large number of papers examining environmental impact make use of LCA as a technique, and those impact studies have increasing become important in recent years (Hellweg *et al*., 2014).

LCA methods can be broadly divided into a process method and an input–output method (Heijungs, 1994; Suh *et al*., 2005, 2007; Fukuyama, *et al*., 2011; Shao *et al*., 2013, 2014). The process method is superior in terms of the preciseness of the analysis results because it utilizes detailed emissions data at production stages in supply chain network. However, the comprehensiveness of the supply chain is considered to be a weakness of this method. This is because the decision regarding which production stages to include in the product's CO_2 emissions calculation is made arbitrarily. Meanwhile, the input–output method uses input–output tables showing intermediate flows for goods/services for the entire country, and so allows a comprehensive analysis of the supply chain associated with final demand for a product (Reich, 2005; Weber *et al*., 2007). Furthermore, if multi-region input–output tables are used, it is possible to estimate emissions induced by final demand of importing regions regions and so to estimate consumption-based emissions, which also makes it possible to discuss how importing regions affect CO_2 emissions in exporting regions.. However, the intermediate inputs shown in input–output tables (i.e. the input of raw materials and parts required for production in each industry) is an average figure for the entire country. The input–output method has the disadvantage that the characteristics of products are not readily apparent (Chang *et al*., 2010; Hertwich, 2005; Peters, 2007; Larsen *et al*., 2012). Hybrid LCAs that use both the process method and the input–output table method have frequently been carried out to estimate CO_2 emissions from industry/business, as well as analyze emissions responsibility at the product level (Treloar, 1999; Treloar *et al*., 2000; Lenzen *et al*., 2009; Strømman *et al*., 2009; Bonvoisin *et al*., 2014).

An important problem in the LCA is system boundary determination (Suh *et al*., 2004). The problem of system boundary determination is the problem of deciding which production processes is included in the estimations of CO_2 emissions associated with the product supply-chains. In a process LCA and a hybrid LCA, the LCA practitioners can freely determine the system boundaries (i.e., target production processes). Consequently, the life-cycle emissions associated with product supply-chains are inevitably underestimated (Lenzen, 2001). In this practical context, it is critically important that LCA system boundaries are determined objectively.

2.4 Research on Cluster Analysis

Cluster analysis has been developed in the field of information processing involving computer science and the field of social networks in sociology. With the aim of extracting portions of images in computer image processing, or, extracting core social networks from communities, many attempts have been made to mathematically solve discrete optimization problems and extract closely related subsets using graph theory (Lorrain *et al*., 1971; Rand, 1971; Donath *et al*., 1973; Fiedler, 1973; Breiger *et al*., 1975; White *et al*., 1975; Batagelj *et al*., 1992; Borgatti *et al*., 1992; Wu *et al*., 1993; Frank, 1995; Hendrickson *et al*., 1995; Lee *et al*., 1999, 2001; Shi *et al*., 2000; Ng *et al*., 2001;Newman, 2003, 2004; Yu *et al*., 2003; Newman *et al*., 2004; Back *et al*., 2005; Ding *et al*., 2005, 2008a, 2008b; Ben-David *et al*., 2007, 2008; Meilă *et al*., 2007; Spielman *et al*., 2007; von Luxburg, 2007, 2010; Hsieh *et al*., 2008; Zhang *et al*., 2008; von Luxburg *et al*., 2008; Nooy *et al*., 2011). Discrete optimization problems that extract closely related sub-networks (clusters) from networks are known as problems that cannot be solved in polynomial time (NP-hard problems) (e.g. Shi *et al*., 2000), and various relaxation problems have been proposed to solve them efficiently. For example, methods for detecting clusters using the eigenvalues and eigenvectors of the Laplacian matrix of network data (spectral clustering) have been proposed (White *et al*., 1975; Wu *et al*., 1993; Shi *et al*., 2000; Yu *et al*., 2003; von Luxburg, 2007, 2010; von Luxburg *et al*., 2008; Zhang *et al*., 2008). Using this method to calculate eigenvalues for the data of one network, it is possible to detect sets that, while having close connections within the same group, show little connection between different groups.

Industry clusters developed in the fields of economics are detected by focusing on similarities between businesses/industries and treating industries with a high degree of similarity as one group, and they are used to evaluate regional policies from the perspective of concentration of industry by analyzing whether similar industries are located in the region (Feser *et al*., 2000; Porter, 2000; Oosterhaven *et al*., 2001; Kelton *et al*., 2008; Delgado *et al*., 2010). These studies do not analyze inter-industry connections.

Kagawa *et al*. (2013a, b) proposed an LCA using the above-mentioned spectral clustering. Specifically, Kagawa *et al*. (2013a, b) attempted to determine emissions-intensive industry groups (industry clusters) by estimating CO_2 emissions associated with intermediate inputs between industries using environmental input–output tables, and extracting groups of intermediate goods industries with high CO_2 emissions from the emissions matrix data using a mathematical top-down approach. This industry cluster analysis makes it possible to evaluate questions such as: If each industry/business is implementing measures to cut emissions, coordination with which industry will make it possible to reduce emissions efficiently? To which industry group should a government subsidy be given to allow efficient reduction of emissions? Furthermore, using the results of an industry cluster analysis, it is possible to objectively determine system boundaries in LCA. Kagawa *et al*. (2013a, b) conducted a case study of the automotive industry and detected CO_2 emissions-intensive upstream industry groups, and they concluded that those upstream industry product systems must be included within the system boundaries of automobile LCAs. Kagawa *et al*. (2013a, b) provided one case study taking the automobile as their example, and they did not analyze the determination of system boundaries in the LCAs of various other products that are important in terms of solving the problem of global warming. Moreover, Kagawa *et al*. (2013a, b) did not examine the validity of their proposed method by comparing the results using several clustering techniques.

2.5 Contributions of this Thesis

This doctoral thesis focuses on CO_2 emissions associated with production and consumption. The research is broadly divided into a macro-analysis focused on emissions control in Japan as a whole, and a meso-analysis focused on emissions control at the industry level.

First, the macro-analysis analyzes the relationship between Japan's industrial structure and the environment. Specifically, it attempts to perform a decomposition analysis of factors of change in CO_2 emissions associated with industrial production using the environmental input–output tables for Japan between 1990 and 2005. The study applies the method of structural decomposition analysis to changes in CO_2 emissions and develops a method for decomposing change in CO_2 emissions into five factors (change in economic scale, change in industrial structure, change in technology, change in import scale, and change in import structure), and then analyzes these factors quantitatively. The analysis results make it possible to understand which factors have caused changes in CO_2 emissions since 1990 (the year established as base year in the Kyoto Protocol) and reveal the role that changes in industrial structure have played in global warming.

Next, the meso-analysis focuses on LCAs carried out by industry/business. The importance of objectively determining LCA system boundaries in the supply chain, which are decided arbitrarily when conducting LCAs, is addressed and an industrial clustering technique is developed to the problem of determining system boundaries. A supply-chain network graph is created showing CO_2 emissions associated with intermediate inputs between industries using environmental input–output tables, and a method for detecting CO_2 emissions-intensive industry clusters in the supply chain is proposed. The fact that it is possible to objectively determine system boundaries is demonstrated empirically by applying the proposed method to the problem of system boundaries in five emissions-intensive industry sectors (the construction industry, etc.) that are key to reducing CO_2 emissions. Moreover, not only is a comparative evaluation of the validity of the results carried out by detecting industry clusters using several clustering techniques, but a method for statistically investigating the instability of clustering techniques is developed.

This thesis discusses emissions control on the national level and the industry level, considers quantitatively the role that industrial structure changes and inter-industry cooperation play in the problem of global warming, and recommends policies that Japan should take to help resolve global warming.

Chapter 3 Impacts of Growth of a Service Economy on CO_2 Emissions: Japan's Case

3.1. Introduction

Increased environmental loads can be understood as arising from a variety of economic factors. For example, the environmental Kuznets curve describes an inverted-U relationship between economic growth (including structural changes) and environmental pollution (Grossman *et al*., 1991, 1995, 1996; Carson 2010 for a literature overview). In particular, this article sheds light on the relationship between structural changes and environmental load in a specific country. As in Levinson (2009), I will focus on influences on CO_2 emissions. In this study, I consider not only the economic scale but also another factor that exhibits significant influence: changes in industrial composition. In Japan, the percentage of domestic Japanese production attributable to secondary industries (manufacturing), which exhibit high rates of CO_2 emissions per unit production (i.e., large direct emissions coefficients), fell drastically, from 49% in 1990 to just 39% in 2005. In contrast, the percentage of domestic Japanese production attributable to tertiary industries (service industries), which exhibit low coefficients of direct CO_2 emissions, rose significantly, from 48% in 1990 to 60% in 2005[2]. This also implies that Japan's transition toward a service-oriented economy has contributed in reducing CO_2 emissions, but the extent to which this has slowed the pace of global warming remains unclear.

Important studies on the relationship between the transition to a service economy and CO_2 emissions

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[2] I estimated the industrial composition rates using the linked input–output tables during 1990–2005 (see Ministry of Internal Affairs and Communication of Japan, 2010, for the linked input–output tables).

include those of Suh (2006) and Nansai *et al*. (2009). Suh (2006) demonstrated that household consumption of services, excluding electric utilities and transportation services, accounts for 37.6% of total industrial GHG emissions in the United States. Nansai *et al*. (2009) analyzed the factors governing life-cycle CO_2 emissions in Japanese service industries between the years 1990 and 2000 and concluded that increased inputs of energy and resources (including materials and components) led to significantly increased CO_2 emissions.

However, the studies of Suh (2006) and Nansai *et al*. (2009) did not quantify the transition to a service economy in terms of the increasing industrial composition attributable to service industries and also did not analyze the impact of the transition to a service economy on production-based CO_2 emissions[3]. In addition, their studies did not argue that the transition to a service economy spurs an increase in imports of CO_2-intensive commodities and that consequently this structural change contributes to global warming. Therefore, in the present study, I apply the Shapley–Sun additive decomposition method (Shapley 1953; Sun 1998, 1999) and decompose the change in production-based CO_2 emissions from domestic industries into five components: that due to changes in the overall scale of the economy (GDP), that due to changes in the industrial composition of the various economic sectors, that due to energy intensity (i.e., technical) changes, which measures CO_2 emissions per unit of domestic production, that due to changes in the import composition of the various commodities, and that due to changes in the import scale. Using this index decomposition method, I will analyze the impact of Japan's transition to a service economy on Japanese CO_2 emissions between 1990 and 2005 and finally argue the environmental benefits of its structural transition.

[3] Production-based CO_2 emissions represent CO_2 emissions from the production activities of domestic industries.

The rest of this chapter is organized as follows: Section 3.2 presents the decomposition method, Section 3.3 describes the data source, Section 3.4 presents a case study of Japan, and Section 3.5 concludes this chapter.

3.2 Methodology

3.2.1 Estimating CO_2 emissions originating from industrial activities

Let $e_{k,i}^{t}$ denote the energy consumption (Gigajoules: GJ) of fuel type $k\left(k=1,2,\ldots,M\right)$ associated with 1 unit (¥1 million) of production in industry sector $i\left(i=1,2,\ldots,N\right)$ during year *t*. Here *N* is the number of industry sectors and *M* is the number of types of fuel. Also, let c_k denote the CO_2 emissions (t CO_2) generated directly from the consumption of 1 GJ worth of fuel type *k* in the specific industry sector. Then the quantity of CO_2 emitted in conjunction with unit production in industry sector i in year t can be expressed in the form $c_k \times e_{k,i}^{t}$ (t CO_2/million yen).

If θ_i^t denotes the industrial composition showing the fraction of output of industry sector i of total production across all industries, and X_d^t denotes total industrial output summed over all industry sectors, the total amount of domestic production contributed by industry sector i in year t is then represented as $\theta_i^t \times X_d^t$ (million yen).

Multiplying the CO_2 emission coefficient of industry sector *i*, $c_k \times e_{k,i}^{t}$, by the domestic output of industry sector *i*, $\theta_i^t \times X_d^t$, yields $c_k e_{k,i}^{t} \theta_i^t X_d^t$ as an estimate of CO_2 emissions arising from the use of fuel type *k* in industry sector *i*. Summing these estimates over all industry sectors and all fuel types, we obtain the following estimate of total domestic production-based emissions Q_d^t (t CO_2):

$$Q_d^t = \sum_{i=1}^{N}\sum_{k=1}^{M} c_k e_{k,i}^t \theta_i^t X_d^t \quad (3.1)$$

3.2.2 Changes in CO_2 emissions: factor decomposition

We now use the Shapley–Sun decomposition method to analyze changes in the quantity of CO_2 emissions originating from industrial activities (i.e., the quantity Q_d^t) into three sources: technical effects, industrial composition effects, and economic scale effects (Levinson 2009). (For details on the decomposition method, see Ang *et al*. 2003, 2009; Ang 2004.)

Let ΔQ_d denote the change from year t to year $t+1$ in CO_2 emissions originating from industrial activities, expressed as follows:

$$\begin{aligned}\Delta Q_d &= Q_d^{t+1} - Q_d^t \\ &= \sum_{i=1}^{N}\sum_{k=1}^{M} c_k e_{k,i}^{t+1} \theta_i^{t+1} X_d^{t+1} - \sum_{i=1}^{N}\sum_{k=1}^{M} c_k e_{k,i}^t \theta_i^t X_d^t \\ &= \mathbf{c}\cdot\mathbf{E}^{t+1}\cdot\boldsymbol{\theta}^{t+1}\cdot X_d^{t+1} - \mathbf{c}\cdot\mathbf{E}^t\cdot\boldsymbol{\theta}^t\cdot X_d^t\end{aligned} \quad (3.2)$$

Here c is a $(1\times M)$ row vector whose *k*th element, c_k , is the emission coefficient of fuel type k; $\mathbf{E}$ is an $(M\times N)$ matrix whose (*k,i*) element, $e_{k,i}$, is the energy consumption (i.e., energy intensity) for fuel type *k* used to produce one unit of output in industry sector *i*; and $\boldsymbol{\theta}$ is an $(N\times 1)$ column vector whose *i*th element, θ_i , is the industrial composition of industry sector i. The superscripts *t* and *t* + 1 indicate the year.

The changes in $\mathbf{E} = \left(e_{k,i}\right)$, $\boldsymbol{\theta} = \left(\theta_i\right)$, and X can be expressed as follows:

$$\Delta\mathbf{E} = \mathbf{E}^{t+1} - \mathbf{E}^{t} \tag{3.3}$$

$$\Delta\boldsymbol{\theta} = \boldsymbol{\theta}^{t+1} - \boldsymbol{\theta}^{t} \tag{3.4}$$

$$\Delta X_d = X_d^{t+1} - X_d^{t} \tag{3.5}$$

Using equations (3.3), (3.4), and (3.5), equation (3.2) can be transformed as follows:

$$\begin{aligned}\Delta Q_d &= \mathbf{c}\cdot\mathbf{E}^{t+1}\cdot\boldsymbol{\theta}^{t+1}\cdot X_d^{t+1} - \mathbf{c}\cdot\mathbf{E}^{t}\cdot\boldsymbol{\theta}^{t}\cdot X_d^{t} \\ &= \mathbf{c}\cdot\left(\mathbf{E}^{t}+\Delta\mathbf{E}\right)\cdot\left(\boldsymbol{\theta}^{t}+\Delta\boldsymbol{\theta}\right)\cdot\left(X_d^{t}+\Delta X_d\right) - \mathbf{c}\cdot\mathbf{E}^{t}\cdot\boldsymbol{\theta}^{t}\cdot X_d^{t+1} \\ &= \mathbf{c}\Delta\mathbf{E}\boldsymbol{\theta}^{t}X_d^{t+1} + \mathbf{c}\mathbf{E}^{t}\Delta\boldsymbol{\theta}X_d^{t} + \mathbf{c}\mathbf{E}^{t}\boldsymbol{\theta}^{t}\Delta X_d + \mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta}X_d^{t} + \mathbf{c}\mathbf{E}^{t}\Delta\boldsymbol{\theta}\Delta X_d + \mathbf{c}\Delta\mathbf{E}\boldsymbol{\theta}^{t}\Delta X_d + \mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta}\Delta X_d\end{aligned} \tag{3.6}$$

The first term on the right-hand side of equation (3.6) represents the influence on emissions of changes in the energy intensity in the industrial sector. The second and third terms represent the influence on emissions of changes in the industrial composition of the industrial sector and the total industrial output, respectively. The simplified additive decomposition method (e.g., Park 1992) ignores second-order interaction terms (such as the fourth, fifth, and sixth terms on the right-hand side of equation (3.6)) and third-order interaction terms (such as the seventh term). As a result, the sum of the contributions of the first three terms on the right-hand side will not be equal to total change in emissions ΔQ_d. The important question is how to treat the influence of the interaction terms (Sun 1998).

In the present study, following Sun (1998), I consider the second-order interaction terms and the third-order interaction term, and employ the following additive decomposition formulation.

$$\Delta Q_d = \underbrace{\mathbf{c}\Delta\mathbf{E}\boldsymbol{\theta}^t X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta} X_d^t + \mathbf{c}\Delta\mathbf{E}\boldsymbol{\theta}^t \Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta}\Delta X_d}_{\text{Technical effect: } \Delta Q_d^{Tech}}$$

$$\underbrace{+\mathbf{c}\mathbf{E}^t\Delta\boldsymbol{\theta} X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta} X_d^t + \mathbf{c}\mathbf{E}^t\Delta\boldsymbol{\theta}\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta}\Delta X_d}_{\text{Industrial composition effect: } \Delta Q_d^{Comp}}$$

$$\underbrace{+\mathbf{c}\mathbf{E}^t\boldsymbol{\theta}^t\Delta X_d + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\boldsymbol{\theta}^t\Delta X_d + \mathbf{c}\mathbf{E}^t\Delta\boldsymbol{\theta}\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\theta}\Delta X_d}_{\text{Economic scale effect: } \Delta Q_d^{Scale}} \qquad (3.7)$$

We refer to the first, second, and third terms on the right-hand side of equation (3.7) respectively as the technical effect, the industrial composition effect, and the economic scale effect, which we denote by ΔQ_d^{Tech}, ΔQ_d^{Comp}, and ΔQ_d^{Scale}. The effect expressed by equation (3.7) is the *total* effect, representing the sum of the effects across all industries; thus, for example, it is not possible to isolate from equation (3.7) the industrial composition effect in the service industry or the technical effect in the manufacturing industry. For this reason, we will further decompose equation (3.7) into the effect in each industry.

We will classify our N industry sectors into four industry groups: (1) primary industries, (2) secondary industries, (3) electricity, gas, and water supply industries, and (4) tertiary industries (service industries). For industry sector i belonging to the group of primary industries (i.e., $i \in primary\ industry$), we define $\mathbf{S}_a$ to be the $(N \times N)$ diagonal matrix with ith diagonal element equal to 1 and all other elements equal to 0. Here the subscript a indicates primary industries (i.e., agriculture, forestry, and fishery industries). The technical effect (i.e., that from changes in the energy intensity) in industry sectors belonging to the group of primary industries and the effect from changes in industrial composition in industry sectors belonging to the primary industries can be quantified using equations (3.8) and (3.9) below:

$$\Delta Q_{d,a}^{Tech} = \mathbf{c}\Delta\mathbf{E}\mathbf{S}_a\boldsymbol{\theta}^t X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_a\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\Delta\mathbf{E}\mathbf{S}_a\boldsymbol{\theta}^t\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_a\Delta\boldsymbol{\theta}\Delta X_d \tag{3.8}$$

$$\Delta Q_{d,a}^{Comp} = \mathbf{c}\mathbf{E}^t\mathbf{S}_a\Delta\boldsymbol{\theta}X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_a\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\mathbf{E}^t\mathbf{S}_a\Delta\boldsymbol{\theta}\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_a\Delta\boldsymbol{\theta}\Delta X_d \tag{3.9}$$

Similarly, the technical effects and industrial composition effects in secondary industries, electricity, gas, and water supply industries, and tertiary industries can be estimated as in equations (3.10) through (3.15) below:

$$\Delta Q_{d,m}^{Tech} = \mathbf{c}\Delta\mathbf{E}\mathbf{S}_m\boldsymbol{\theta}^t X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_m\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\Delta\mathbf{E}\mathbf{S}_m\boldsymbol{\theta}^t\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_m\Delta\boldsymbol{\theta}\Delta X_d \tag{3.10}$$

$$\Delta Q_{d,m}^{Comp} = \mathbf{c}\mathbf{E}^t\mathbf{S}_m\Delta\boldsymbol{\theta}X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_m\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\mathbf{E}^t\mathbf{S}_m\Delta\boldsymbol{\theta}\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_m\Delta\boldsymbol{\theta}\Delta X_d \tag{3.11}$$

$$\Delta Q_{d,g}^{Tech} = \mathbf{c}\Delta\mathbf{E}\mathbf{S}_g\boldsymbol{\theta}^t X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_g\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\Delta\mathbf{E}\mathbf{S}_g\boldsymbol{\theta}^t\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_g\Delta\boldsymbol{\theta}\Delta X_d \tag{3.12}$$

$$\Delta Q_{d,g}^{Comp} = \mathbf{c}\mathbf{E}^t\mathbf{S}_g\Delta\boldsymbol{\theta}X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_g\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\mathbf{E}^t\mathbf{S}_g\Delta\boldsymbol{\theta}\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_g\Delta\boldsymbol{\theta}\Delta X_d \tag{3.13}$$

$$\Delta Q_{d,s}^{Tech} = \mathbf{c}\Delta\mathbf{E}\mathbf{S}_s\boldsymbol{\theta}^t X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_s\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\Delta\mathbf{E}\mathbf{S}_s\boldsymbol{\theta}^t\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_s\Delta\boldsymbol{\theta}\Delta X_d \tag{3.14}$$

$$\Delta Q_{d,s}^{Comp} = \mathbf{c}\mathbf{E}^t\mathbf{S}_s\Delta\boldsymbol{\theta}X_d^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\mathbf{S}_s\Delta\boldsymbol{\theta}X_d^t + \mathbf{c}\mathbf{E}^t\mathbf{S}_s\Delta\boldsymbol{\theta}\Delta X_d\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\mathbf{S}_s\Delta\boldsymbol{\theta}\Delta X_d \tag{3.15}$$

Here $\mathbf{S}_m$, $\mathbf{S}_g$, and $\mathbf{S}_s$, where the subscripts *m*, *g*, and *s* respectively denote secondary industries, electricity, gas, and water supply industries, and tertiary industries, are $\left(N \times N\right)$ diagonal matrices whose *i*th diagonal element is 1 for all *i* in the corresponding industry group and all other elements are zero.

3.3. Data

I used CO_2 emissions data obtained from industrial tables contained in the Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables: 3EID data book released by the Center for Global Environmental Research at the National Institute for Environmental Studies of Japan (2012). In addition, I used the 1990–1995–2000–2005 linked environmental input–output tables (396 industry sectors) (Nansai *et al*. 2009).

Using the 3EID data book allows energy intensity data for joules of 32 types of raw fuel directly consumed by producing one unit of output in each of 396 industry sectors in the years 1990, 1995, 2000, and 2005 (see Appendix 3A for the 32 raw fuel types). From this database, we can obtain values of $e^t_{k,i}$. In addition, from the same database, we can obtain data on the quantity c_k (Appendix 3A).

From the 1990–1995–2000–2005 linked input–output tables (which are evaluated in terms of 2005 producer prices), we can obtain not only data on the total production in each industry sector in each year, but also data on the quantity X^t_d . This, in turn, allows us to easily compute θ_i , which measures the industrial composition of industry sector i. For details on the categorization of industry sectors, see Appendix 3B.

3.4. Results

3.4.1 Macro-level decomposition results

According to the 1990–1995–2000–2005 linked input–output tables, Japan's total industrial output was ¥841 trillion in 1990, ¥886 trillion in 1995, ¥922 trillion in 2000, and ¥962 trillion in 2005. Meanwhile, CO_2 emissions originating from industrial activity were 1.04 billion t CO_2 in 1990, 1.10 billion t CO_2 in 1995, 1.13 billion t CO_2 in 2000, and 1.17 billion t CO_2 in 2005. The increase in CO_2 emissions can be attributed to the growth in total industrial output. However, the CO_2 intensity, which can be defined by dividing CO_2 emissions originating from each year's industrial activity by total industrial output, was 1.24 t CO_2/million yen in 1990, 1.25 t CO_2/million yen in 1995, 1.22 t CO_2/million yen in 2000, and 1.22 t CO_2/million yen in 2005. Thus, Japan's CO_2 intensity has been gradually improving, indicating that factors such as technological progress and the transition to cleaner fuels have contributed to reducing CO_2 emissions.

Figure 3.1 shows the results of decompositions, using equation (3.7), of the changes in Japanese CO_2 emissions originating from industrial activity over the 15-year period from 1990 to 2005, as decomposed into three factors: technical effects, industrial composition effects, and economic scale effects. Between 1990 and 1995, the change in CO_2 emissions was +64 Mt CO_2; from the figure, we see that this number breaks down into −2 Mt CO_2 arising from technical effects, +8 Mt CO_2 arising from industrial composition effects, and +58 Mt CO_2 arising from economic scale effects. Next, between 1995 and 2000, the change in CO_2 emissions was +25 Mt CO_2; this number breaks down into −99 million t CO_2 arising from technical effects, +78 Mt CO_2 arising from industrial composition effects, and +46 Mt CO_2 arising from economic scale effects. Finally, between 2000 and

2005, the change in CO_2 emissions was +46 Mt CO_2; this number breaks down into +98 Mt CO_2 arising from technical effects, −102 Mt CO_2 arising from industrial composition effects, and +50 Mt CO_2 arising from economic scale effects.

Thus we see that, during the 10-year period from 1990 to 2000, economic scale effects and industrial composition effects both contributed to increasing CO_2 emissions, while technical effects contributed to reducing CO_2 emissions. However, this trend reversed itself in the years between 2000 and 2005, during which technical effects contributed significantly to increasing CO_2 emissions, whereas industrial composition effects contributed significantly to reducing CO_2 emissions.

Because the results presented in Figure 3.1 are aggregate totals over all industry sectors, they do not allow us to identify the particular industry sectors in which technical effects and industrial composition effects influenced CO_2 emissions. To investigate these questions, we use equations (3.8) through (3.15) to analyze technical effects and industrial composition effects in each of our four industry groups: primary industries, secondary industries, electricity, gas, and water supply industries, and tertiary industries.

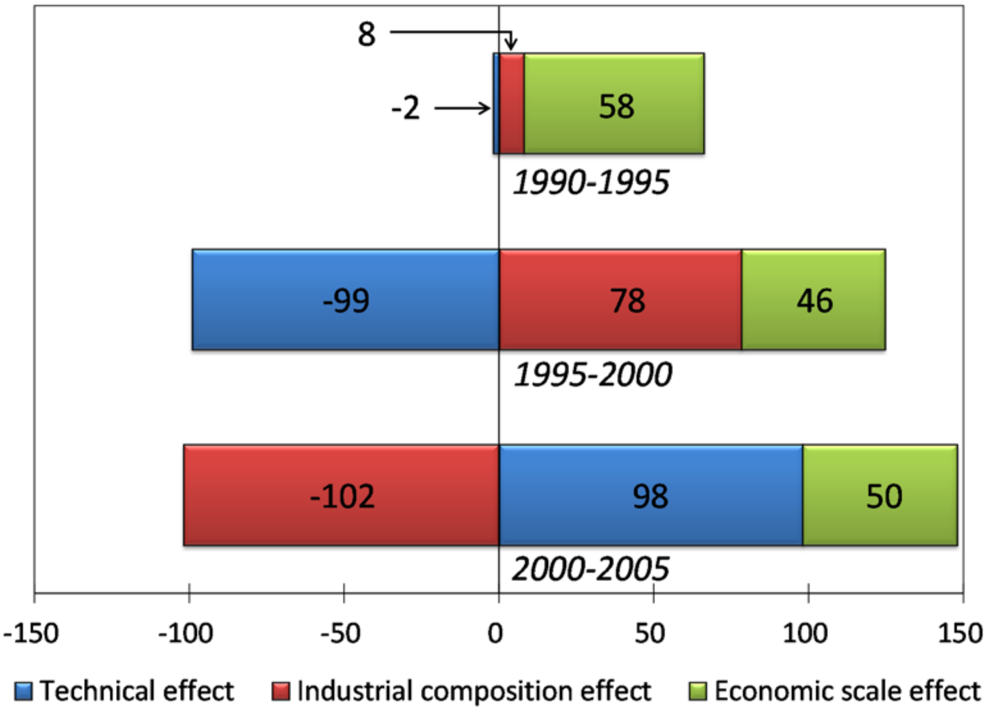

Figure 3.1 CO_2 decomposition result using the Shapley–Sun decomposition method (units: Mt CO_2)

3.4.2 Technical effects for the four industry groups

Within each industry, the technical effect measures the impact on CO_2 emissions of changes in the industrial energy intensity. A negative technical effect for an industry signifies that the industry has successfully reduced energy consumption or shifted its use of energy in a way that reduces CO_2 emissions. Figure 3.2 shows technical effects for the four industry groups considered in this study. As shown, electricity, gas, and water supply industries exhibited a negative technical effect throughout the 10-year period from 1990 to 2000 but crossed over to a large positive technical effect (+102 Mt CO_2) during the interval between 2000 and 2005.

Thus we see that, in the past 15 years, the technical effects in electricity, gas, and water supply industries have varied widely. In particular, one factor contributing to the increase in emissions during the 5-year period from 2000 to 2005 was the high technical effect of +62 Mt CO_2 observed for the commercial electric power sector. The primary cause of this phenomenon in the commercial electric power sector is the fact that, although the energy intensity for crude oil decreased during this period, the energy intensity for coal, lignite, and anthracite increased, and an energy shift to these fuels, which exhibit relatively higher concentrations of CO_2 emissions, has occurred.

Figure 3.2 also reveals that technical effects in tertiary industries led to a significant decrease in CO_2 emissions between the years 2000 and 2005. Considering the technical effects in specific sectors, we see that the technical effect in the ocean cargo transport industry was −8 Mt CO_2 and that in the road cargo transport industry was −7 Mt CO_2. Improved fuel efficiency in both these sectors significantly reduced the quantity of heavy oil needed to power ships and the quantity of light oil needed to power trucks, accounting for 88% of the technical effects observed in tertiary industries.

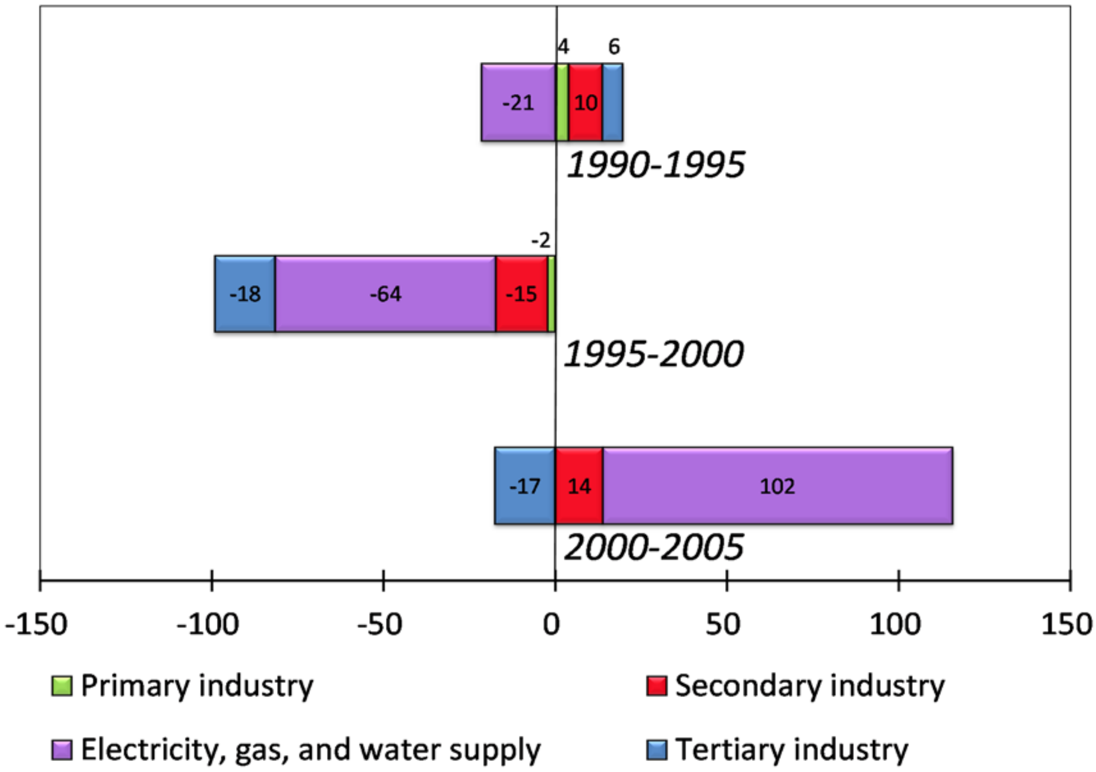

Figure 3.2 Technical effects for the four industry groups (units: Mt CO_2)

3.4.3 Industrial composition effects for the four industry groups

Within each industry, the industrial composition effect measures the impact of changes in the fraction of the overall industry accounted for by the various sectors. A negative value for this effect indicates that an industry sector contributed to reducing CO_2 emissions by decreasing the industrial composition. Figure 3.3 displays industrial composition effects for the four industry groups. As indicated in the figure, both primary and secondary industries exhibited negative industrial composition effects throughout the 15-year period from 1990 to 2005, whereas tertiary industries exhibited an overall positive effect throughout this period.

The total industrial composition effect for primary, secondary, and tertiary industries was −18.8 Mt CO_2 between 1990 and 1995, −15.8 Mt CO_2 between 1995 and 2000, and −30.4 Mt CO_2 between 2000 and 2005. These observations indicate that, throughout this 15-year period, the market for primary and secondary industries contracted, whereas the market for tertiary industries expanded (indicating the transition to a service economy); these changes consequently reduced CO_2 emissions by 65 Mt CO_2.

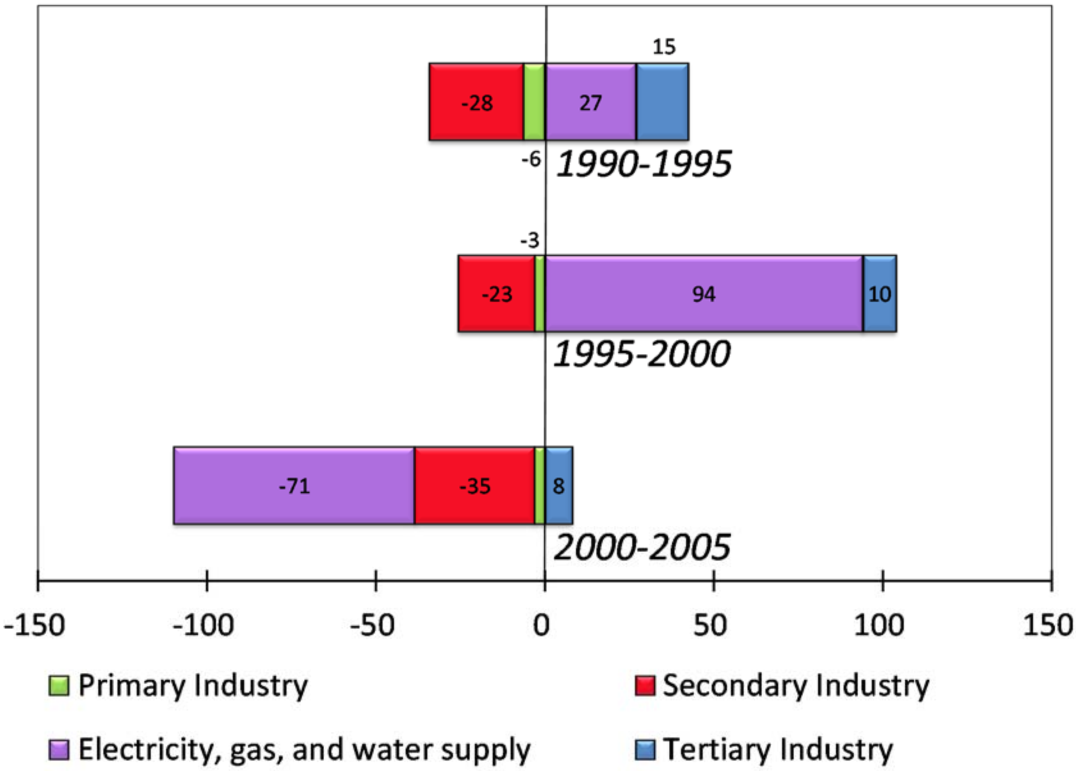

Figure 3.3 Industrial composition effects for the four industry groups (units: Mt CO_2)

3.4.4 Role of the service economy and international trade on CO_2 emissions

Figure 3.4 compares the total technical effect for primary, secondary, and tertiary industries to the total industrial composition effect for these three industry groups[4]. Considering the overall effect (that is, the sum of the technical effect and the industrial composition effect), we see that, in the years between 1990 and 1995, technical effects and industrial composition effects together accounted for an increase in CO_2 emissions of 880 kt CO_2 (the sum of the technical effect and the industrial composition effect for 1990–1995 shown in Figure 4). On the other hand, between 1995 and 2000, technical effects and industrial composition effects led to a decrease in CO_2 emissions of 50.7 Mt CO_2, and between 2000 and 2005 these effects led to a further decrease of 34.2 Mt CO_2. Thus, the overall decrease was particularly significant between 1995 and 2000; from the figure, we can see that this is largely attributable to the relatively large technical effects exhibited by tertiary industries during this interval.

The 1990–1995 overall effect of +880 kt CO_2 corresponds to 0.1% of total emissions in 1990, which is the base year of the Kyoto Protocol. Whereas the industrial composition effect during this period was a large negative effect due to the transition to a service economy, the technical effect contributed significantly to increased CO_2 emissions. Between 1995 and 2000, the overall effect was −50.7 Mt CO_2, corresponding to 4.6% of total emissions in 1995; between 2000 and 2005, the overall effect was −34.2 Mt CO_2, or a 3% decrease compared to total emissions in 2000.

Nansai *et al*. (2009) analyzed the domestic CO_2 emissions associated with the energy and material

[4] Figures 3.2 and 3.3 show that the technical effects and industrial composition effects of electricity, gas, and water supply industries were large during the study period. In this section, I would like to discuss how the structural changes affected the CO_2 emissions when excluding these effects of electricity, gas, and water supply industries.

goods absorbed by services through the supply chain during the decade 1990−2000. They found that the CO_2 emissions contributed by way of the material goods absorbed by service industries rose from 68 Mt CO_2 in 1990 to 87 Mt CO_2 in 2000. As a result, the material dependence of service industries increased by 19 Mt CO_2 during 1990−2000. On the other hand, this study found that the CO_2 reduction due to the transition of a service economy was 35 Mt CO_2[5]. This reveals that the structural transition to a service economy was much more important than the material dependence of service industries.

Over the past 15 years, the declining share of domestic output by Japan's manufacturing industries has contributed to the mitigation of global warming, but the corresponding increase in the share of manufactured goods imported from overseas has increased CO_2 emissions in foreign countries. This leads to the question of whether it is possible that the net impact has been to *exacerbate* the phenomenon of global warming. To address this question, we considered the impact on CO_2 emissions of the changing share of imports; we decomposed import-based CO_2 emissions into three sources, as formulated in Appendix 3C[6]. Figures 3.5 and 3.6 present the results of this decomposition analysis. As shown in Figure 3.5, over the past 15 years, the absolute quantity of imports from foreign countries to Japan rose and at the same time domestic CO_2 emissions rose by the equivalent of 38 Mt CO_2 (the total import scale effect). In contrast, as shown in Figure 3.6, changes in the import composition decreased domestic CO_2 emissions by 8 Mt CO_2. These results demonstrate that Japan's increasing dependence on imports during the past 15 years has accelerated global warming.

In this study, we have employed the domestic technology assumption to estimate import-based

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[5] The CO_2 reduction effect due to the transition to a service economy during 1990−2000 was estimated by summing total industrial composition effects during 1990−1995 and 1995−2000 (see Figure 4).

[6] The import-based CO_2 emissions represent CO_2 emitted by producing imported goods and services overseas.

CO_2 emissions by multiplying Japanese import volumes by Japanese CO_2 emission coefficients for each of 396 industries. For this reason, we might have underestimated CO_2 emissions due to imports from developing countries with relatively high emission coefficients. As the Japanese economy transitions from agricultural and manufacturing industries to service-based industries, it depends increasingly on imports of agricultural products and manufactured goods; on the basis of the domestic technology assumption, these imports changes (especially, the increase in the import scale of manufacturing products) and the previous industrial composition changes (i.e., the transition to a service economy) have consequently brought about a reduction in production-based CO_2 emissions of 35 Mt CO_2, or approximately 3% of total emissions in 1990.

However, this reduction effect may be considerably overestimated due to differences in CO_2 emission intensities between Japan and other countries. Based on the World Input–Output Database (40 countries and 35 industrial sectors)[7], the Japanese industrial CO_2 intensities are approximately half those of China (one of the more CO_2-intensive countries) *on average*. Although the Chinese CO_2 emission intensities from the World Input–Output Database cannot be easily used for our study due to the highly aggregated sectoral classifications, it is clear that if we simply assume all the Japanese CO_2 intensities for a particular year (1990, 1995, 2000, and 2005) to be double their actual values, both the import scale effect and the import composition effect would be also double, accounting for 76 Mt CO_2 and −16 Mt CO_2, respectively. As a result, this assumption leads to the findings that the imports change effect, including their scale and composition effects, is 60 Mt CO_2 and the reduction effect due to the industrial composition changes over the entire 15-year period was offset by the imports change effect (see Section 4.3 for the industrial composition effects). Thus, the CO_2 emission leakage of Japan might not be negligible.

[7] The WIOD is downloadable from the website: http://www.wiod.org/.

Under the terms of the Kyoto Protocol, Japan's target was to reduce *domestic* emissions by 6% of total emissions in 1990; thus, if we consider only the domestic industrial composition effect (−65 Mt CO_2) discussed in Section 3.4.3, then we must conclude that this structural transition has contributed significantly to Japan's attainment of its emissions-reduction goals under the Kyoto Protocol. Moreover, the CO_2 emissions tax under consideration by Japan's Ministry of the Environment is 289 yen/t CO_2, and, based on this tax rate, the environmental benefit of the transition to a service economy will amount to ¥18.7 billion (=289 yen/t $CO_2 \times$ 65 Mt CO_2). Thus, we cannot ignore these structural change effects when considering the mitigation of domestic greenhouse gas emissions. Industrial policies that accelerate Japan’s transition to a service economy are an effective means of reducing Japanese domestic CO_2 emissions. However, such policies may result in increased emissions overall, by steering the production of manufactured industrial goods to foreign producers exhibiting high concentrations of CO_2 emissions. The important point is to strive for the dematerialization of society as a whole, thereby reducing CO_2 emissions from manufacturing sectors both in Japan and abroad.

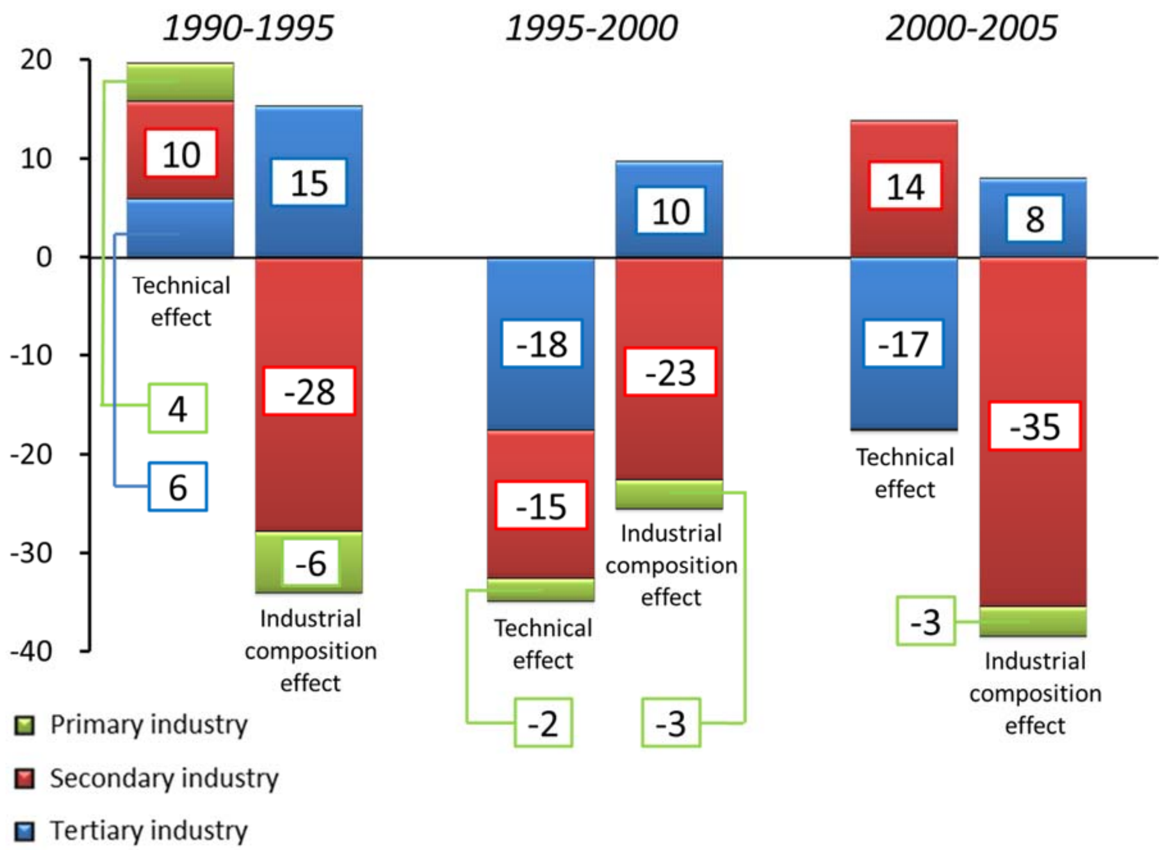

Figure 3.4 Overall effects for three industry groups (units: Mt CO_2)

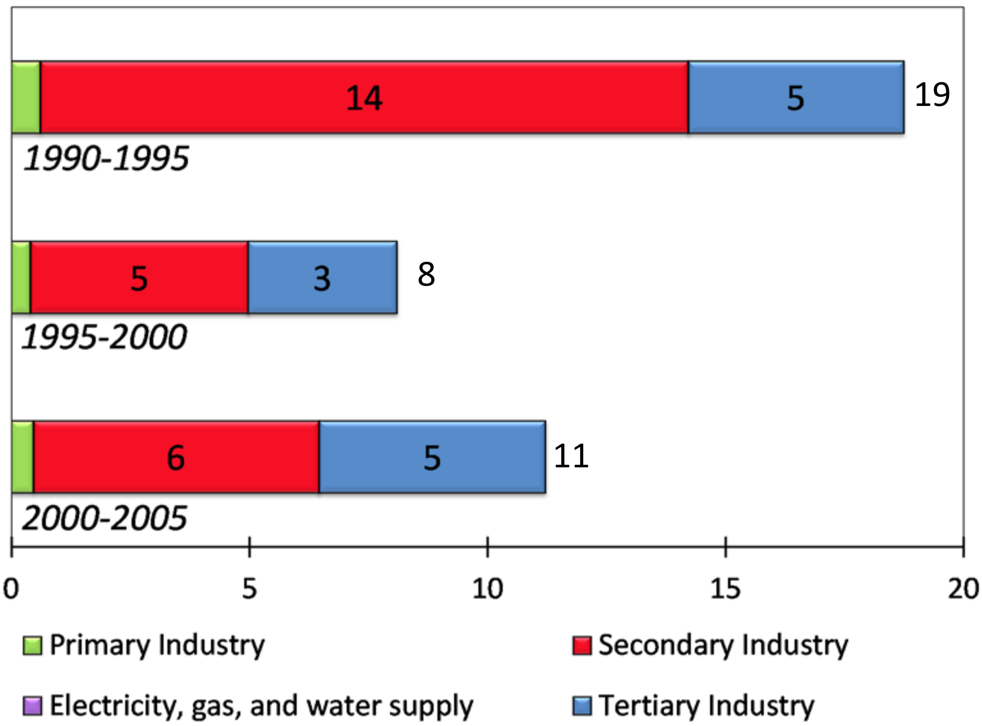

Figure 3.5 Import scale effects for three industry groups (units: Mt CO_2)

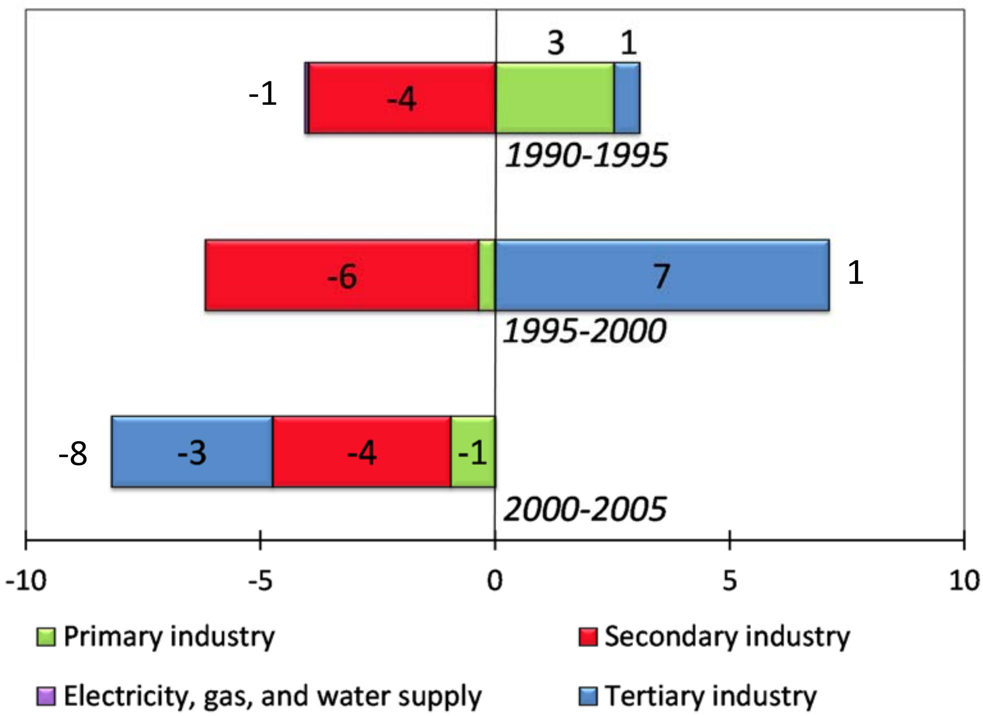

Figure 3.6 Import composition effects for three industry groups (units: Mt CO_2)

3.5. Conclusions

In this chapter, I considered the Japanese economy during three time periods, from 1990 to 1995, from 1995 to 2000, and from 2000 to 2005, and I decomposed changes in CO_2 emissions originating from detailed industrial activities into five contributing factors, technical effects, industrial composition effects, economic scale effects, import scale effects, and import composition effects.

The major findings of this study are as follows.

(1) During the 15-year period from 1990 to 2005, technical effects in the ocean and road cargo transport sectors (including, among other factors, increased fuel efficiency for ships and trucks) helped to ensure an overall technical effect of −29 Mt CO_2 for tertiary industries as a whole, thus contributing significantly to a reduction in CO_2 emissions.

(2) The industrial composition changes during the period from 2000 to 2005 contributed to a decrease in CO_2 emissions, while those changes during the 10-year period from 1990 to 2000 led to an increase in CO_2 emissions. The main reason is that the Japanese economy experienced a significant decarbonization due to structural changes toward a service economy during 2000 to 2005.

(3) During the 15-year period from 1990 to 2005, structural change effects under the domestic technology assumption (which include industrial composition effects, import scale effects, and import composition effects) totaled −35 Mt CO_2, or 3% of total CO_2 emissions in 1990. These effects were instrumental in allowing Japan to attain its emissions-reduction target under the Kyoto Protocol, which was a 6% reduction from 1990 emissions levels.

(4) I demonstrated that the domestic environmental benefit arising from the transition to a service economy would amount to ¥18.7 billion.

Appendix 3A The classification of fuel types

Table 3A The Classification of fuel types

	Fuel type	CO_2 emission intensity	Unit
1	Coking coal	0.092	t CO_2/GJ
2	Steam coal, lignite and anthracite	0.089	t CO_2/GJ
3	Coke	0.108	t CO_2/GJ
4	Blast furnace coke	0.108	t CO_2/GJ
5	Coke oven gas (COG)	0.040	t CO_2/GJ
6	BFG (Consumption)	0.108	t CO_2/GJ
7	BFG (Generation)	0.108	t CO_2/GJ
8	LDG (Consumption)	0.108	t CO_2/GJ
9	LDG (Generation)	0.108	t CO_2/GJ
10	Crude oil	0.069	t CO_2/GJ
11	Fuel oil A	0.071	t CO_2/GJ
12	Fuel oils B and C	0.071	t CO_2/GJ
13	Kerosene	0.068	t CO_2/GJ
14	Diesel oil	0.069	t CO_2/GJ
15	Gasoline	0.067	t CO_2/GJ
16	Jet fuel	0.067	t CO_2/GJ
17	Naphtha	0.065	t CO_2/GJ
18	Petroleum-based hydrocarbon gas	0.046	t CO_2/GJ
19	Hydrocarbon oil	0.077	t CO_2/GJ
20	Petroleum coke	0.093	t CO_2/GJ
21	Liquefied petroleum gas (LPG)	0.060	t CO_2/GJ
22	Natural gas, LNG	0.051	t CO_2/GJ
23	Mains gas	0.052	t CO_2/GJ
24	Black liquor	0.094	t CO_2/GJ
25	Waste wood	0.077	t CO_2/GJ
26	Waste tires	0.080	t CO_2/GJ
27	Municipal waste	0.031	t CO_2/GJ
28	Industrial waste	0.049	t CO_2/GJ
29	Recycled plastic of packages origins	0.065	t CO_2/GJ
30	Nuclear power generation		-
31	Hydro and other power generations		-
32	Limestone	0.0105	t CO_2/GJ

Source: Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables (3EID) data book released by the Center for Global Environmental Research at the National Institute for Environmental Studies of Japan (2012)
The 3EID data are described with the unit of TOE (Tons of Oil Equivalent).

Appendix 3B The categorization of industrial sectors

Table 3B The categorization of industrial sectors

1 Rice	71 Tobacco
2 Wheat, barley and the like	72 Fiber yarns
3 Potatoes and sweet potatoes	73 Cotton and staple fiber fabrics (inc. fabrics of synthetic spun fibers)
4 Pulses	74 Silk and artificial silk fabrics (inc. fabrics of synthetic filament fibers)
5 Vegetables	75 Woolen fabrics, hemp fabrics and other fabrics
6 Fruits	76 Knitting fabrics
7 Sugar crops	77 Yarn and fabric dyeing and finishing (processing on commission only)
8 Crops for beverages	78 Ropes and nets
9 Other edible crops	79 Carpets and floor mats
10 Crops for feed and forage	80 Fabricated textiles for medical use
11 Seeds and seedlings	81 Other fabricated textile products
12 Flowers and plants	82 Woven fabric apparel
13 Other inedible crops	83 Knitted apparel
14 Dairy cattle farming	84 Other wearing apparel and clothing accessories
15 Hen eggs	85 Bedding
16 Fowls and broilers	86 Other ready-made textile products
17 Hogs	87 Timber
18 Beef cattle	88 Plywood
19 Other livestock	89 Wooden chips
20 Veterinary service	90 Other wooden products
21 Agricultural services (except veterinary service)	91 Wooden furniture and fixtures
22 Silviculture	92 Wooden fixtures
23 Logs	93 Metallic furniture and fixture
24 Special forest products (inc. hunting)	94 Pulp
25 Marine fisheries	95 Paper
26 Marine culture	96 Paperboard
27 Inland water fisheries and culture	97 Corrugated cardboard
28 Metallic ores	98 Coated paper and building (construction) paper
29 Materials for ceramics	99 Corrugated card board boxes
30 Gravel and quarrying	100 Other paper containers
31 Crushed stones	101 Paper textile for medical use
32 Other non-metallic ores	102 Other pulp, paper and processed paper products
33 Coal mining , crude petroleum and natural gas	103 Printing, plate making and book binding
34 Slaughtering and meat processing	104 Chemical fertilizer
35 Processed meat products	105 Industrial soda chemicals
36 Bottled or canned meat products	106 Inorganic pigment
37 Dairy farm products	107 Compressed gas and liquefied gas
38 Frozen fish and shellfish	108 Salt
39 Salted, dried or smoked seafood	109 Other industrial inorganic chemicals
40 Bottled or canned seafood	110 Petrochemical basic products
41 Fish paste	111 Petrochemical aromatic products (except synthetic resin)
42 Other processed seafood	112 Aliphatic intermediates
43 Grain milling	113 Cyclic intermediates
44 Flour and other grain milled products	114 Synthetic rubber
45 Noodles	115 Methane derivatives
46 Bread	116 Oil and fat industrial chemicals
47 Confectionery	117 Plasticizers
48 Bottled or canned vegetables and fruits	118 Synthetic dyes
49 Preserved agricultural foodstuffs (other than bottled or canned)	119 Other industrial organic chemicals
50 Sugar	120 Thermo-setting resins
51 Starch	121 Thermoplastics resins
52 Dextrose, syrup and isomerized sugar	122 High function resins
53 Vegetable oils and meal	123 Other resins
54 Animal oils and fats	124 Rayon and acetate
55 Condiments and seasonings	125 Synthetic fibers
56 Prepared frozen foods	126 Medicaments
57 Retort foods	127 Soap, synthetic detergents and surface active agents
58 Dishes, sushi and lunch boxes	128 Cosmetics, toilet preparations and dentifrices
59 School lunch (public) **	129 Paint and varnishes
60 School lunch (private) *	130 Printing ink
61 Other foods	131 Photographic sensitive materials
62 Refined sake	132 Agricultural chemicals
63 Beer	133 Gelatin and adhesives
64 Whiskey and brandy	134 Other final chemical products
65 Other liquors	135 Petroleum refinery products (inc. greases)
66 Tea and roasted coffee	136 Coal products
67 Soft drinks	137 Paving materials
68 Manufactured ice	138 Plastic products
69 Animal feed	139 Tires and inner tubes
70 Organic fertilizers, n.e.c.	140 Rubber footwear

Source: Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables (3EID) data book released by the Center for Global Environmental Research at the National Institute for Environmental Studies of Japan (2012)

Note: "Primary industry" includes sectors from #1 to #27
"Secondary industry" includes sectors from #28 to #287
"Tertiary industry" includes sectors from #297 to #396
"Electricity industry" includes sectors from #288 to #296

Table 3B The categorization of industrial sectors (Continued)

141 Plastic footwear	211 Other general machines and parts
142 Other rubber products	212 Copy machine
143 Leather footwear	213 Other office machines
144 Leather and fur skins	214 Machinery for service industry
145 Miscellaneous leather products	215 Rotating electrical equipment
146 Sheet glass and safety glass	216 Transformers and reactors
147 Glass fiber and glass fiber products, n.e.c.	217 Relay switches and switchboards
148 Other glass products	218 Wiring devices and supplies
149 Cement	219 Electrical equipment for internal combustion engines
150 Ready mixed concrete	220 Other electrical devices and parts
151 Cement products	221 Applied electronic equipment
152 Pottery, china and earthenware	222 Electric measuring instruments
153 Clay refractories	223 Electric bulbs
154 Other structural clay products	224 Electric lighting fixtures and apparatus
155 Carbon and graphite products	225 Batteries
156 Abrasive	226 Other electrical devices and parts
157 Miscellaneous ceramic, stone and clay products	227 Household air-conditioners
158 Pig iron	228 Household electric appliances (except air-conditioners)
159 Ferro alloys	229 Video recording and playback equipment
160 Crude steel (converters)	230 Electric audio equipment
161 Crude steel (electric furnaces)	231 Radio and television sets
162 Scrap iron	232 Wired communication equipment
163 Hot rolled steel	233 Cellular phones
164 Steel pipes and tubes	234 Radio communication equipment (except cellular phones)
165 Cold-finished steel	235 Other communication equipment
166 Coated steel	236 Personal Computers
167 Cast and forged steel	237 Electronic computing equipment (except personal computers)
168 Cast iron pipes and tubes	238 Electronic computing equipment (accessory equipment)
169 Cast and forged materials (iron)	239 Semiconductor devices
170 Iron and steel shearing and slitting	240 Integrated circuits
171 Other iron or steel products	241 Electron tubes
172 Copper	242 Liquid crystal element
173 Lead and zinc (inc. regenerated lead)	243 Magnetic tapes and discs
174 Aluminum (inc. regenerated aluminum)	244 Other electronic components
175 Other non-ferrous metals	245 Passenger motor cars
176 Non-ferrous metal scrap	246 Trucks, buses and other cars
177 Electric wires and cables	247 Two-wheel motor vehicles
178 Optical fiber cables	248 Motor vehicle bodies
179 Rolled and drawn copper and copper alloys	249 Internal combustion engines for motor vehicles and parts
180 Rolled and drawn aluminum	250 Motor vehicle parts and accessories
181 Non-ferrous metal castings and forgings	251 Steel ships
182 Nuclear fuels	252 Ships (except steel ships)
183 Other non-ferrous metal products	253 Internal combustion engines for vessels
184 Metal products for construction	254 Repair of ships
185 Metal products for architecture	255 Rolling stock
186 Gas and oil appliances and heating and cooking apparatus	256 Repair of rolling stock
187 Bolts, nuts, rivets and springs	257 Aircrafts
188 Metal containers, fabricated plate and sheet metal	258 Repair of aircrafts
189 Plumber's supplies, powder metallurgy products and tools	259 Bicycles
190 Other metal products	260 Other transport equipment
191 Boilers	261 Camera
192 Turbines	262 Other photographic and optical instruments
193 Engines	263 Watches and clocks
194 Conveyors	264 Professional and scientific instruments
195 Refrigerators and air conditioning apparatus	265 Analytical instruments, testing machine, measuring instruments
196 Pumps and compressors	266 Medical instruments
197 Machinists' precision tools	267 Toys and games
198 Other general industrial machinery and equipment	268 Sporting and athletic goods
199 Machinery and equipment for construction and mining	269 Musical instruments
200 Chemical machinery	270 Audio and video records, other information recording media
201 Industrial robots	271 Stationery
202 Metal machine tools	272 Jewelry and adornments
203 Metal processing machinery	273 "Tatami" (straw matting) and straw products
204 Machinery for agricultural use	274 Ordnance
205 Textile machinery	275 Miscellaneous manufacturing products
206 Food processing machinery and equipment	276 Residential construction (wooden)
207 Semiconductor making equipment	277 Residential construction (non-wooden)
208 Other special machinery for industrial use	278 Non-residential construction (wooden)
209 Metal molds	279 Non-residential construction (non-wooden)
210 Bearings	280 Repair of construction

Source: Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables (3EID) data book released by the Center for Global Environmental Research at the National Institute for Environmental Studies of Japan (2012)

Note: "Primary industry" includes sectors from #1 to #27
"Secondary industry" includes sectors from #28 to #287
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"Electricity industry" includes sectors from #288 to #296

Table 3B The categorization of industrial sectors (Continued)

281 Public construction of roads
282 Public construction of rivers, drainages and others
283 Agricultural public construction
284 Railway construction
285 Electric power facilities construction
286 Telecommunication facilities construction
287 Other civil engineering and construction
288 Electricity
289 On-site power generation
290 Gas supply
291 Steam and hot water supply
292 Water supply
293 Industrial water supply
294 Sewage disposal **
295 Waste management services (public) **
296 Waste management services (private)
297 Wholesale trade
298 Retail trade
299 Financial service
300 Life insurance
301 Non-life insurance
302 Real estate agencies and managers
303 Real estate rental service
304 House rent
305 Railway transport (passengers)
306 Railway transport (freight)
307 Bus transport service
308 Hired car and taxi transport
309 Road freight transport(except Self-transport by private cars)
310 Ocean transport
311 Coastal and inland water transport
312 Harbor transport service
313 Air transport
314 Consigned freight forwarding
315 Storage facility service
316 Packing service
317 Facility service for road transport
318 Port and water traffic control **
319 Services relating to water transport
320 Airport and air traffic control (public) **
321 Airport and air traffic control (industrial)
322 Services relating to air transport
323 Travel agency and other services relating to transport
324 Postal service*
325 Fixed telecommunication
326 Mobile telecommunication
327 Other services relating to communication
328 Public broadcasting
329 Private broadcasting
330 Cable broadcasting
331 Information services
332 Internet based services
333 Image information production and distribution industry
334 Newspaper
335 Publication
336 News syndicates and private detective agencies
337 Public administration (central) **
338 Public administration (local) **
339 School education (public) **
340 School education (private) *
341 Social education (public) **
342 Social education (private, non-profit) *
343 Other educational and training institutions (public) **
344 Other educational and training institutions (profit-making)
345 Research institutes for natural science (pubic) **
346 Research institutes for cultural and social science (public) **
347 Research institutes for natural sciences (private, non-profit) *
348 Research institutes for cultural and social science (private,non-profit) *
349 Research institutes for natural sciences (profit-making)
350 Research institutes for cultural and social science (profit-making)
351 Research and development (intra-enterprise)
352 Medical service (public)
353 Medical service (non-profit foundations, etc.)
354 Medical service (medical corporations, etc.)
355 Health and hygiene (public) **
356 Health and hygiene (profit-making)
357 Social insurance (public) **
358 Social insurance (private, non-profit) *
359 Social welfare (public) **
360 Social welfare (private, non-profit) *
361 Social welfare (profit-making)
362 Nursing care (In-home)
363 Nursing care (In-facility)
364 Private non-profit institutions serving enterprises
365 Private non-profit institutions serving households, n.e.c. *
366 Advertising services
367 Goods rental and leasing (except car rental)
368 Car rental and leasing
369 Repair of motor vehicles
370 Repair of machine
371 Building maintenance services
372 Judicial, financial and accounting services
373 Civil engineering and construction services
374 Worker dispatching services
375 Other business services
376 Movie theaters
377 Performances (except otherwise claasified), theatrical comranies
378 Amusement and recreation facilities
379 Stadiums and companies of bicycle, horse, motorcar and motorboat races
380 Sport facility service, public gardens and amusement parks
381 Other amusement and recreation services
382 General eating and drinking places (except coffee shops)
383 Coffee shops
384 Eating and drinking places for pleasures
385 Hotels
386 Cleaning
387 Barber shops
388 Beauty shops
389 Public baths
390 Other cleaning, barber shops, beauty shops and public baths
391 Photographic studios
392 Ceremonial occasions
393 Miscellaneous repairs, n.e.c.
394 Supplementary tutorial schools, instruction services for arts, culture and technical skills
395 Other personal services
396 Office supplies

Source: Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables (3EID) data book released by the Center for Global Environmental Research at the National Institute for Environmental Studies of Japan (2012)

Note: "Primary industry" includes sectors from #1 to #27
"Secondary industry" includes sectors from #28 to #287
"Tertiary industry" includes sectors from #297 to #396
"Electricity industry" includes sectors from #288 to #296

Appendix 3C

Using the same decomposition as in eq. (3.7), the decomposition formula regarding the CO_2 emissions induced by imports can be obtained as

$$\Delta Q_m = \underbrace{\mathbf{c}\Delta\mathbf{E}\boldsymbol{\pi}^t X_m^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\pi} X_m^t + \mathbf{c}\Delta\mathbf{E}\boldsymbol{\pi}^t \Delta X_m\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\pi}\Delta X_m}_{\text{Technical effect: } \Delta Q_m^{Tech}}$$

$$\underbrace{+\mathbf{c}\mathbf{E}^t\Delta\boldsymbol{\pi} X_m^t + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\pi} X_m^t + \mathbf{c}\mathbf{E}^t\Delta\boldsymbol{\pi}\Delta X_m\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\pi}\Delta X_m}_{\text{Import composition effect: } \Delta Q_m^{Comp}}$$

$$\underbrace{+\mathbf{c}\mathbf{E}^t\boldsymbol{\pi}^t\Delta X_m + \frac{1}{2}\left(\mathbf{c}\Delta\mathbf{E}\boldsymbol{\pi}^t\Delta X_m + \mathbf{c}\mathbf{E}^t\Delta\boldsymbol{\pi}\Delta X_m\right) + \frac{1}{3}\mathbf{c}\Delta\mathbf{E}\Delta\boldsymbol{\pi}\Delta X_m}_{\text{Import scale effect: } \Delta Q_m^{Scale}}$$

where $\boldsymbol{\pi}$ is an $(N\times 1)$ column vector whose *i*th element, π_i, is the import composition of imported commodity i, and X_m is the total amount of imports to Japan.

Chapter 4 LCA Boundary Decisions Based on an Industrial Clustering Technique

4.1 Background and aims

For reducing environmental pollutants, including CO_2 emissions, reduction activities at the state level described in Chapter 3 are considered to be inefficient, and so it is extremely important to reduce such pollutants at the industry level. The ISO 14001 certification can offer us a clue on how to judge whether industries or companies produce their goods considering their responsibility for the environmental cost within their management framework[8]. To obtain this certification, third-party organizations must judge that the applying organization produces its goods in an environmentally friendly way. In one stage of the judgment, they calculate the environmental impacts based on the framework of life-cycle assessment (LCA). LCA is a method to calculate and assess the environmental costs associated with the entire supply chain, from the upstream to the downstream industries, in terms of the production of a specified product (Suh *et al*., 2005).

According to data from the Japan Accreditation Board (2013), the number of organizations which have ISO 14001 certification in Japan is 20,689[9]; the breakdown by industry of these organizations is shown in Figure 4.1. As shown, the construction industry is the top industry in this respect, and it is a so-called CO_2-intensive industry. In addition, the tertiary industry including the wholesale trade industry is ranked as high; this industry is also relatively CO_2-intensive if one considers indirect emissions (Suh, 2006).

[8] See also the following URL for further details about ISO 14001:
http://www.iso.org/iso/home/standards/management-standards/iso14000.htm

[9] See also the number of organizations which have ISO 14001 certification in Japan:
http://www.jab.or.jp/en/certified_organization/iso14001/

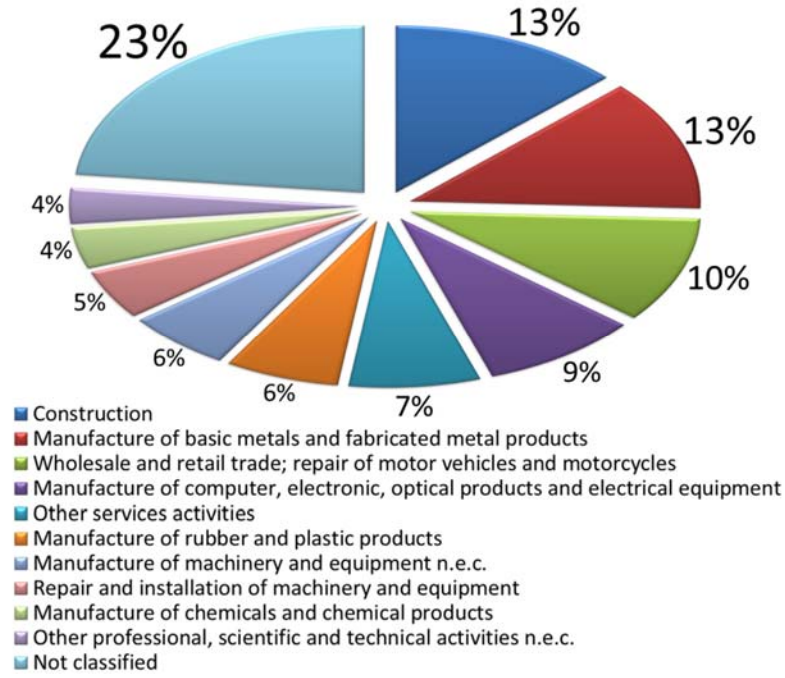

Figure 4.1 Breakdown by industry of organizations obtaining ISO 14001 certification

An LCA consists of two sub-analyses: a process analysis and an input–output analysis (Suh *et al*., 2005, 2007). A process analysis is a method to add up the amounts of environmental pollutants from each related production process (Farrency *et al*., 2008). An input–output analysis (environmental input–output method) is a method to calculate the amount of life-cycle environmental pollutants from the entire supply chain induced by final demand of an industry using an environmentally extended input–output table. In previous studies, a hybrid analysis of the two methods has also been proposed (Heijungs, 1994; Suh *et al*., 2004; Larsen *et al*., 2009; Lenzen *et al*., 2009; Strømman *et al*., 2009).

A process analysis has the advantage of accuracy in calculating pollutant amounts from complex production processes. However, a process analysis cannot cover the entire supply chain. Therefore, analysts have to select the important process arbitrarily. This problem is referred to as the LCA system boundary decision problem (Raynolds *et al*., 2000; Reich, 2005; Gaudreault *et al*., 2010). In the hybrid analysis, analysts also have to decide the system boundary. The crucial point of worry in this decision is that the process analysis might leave out an environmentally important point within the supply chain (Suh *et al.*, 2004).

For solving this system boundary decision problem, Kagawa *et al.* (2013a) proposed an industrial cluster analysis employing graph theory developed in the computer image processing area. Applying clustering analysis to the input–output table, in which the transactions between the industrial sectors are recorded at the level of 4-digit average commodities, it is possible to extract the pollutant-intensive processes from the supply chain induced by the final demand of an average commodity. Kagawa *et al.* (2013a) proposed including the extracted production processes in the framework of the LCA analysis.

In the study by Kagawa *et al.* (2013a), a case study regarding the supply chain induced by the final demand of the passenger motor cars industry was presented. However, results for the remaining industries have not yet been reported. In this chapter, we try to extract CO_2-intensive clusters in the Japanese economy by applying a graph partitioning method based on nonnegative matrix factorization to the supply chain network data covering the main Japanese industries which have ISO 14001 certification. This chapter analyses CO_2 emissions induced by each cluster and discusses the system boundary decision which is important for LCA of a specified industry.

4.2 Methodology

4.2.1 Construction of a supply chain network graph

First, it is necessary to construct the supply chain network data for the clustering analysis. When the final demand appears for a specified industry, other industries produce their products as the intermediate products, which are the products needed directly or indirectly for the final production (Leontief, 1941; Miller *et al.*, 2009). Following the unit structure model shown in Kagawa *et al.* (2013a), the intermediate matrix $\mathbf{B}^{j^*}$ induced by the final demand for the j^*th industry is described in equation (4.1).

$$\mathbf{B}^{j^*} = \text{diag}\left(\mathbf{f}^{j^*}\right) + \mathbf{A}\text{diag}\left(\mathbf{f}^{j^*}\right) + \mathbf{A}\text{diag}\left(\mathbf{A}\mathbf{f}^{j^*}\right). \qquad (4.1)$$

Here, $\mathbf{A} = \left(a_{ij}\right)\left(i, j = 1, 2, \cdots, n\right)$ is the input coefficient matrix, whose entries a_{ij} denote the intermediate input from industry i per unit of output of industry j; $\mathbf{f}^{j^*}$ is the final demand vector, whose j^*th element is the final demand for industry j^* and whose other elements are all 0; and diag () denotes the operator creating a diagonal matrix from the argument vector. The life-cycle CO_2 emissions induced by the final demand for industry j^* is described in equation (4.2).

$$\mathbf{G}^{j^*} = \text{diag}\left(\boldsymbol{\alpha}\right)\mathbf{B}^{j^*}. \qquad (4.2)$$

Here, $\boldsymbol{\alpha} = \left(\alpha_j\right)$ is the direct CO_2 emissions per unit of output of industry j. $\mathbf{G}^{j^*}$ describes the life-cycle CO_2 emissions associated with the entire supply chain induced by the final demand for industry j^*. In this study, to apply nonnegative matrix factorization, the matrix $\mathbf{G}^{j^*}$ is transformed according to equation (4.3).

$$\tilde{\mathbf{G}}^{j^*} = \begin{cases} \frac{1}{2}\left(g_{ij}^{j^*} + g_{ji}^{j^*}\right) & (i \neq j) \\ 0 & (i = j) \end{cases} . \qquad (4.3)$$

Previously proposed input–output analysis methods include the direction of the transaction between the ith industry and the jth industry, whereas that in the present study does not. However, due to the focus here being on relationships between industries, transactions within the same industries are excluded. Using the supply chain network data described according to equation (4.3), we try to extract the CO_2-intensive clusters.

4.2.2 Application of nonnegative matrix factorization

Here, the problem of detecting relatively strong sub-networks (i.e., *clusters*) in a given graph representing a network structure is considered. Let n denote the number of nodes in the structure, and let c denote the number of clusters when the nodes are partitioned into appropriate subsets. Denote the sets of nodes and edges by $V=\{1, 2, \ldots, n\}$ and $E=\{(i, j)$: nodes i and j are related$\}$, respectively. The affinity matrix indicating relationships between nodes i and j is $\tilde{\mathbf{G}}^{j*} = \left(\tilde{g}_{ij}^{j*}\right)\left(i, j = 1, 2, \cdots, n\right)$, and the degree matrix $\mathbf{D}$ is the diagonal matrix whose ith diagonal entry d_i is the degree of node i, defined by $d_i = \sum_{j=1}^{n} g_{ij}^{j*}$. A matrix which plays a key role in clustering methods is the normalized Laplacian matrix, defined as $\mathbf{L} = \mathbf{D}^{-\frac{1}{2}}\left(\mathbf{D}-\mathbf{G}\right)\mathbf{D}^{-\frac{1}{2}}$ (von Luxburg, 2007; von Luxburg *et al*., 2008). It is useful to define a "normalized cut" value *Ncut* (Shi *et al*, 2000; Zhang *et al*., 2008) in formulating a criterion for maximizing the number of edges connecting nodes within a cluster while minimizing the number of edges connecting nodes outside the cluster. In the present case, *Ncut* is given by

$$Ncut = \sum_{k=1}^{c} \frac{\sum_{i \in V_k, j \in V} \tilde{g}_{ij}^{j*} - \sum_{i \in V_k, j \in V_k} \tilde{g}_{ij}^{j*}}{\sum_{i \in V_k} d_i}, \qquad (4.4)$$

where $V_k\ (k = 1, 2, \ldots, c)$ is the subset of nodes assigned to cluster k. The denominator of the right-hand side of equation (4.4) is the sum of the degrees of the nodes in cluster k, whereas the numerator characterizes the strength of the relationship between the set of nodes assigned to cluster k and the set of nodes assigned to all other clusters. Our goal is to find the cluster assignment that minimizes *Ncut*. If the nodes and edges express products and life-cycle CO_2 emissions associated with the product systems, respectively, then finding the solution to this minimization problem corresponds to identifying the CO_2-intensive product systems in LCA studies (see Kagawa *et al.*, 2013b). Rewriting equation (4.4) in matrix notation, we have

$$Ncut = \sum_{k=1}^{c} \frac{\mathbf{h}_k^T \left(\mathbf{D} - \tilde{\mathbf{G}}^{j*}\right)\mathbf{h}_k}{\mathbf{h}_k^T \mathbf{D}\mathbf{h}_k}, \qquad (4.5)$$

where the superscript T denotes matrix transposition, and the cluster allocation vector $\mathbf{h}_k$ is given by

$$\mathbf{h}_k = \left(h_{ik}\right) = \begin{cases} 0 & \left(i \notin V_k\right) \\ \dfrac{1}{n_k^{1/2}} & \left(i \in V_k\right) \end{cases},$$

in which n_k is the number of nodes assigned to cluster k. Thus we have the problem of partitioning a network of n nodes into c clusters in such a way that the value of *Ncut* defined by equation (4.5) is minimized.

According to Ding *et al*. (2005), one approach to this problem is to form the normalized affinity matrix $\mathbf{D}^{-\frac{1}{2}}\tilde{\mathbf{G}}^{j*}\mathbf{D}^{-\frac{1}{2}}$ and compute its nonnegative matrix factorization $\mathbf{D}^{-\frac{1}{2}}\tilde{\mathbf{G}}^{j*}\mathbf{D}^{-\frac{1}{2}} \approx \mathbf{H}\mathbf{H}^T$; then the c nonnegative vectors $\mathbf{h}_k^{NMF}$ $\left(k = 1, 2, \cdots, c\right)$ may be taken as approximate solutions for the assignment vectors, where $\mathbf{H} = \left[\mathbf{h}_1^{NMF}\ \mathbf{h}_2^{NMF}\ \cdots\ \mathbf{h}_c^{NMF}\right]$.

This clustering method based on nonnegative matrix factorization of the normalized affinity matrix is expressed as the following Algorithm.

Algorithm

Step 1: Form the normalized affinity matrix $\mathbf{D}^{-\frac{1}{2}}\tilde{\mathbf{G}}^{j^*}\mathbf{D}^{-\frac{1}{2}}$.

Step 2: Form the matrix $\mathbf{H} = \left[\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_c\right]$, whose columns are the c vectors $\mathbf{h}_k \left(k = 1, 2, \cdots, c\right)$, each of which has dimension $\left(n \times 1\right)$.

Step 3: Solve the problem of minimizing $J = \left\|\mathbf{D}^{-\frac{1}{2}}\tilde{\mathbf{G}}^{j^*}\mathbf{D}^{-\frac{1}{2}} - \mathbf{H}\mathbf{H}^T\right\|_F^2$ to construct the nonnegative matrix factorization of the normalized affinity matrix and take the resulting matrix $\mathbf{H}^{NMF} = \left[\mathbf{h}_1^{NMF}, \mathbf{h}_2^{NMF}, \cdots, \mathbf{h}_c^{NMF}\right]$ as an approximate solution for the assignment matrix.

Step 4: Apply the *K*-means rounding procedure *m* times to the approximate assignment matrix obtained in Step 3, thus producing *m* cluster assignment matrices consisting of zeros and ones.

Step 5: For each of the *m* assignment matrices $\mathbf{H}^{NMF,l} = \left[\mathbf{h}_1^{NMF,l}, \mathbf{h}_2^{NMF,l}, \cdots, \mathbf{h}_c^{NMF,l}\right] \left(l = 1, 2, \cdots, m\right)$ obtained in Step 4, insert the assignment vectors $\mathbf{h}_k^{NMF,l} \left(k = 1, 2, \cdots, c\right)\left(l = 1, 2, \cdots, m\right)$ into Equation (4.5) to compute *m* values of *Ncut*, $Ncut^{NMF,l} \left(l = 1, 2, \cdots, m\right)$.

Step 6: Take the assignment matrix corresponding to the smallest of the *m* values $Ncut^{NMF,l} \left(l = 1, 2, \cdots, m\right)$ obtained in Step 5 as the optimal solution.

4.2.3 Determining the number of clusters

Before the clustering analysis, the number of clusters should be decided. In other words, we have to decide into how many clusters we will allocate the industries. This study employs the modularity index introduced in Newman and Girvan (2004). This modularity index is calculated according to equation (4.6).

$$Q(K)=\sum_{k=1}^{K}\left\{\frac{\sum_{i\in C_k}\sum_{j\in C_k}\tilde{g}_{ij}^{j*}}{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{g}_{ij}^{j*}}-\left(\frac{\sum_{i\in C_k}\sum_{j}\tilde{g}_{ij}^{j*}}{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{g}_{ij}^{j*}}\right)^2\right\} \quad . \qquad (4.6)$$

Here, C_k represents each cluster after deciding the allocation. In short, a relatively high modularity index corresponds to a relatively better clustering allocation. Following this methodology, we can calculate the value of the modularity index for each *K* and finally adopt the most optimal number for *K*.

4.3 Data

As the data to construct the transaction networks regarding CO_2 emissions from each industry, we employed two databases.

1) 2005 Input-Output tables for Japan classified into basic sector $(520 \text{ rows} \times 407 \text{ columns})$
(http://www.stat.go.jp/english/data/io/io05.htm)
2) 2005 Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables (3EID) [10]
(http://www.cger.nies.go.jp/publications/report/d031/eng/datafile/index.htm#data2005).

The data for the matrix **A** and the vector $\mathbf{f}^{j^*}$ employ 1) the Input-Output tables and the data for the vector $\boldsymbol{\alpha}$ employ 2) 3EID. The data for the vector $\mathbf{f}^{j^*}$ basically employ the value of consumption expenditure (private). Because the number of sectors in the 3EID data is 403, we reformulated the Input-Output table to make it agree with 3EID, changing its size from $(520 \text{ rows} \times 407 \text{ columns})$ to $(403 \text{ rows} \times 403 \text{ columns})$ for this study.

[10] Nansai *et al*. (2012)

4.4 Results and discussion

4.4.1 Life-cycle emissions of industries which are conscious of the ISO 14001 certification requirements

As shown in Figure 4.1, many organizations have the ISO14001 certification, which indicates a consciousness of responsibilities regarding environmental policy. This research analyzes four industries (construction; manufacture of basic metals and fabricated metal products; wholesale and retail trade, etc.; and manufacture of computers, electronics, optical products, and electrical equipment) on the basis of the data which are obtainable from the Japan Accreditation Board. The industrial categories used by the Japan Accreditation Board follow the NACE codes[11], which do not match the codes of the Japanese input-output table (IO codes). Therefore, for this study, we used the correspondences between the industrial categories shown in Table 4.1.

[11] For a detailed list of the NACE codes, see the following URL.
http://ec.europa.eu/competition/mergers/cases/index/nace_all.html

Table 4.1 Correspondences between NACE codes and IO codes

NACE code	IO code
Construction	Non-residential construction (non-wooden)
	Residential construction (wooden)
Manufacture of basic metals and fabricated metal products	Bolts, nuts, rivets and springs
Wholesale and retail trade, etc.	Wholesale trade
Manufacture of computer, electronic, optical products and electrical equipment	Household electric appliances (except air-conditioners)

From equations (4.1) and (4.2), we can calculate the life-cycle CO_2 intensity of industry j^* by summing the elements in the matrix $\tilde{\mathbf{G}}^{j^*}$ induced by 1 unit of the final demand. We can calculate the life-cycle CO_2 emissions for the j^*th industry, multiplying the life-cycle CO_2 intensity by the volume of the final demand. Figure 4.2 shows the relationships between the life-cycle CO_2 intensity and the volume of the final demand for each of five industries. Here, it should be noted that the volumes of the final demand of non-residential construction (non-wooden) and residential construction (wooden) are the values of gross domestic fixed capital formation (private) in the input–output table, because the values of consumption expenditure (private) for these industries are 0.

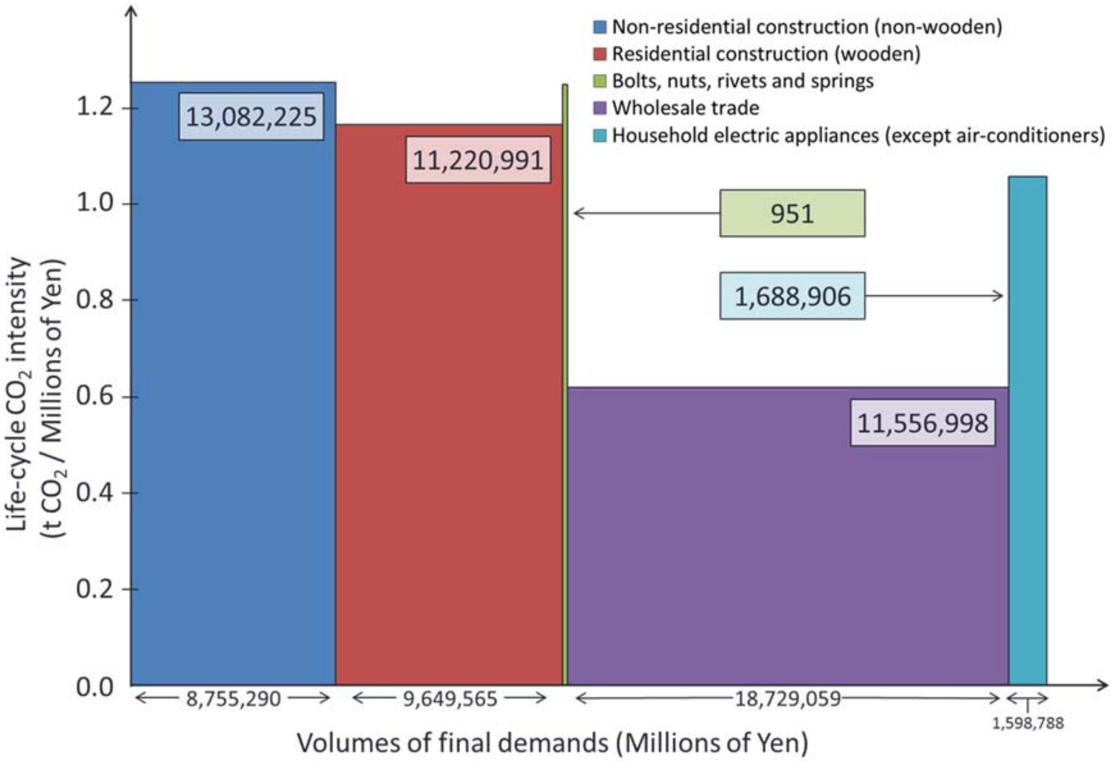

Figure 4.2 Skyline graph of CO_2 intensities and volumes of final demand and life-cycle CO_2 emissions for each industry (unit: t CO_2)

As shown in Figure 4.2, the industries which emit the smallest amounts of CO_2 are very interested in obtaining ISO 14001 certification. Despite of smallness of their amounts of CO_2 emissions, for environmentally conscious industries, it is very important to consider how they can cooperate with other industries to reduce CO_2 emissions through environmental management.

4.4.2 Results of the CO_2 clustering analysis regarding emissions induced by the supply chain of the non-residential construction (non-wooden) industry

The life-cycle CO_2 emissions calculated by summing the elements of the matrix $\mathbf{B}^{j^*}$, which are the emissions induced by the final demand for the non-residential construction (non-wooden) industry, are 13082 kt CO_2. The largest CO_2 emission value in the matrix $\mathbf{B}^{j^*}$ is the transaction between the cement industry and the ready mixed concrete industry, at 1664 kt CO_2. From these results, the CO_2 emissions from the transaction between the cement industry and the ready-mixed concrete industry are just 12.7% of the total CO_2 emissions induced by the entire supply chain of the non-residential construction (non-wooden) industry.

In the case of the usual sectoral approach[12] for subsidy policy or technical cooperation for production, it is enough to consider the main industries (or the cement industry and the ready mixed concrete industry in the above example). However, from the perspective of reduction of the life-cycle CO_2 emissions induced by the non-residential construction (non-wooden) industry, it is hard to reduce the emissions independently for just one industry. It will be possible to produce products in an environmentally friendly manner by realizing production planning after cooperation between the upstream industry (or other industries including the cement industry) and the downstream industry (or the non-residential construction (non-wooden) industry).

The results of this study suggest that a reduction of life-cycle CO_2 emissions can be realized by considering the CO_2-intensive groups (or the CO_2 cluster), rather than an independent industry.

[12] For information about the sectoral approach, see also the following URL.
http://www.c2es.org/docUploads/International%20Sectoral%20Aggreements%20in%20a%20Post-2012%20Climate%20Framework.pdf#search='international+sectoral+agreement+in+a+post+2012+climate+framework'

However, in the case of the absence of a strict definition for the CO_2 cluster, a research suggestion might be arbitrary and subjective. For example, it is easy to briefly define as a CO_2-intensive cluster the group in which the plywood industry, hot rolled steel industry, and cement industry are involved. However, this definition is very arbitrary and not strict.

The clustering method in this study is objective and overcomes the disadvantages mentioned above. This method employs an environmental input–output table which covers entire supply chains and then it could include all the industries. Moreover, by applying the clustering method based on a mathematical optimization to the supply chain network data from the environmental input–output table, it should be possible to extract objectively the CO_2-intensive clusters. Then it would be expected that a CO_2 reduction policy or technical and economic association would be effective when it acts within the framework of the CO_2-intensive clusters.

Simultaneous with clustering allocation, the number of clusters should be decided objectively. The problem of the decision of the number of clusters is a crucially important problem because it affects the LCA boundary decision problem directly, in the meaning of the decision to how many clusters we allocate the industries. In this study, the optimal number of clusters is decided on the basis of the modularity index shown in equation (4.6).

The purpose of this study is to try to extract the CO_2-intensive clusters by clustering analysis of the life-cycle CO_2 emissions induced by five specific industries which are interested in obtaining ISO 14001 certification. Figure 4.3 shows the relationships between the number of clusters (K=1, 2, …, 30) and the values of the modularity index.

Figure 4.3 implies that, for example, with respect to the life-cycle CO_2 emissions induced by the final demand, it is optimal to allocate CO_2-intensive industries to 6 groups in the case of the non-residential construction (non-wooden) industry. In addition, it is optimal to allocate CO_2-intensive industries to 13 groups in the case of the residential construction (wooden) industry, 19 groups in the case of the bolts, nuts, rivets, and springs industry, 21 groups in the case of the wholesale trade industry, and 25 groups in the case of the household electric appliances (except air-conditioners) industry.

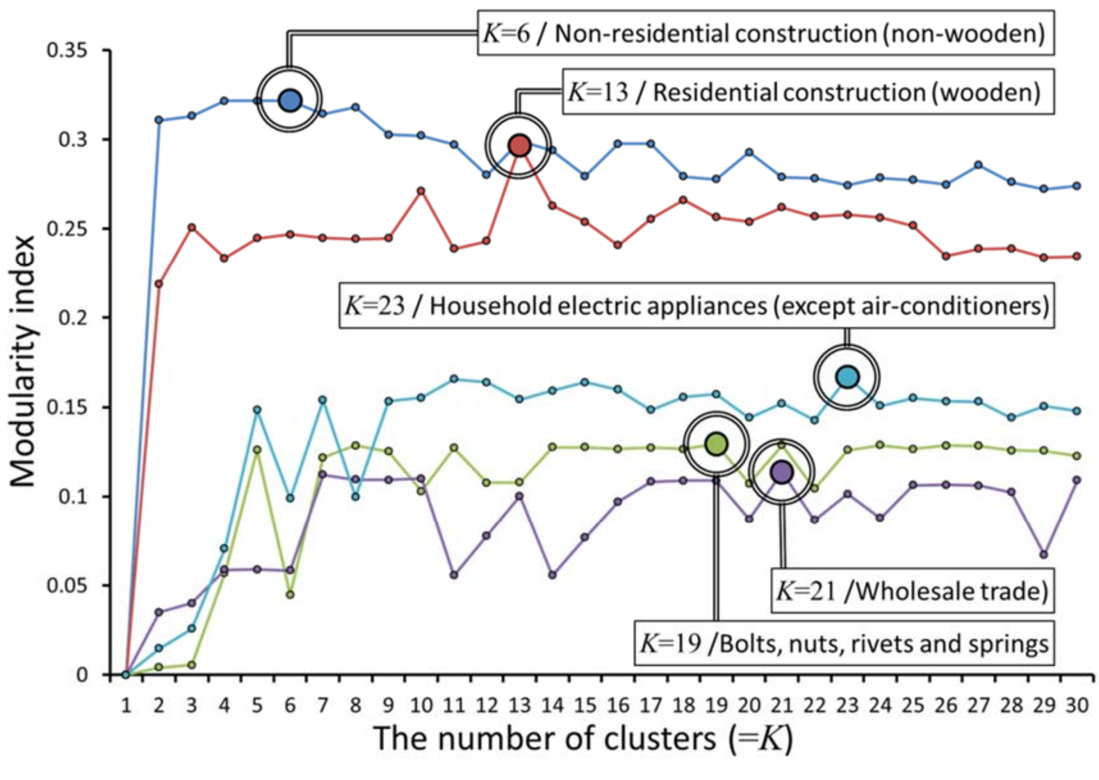

Figure 4.3 Modularity index for clustering analysis on each industry

The clustering result regarding life-cycle CO_2 emissions induced by the final demand for the non-residential construction (non-wooden) industry is shown in Table 4.2. The largest cluster is extracted as the cluster in which the non-residential construction (non-wooden) and 290 other industries are involved. In this cluster, many industries are included, but it is considered that these industries have strong connections with each other and so they should not be allocated to different clusters. In addition, the cement industry and the ready mixed concrete industry are involved in the 4th cluster and the crude steel (converters) industry and the hot rolled steel industry are involved in the 2nd cluster. The 1st cluster includes the petrochemical aromatic products (except synthetic resin) industry, and the paint and varnishes industry. The products produced in the industries involved in these top clusters are, for example, metal materials and coating equipment which are essential for the construction of new commercial buildings and educational facilities. This clustering result implies which product systems are important for managing the life-cycle CO_2 emissions induced by the supply chain of the non-residential construction (non-wooden) industry.

Within-cluster and between-cluster CO_2 emissions for the extracted CO_2-intensive clusters are shown in Figure 4.3. From the figure, it can be found that CO_2 emissions among industries in the same clusters along with the direct or indirect transaction of the goods and services are large due to the diagonal elements shown being relatively large. In particular, the CO_2 emissions from the 4th and 5th clusters are large, and we can also find the CO_2 emissions from the between-cluster transactions.

The amount of the CO_2 emissions from the top three clusters is 10810 kt CO_2. This value is equal to 82.6% of the total CO_2 emissions induced by the entire supply chain network of the non-residential construction (non-wooden) industry.

Table 4.2. CO_2 clusters induced by the supply chain of the non-residential construction (non-wooden) industry

Industry name	Cluster number	Within-cluster emissions
Non-residential construction (non-wooden) (other 298 industries are included)	5	7,279,236
Cement	4	3,327,993
Ready mixed concrete	4	
Crude steel (converters)	2	202,867
Hot rolled steel	2	
Inorganic pigment	1	33,373
Other industrial inorganic chemicals	1	
Petrochemical aromatic products (except synthetic resin)	1	
Aliphatic intermediates	1	
Other industrial organic chemicals	1	
Thermo-setting resins	1	
Paint and varnishes	1	
Plastic products	1	

Here, we will pay attention to the real state of the CO_2 emission management of the non-residential construction (non-wooden) industry in Japan and check the CSR report of the companies. For example, in *TAISEI CORPORATE REPORT 2013 DATA BOOK*[13] published by Taisei Corporation and *Environmental Aspect Data*[14] published by Obayashi Corporation, CO_2 emissions are calculated at the stage of building operation or building construction, following the criteria of CO_2 emission management defined as Scope 1, Scope 2, and Scope 3 in the GHG protocol. However, these calculations are limited to the CO_2 emissions related to a construction site. In addition, this LCA system boundary is very subjective because the range of the analysis is also limited to the transport industry.

From the result of this study, it is found that the CO_2 emission management using the clustering approach is very important because the top clusters (the 5th, 4th, and 2nd cluster in Table 4.2) can

[13] http://www.taisei.co.jp/english/csr/reports/pdf/2013/Taisei_DataBook_2013.pdf
[14] http://www.obayashi.co.jp/english/ir/corporate_report/2013/ir2013en_24.pdf#page=4

cover about 80% of the total life-cycle CO_2 emissions. The usual LCA in the non-residential construction (non-wooden) industry ignores the CO_2 emissions along with the supply chain. The clustering approach mentioned above is needed for more useful LCA in managing the life-cycle CO_2 emissions.

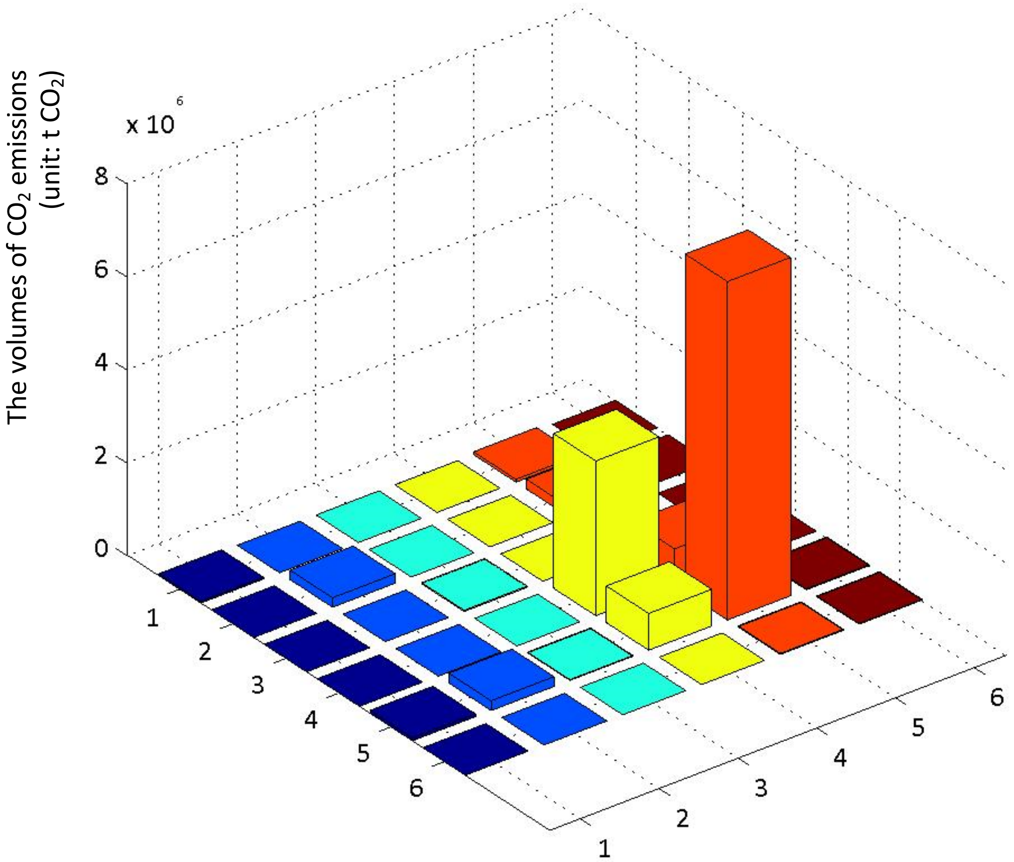

Figure 4.4 Within-cluster and between-cluster emissions induced by the final demand of the non-residential construction (non-wooden) industry

4.4.3 Results of the CO_2 clustering analysis regarding emissions induced by the supply chain of the residential construction (wooden) industry

The life-cycle CO_2 emissions calculated by summing the elements of the matrix $\mathbf{B}^{j^*}$, which are the emissions induced by the final demand for the residential construction (wooden) industry, are 11221 kt CO_2. The clustering result regarding life-cycle CO_2 emissions induced by the final demand for the residential construction (wooden) industry is shown in Table 4.3.

The largest cluster is extracted as the cluster in which the petroleum refinery products (inc. greases) industry and the pottery, china, and earthenware industry (among others) are involved. In addition, the residential construction (wooden) industry, the wholesale trade industry, and the road freight transport (except self-transport by private cars) industry are involved in the 7th cluster. These industries produce the essential products (for example, ceramic products or pottery including tiles) for residence construction and distribute these products. Therefore, this cluster could be seen as the material and transporting cluster. The cement industry and the ready mixed concrete industry are involved in the 4th cluster, and this cluster is similar to the cluster shown in the results of 4.4.2. This similarity could be seen as a feature which is common among the construction industry. The plywood industry, the other wooden products industry, and the metal products for architecture industry are involved in the 12th cluster. These industries produce products which are needed for doors with metal knob or flooring materials with metal joints, for example.

Within-cluster and between-cluster CO_2 emissions for the extracted CO_2-intensive clusters are shown in Figure 4.5. The amount of CO_2 emissions from the top three clusters is 5932 kt CO_2. This value is equal to 52.8% of the total CO_2 emissions induced by the entire supply chain network of the residential construction (wooden) industry.

Table 4.3 CO_2 clusters induced by the supply chain of the residential construction (wooden) industry

Industry name	Cluster number	Within-cluster emissions
Petroleum refinery products (inc. greases)	7	3,063,263
Pottery, china and earthenware	7	
Other structural clay products	7	
Residential construction (wooden)	7	
Wholesale trade	7	
Road freight transport(except Self-transport by private cars)	7	
Self-transport by private cars (passengers)	7	
Self-transport by private cars (freight)	7	
Cement	4	2,291,453
Ready mixed concrete	4	
Cement products	4	
Pig iron	4	
Cast iron pipes and tubes	4	
Plywood	12	577,124
Other wooden products	12	
Thermoplastics resins	12	
Plastic products	12	
Cold-finished steel	12	
Coated steel	12	
Metal products for architecture	12	
Other metal products	12	
Electricity	12	
On-site power generation	12	
Railway transport (passengers)	12	

For example, in *Sustainability Report 2013*[15] published by Sekisui House Limited and *CSR Report 2013*[16] published by Sumitomo Forestry Company Limited, as in the non-residential construction (non-wooden) industry analysis mentioned above, CO_2 emissions are calculated in terms of the CO_2 emissions related to the construction site or transportation. On the other hand, this industry shows the trend toward spreading the range of CO_2 emission management regarding Scope 3 in the GHG protocol. Therefore, the result of the clustering analysis in this study can offer useful information to this new trend. Looking at qualitative aspects, the residential construction (wooden) industry uses a large amount of wood or wooden products as intermediate products. The forests

[15] http://www.sekisuihouse.co.jp/english/sr/datail/__icsFiles/afieldfile/2013/08/26/all.pdf
[16] http://sfc.jp/english/information/society/environment/reduction.html

which supply these intermediate products also play the role of CO_2 sinks, which is very important from the viewpoint of domestic CO_2 emission management. These industries involved in wooden products are extracted as the CO_2-intensive cluster in this study. When it comes to the system boundary decision problem in LCA, it is desirable to consider the emission management policy within the framework of the clustering approach.

From the result of this study, it is found that the CO_2 emission management using clustering approach is very important because the top clusters (the 7th, 4th, and 12th clusters in Table 4.3) can cover 50% of the total life-cycle CO_2 emission.

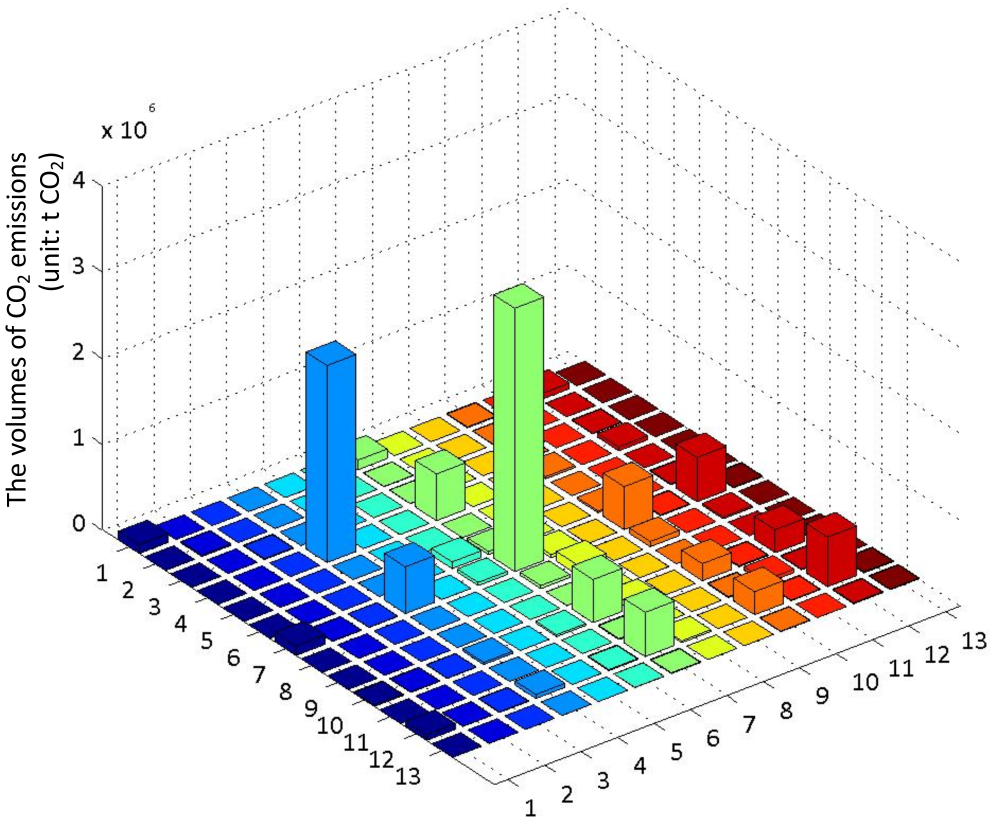

Figure 4.5 Within-cluster and between-cluster emissions induced by the final demand of the residential construction (wooden) industry

4.4.4 Results of the CO_2 clustering analysis regarding emissions induced by the supply chain of the bolts, nuts, rivets, and springs industry

The life-cycle CO_2 emissions calculated by summing the elements of the matrix $\mathbf{B}^{j^*}$, which are the emissions induced by the final demand for the bolts, nuts, rivets and springs industry, are 951 t CO_2. The clustering result regarding life-cycle CO_2 emissions induced by the final demand for the bolts, nuts, rivets, and springs industry is shown in Table 4.4.

Table 4.4 CO_2 clusters induced by the supply chain of the bolts, nuts, rivets, and springs industry

Industry name	Cluster number	Within-cluster emissions
Bolts, nuts, rivets and springs	5	203
Electricity	5	
Cold-finished steel	8	73
Coated steel	8	
On-site power generation	8	
Crude steel (converters)	15	67
Hot rolled steel	15	

The largest cluster is extracted as the cluster in which the bolts, nuts, rivets, and springs industry and the electricity industry are involved. In addition, the cold-finished steel industry, the coated steel industry, and the on-site power generation industry are involved in the 8th cluster and the crude steel (converters) industry and the hot rolled steel industry are involved in the 15th cluster. Rather than the metal parts including bolts or nuts, the steel products needed for producing machinery are extracted as the CO_2-intensive clusters.

Within-cluster and between-cluster CO_2 emissions for the extracted CO_2-intensive clusters are shown in Figure 4.6. The amount of the CO_2 emissions from the top three clusters is 343 t CO_2. This value is equal to 36% of the total CO_2 emissions induced by the entire supply chain network of the bolts, nuts, rivets, and springs industry.

As shown in Figure 4.1, the bolts, nuts, rivets, and springs industry is very interested in obtaining ISO 14001 certification. However, as shown in Figure 4.2, the life-cycle CO_2 emissions from the industry are relatively small. Looking at environmental reports from the industry, we can find the fact that their members have ISO 14001 certification, but we cannot find reports about the amounts of their CO_2 emissions. Compared with other industries, this industry is characterized as being of an economic scale that the amount of capital per company is relatively small, and this relates to the fact that the CO_2 emissions from each company are relatively small. For this reason, it is considered that they are not being open about the CO_2 emissions from their production processes.

The bolts, nuts, rivets, and springs industry produces the intermediate products which are necessary for the production of passenger cars, construction materials, and metal parts of furniture, and this industry is located in the upstream of many parts of the supply chain. Therefore, the industry plays an important role when we consider the life-cycle CO_2 emissions induced by the entire supply chain. For these reason, it is very helpful to analyze within the clustering approach framework for LCA of the bolts, nuts, rivets, and springs industry.

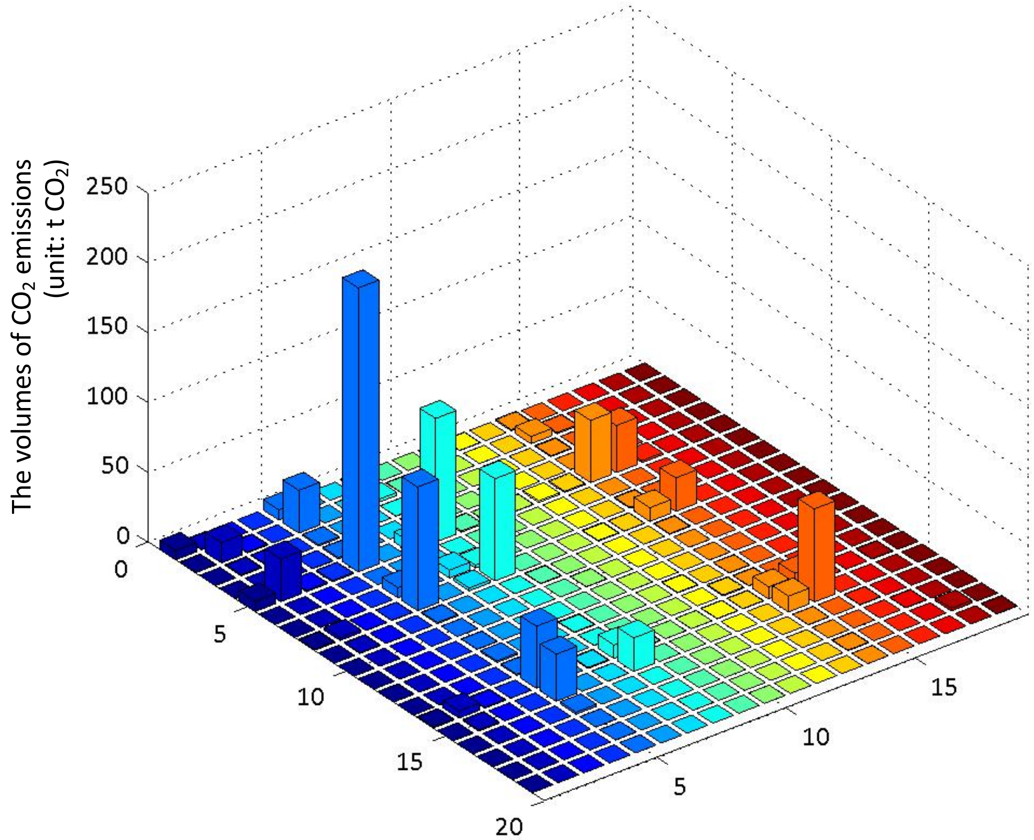

Figure 4.6 Within-cluster and between-cluster emissions induced by the final demand of the bolts, nuts, rivets, and springs industry

4.4.5 Results of the CO_2 clustering analysis of emissions induced by the supply chain of the wholesale trade industry

The life-cycle CO_2 emissions calculated by summing the elements of the matrix $\mathbf{B}^{j^*}$, which are the emissions induced by the final demand for the wholesale trade industry, are 11556 kt CO_2. The clustering result regarding life-cycle CO_2 emissions induced by the final demand for the wholesale trade industry is shown in Table 4.5.

Table 4.5 CO_2 clusters induced by the supply chain of the wholesale trade industry

Industry name	Cluster number	Within-cluster emissions
Wholesale trade	12	5,808,676
Self-transport by private cars (passengers)	12	
Self-transport by private cars (freight)	12	
Air transport	12	
Repair of rolling stock	18	858,691
Electricity	18	
On-site power generation	18	
Waste management services (private)	18	
Retail trade	18	
Financial service	18	
Real estate agencies and managers	18	
Real estate rental service	18	
Railway transport (passengers)	18	
Fixed telecommunication	18	
Mobile telecommunication	18	
Other telecommunication	18	
Other educational and training institutions (profit-making)	18	
Research institutes for natural sciences (profit-making)	18	
Research and development (intra-enterprise)	18	
Other business services	18	
Paper	16	208,410
Paperboard	16	
Other paper containers	16	
Other pulp, paper and processed paper products	16	
Printing, plate making and book binding	16	
Newspaper	16	
Publication	16	
Office supplies	16	

The largest cluster is extracted as the cluster in which the wholesale trade industry, the self-transport by private cars (freight) industry, and the air transport industry are involved. In addition, the electricity industry, the fixed telecommunication industry, and the real estate rental service industry are involved in the 18th cluster, and the paper industry, the newspaper industry, and the printing, plate making, and book binding industry are involved in the 16th cluster. The 18th cluster is constructed on the basis of the industries related to the communication and circulation of goods or services (for example, the financial service industry, the real estate agencies and managers industry, the real estate rental service industry, the fixed telecommunication industry, and the mobile telecommunication industry). The 16th cluster is constructed on the basis of the industries related to paper-based advertising (for example, the other paper containers industry, the newspaper industry, and the publication industry)

Within-cluster and between-cluster CO_2 emissions for the extracted CO_2-intensive clusters are shown in Figure 4.7. The amount of the CO_2 emissions from the top three clusters is 6876 kt CO_2. This value is equal to 59.5% of the total CO_2 emissions induced by the entire supply chain network of the wholesale trade industry.

From the results, for the LCA of the wholesale trade industry, it is very helpful to analyze within the framework of clusters in which the paper-based advertising industries are involved. By taking the top clusters shown in Table 4.5 into account, we could calculate about 60% of the life-cycle CO_2 emissions.

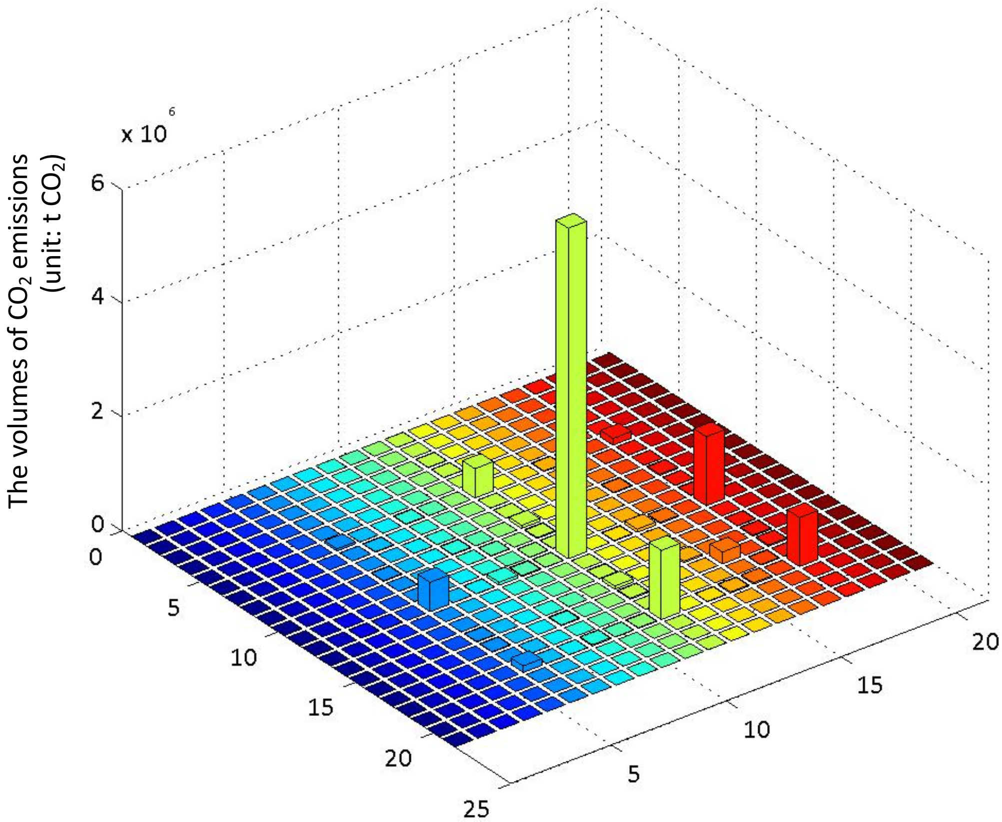

Figure 4.7 Within-cluster and between-cluster emissions induced by the final demand of the wholesale trade industry

4.4.6 Result of the CO_2 clustering analysis regarding emissions induced by the supply chain of the household electric appliances (except air-conditioners) industry

The life-cycle CO_2 emissions calculated by summing the elements of the matrix $\mathbf{B}^{j^*}$, which are induced by the final demand for the household electric appliances (except air-conditioners) industry, are 1689 kt CO_2. The clustering result regarding life-cycle CO_2 emissions induced by the final demand for the household electric appliances (except air-conditioners) industry is shown in Table 4.6.

Table 4.6 CO_2 clusters induced by the supply chain of the household electric appliances (except air-conditioners) industry

Industry name	Cluster number	Within-cluster emissions
Household electric appliances (except air-conditioners)	6	527,495
Integrated circuits	6	
Electricity	6	
Research and development (intra-enterprise)	6	
Cold-finished steel	8	70,415
Coated steel	8	
Iron and steel shearing and slitting	8	
On-site power generation	8	
Wholesale trade	5	34,405
Self-transport by private cars (passengers)	5	
Self-transport by private cars (freight)	5	

The largest cluster is extracted as the cluster in which the household electric appliances (except air-conditioners) industry and the integrated circuits industry are involved. In addition, the cold-finished steel industry and the coated steel industry are involved in the 8th cluster, and the wholesale trade industry and the self-transport by private cars (freight) industry are involved in the 5th cluster. The 6th cluster is constructed on the basis of the industries related to the material products produced at the upstream industries needed for the production systems of electric appliances, and this cluster is responsible for 30% of the total life-cycle CO_2 emissions induced by the entire supply chain. The 8th cluster is constructed on the basis of the industries which supply the metal materials necessary in producing electric appliances.

Within-cluster and between-cluster CO_2 emissions for the extracted CO_2 intensive clusters are shown in Figure 4.8. The amount of the CO_2 emissions from the top three clusters is 632 kt CO_2. This value is equal to 37% of the total CO_2 emissions induced by the entire supply chain network of the household electric appliances (except air-conditioners) industry.

Considering the reduction of life-cycle CO_2 emissions induced by the household electric appliances (except air-conditioners) industry, we can take 37% of the life-cycle CO_2 emission into account, by using the framework of the clustering approach, which lists this industry as the involved industry in the top cluster in Table 4.6.

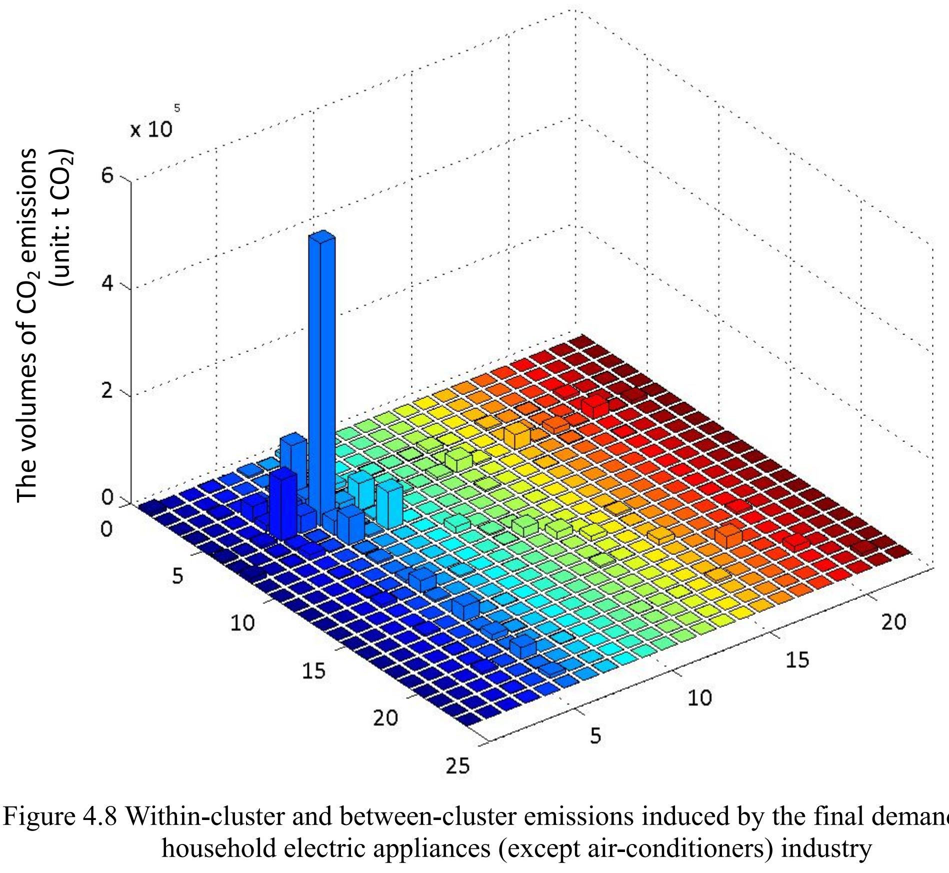

Figure 4.8 Within-cluster and between-cluster emissions induced by the final demand of the household electric appliances (except air-conditioners) industry

4.5 Conclusion

In this chapter, we tried to extract the CO_2-intensive clusters of industries which are interested in obtaining ISO 14001 certification. A cluster in this analysis is defined as an intensive group in terms of CO_2 emissions. From the viewpoint of the LCA perspective needed for obtaining the certification, it is very important to calculate and assess the life-cycle CO_2 emissions induced by the supply chain and consider how the industries can cooperate with each other effectively for the reduction of the life-cycle CO_2 emissions. From the results of the clustering analyses regarding the CO_2 emissions induced by the final demand of the non-residential construction (non-wooden) industry, the residential construction (wooden) industry, the bolts, nuts, rivets, and springs industry, the wholesale trade industry, and the household electric appliances (except air-conditioners) industry, the top CO_2 intensive clusters are responsible for 36% to 82% of the life-cycle CO_2 emissions.

This study can shed light on the system boundary decision problem by suggesting the industrial CO_2-intensive clusters (for example, the cluster in which the metal material industries are involved). These objective clusters shown in Tables 4.2 through 4.6 can offer clues on how to reduce CO_2 emissions effectively through environmental policy or technical and economic cooperation.

Chapter 5 Analyzing Instability of Industrial Clustering Techniques

5.1. Introduction

In Japan, a large number of organizations have regularly published life-cycle assessment (LCA) reports as specified in the ISO 14000 series (Suh *et al*., 2004). An important issue of the LCA is how an organization estimates its life-cycle CO_2 emissions through the entire supply-chain network. An LCA is categorized into two analyses: a process analysis and an input-output analysis (Heijungs, 1994; Joshi, 1999; Suh *et al*., 2005, 2007; Lenzen *et al*., 2009; Strømman *et al*., 2009; Fukuyama, *et al*., 2011; Shao *et al*., 2013, 2014). The process analysis has an advantage in accuracy in the production processes, while the input-output analysis has an advantage in its completeness with regards to the supply-chain network (i.e., it uses a complete system boundary) (Suh *et al*., 2004). The process LCA method is subjective, in the sense that the LCA system boundary is freely decided by LCA practitioners, which consequently leads to truncation error and underestimation of life-cycle emissions (Lenzen, 2001). Kagawa *et al*. (2013a, b) developed a graph partitioning method that combines the spectral clustering method and input-output analysis to find environmentally important supply-chain clusters and proposed that one of the implications of the results of their analyses is that LCA practitioners will be able to determine the critical LCA system boundary based on the cluster information. In addition, recent mixed research on clustering and component analysis has contributed to unifying the assessment of industry-based CO_2 emissions in China (Xia *et al*., 2011; Zhang *et al*., 2012).

Graph partitioning methods were originally developed in the fields of computer image processing and discrete optimization (Donath *et al*., 1973; Fiedler, 1973; Lee *et al*., 1999, 2001; Shi *et al*., 2000;

Ding *et al*., 2005; von Luxburg, 2007; von Luxburg *et al.*, 2008; Zhang *et al*., 2008) and have since been applied to a wide range of fields, including economics, sociology, and industrial ecology (see, for example, Kagawa *et al.*, 2013a, b). Graph partitioning methods operate on network structures consisting of nodes and edges; in economics, for example, the nodes might correspond to industrial sectors and the edges might correspond to transactions between industries, whereas in sociology the nodes and edges might correspond to actors and the interconnections between them, respectively. These methods detect relatively strong sub-networks, i.e., *clusters*, in these economic and social networks.

As noted by Kagawa *et al*. (2013a, b), cluster analysis methods for network partition can be categorized into methods based on the eigenvalue decomposition of the normalized Laplacian matrix (see, for example, Zhang *et al*., 2008) and methods based on the nonnegative matrix factorization of the normalized affinity matrix (see, for example, Ding *et al*., 2005). It is still unclear whether one of these two classes of methods yields approximate solutions of greater accuracy than the other, and what the extent of the superiority is.

Both clustering methods based on eigenvalue decomposition and nonnegative matrix factorization ultimately use rounding procedures via the *K*-means method to convert an approximate assignment matrix including real values into a (0, 1) assignment matrix, which identifies the clusters to which individual nodes should be assigned. It is well known that rounding via the *K*-means method is unstable due to random initialization of cluster centers (Ben-David *et al.*, 2007, 2008; von Luxburg, 2010), and therefore in Kagawa *et al.* (2013b), the *K*-means method was applied 100 times in order to try to reduce the instability of the *K*-means method. However, there is no guarantee that 100 repetitions of the *K*-means procedure suffices to yield a reliable solution (i.e., an accurate assignment matrix). In general, although increasing the number of repetitions might bring the second best solution closer to the global optimum, using an extremely large number of repetitions in the *K*-means method requires a dramatically larger computation time.

Herein, this chapter focuses on two clustering methods based on nonnegative matrix factorization and eigenvalue decomposition, and compares the reliability of the solutions obtained using the two methods. In addition, the number of *K*-means repetitions required to obtain a reliable solution is investigated. As a case study, the network data describing supply chains for passenger vehicles studied by Kagawa *et al.* (2013a, b) are considered.

The remainder of the chapter is as follows. Section 5.2 formulates the two clustering methods. Section 5.3 describes the data used in this study. Section 5.4 presents results obtained by applying the two clustering methods to network data for passenger-vehicle supply chains; a comparative assessment of the results and discuss on how the solution is affected by the number of repetitions of the *K*-means rounding procedure are presented. Conclusions are given in Section 5.5.

5.2. Methodology

This chapter considers the problem of detecting relatively strong sub-networks (i.e., *clusters*) in a given graph representing a network structure. Let n denote the number of nodes in the structure, and let c denote the number of clusters when the nodes are partitioned into appropriate subsets. Denote the sets of nodes and edges by $V=\{1, 2, \ldots, n\}$ and $E=\{(i, j)$: nodes i and j are related$\}$, respectively. The affinity matrix indicating relationships between nodes i and j is $\mathbf{G}=\left(g_{ij}\right)\left(i,j=1,2,\cdots,n\right)$, and the degree matrix $\mathbf{D}$ is the diagonal matrix whose ith diagonal entry d_i is the degree of node i, defined by $d_i=\sum_{j=1}^{n} g_{ij}$. A matrix which plays a key role in clustering methods is the normalized Laplacian matrix, defined as $\mathbf{L}=\mathbf{D}^{-\frac{1}{2}}\left(\mathbf{D}-\mathbf{G}\right)\mathbf{D}^{-\frac{1}{2}}$ (von Luxburg, 2007; von Luxburg *et al.*, 2008). It is useful to define a "normalized cut" value *Ncut* (Shi *et al.*, 2000; Zhang *et al.*, 2008) in formulating a criterion for maximizing the number of edges connecting nodes within a cluster while minimizing the number of edges connecting nodes outside the cluster. In the present case, *Ncut* is given by

$$Ncut=\sum_{k=1}^{c}\frac{\sum_{i\in V_k, j\in V} g_{ij}-\sum_{i\in V_k, j\in V_k} g_{ij}}{\sum_{i\in V_k} d_i}, \qquad (5.1)$$

where $V_k\ \left(k=1,2,\ldots,c\right)$ is the subset of nodes assigned to cluster k. The denominator of the right-hand side of equation (5.1) is the sum of the degrees of the nodes in cluster k, whereas the numerator characterizes the strength of the relationship between the set of nodes assigned to cluster k and the set of nodes assigned to all other clusters. Our goal is to find the cluster assignment that minimizes *Ncut*. If the nodes and edges express products and life-cycle CO_2 emissions associated with the product systems, respectively, then the solution of this minimization problem corresponds to identifying the CO_2-intensive product systems in LCA studies (see Kagawa *et al.*, 2013b). Rewriting equation (5.1) in matrix notation, we have

$$Ncut = \sum_{k=1}^{c} \frac{\mathbf{h}_k^T (\mathbf{D} - \mathbf{G}) \mathbf{h}_k}{\mathbf{h}_k^T \mathbf{D} \mathbf{h}_k} \qquad (5.2)$$

where the superscript T denotes matrix transposition, and the cluster allocation vector $\mathbf{h}_k$ is given by

$$\mathbf{h}_k = (h_{ik}) = \begin{cases} 0 & (i \notin V_k) \\ \dfrac{1}{n_k^{1/2}} & (i \in V_k) \end{cases},$$

in which n_k is the number of nodes assigned to cluster k. Thus we have the problem of partitioning a network of n nodes into c clusters in such a way that the value of *Ncut* defined by equation (5.2) is minimized.

According to Zhang *et al.* (2008), one approach to this problem is to compute the eigenvalue decomposition of the normalized Laplacian matrix $\mathbf{L} = \mathbf{D}^{-\frac{1}{2}} (\mathbf{D} - \mathbf{G}) \mathbf{D}^{-\frac{1}{2}}$; then the $c-1$ eigenvectors $\mathbf{h}_k^{ED}$ $(k = 2, 3, \cdots, c)$ corresponding to the 2nd, 3rd, … c-th eigenvalues can be taken as approximate solutions for the assignment vectors.

An alternative strategy, due to Ding *et al.* (2005), is to form the normalized affinity matrix $\mathbf{D}^{-\frac{1}{2}} \mathbf{G} \mathbf{D}^{-\frac{1}{2}}$ and compute its nonnegative matrix factorization $\mathbf{D}^{-\frac{1}{2}} \mathbf{G} \mathbf{D}^{-\frac{1}{2}} \approx \mathbf{H}\mathbf{H}^T$; then the c

nonnegative vectors $\mathbf{h}_k^{NMF}\ (k = 1, 2, \cdots, c)$ may be taken as approximate solutions for the assignment vectors, where $\mathbf{H} = \left[\mathbf{h}_1^{NMF}\ \mathbf{h}_2^{NMF}\ \cdots\ \mathbf{h}_c^{NMF} \right]$.

Two clustering methods based on eigenvalue decomposition of the normalized Laplacian matrix and nonnegative matrix factorization of the normalized affinity matrix are expressed as the following Algorithm 1 and Algorithm 2, respectively.

Algorithm 1

Step 1: Form the normalized Laplacian matrix $\mathbf{L} = \mathbf{D}^{-\frac{1}{2}}\left(\mathbf{D}-\mathbf{G}\right)\mathbf{D}^{-\frac{1}{2}}$.

Step 2: Solve the eigenvalue problem of the normalized Laplacian matrix, $\mathbf{Lh} = \lambda\mathbf{h}$.

Step 3: To detect c clusters, assemble the eigenvectors $\mathbf{h}_k^{ED}\left(k = 2,3,\cdots,c\right)$ corresponding to the 2nd, 3rd, … c-th eigenvalues into a matrix $\mathbf{H}^{ED} = \left(\mathbf{h}_2^{ED},\mathbf{h}_3^{ED},\cdots,\mathbf{h}_c^{ED}\right)$, which approximates the cluster assignment matrix.

Step 4: Apply the K-means rounding procedure m times to the approximate assignment matrix obtained in Step 3, thus producing m cluster assignment matrices including zeros and ones.

Step 5: For each of the m assignment matrices $\mathbf{H}^{ED,l} = \left[\mathbf{h}_2^{ED,l},\mathbf{h}_3^{ED,l},\cdots,\mathbf{h}_c^{ED,l}\right]\left(l = 1,2,\cdots,m\right)$ obtained in Step 4, insert the assignment vectors $\mathbf{h}_k^{ED,l}\left(k = 2,3,\cdots,c\right)\left(l = 1,2,\cdots,m\right)$ into equation (5.2) to compute m values of *Ncut*, $Ncut^{ED,l}\left(l = 1,2,\cdots,m\right)$.

Step 6: Take the assignment matrix corresponding to the smallest of the m values $Ncut^{ED,l}$ obtained in Step 5 as the optimal solution.

Algorithm 2

Step 1: Form the normalized affinity matrix $\mathbf{D}^{-\frac{1}{2}}\mathbf{G}\mathbf{D}^{-\frac{1}{2}}$.

Step 2: Form the matrix $\mathbf{H}=\left[\mathbf{h}_1,\mathbf{h}_2,\cdots,\mathbf{h}_c\right]$, whose columns are the c vectors $\mathbf{h}_k\left(k=1,2,\cdots,c\right)$, each of which has dimension $\left(n\times 1\right)$.

Step 3: Solve the problem of minimizing $J=\left\|\mathbf{D}^{-\frac{1}{2}}\mathbf{G}\mathbf{D}^{-\frac{1}{2}}-\mathbf{H}\mathbf{H}^T\right\|_F^2$ to construct the nonnegative matrix factorization of the normalized affinity matrix and take the resulting matrix $\mathbf{H}^{NMF}=\left[\mathbf{h}_1^{NMF},\mathbf{h}_2^{NMF},\cdots,\mathbf{h}_c^{NMF}\right]$ as an approximate solution for the assignment matrix.

Step 4: Apply the K-means rounding procedure m times to the approximate assignment matrix obtained in Step 3, thus producing m cluster assignment matrices including zeros and ones.

Step 5: For each of the m assignment matrices $\mathbf{H}^{NMF,l}=\left[\mathbf{h}_1^{NMF,l},\mathbf{h}_2^{NMF,l},\cdots,\mathbf{h}_c^{NMF,l}\right]\left(l=1,2,\cdots,m\right)$ obtained in Step 4, insert the assignment vectors $\mathbf{h}_k^{NMF,l}\left(k=1,2,\cdots,c\right)\left(l=1,2,\cdots,m\right)$ into Equation (5.2) to compute m values of *Ncut*, $Ncut^{NMF,l}\left(l=1,2,\cdots,m\right)$.

Step 6: Take the assignment matrix corresponding to the smallest of the m values $Ncut^{NMF,l}\left(l=1,2,\cdots,m\right)$ obtained in Step 5 as the optimal solution.

This paper compares the results of the eigenvalue decomposition method and the nonnegative matrix factorization method for five different values of the number of K-means repetitions, m, namely, m=1, 10, 100, 1000, and 10000.

5.3. Data

For this work, network data from a 2005 input-output table covering 403 industrial sectors and 2005 Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables (3EID) (Nansai *et al*., 2012) were constructed. In particular, network data describing supply chains for passenger vehicles were constructed and, following Kagawa *et al.* (2013a, b), the focus was on the embodied CO_2 emissions induced by producing the intermediate products, which were purchased to produce the product j* (i.e., passenger car in this study) according to

$$\mathbf{B}^{j^*} = \mathrm{diag}(\boldsymbol{\alpha})\mathrm{diag}\left(\mathbf{f}^{j^*}\right) + \mathrm{diag}(\boldsymbol{\alpha})\mathbf{A}\mathrm{diag}\left(\mathbf{f}^{j^*}\right) + \mathrm{diag}(\boldsymbol{\alpha})\mathbf{A}\mathrm{diag}\left(\mathbf{A}\mathbf{f}^{j^*}\right). \qquad (5.3)$$

Here, $\mathbf{A} = (a_{ij})\ (i, j = 1, 2, \cdots, n)$ is the input coefficient matrix, whose entries a_{ij} denote the intermediate input from industry i per unit of output of industry j; $\mathbf{f}^{j^*}$ is the final demand vector, whose j^* th element is the final demand for industry j^* and whose other elements are all 0; $\boldsymbol{\alpha} = (\alpha_j)$ is the direct CO_2 emissions per unit of output of industry j and diag () denotes an operator of diagonalization. Here, we analyze the industries producing parts directly required for passenger vehicle manufacturing, the industries producing raw materials needed to produce those parts, and the relationships between all these industries. Using the matrix constructed in equation (5.3), an affinity matrix $\mathbf{G}$ is defined that quantifies the volume of economic transactions between industries producing automotive parts and industries producing raw materials, as follows:

$$\mathbf{G} = (g_{ij}) = \begin{cases} \frac{1}{2}\left(b_{ij}^{j^*} + b_{ji}^{j^*}\right) & (i \neq j) \\ 0 & (i = j) \end{cases}, \qquad (5.4)$$

where $b_{ij}^{j^*}$ is the (i, j) entry of the matrix $\mathbf{B}^{j^*}$ defined in equation (5.3). Algorithm 1 and Algorithm 2 are applied to the affinity matrix **G** defined by equation (5.4), and we consider the problem of identifying the optimal clustering of network nodes to produce the minimal value of *Ncut* and investigate the instability of the industrial clustering methods.

5.4. Results and Discussion

5.4.1 Instability analysis of Ncut values

Figure 1 compares the values of *Ncut* obtained using the eigenvalue decomposition method and using the nonnegative matrix factorization method for a single *K*-means repetition. In this figure, the horizontal axis indicates *c*, the number of clusters requested in the solution to the cluster partitioning problem, which in this study ranges from 2 to 20. A smaller value of *Ncut* indicates stronger individual sub-networks (i.e., *clusters*) identified within the overall supply-chain network structure, and thus a more optimal cluster assignment. As shown in the figure, for most values of *c*, the value of *Ncut* obtained by the nonnegative matrix factorization method is less than that obtained by the eigenvalue decomposition method. It is therefore concluded that, when the number of *K*-means repetitions is fixed at 1, the nonnegative matrix factorization method produces a more optimal cluster assignment (see the Appendix 5A for a more detailed result). Importantly, the result from Figure 5.1 empirically supports the remark of Ding *et al*. (2008a, p. 184) that "*the mixed signs of the eigenvector solutions make the cluster assignment difficult*". It should be noted that this remark of Ding *et al*. (2008a) implies that the method based on the nonnegative matrix factorization is much superior to that based on the eigenvalue decomposition.

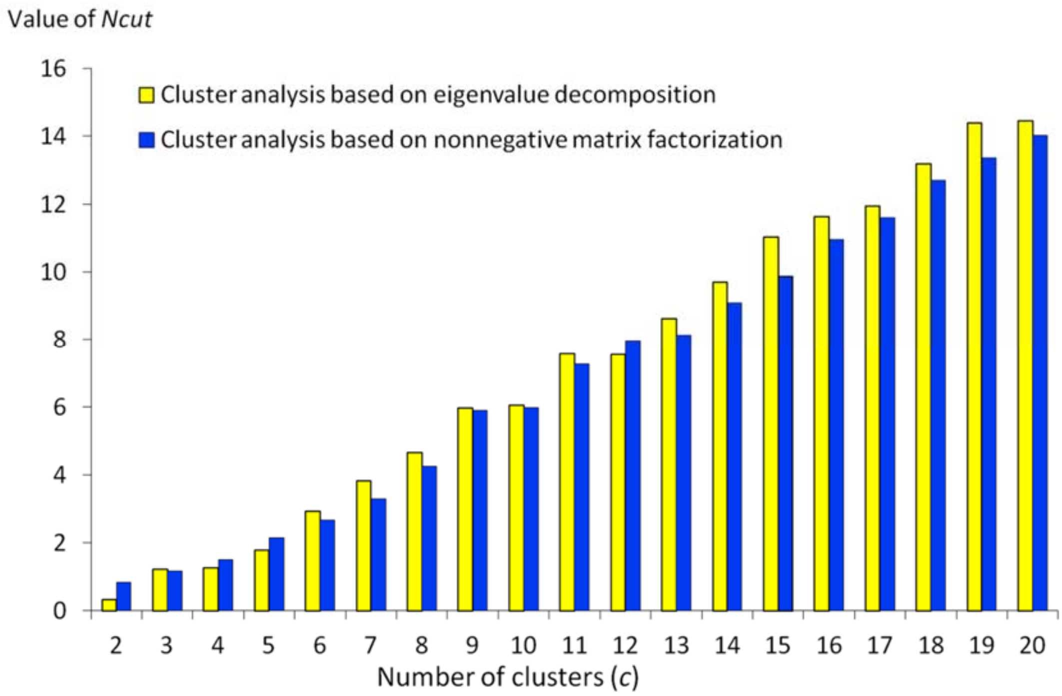

Figure 5.1 Values of *Ncut* obtained by eigenvalue decomposition and by nonnegative matrix factorization for a single *K*-means repetition (m=1)

However, since the operation of rounding via the *K*-means method is unstable, increasing the number of repetitions is considered in an effort to identify smaller values of *Ncut* and drive the obtained solution toward the global optimum. To this end, the values of *Ncut* obtained from the eigenvalue decomposition method and from the nonnegative matrix factorization method are compared for several values of m, the number of *K*-means repetitions, namely, m=10, 100, 1000, and 10000. Figures 5.2, 5.3, 5.4, and 5.5 correspond to Fig. 5.1 for the cases m=10, 100, 1000, and 10000, respectively.

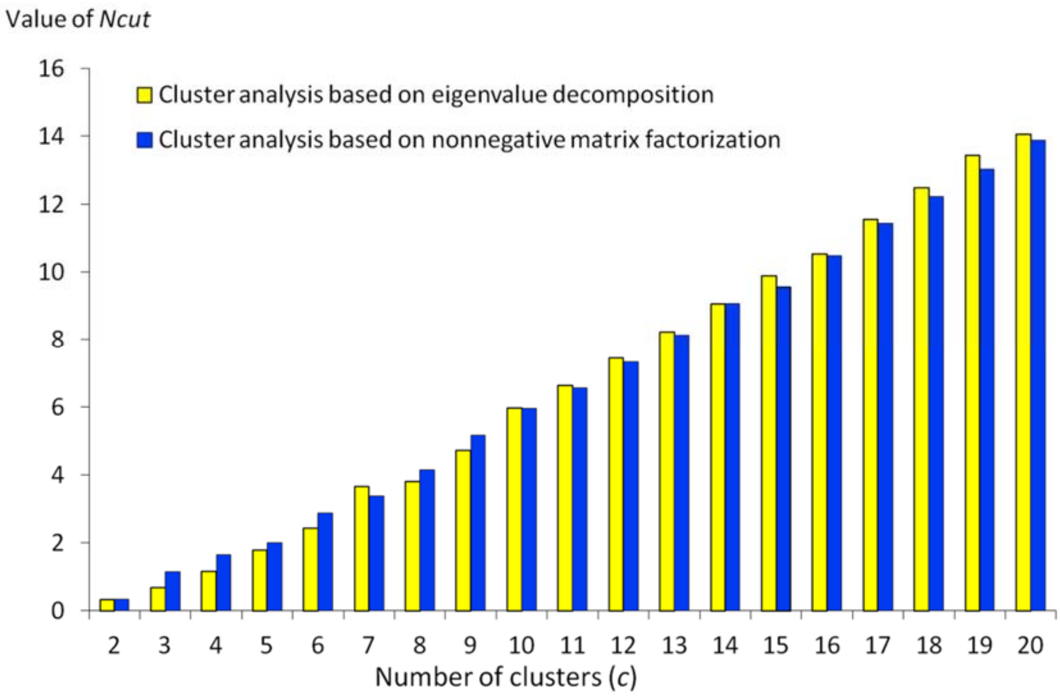

Figure 5.2 Values of *Ncut* obtained by eigenvalue decomposition and by nonnegative matrix factorization (m=10)

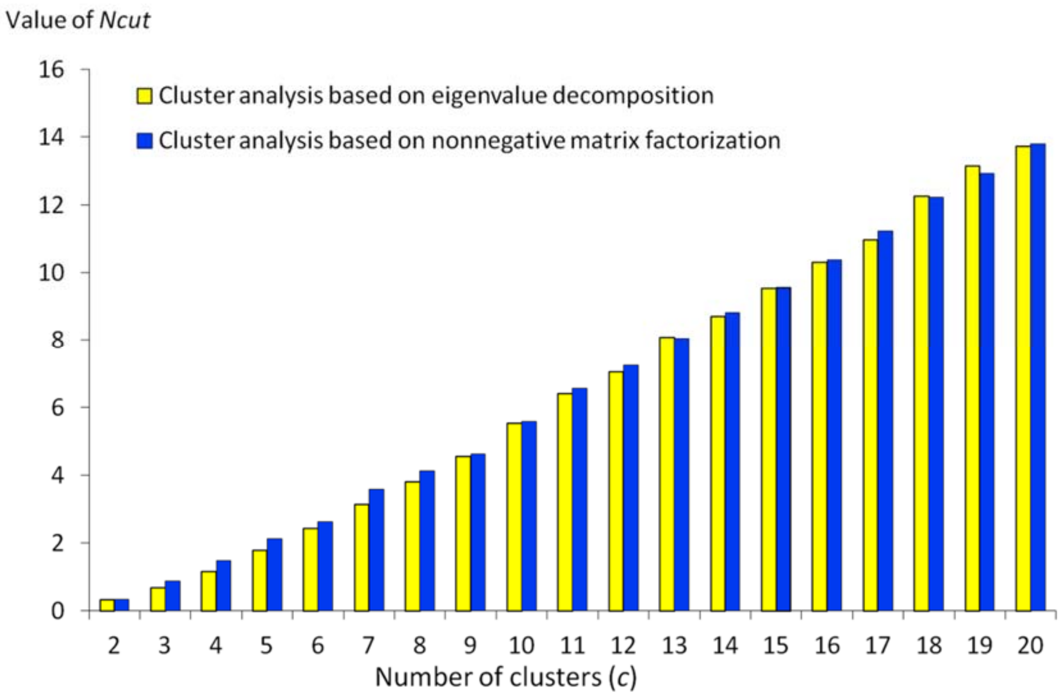

Figure 5.3 Values of *Ncut* obtained by eigenvalue decomposition and by nonnegative matrix factorization (m=100)

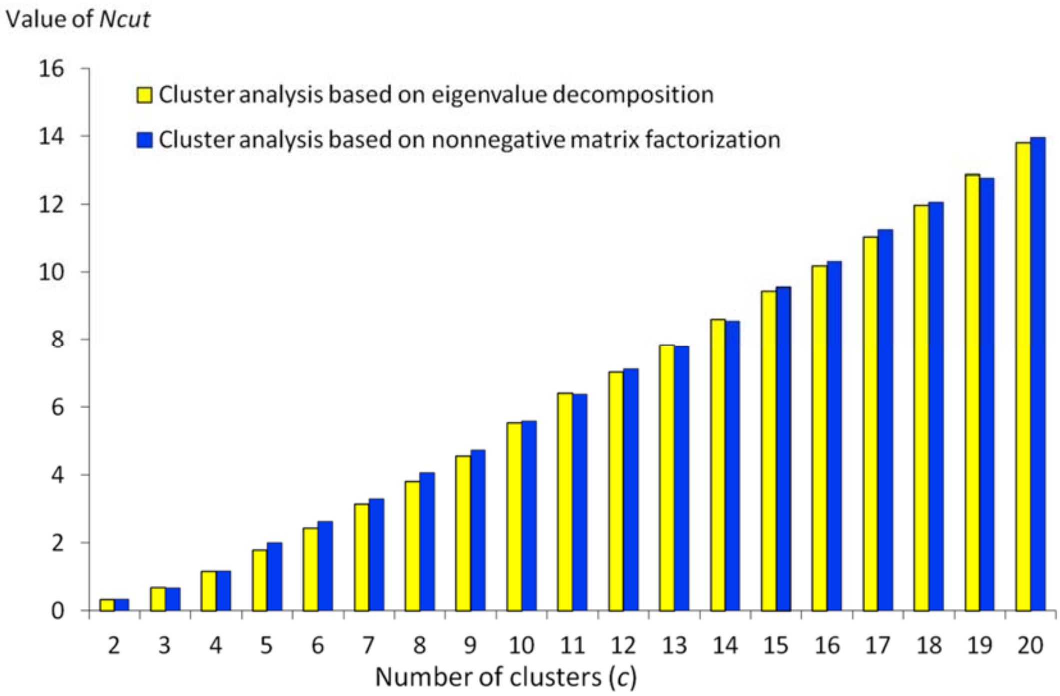

Figure 5.4 Values of *Ncut* obtained by eigenvalue decomposition and by nonnegative matrix factorization (m=1000)

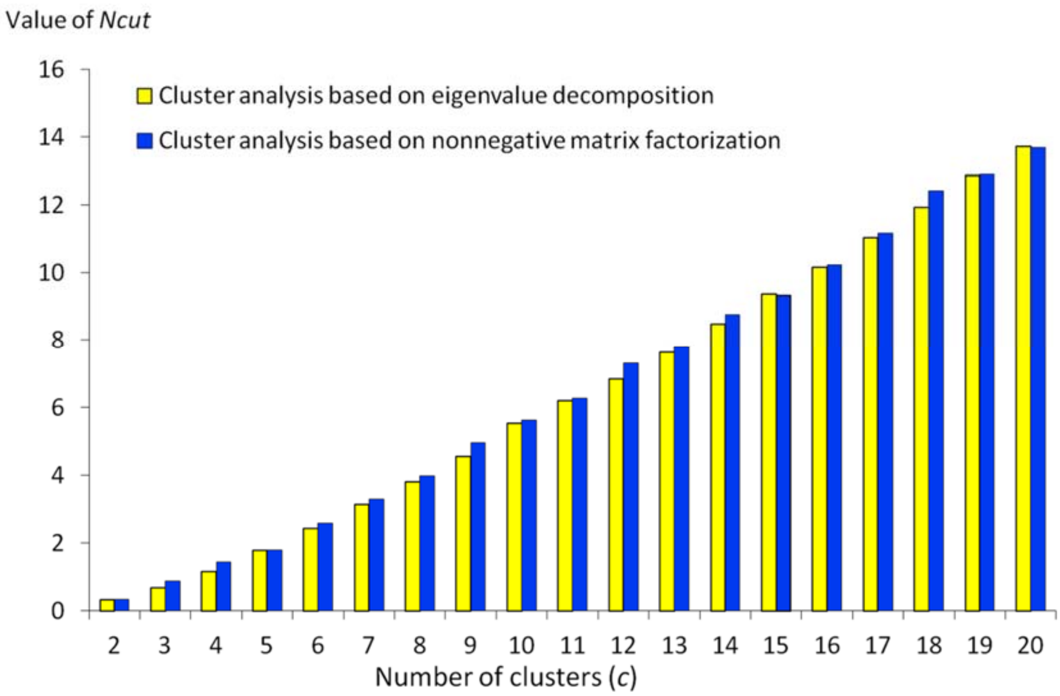

Figure 5.5 Values of *Ncut* obtained by eigenvalue decomposition and by nonnegative matrix factorization (m=10000)

In Figure 5.2 (m=10 repetitions), we see that, as in the case of Figure 5.1 (m=1), for most values of c, the values of *Ncut* obtained from the nonnegative matrix factorization method are smaller than those obtained from the eigenvalue decomposition method. However, in the cases m=100, 1000, and 10000, this trend no longer holds in general, with the eigenvalue decomposition method yielding smaller values of *Ncut* in many cases. Thus, for large numbers of K-means repetitions, it is no longer clearly discernible which of the two methods (eigenvalue decomposition or nonnegative matrix factorization) exhibits superior performance. For both methods, the K-means rounding procedure is unstable, but as the number m of K-means repetitions is increased, the obtained value of *Ncut* approaches the global optimum; for values of m above a certain threshold, the obtained values of *Ncut* cease to exhibit any noticeable variation.

To quantify this observation, the values of *Ncut* obtained for each value of *c* are plotted in Figures 5.6 and 5.7 for *m*=1, 10, 100, 1000, and 10000 for the nonnegative matrix factorization method and the eigenvalue decomposition method, respectively.

In both Figures 5.6 and 5.7, increasing the number of *K*-means repetitions beyond *m*=1 tends to decrease the obtained value of *Ncut*. In the case of Figure 5.6 (for the nonnegative matrix factorization method), increasing *m* beyond the value *m*=100 does not always decrease the value of *Ncut.* In the case of Figure 5.7 (for the eigenvalue decomposition method), the value of *Ncut* does tend to decrease monotonically with increasing *m*, but there is essentially no difference between the values obtained for *m*=1000 and *m*=10000. For both methods, the differences in the values of *Ncut* obtained for *m*=100, 1000, and 10000 were on the order of 1% (see Table 5A of the Appendix 5A).

Because the impact of such 1% differences on final cluster assignment is extremely small, and considering the computation time required to perform cluster analyses, it is concluded that *m*=100 is approximately the optimal number of *K*-means repetitions, at least in this case study.

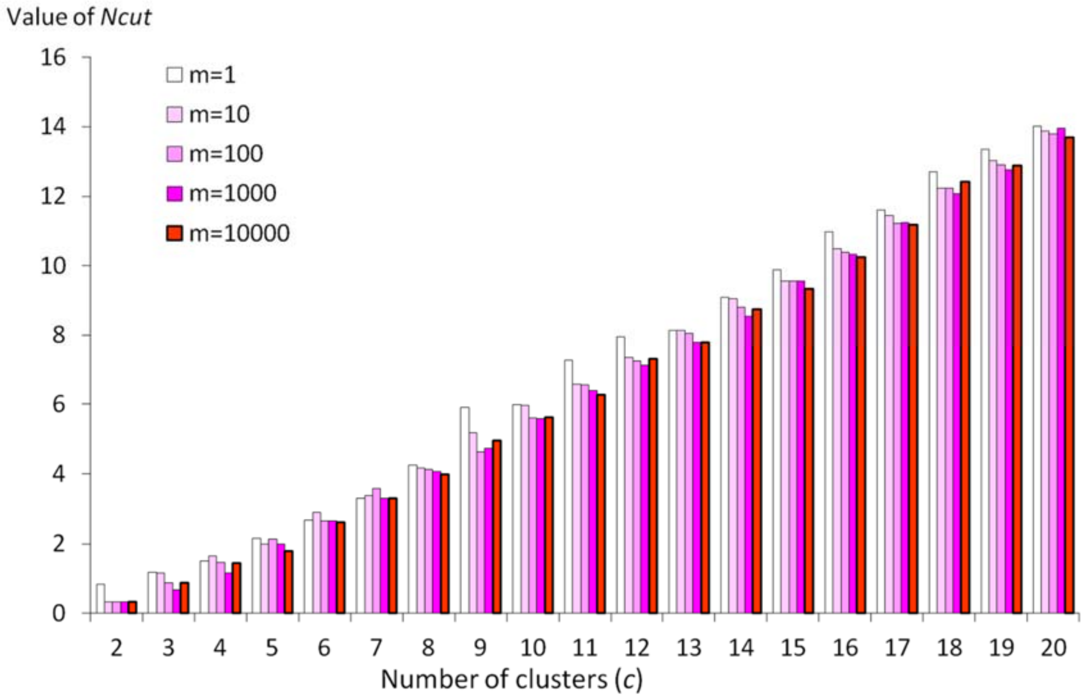

Figure 5.6 Values of *Ncut* obtained by the nonnegative matrix factorization method for various numbers *m* of *K*-means repetitions

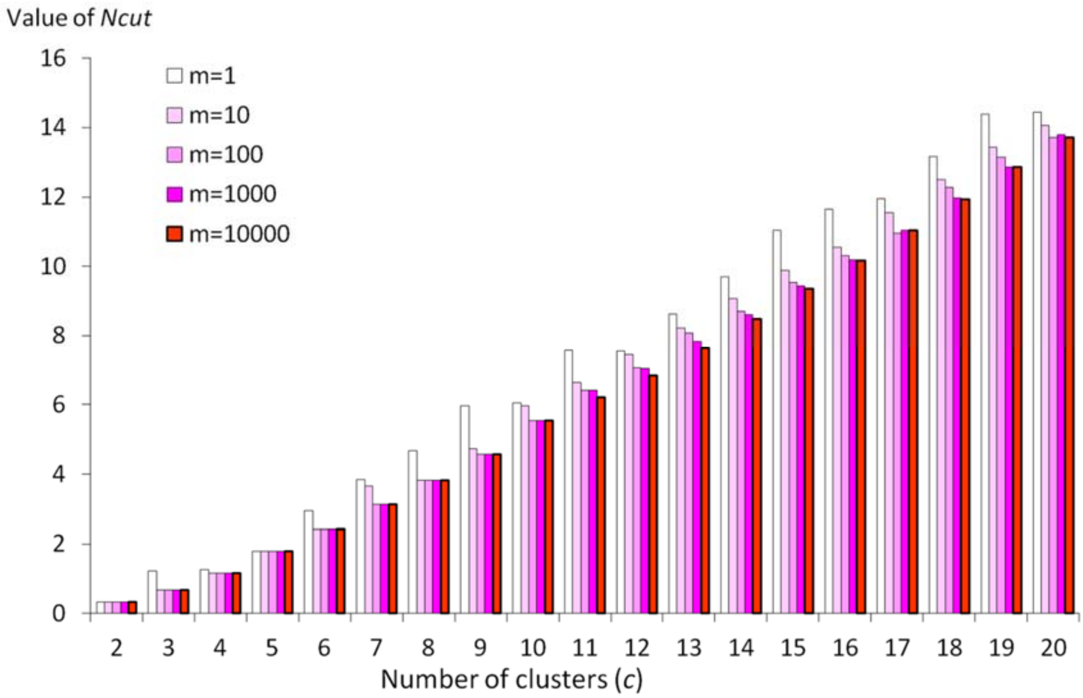

Figure 5.7 Values of *Ncut* obtained by the eigenvalue decomposition method for various numbers *m* of *K*-means repetitions

5.4.2 Percentile confidence intervals for Ncut values

Therefore, the present study focuses exclusively on $Ncut^{opt}$, defined as the smallest of the m values computed for $Ncut$, but we must also ask how reliably we are able to compute the value of this quantity. To perform a statistical analysis of the reliability of this detection of $Ncut^{opt}$, the probability α of obtaining certain $Ncut$ values is investigated. Specifically, α is defined as the probability that m computed values of $Ncut$ lie within $+\gamma\%$ of $Ncut^{opt}$, which is computed as follows:

$$\alpha = P\left\{ Ncut < \left(1 + 0.01 \times \gamma\right) \times Ncut^{opt} \right\} \qquad (5.5)$$

Suppose, for example, that equation (5.5) with parameter values $\gamma = 1$, $m = 10000$ predicts a value of α=0.9. This implies that, if we compute 10000 values of $Ncut$, any given $Ncut$ value is expected to lie within +1% of $Ncut^{opt}$ with a probability of 90%. A cluster analysis method may be deemed stable if the value of α is close to 1 for values of γ that are close to 0. Table 5.1 describes the relationship between α and γ for the cluster analysis methods based on eigenvalue decompositions and on nonnegative matrix factorizations.

Table 5.1 Probability α that *Ncut* lies within +γ% of $Ncut^{opt}$

Cluster analysis based on eigenvalue decomposition

	γ=1			γ=5			γ=10		
	Number of K-means repetitions m								
c	100	1000	10000	100	1000	10000	100	1000	10000
2	0.920	0.914	0.908	0.920	0.914	0.908	0.920	0.914	0.908
3	0.480	0.428	0.451	0.480	0.428	0.451	0.480	0.428	0.451
4	0.270	0.261	0.285	0.270	0.261	0.285	0.280	0.279	0.312
5	0.260	0.272	0.281	0.260	0.272	0.281	0.520	0.533	0.527
6	0.400	0.343	0.353	0.500	0.468	0.468	0.640	0.610	0.578
7	0.150	0.142	0.128	0.170	0.156	0.143	0.210	0.198	0.181
8	0.040	0.035	0.038	0.040	0.044	0.043	0.290	0.279	0.291
9	0.020	0.034	0.026	0.070	0.097	0.088	0.350	0.400	0.389
10	0.030	0.036	0.034	0.140	0.069	0.073	0.390	0.288	0.306
11	0.020	0.015	0.000	0.080	0.115	0.017	0.420	0.437	0.234
12	0.010	0.014	0.001	0.050	0.053	0.023	0.270	0.341	0.138
13	0.010	0.006	0.000	0.190	0.071	0.006	0.660	0.404	0.148
14	0.010	0.003	0.000	0.090	0.063	0.020	0.530	0.425	0.263
15	0.010	0.003	0.003	0.140	0.095	0.045	0.660	0.532	0.454
16	0.010	0.005	0.004	0.170	0.123	0.100	0.650	0.649	0.579
17	0.010	0.005	0.003	0.100	0.083	0.080	0.540	0.602	0.587
18	0.050	0.006	0.002	0.330	0.125	0.092	0.910	0.723	0.645
19	0.050	0.004	0.004	0.490	0.150	0.166	0.970	0.812	0.827
20	0.010	0.006	0.004	0.200	0.245	0.194	0.860	0.907	0.865
21	0.030	0.004	0.001	0.510	0.352	0.183	0.960	0.942	0.901
22	0.030	0.013	0.001	0.570	0.358	0.172	1.000	0.956	0.888
23	0.080	0.001	0.006	0.770	0.477	0.456	1.000	0.982	0.982
24	0.080	0.012	0.006	0.780	0.615	0.522	1.000	0.996	0.990
25	0.020	0.010	0.007	0.620	0.589	0.503	1.000	0.994	0.990
26	0.020	0.012	0.008	0.700	0.646	0.592	1.000	0.998	0.996
27	0.040	0.010	0.010	0.770	0.663	0.655	1.000	1.000	0.999
28	0.030	0.022	0.007	0.720	0.732	0.648	1.000	1.000	0.998
29	0.080	0.009	0.008	0.860	0.743	0.711	1.000	1.000	0.999
30	0.020	0.010	0.008	0.870	0.723	0.720	1.000	1.000	1.000
31	0.040	0.017	0.011	0.830	0.836	0.804	1.000	1.000	1.000
32	0.070	0.027	0.005	0.920	0.894	0.802	1.000	1.000	1.000
33	0.090	0.030	0.019	0.980	0.908	0.906	1.000	1.000	1.000
34	0.040	0.047	0.008	0.950	0.951	0.892	1.000	1.000	1.000
35	0.170	0.034	0.030	0.980	0.946	0.951	1.000	1.000	1.000
36	0.180	0.036	0.012	0.980	0.966	0.926	1.000	1.000	1.000
37	0.090	0.007	0.017	0.970	0.902	0.945	1.000	1.000	1.000
38	0.050	0.018	0.013	0.970	0.944	0.933	1.000	1.000	1.000
39	0.070	0.052	0.014	0.990	0.983	0.959	1.000	1.000	1.000
40	0.040	0.066	0.023	0.990	0.991	0.971	1.000	1.000	1.000
41	0.110	0.060	0.028	0.990	0.991	0.982	1.000	1.000	1.000
42	0.130	0.105	0.023	1.000	0.999	0.989	1.000	1.000	1.000
43	0.160	0.064	0.035	1.000	0.995	0.991	1.000	1.000	1.000
44	0.190	0.027	0.026	0.990	0.990	0.987	1.000	1.000	1.000
45	0.240	0.048	0.018	1.000	0.994	0.989	1.000	1.000	1.000
46	0.210	0.107	0.033	1.000	0.997	0.992	1.000	1.000	1.000
47	0.210	0.094	0.051	1.000	0.997	0.996	1.000	1.000	1.000
48	0.280	0.103	0.082	0.990	0.999	0.998	1.000	1.000	1.000
49	0.240	0.123	0.044	1.000	1.000	0.997	1.000	1.000	1.000
50	0.290	0.110	0.036	1.000	0.999	0.997	1.000	1.000	1.000

Cluster analysis based on nonnegative matrix factorization

	γ=1			γ=5			γ=10		
	Number of K-means repetitions m								
c	100	1000	10000	100	1000	10000	100	1000	10000
2	0.110	0.140	0.140	0.110	0.140	0.140	0.110	0.140	0.140
3	0.030	0.020	0.022	0.030	0.020	0.025	0.030	0.020	0.025
4	0.130	0.001	0.002	0.130	0.001	0.002	0.130	0.002	0.002
5	0.050	0.173	0.000	0.330	0.187	0.000	0.440	0.403	0.000
6	0.070	0.103	0.271	0.440	0.462	0.538	0.590	0.624	0.718
7	0.180	0.008	0.014	0.440	0.303	0.115	0.760	0.591	0.544
8	0.150	0.026	0.000	0.160	0.052	0.125	0.440	0.426	0.175
9	0.010	0.007	0.195	0.380	0.250	0.475	0.690	0.541	0.758
10	0.020	0.088	0.021	0.150	0.235	0.035	0.590	0.732	0.536
11	0.090	0.008	0.006	0.590	0.344	0.037	0.840	0.710	0.488
12	0.040	0.063	0.076	0.500	0.469	0.467	0.780	0.788	0.816
13	0.110	0.054	0.006	0.610	0.512	0.217	0.930	0.870	0.755
14	0.010	0.004	0.017	0.530	0.206	0.404	0.860	0.826	0.900
15	0.080	0.012	0.019	0.630	0.366	0.406	0.970	0.917	0.917
16	0.100	0.008	0.015	0.730	0.608	0.428	0.950	0.947	0.943
17	0.040	0.085	0.017	0.350	0.646	0.422	0.960	0.977	0.951
18	0.030	0.035	0.148	0.710	0.715	0.813	0.970	0.992	0.996
19	0.040	0.015	0.058	0.600	0.573	0.727	1.000	0.979	0.993
20	0.100	0.132	0.026	0.850	0.842	0.678	1.000	0.998	0.994
21	0.110	0.021	0.022	0.840	0.684	0.680	1.000	0.995	0.994
22	0.060	0.048	0.018	0.940	0.790	0.649	1.000	0.998	0.997
23	0.070	0.027	0.083	0.880	0.860	0.911	1.000	0.999	0.999
24	0.100	0.025	0.031	0.980	0.876	0.882	1.000	1.000	1.000
25	0.150	0.125	0.066	0.970	0.946	0.886	1.000	1.000	1.000
26	0.100	0.073	0.032	0.950	0.965	0.904	1.000	1.000	1.000
27	0.130	0.122	0.058	0.950	0.969	0.955	1.000	1.000	1.000
28	0.190	0.048	0.029	0.980	0.966	0.950	1.000	1.000	1.000
29	0.230	0.045	0.077	0.980	0.951	0.974	1.000	1.000	1.000
30	0.350	0.087	0.042	1.000	0.980	0.977	1.000	1.000	1.000
31	0.050	0.092	0.029	1.000	0.992	0.977	1.000	1.000	1.000
32	0.130	0.103	0.036	1.000	0.986	0.980	1.000	1.000	1.000
33	0.120	0.103	0.046	0.990	0.993	0.984	1.000	1.000	1.000
34	0.250	0.072	0.038	1.000	0.994	0.982	1.000	1.000	1.000
35	0.220	0.076	0.094	0.990	0.991	0.994	1.000	1.000	1.000
36	0.220	0.178	0.258	1.000	0.998	0.998	1.000	1.000	1.000
37	0.390	0.146	0.081	0.990	0.996	0.996	1.000	1.000	1.000
38	0.220	0.265	0.124	1.000	0.998	0.998	1.000	1.000	1.000
39	0.440	0.452	0.223	1.000	1.000	0.999	1.000	1.000	1.000
40	0.430	0.258	0.214	1.000	0.999	0.999	1.000	1.000	1.000
41	0.400	0.324	0.173	1.000	1.000	0.999	1.000	1.000	1.000
42	0.290	0.298	0.154	1.000	1.000	0.999	1.000	1.000	1.000
43	0.330	0.254	0.180	1.000	1.000	1.000	1.000	1.000	1.000
44	0.440	0.359	0.316	1.000	1.000	1.000	1.000	1.000	1.000
45	0.410	0.325	0.196	1.000	1.000	1.000	1.000	1.000	1.000
46	0.600	0.320	0.259	1.000	1.000	1.000	1.000	1.000	1.000
47	0.650	0.327	0.228	1.000	1.000	1.000	1.000	1.000	1.000
48	0.630	0.540	0.354	1.000	1.000	1.000	1.000	1.000	1.000
49	0.640	0.456	0.360	1.000	1.000	1.000	1.000	1.000	1.000
50	0.500	0.379	0.277	1.000	1.000	1.000	1.000	1.000	1.000

As shown in Table 5.1, the probability α with which *Ncut* lies within +10% of $Ncut^{opt}$ is close to 1, in many cases of the number of K-means repetitions used, for both clustering methods. In other words, if the threshold value γ for assessing the stability of the procedure, which is freely chosen by the analyst, is set to 10, then the value of α lies close to 1, and the results of the cluster analysis may be deemed stable. On the other hand, setting γ to 1 yields values of α close to 0, in which case, the results of the cluster analysis must be considered unstable. From Table 5.1, we can see that similar reasoning suggests that, at a value of γ=5, the results of the cluster analysis may be considered stable.

For a given number of repetitions, smaller values of α indicate that values of *Ncut* lying close to $Ncut^{opt}$ are difficult to identify. The results of Table 5.1 for the clustering methods based on the eigenvalue decomposition and on the nonnegative matrix factorization indicate that, for this case study involving supply chains for passenger vehicles, increasing the number of repetitions of the *K*-means rounding procedure from 100 to 10000 did *not* yield any significant change in the value of α. This demonstrates that, in this regime, performing more repetitions of the rounding procedure does not significantly increase the probability of identifying a smaller value of $Ncut^{opt}$.

5.5. Implication and conclusions

This study investigated the instability of two clustering methods: a method based on the nonnegative matrix factorization and a method based on the eigenvalue decomposition. The results indicate that, in cases involving a relatively small number of K-means repetitions (approximately 10), choosing the nonnegative matrix factorization method over the eigenvalue decomposition method yields smaller values of *Ncut*, the benchmark indicating optimal cluster assignment. On the other hand, for a larger number of K-means repetitions (100 or more), neither method is universally superior to the other.

A comparison of the impact of the number of K-means repetitions on the results obtained by the two methods revealed that, for both methods, computed values of *Ncut* remained essentially unchanged as the number of repetitions varied in the range 100 to 10000. Based on these findings, it is concluded that, for example, in a problem involving a network containing around 400 nodes, one would expect no significant discrepancy in the magnitude of the final *Ncut* values obtained by the nonnegative factorization method and the eigenvalue decomposition method, as long as approximately 100 K-means repetitions are performed; for such a problem, the results of this study suggest that industrial cluster analysis should be performed via eigenvalue decomposition of the normalized Laplacian matrix, which is computationally the simpler of the two methods. The findings indicated that increasing the number of repetitions of the K-means rounding procedure even to extremely large numbers offers a negligible probability of yielding smaller values of $Ncut^{opt}$.

On the other hand, for large-scale networks involving (for example) 10000 or more nodes, one should instead seek to restrict the number of computationally expensive K-means repetitions, and in such cases the nonnegative matrix factorization method may be the more attractive of the two methods.

In traditional methods of LCA analysis, system boundaries have tended to be determined somewhat subjectively. In this paper, we examined the stability of a cluster analysis method whose adoption allows system boundaries to be determined *objectively*, in a manner which incorporates environmentally important product systems. The popular process LCA method leads to truncation error and underestimation of life-cycle emission. Our results suggest that the process LCA practitioners should consider the CO_2 intensive product systems identified by using the clustering method and evaluate the bias of life-cycle CO_2 emissions resulting from its stability analysis.

Appendix 5A

Table 5A Values of *Ncut* obtained from a clustering method based on eigenvalue decomposition and those based on nonnegative matrix factorization

Cluster analysis based on eigenvalue decomposition					
	Number of K-means repetitions m				
c	1	10	100	1000	10000
2	0.33	0.33	0.33	0.33	0.33
3	1.22	0.68	0.68	0.68	0.68
4	1.26	1.17	1.17	1.17	1.17
5	1.80	1.80	1.80	1.80	1.80
6	2.94	2.43	2.43	2.43	2.43
7	3.83	3.65	3.13	3.13	3.13
8	4.67	3.82	3.82	3.82	3.82
9	5.98	4.73	4.57	4.57	4.57
10	6.06	5.98	5.54	5.54	5.54
11	7.57	6.64	6.41	6.41	6.21
12	7.55	7.46	7.07	7.03	6.84
13	8.63	8.23	8.07	7.84	7.64
14	9.70	9.06	8.71	8.60	8.47
15	11.03	9.89	9.54	9.43	9.36
16	11.64	10.54	10.32	10.19	10.17
17	11.95	11.55	10.97	11.03	11.03
18	13.18	12.49	12.27	11.97	11.93
19	14.38	13.44	13.14	12.86	12.86
20	14.45	14.06	13.72	13.80	13.72
21	16.20	14.99	14.93	14.74	14.60
22	16.78	16.21	15.86	15.63	15.46
23	17.27	16.98	16.87	16.57	16.57
24	18.18	17.95	17.64	17.49	17.44
25	18.85	18.80	18.53	18.47	18.41
26	19.72	19.59	19.46	19.38	19.35
27	21.35	20.70	20.39	20.31	20.29
28	23.08	21.70	21.25	21.24	21.14
29	23.35	22.34	22.34	22.11	22.08
30	24.04	23.78	23.19	23.02	22.99
31	24.32	24.57	24.08	24.04	23.98
32	25.71	25.64	25.09	25.02	24.87
33	26.48	26.39	26.07	25.92	25.89
34	27.32	27.21	26.92	26.96	26.80
35	28.39	28.13	27.96	27.79	27.82
36	29.96	29.32	29.21	28.95	28.85
37	30.24	30.33	30.01	29.74	29.86
38	32.04	31.22	30.89	30.76	30.72
39	32.99	32.37	31.81	31.85	31.72
40	34.00	33.22	32.81	32.89	32.73
41	33.88	33.90	33.96	33.79	33.71
42	35.55	35.25	34.89	34.87	34.71
43	37.53	36.26	35.96	35.82	35.74
44	37.02	37.11	37.00	36.72	36.71
45	38.22	38.24	37.97	37.71	37.62
46	39.11	38.97	38.94	38.80	38.67
47	40.38	40.15	39.92	39.74	39.68
48	42.11	40.98	40.96	40.76	40.72
49	42.38	42.07	41.86	41.78	41.65
50	44.21	43.08	42.87	42.75	42.61

Cluster analysis based on nonnegative matrix factorization					
	Number of K-means repetitions m				
c	1	10	100	1000	10000
2	0.83	0.33	0.33	0.33	0.33
3	1.17	1.15	0.88	0.68	0.88
4	1.50	1.66	1.48	1.17	1.45
5	2.15	2.00	2.14	2.00	1.80
6	2.67	2.89	2.64	2.64	2.60
7	3.30	3.37	3.59	3.30	3.30
8	4.25	4.16	4.13	4.07	3.98
9	5.91	5.18	4.62	4.73	4.96
10	5.99	5.96	5.60	5.59	5.63
11	7.27	6.58	6.56	6.39	6.28
12	7.96	7.34	7.25	7.12	7.31
13	8.13	8.14	8.05	7.80	7.80
14	9.10	9.06	8.81	8.55	8.75
15	9.87	9.56	9.55	9.55	9.33
16	10.97	10.49	10.38	10.32	10.24
17	11.60	11.45	11.23	11.25	11.18
18	12.71	12.23	12.23	12.07	12.42
19	13.35	13.02	12.91	12.77	12.89
20	14.02	13.88	13.79	13.97	13.70
21	15.43	14.94	14.86	14.59	14.56
22	15.78	15.55	15.60	15.44	15.47
23	16.61	16.63	16.51	16.68	16.58
24	18.32	17.84	17.61	17.45	17.31
25	18.93	18.69	18.54	18.41	18.37
26	19.76	19.56	19.46	19.66	19.34
27	21.05	20.46	20.34	20.32	20.28
28	21.44	21.67	21.39	21.34	21.23
29	22.68	22.55	22.36	22.18	22.19
30	23.43	23.56	23.35	23.22	23.24
31	24.79	24.48	24.01	24.17	24.15
32	25.77	25.32	25.02	25.10	25.03
33	26.64	26.15	26.09	26.05	25.99
34	27.62	27.19	27.15	27.00	26.91
35	28.26	28.12	28.20	27.94	27.90
36	29.63	29.34	29.05	29.05	29.07
37	30.38	30.21	30.18	30.06	29.92
38	31.55	31.21	30.94	31.02	31.03
39	32.77	32.34	32.05	31.99	31.92
40	33.70	33.11	32.94	32.97	32.96
41	34.20	34.19	34.19	33.98	34.02
42	35.74	35.10	34.97	35.03	34.94
43	36.92	36.18	35.99	35.99	35.85
44	37.44	37.17	37.03	36.92	36.89
45	38.46	38.14	38.03	37.99	37.68
46	39.39	39.01	39.01	38.86	38.83
47	40.00	40.27	40.12	39.82	39.85
48	41.21	41.11	40.98	40.86	40.70
49	42.85	42.09	41.98	41.89	41.78
50	43.07	43.02	43.01	42.91	42.94

Chapter 6 Conclusions

This doctoral thesis presents a comprehensive structural analysis of the Japanese CO_2 emissions, argues how the Japanese structural changes at the macro-level affect the environment and demonstrates how Life Cycle Assessment (LCA) based on industry cluster techniques is useful in monitoring life-cycle CO_2 emissions associated with product supply-chains of a specific industry.

First, as a macro-analysis, Chapter 3 analyzed the relationship between Japan's industrial structure and the environment. Environmental input–output tables for Japan between 1990 and 2005 were used to estimate the effects of changes in economic scale, changes in industrial structure, changes in emission factor, changes in import scale, and changes in import structure on CO_2 emissions. The results revealed that changes in emission factor accompanying improvements in energy efficiency greatly reduced CO_2 emissions originating from industrial activities. This reduction is equivalent to approximately 1.5% of CO_2 emissions in base year 1990. Further, changes in industrial structure reduced CO_2 emissions originating from domestic industrial activities. This reduction is equivalent to approximately 5.7% of CO_2 emissions in base year 1990. This means that changes in the industrial structure in Japan, including the shift to a service economy, and changes in emission factor have reduced CO_2 emissions from domestic industry by 7.2% since 1990, and the role that this change in economic structure plays in mitigating warming cannot be ignored.

Next, as a meso-analysis, Chapter 4 focused on LCAs carried out by industry/business to address the problem of system boundaries in supply chains, which are determined arbitrarily when conducting LCAs. This chapter succeeded in detecting CO_2 emissions-intensive industry groups from supply chain networks using industry cluster analysis as a method for objectively determining system boundaries. An industry cluster analysis was conducted of the construction industry, which is the industry with the highest number of ISO 14001 certificates (an international standard for environmental management systems that includes environmental management standards using LCAs). In this analysis, industries associated with building materials, such as paint-related products and metal materials that are essential when constructing buildings, were detected as a closely related industry cluster, and it was demonstrated quantitatively that the product systems for these building materials are important in terms of managing the life cycle CO_2 emissions associated with the supply chains of buildings. It is important that these objectively detected building material production systems are included within the system boundaries when conducting an LCA of a building, and the critical production systems should also be clearly noted in the guidelines for LCA of buildings.

Chapter 5 analyzed the instability of clustering techniques useful in determining LCA system boundaries. The two main types of clustering technique are eigenvalue decomposition of the normalized Laplacian matrix and non-negative matrix factorization of the normalized adjacency matrix, and the method to be used must be chosen carefully according to the size of the network data. This chapter also developed a method for statically examining the instability of clustering techniques, and this method makes it possible to investigate an efficient number of roundings.

The results obtained in this doctoral thesis clarify, not only the role that Japan's industrial structure plays in global warming, but also the role that industries themselves play in global warming through their supply chain networks. This research was focused on Japan, but the role of the world structural changes in global warming can be analyzed in detail using the methods proposed in this thesis. This is a future research. The accumulation of this kind of quantitative analysis is extremely useful when addressing future global warming in the international community, and it is critically important when proposing global warming policies through international cooperation. This doctoral thesis also points out that it is crucial to create the LCA guidelines for determining LCA system boundaries (i.e., environmentally-important production processes).

Acknowledgements

Completing my dissertation and earning my PhD in Economics would not have been possible without the kind help of many friends, family members, and colleagues.

I would first like to express sincere gratitude to my supervisor, Associate Professor Shigemi Kagawa from Kyushu University in Japan. During the 6 years it took me to complete my dissertation, Professor Kagawa provided me with opportunities for many important experiences, such as conducting laboratory research, participating in academic courses, attending domestic and international academic conferences, and writing research papers. I believe that these experiences have provided me with a strong foundation of fundamentals for my future research. Although I may not have been the most diligent student researcher, his strictness toward my behavior was equally matched by his kindness. I also owe him a debt of gratitude for the vast connections I was able to make with domestic and international researchers, as these connections fostered great improvements in my research. Professor Kagawa, you have my deep appreciation for your constant support and encouragement.

Professor Toshiyuki Fujita and Associate Professor Nobuhiro Hori from the Faculty of Economics provided me with a number of important comments concerning my dissertation. Their extensive knowledge and insight regarding social problems helped to improve my research, and for this I also wish to express my profound appreciation.

During my graduate studies, through either research meetings or academic conferences, I received advice and support from Dr. Keisuke Nansai at the National Institute for Environmental Studies, Professor Yasushi Kondo at Waseda University, and Dr. Yuki Kudo at the National Institute of

Advanced Industrial Science and Technology. I would also like to express my appreciation for their kindness and helpfulness.

At international conferences such as the International Input-Output Association, I received positive and encouraging comments from Professors Sangwon Suh from the University of California, Santa Barbara, and Manfred Lenzen from The University of Sydney in Australia. Their comments provided me with additional motivation for my research, and for this I would like to express my gratitude.

Every summer, Professor Kagawa's laboratory hosts research meetings with laboratories from other universities. During these meetings, Professors Hiroki Tanikawa from Nagoya University and Seiji Hashimoto from Ritsumeikan University provided me with advice and support related to my research and promoted my studies. In addition, these meetings allowed me to expand my network within the student community. I would like to express my genuine appreciation to these gifted researchers and students for enabling me to have these important experiences.

My work was also motivated by the young researchers in the Student Communication Network at The Institute of Life Cycle Assessment. Their enlightening insights into my research provided me with new perspective and stimulated my attitude toward social problems. Whenever I felt confused about academic problems or my future, these young researchers were kind enough to offer their advice. The PhD students at Kyushu University were also kind enough to discuss research and coursework, and the fact that I was able to consult with them at any time was extremely encouraging. To these students and researchers, I also wish to convey my sincere appreciation.

During these past 6 years, I feel that I have made the strongest connections with members of Professor Shigemi's laboratory. In addition to great personal pleasure, these connections have provided me with an abundance of knowledge and a spirit of inquiry, and the experiences I have gained have been a very exciting and encouraging part of my life as both a student and a researcher. I would like to express my deepest thanks to these members for all of their assistance.

Finally, last but not least, I would like to express my deepest heartfelt appreciation to my sister, my mother, and my father for their lifelong support. I am unable to thank you enough.

November 2014

Shunsuke Okamoto

References

1) Ahmad, N., Wyckoff, A. (2003) Carbon dioxide emissions embodied in international trade of goods, *OECD Science, Technology and Industry Working Papers*, OECD Publishing.

2) Alcott, B. (2012) Mill's scissors: structural change and the natural-resource inputs to labour, *Journal of Cleaner Production*, vol. 21, pp. 83–92.

3) Allen, M.R., Frame, D.J., Huntingford, C., Jones, C.D., Lowe, J.A., Meinshausen, M., Meinshausen, M. (2009) Warming caused by cumulative carbon emissions towards the trillionth tonne, *Nature*, vol. 458, pp. 1163–1166.

4) Altizer, S., Ostfeld, R.S., Johnson, P.T.J, Kutz, S., Harvell, C.D. (2013) Climate Change and Infectious Diseases: From Evidence to a Predictive Framework, *Science*, vol. 341, 514–519.

5) Andrew, R., Peters, G.P., Lennox, J. (2009) Approximation and regional aggregation in multi-regional input–output for national carbon footprint accounting, *Economic Systems Research*, vol. 21, pp. 311–335.

6) Ang, B.W., Liu, F.L., Chew, E.P. (2003) Perfect decomposition techniques in energy and environmental analysis, *Energy Policy*, vol. 31, pp. 1561–1566.

7) Ang, B.W. (2004) Decomposition analysis for policymaking in energy: which is the preferred method?, *Energy Policy*, vol. 32, pp. 1131–1139.

8) Ang, B.W., Huang, H.C., Mu, A.R. (2009) Properties and linkages of some index decomposition analysis methods, *Energy Policy*, vol. 37, pp. 4624–4632.

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

10) Atkinson, G., Hamilton, K., Ruta, G., van der Mensbrugghe, D. (2011) Trade in 'virtual carbon': Empirical results and implications for policy, *Global Environmental Change*, vol. 21, pp. 563–574.

11) Auffhammer, M., Carson, R.T. (2008) Forecasting the path of China's CO_2 emissions using province level information, *Journal of Environmental Economics and Management*, vol.55, pp. 229–247.

12) Bach, F.R., Jordan, M.I. (2005) Learning spectral clustering, with application to speech separation, *Journal of Machine Learning Research*, vol. 7, pp. 1963–2001.

13) Baiocchi, G., Minx, J.C. (2010) Understanding changes in the UK's CO_2 emissions: A global perspective, *Environmental Science & Technology*, vol. 44, pp. 1177–1184.

14) Barrett, J., Peters, G.P., Wiedmann, T., Scott, K. (2013) Consumption-based GHG emission accounting: a UK case study, *Climate Policy*, vol. 13, pp. 451–470.

15) Batagelj, V., Ferligoj, A., Doreian, P. (1992) Direct and indirect methods for structural equivalence, *Social Networks*, vol. 14, pp. 63–90.

16) Ben-David, S., Pál, D., Simon, H.U. (2007) Stability of *K*-means clustering, *Lecture Notes in Computer Science*, vol. 4539, pp. 20–34.

17) Ben-David, S., von Luxburg, U. (2008) Relating clustering stability to properties of cluster boundaries, *Proceedings of the 21st Annual Conference on Learning Theory (COLT)*, pp. 379–390.

18) Bernstein, L., Roy, J., Delhotal, K.C., Harnisch, J., Matsuhashi, R., Price, L., Tanaka, K., Worrell, E., Yamba, F., Fengqi, Z. (2007) Chapter 7: Industry, in Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (eds.), *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

19) Bin, S., Dowlatabadi, H. (2005) Consumer lifestyle approach to US energy use and the related CO_2 emissions, *Energy Policy*, vol.33, pp.197–208.

20) Bloc, K., Höhne, N., van der Leun, K., Harrison, N. (2012) Bridging the greenhouse-gas emissions gap, *Nature Climate Change*, vol. 2, pp. 471–474.

21) Bonvoisin, J., Lelah, A., Mathieux, F., Brissaud, D. (2014) An integrated method for environmental assessment and ecodesign of ICT-based optimization services, *Journal of Cleaner Production*, vol. 68, pp. 144–154.

22) Booth, B.B.B., Jones, C.D., Collins, M., Totterdell, I., Cox, P.M., Sitch, S., Huntingford, C., Betts, R.A., Harris, G.R., Lloyd, J. (2012) High sensitivity of future global warming to land carbon cycle processes, *Environmental Research Letters*, vol. 7, pp. 1–8.

23) Borgatti, S.P., Everett, M.G. (1992) Regular blockmodels of multiway, multimode matrices,

Social Networks, vol. 14, pp. 91–120.

24) Breiger, R.L., Boorman, S., Arabie, P. (1975) An algorithm for clustering relational data with applications to social network analysis, *Journal of Mathematical Psychology*, vol. 12, pp. 329–383.

25) Brown, L.H., Buettner, P.G., Canyon, D.V., Mac Crawfold, J., Judd, J. (2012) Estimating the life cycle greenhouse gas emissions of Australian ambulance services, *Journal of Cleaner Production*, vol. 37, pp. 135–141.

26) Butnar, I., Llop, M. (2011) Structural decomposition analysis and input–output subsystems: Changes in CO_2 emissions of Spanish service sectors (2000–2005), *Ecological Economics*, vol. 70, pp. 2012–2019.

27) Cadarso, M., López, L., Gómez, N., Tobarra, M. (2012) International trade and shared environmental responsibility by sector. An application to the Spanish economy, *Ecological Economics*, vol. 83, pp. 221–235.

28) Caldeira, K., Davis, S.J. (2011) Accounting for carbon dioxide emissions: A matter of time, *Proceedings of the National Academy of Sciences*, vol.108, pp. 8533–8534.

29) Canadell, J.G., Quéré, C.L., Raupach, M.R., Field, C.B., Buitenhuis, E.T., Ciais, P., Conway, T.J., Gillett, N.P., Houghton, R.A., Marland, G. (2007) Contributions to accelerating atmospheric CO_2 growth from economic activity, carbon intensity, and efficiency of natural sinks, *Proceedings of the National Academy of Sciences*, vol. 107, pp. 18866–18870.

30) Carson, R.T. (2010) The environmental Kuznets curve: Seeking empirical regularity and theoretical structure, *Review of Environmental Economics and Policy*, vol. 4, pp. 3–23.

31) Casler, S.D., Hadlock, D. (1997) Contributions to change in the input-output model: the search for inverse important coefficients, *Journal of Regional Science*, vol.37, pp.175–193.

32) Chang, Y., Ries, R.J., Wang, Y. (2010) The embodied energy and environmental emissions of construction projects in China: An economic input–output LCA model, *Energy Policy*, vol. 38, pp. 6597–6603.

33) Chertow, M.R. (2000) The IPAT equation and its variants, *Journal of Industrial Ecology*, vol. 4, pp. 13–29.

34) Courchamp, F., Hoffmann, B.D., Russell, J.C., Leclerc, C., Bellard, C. (2014) Climate change,

sea-level rise, and conservation: keeping island biodiversity afloat, *Trends in economy & evolution*, vol. 29, pp. 127–130.

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

36) Davis, S.J. Caldeira, K. (2010) Consumption-based accounting of CO_2 emissions, *Proceedings of the National Academy of Sciences*, vol.107, pp.5687–5692.

37) Davis, S.J., Peters, G.P., Caldeira, K. (2011) The supply chain of CO_2 emissions, *Proceedings of the National Academy of Sciences*, vol. 108, pp. 18554–18559.

38) Defourny, J., Thorbecke, E. (1984) Structural path analysis and multiplier decomposition within a social accounting matrix framework, *The Economic Journal*, vol. 94, pp. 111–136.

39) Delgado, M., Porter, M.E., Stern, S. (2010) Clusters and entrepreneurship, *Journal of Economic Geography*, vol.10, pp. 1–24.

40) Dietzenbacher, E., Los, B. (1998) Structural decomposition techniques: Sense and sensitivity, *Economic Systems Research*, vol.10, pp. 307–323.

41) Dietzenbacher, E., Los, B. (2000) Structural decomposition analysis with dependent determinants, *Economic Systems Research*, vol.12, pp. 497–514.

42) Dietzenbacher, E. (2005) More on multipliers, *Journal of Regional Science*, vol. 45, pp. 421–426.

43) Dietzenbacher, E., Temurshoev, U. (2012) Input-output impact analysis in current or constant prices: does it matter?, *Journal of Economic Structures*, vol. 1, pp. 1–18.

44) Ding, C., He, X., Simon, H.D. (2005) On the equivalence of nonnegative matrix factorization and spectral clustering, *Proceedings of SIAM International Conference on Data Mining*, pp. 606–610.

45) Ding, C., Li, T., Jordan, M.I. (2008a) Nonnegative matrix factorization for combinatorial optimization: Spectral clustering, graph matching, and clique finding, *Proceedings of 2008 Eighth IEEE International Conference on Data Mining*, pp. 183–192.

46) Ding, C., Li, T., (2008b) On the equivalence between non-negative matrix factorization and probabilistic latent semantic indexing, *Computational Statistics & Data Analysis*, vol. 52, pp.

3913–3927.

47) Donath, W.E., Hofmann, A.J. (1973) Lower bounds for the partitioning of graphs, *IBM Journal of Research and Development*, vol. 17, pp. 420–425.

48) Droege, S. (2011) Using border measures to address carbon flows, *Climate Policy*, vol. 11, pp. 1191–1201.

49) Edens, B., Delahaye, R., van Rossum, M., Schenau, S. (2011) Analysis of changes in Dutch emission trade balances(s) between 1996 and 2007, *Ecological Economics*, vol. 70, pp. 2334–2340.

50) Farreny, R., Gabarrell, X., Rieradevall, J. (2008) Energy intensity and greenhouse gas emission of a purchase in the retail park service sector: An integrative approach, *Energy Policy*, vol. 36, pp. 1957–1968.

51) Feng, K., Davis, S.J., Sun, L., Li, X., Guan, D., Liu, W., Liu, Z., Hubacek, K. (2013) Outsourcing CO_2 within China, *Proceedings of the National Academy of Sciences*, vol. 110, pp. 11654–11659.

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

53) Fiedler, M. (1973) Algebraic connectivity of graphs, *Czechoslovak Mathematical Journal*, vol. 23, pp. 298–305.

54) Fodha, M., Zaghdoud, O. (2010) Economic growth and pollutant emissions in Tunisia: An empirical analysis of the environmental Kuznets curve, *Energy Policy*, vol. 38, pp. 1150–1156.

55) Fourcroy, C., Gallouji, F., Decellas, F. (2012) Energy consumption in service industries: Challenging the myth of non-materiality, *Ecological Economics*, vol. 81, pp. 155–164.

56) Frank, K.A. (1995) Identifying cohesive subgroups, *Social Networks*, vol. 17, pp. 27–56.

57) Fukuyama H., Yoshida, Y., Managi, S. (2011) Modal choice between air and rail: a social efficiency benchmarking analysis that considers CO_2 emissions, *Environmental Economics and Policy Studies*, vol. 13, pp. 89–102.

58) Gaudreault, C., Samson, R., Stuart, P.R. (2010) Energy decision making in a pulp and paper mill: selection of LCA system boundary, *The International Journal of Life Cycle Assessment*, vol.

15, pp. 198–211.

59) Green, C. (1992) Economics and the 'greenhouse effect,' *Climate Change*, vol. 22, pp. 265–291.

60) Grossman, G. M., Krueger, A. B. (1991) *Environmental impacts of a North American free trade agreement* (No. w3914), National Bureau of Economic Research.

61) Grossman, G.M, Krueger, A.B. (1995) Economic growth and the environment, *Quarterly Journal of Economics*, vol. 110, pp. 353–377.

62) Grossman, G.M, Krueger, A.B. (1996) The inverted U: What does it mean? *Environment and Development Economics*, vol. 1, pp. 119–22.

63) Guan, D., Hubacek, K., Weber, C.L., Peters, G.P., Reiner, D.M. (2008) The drivers of Chinese CO_2 emissions from 1980 to 2030, *Global Environmental Change*, vol. 18, pp. 626–634.

64) Guan, D., Peters, G.P., Weber, C.L., Hubacek, K. (2009) Journey to world top emitter: An analysis of the driving forces of China's recent CO_2 emissions surge, *Geophysical Research Letters*, vol. 36.

65) Halsnæs, K., Shukla, P., Ahuja, D., Akumu, G., Beale, R., Edmonds, J., Gollier, C., Grübler, A., Duong, M. H., Markandya, A., McFarland, M., Nikitina, E., Sugiyama, T., Villavicencio, A., Zou, J. (2007) Framing issues, in Metz, B., Davidson, O. R., Bosch, P. R., Dave, R., Meyer, L.A. (eds.), *Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

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

67) He, J., Richard, P. (2010) Environmental Kuznets curve for CO_2 in Canada, *Ecological Economics*, vol. 69, pp. 1083–1093.

68) Heijungs, R. (1994) A generic method for the identification of options for cleaner products, *Ecological Economics*, vol. 10, pp. 69–81.

69) Hellweg, S., Canals, L. (2014) Emerging approaches, challenges and opportunities in life cycle assessment, *Science*, vol. 344, pp. 1109–1113.

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

71) Hertwich, E.G. (2005) Lifecycle approaches to sustainable consumption: a critical review, *Environmental Science & Technology*, vol. 39, pp. 4637–4684.

72) Hertwich, E.G., Peters, G.P. (2009) Carbon footprint of nations: A global, trade-linked analysis, *Environmental Science & Technology*, vol. 43, pp. 6414–6420.

73) Hoen, A.R. (2002) An input-output analysis of European integration, in Baltagi, B.H., Sadka, E. (eds.), *Contributions to Economic Analysis*, Elsevier.

74) Hoekstra, R., van den Bergh, J.J.C.J.M. (2003) Comparing structural and index decomposition analysis, *Energy Economics*, vol. 25, pp. 39–64.

75) Houghton, J.T., Callander, B.A. Varney, S.K. (1992) *Climate change 1992: the supplementary report to the IPCC scientific assessment*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

76) Hsieh, M., Magee, C.L. (2008) An algorithm and metric for network decomposition from similarity matrices: Application to positional analysis, *Social Networks*, vol. 30, pp. 146–158.

77) Huppes, G., de Koning, A., Suh, S., Heijungs, R., van Oers, L., Nielsen, P., Guinee, J.B. (2006) Environmental impacts of consumption in the European union using detailed input–output analysis, *Journal of Industrial Ecology*, vol. 10, pp. 129–146.

78) Institute of Developing Economies (2006) *Asian international input-output table 2000, Institute of Developing Economies*, Japan External Trade Organization Japan.

79) Intergovernmental Panel on Climate Change (2014) *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

80) Joshi, S. (1999) Product environmental life-cycle assessment using input-output techniques, *Journal of Industrial Ecology*, vol. 3, pp. 95–120.

81) Kagawa, S. (2011) *Frontiers of Environmental input-output analysis*, Routledge.

82) Kagawa, S., Okamoto, S., Suh, S., Kondo, Y., Nansai, K. (2013a) Finding environmentally important industry clusters: Multiway cut approach using nonnegative matrix factorization,

Social Networks, vol. 35, pp. 423–438.

83) Kagawa, S., Suh, S., Kondo, Y., Nansai, K. (2013b) Identifying environmentally important supply chain clusters in the automobile industry, *Economic Systems Research*, vol. 25, pp. 265–286.

84) Kanemoto, K., Lenzen, M., Peters, G.P., Moran, D.D., Geschke, A. (2012) Frameworks for comparing emissions associated with production, consumption, and international trade, *Environmental Science & Technology*, vol. 46, pp. 172–179.

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

86) Labandeira, X., Labeaga, J.M. (2002) Estimation and control of Spanish energy-related CO_2 emissions: An input–output approach, *Energy Policy*, vol. 30, pp. 597–611.

87) Larsen, H.N., Hertwich, E.G. (2009) The case for consumption-based accounting of greenhouse gas emissions to promote local climate action, *Environmental Science & Policy*, vol. 12, pp. 791–798.

88) Larsen, H.N., Hertwich, E.G. (2011) Analyzing the carbon footprint from public services provided by counties, *Journal of Cleaner Production*, vol. 19, pp. 1975–1981.

89) Larsen, H.N., Solli, C., Pettersena, J. (2012) Supply chain management – How can we reduce our energy / climate footprint?, *Energy Procedia*, vol. 20, pp. 354–363.

90) Lee, D.D., Seung, H.S. (1999) Learning the parts of objects by non-negative matrix factorization, *Nature*, vol. 401, pp. 788–791.

91) Lee, D.D., Seung, H.S. (2001) Algorithms for non-negative matrix factorization, in Dietterich, T.G., Tresp, V. (eds.), *Advances in Neural Information Processing Systems 13*, The MIT Press.

92) Lenzen, M. (2001) Errors in conventional and input-output-based life-cycle inventories, *Journal of Industrial Ecology*, vol. 4, pp. 127–148.

93) Lenzen, M., Murray, S.A. (2001) A modified ecological footprint method and its application to Australia, *Ecological Economics*, vol. 37, pp. 229–255.

94) Lenzen, M. (2003) Environmentally important paths, linkages and key sectors in the Australian

economy, *Structural Change and Economic Dynamics*, vol. 14, pp. 1–34.

95) Lenzen, M., Pade, L.L., Munksgaard, J. (2004) CO_2 Multipliers in Multi-region Input-Output Models, *Economic Systems Research*, vol. 16, pp. 391–412.

96) Lenzen, M. (2007) Structural path analysis of ecosystem networks, *Ecological Modeling*, vol. 200, pp. 334–342.

97) Lenzen, M., Crawford, R. (2009) The path exchange method for hybrid LCA, *Environmental Science & Technology*, vol. 43, pp. 8251–8256.

98) Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., Geschke, A. (2012) International trade drives biodiversity threats in developing nations, *Nature*, vol. 486, 109–112.

99) Leontief, W. W. (1941) *Structure of the American Economy*, Oxford University Press, New York.

100) Leontief, W. (1970) Environmental repercussions and the economic structure: an input–output approach, *Review of Economics & Statistics*, vol. 52, pp. 262–271.

101) Leontief, W., Ford, D. (1972) Air pollution and the economic structure: empirical results of input–output computations, in Bródy, A., Carter, A.P. (eds.), *Input-Output techniques : proceedings of the Fifth International Conference on Input–Output Techniques*, North-Holland Publishing Company, Switzerland, pp. 9–30.

102) Leontief, W. (1986) *Input–Output Economics*, Oxford University Press, New York, USA.

103) Levinson (2002) The Ups and Downs of the Environmental Kuznets Curve, in List, J., Zeeuw, A. (eds.), *Recent Advances in Environmental Economic*, Edward Elgar Publishing.

104) Levinson, A. (2009) Technology, international trade, and pollution from US manufacturing, *American Economic Review*, vol. 99, pp. 2177–2192.

105) Liu, H.T., Guo, J.E., Qian, D., Xi, Y.M. (2009) Comprehensive evaluation of household indirect energy consumption and impacts of alternative energy policies in China by input–output analysis, *Energy Policy*, vol. 37, pp. 3194–3204.

106) Lorrain, F., White, H.C. (1971) Structural equivalence of individuals in social networks, *Journal of Mathematical Sociology*, vol. 1, pp. 49–80.

107) Ma, C., Stern, D.I. (2008) China's changing energy intensity trend: A decomposition analysis, *Energy Economics*, vol. 30, pp. 1037–1053.

108) Martínez, C.I.P. (2013) An analysis of eco-efficiency in energy use and CO_2 emissions in the Swedish service industries, *Socio-Economic Planning Science*, vol. 47, pp. 120–130.

109) Meilă, M., Pentney, W. (2007) Clustering by weighted cuts in directed graphs, *Proceedings of SIAM International Conference on Data Mining*, pp. 135–144.

110) Meinshausen, M., Meinshausen, N., Hare, W., Raper, S.C.B., Frieler, K., Knutti, R., Frame, D.J., Allen, M.R. (2009) Greenhouse-gas emission targets for limiting global warming to 2 °C, *Nature*, vol. 458, pp. 1158–1162.

111) Melitz, M.J. (2003) The impact of trade on intra-industry reallocations and aggregate industry productivity, *Econometrica*, vol. 71, pp. 1695–1725.

112) Miller, R.E., Blair, R.E. (2009) *Input–Output Analysis: Foundations and Extensions*, Cambridge University Press, Cambridge.

113) Munksgaard, J., Pedersen, K.A. (2001) CO_2 accounts for open economies: Producer or consumer responsibility?, *Energy Policy*, vol. 29, pp. 327–334.

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

115) Nansai, K., Moriguchi, Y. (2012) *Embodied energy and emission intensity data for Japan using input–output tables (3EID)*, CGER, National Institute for Environmental Studies, Japan, http://www.cger.nies.go.jp/publications/report/d031/index.html

116) Nasir, M., Rehman, F.U. (2011) Environmental Kuznets Curve for carbon emissions in Pakistan: An empirical investigation, *Energy Policy*, vol. 39, pp. 1857–1864.

117) Neil, B.C.O., Riahi, K., Keppo, I. (2010) Mitigation implications of midcentury targets that preserve long-term climate policy options, *Proceedings of the National Academy of Sciences*, vol. 107, pp. 1011–1016.

118) Newman, M.E.J. (2003) Mixing patterns in networks, *Physical Review E*, vol. 67, pp. 1–144.

119) Newman, M.E.J. (2004) Fast algorithm for detecting community structure in networks, *Physical Review E*, vol. 69, 066133.

120) Newman, M.E.J., Girvan, M. (2004) Finding and evaluating community structure in networks, *Physical Review E*, vol. 69, 026113.

121) Ng, A.Y., Jordan, M.I., Weiss, Y. (2001) On spectral clustering: Analysis and an algorithm, in Dietterich, T., Becker, S., Ghahramani, Z. (eds.), *Advances in Neural Information Processing Systems 14*.

122) Nooy, W.D., Mrvar, A., Batagelj, V. (2011) *Exploratory Social Network Analysis With Pajek*, Cambridge University Press, New York, USA.

123) Okamoto, S. (2013) Impacts of growth of a service economy on CO_2 emissions: Japan's case, *Journal of Economic Structures*, vol. 2, pp. 1–21.

124) Oliver-Solà, J., Núñez, M., Gabarrell, X., Boada, M., Rieradevall, J. (2007) Service sector metabolism: Accounting for energy impacts of the Montjuic Urban Park in Barcelona, *Journal of Industrial Ecology*, vol. 11, pp. 83–98.

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

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

127) Osita, Y. (2012) Identifying critical supply chain paths that drive changes in CO_2 emissions, *Energy Economics*, vol. 34, pp. 1041–1050.

128) Park, S.H. (1992) Decomposition of industrial energy consumption: An alternative method, *Energy Economics*, vol. 13, pp. 265–270.

129) Peters, G.P. (2007) Efficient algorithms for life cycle assessment, input - output analysis, and Monte-Carlo analysis, *The International Journal of Life Cycle Assessment*, vol. 12, pp. 373–380.

130) Peters, G.P. (2008) From production-based to consumption-based national emission inventories, *Ecological Economics*, vol. 65 , pp. 13–23.

131) Peters, G.P. (2010) Managing carbon leakage, *Carbon Management*, vol. 1, pp. 35–37.

132) Peters, G., Minx, J., Weber, C.L., Edenhofer, O. (2011) Growth in emission transfers via international trade from 1990 to 2008, *Proceedings of the National Academy of Sciences*, vol. 108, pp. 8903–8908.

133) Pfaff, A.S.P., Chaudhuri, S., Nye, H.L.M. (2004) Household Production and Environmental Kuznets Curves, *Environmental and Resource Economics*, vol. 27, pp. 187–200.

134) Porter, M.E. (2000) Location, competition and economic development: Local clusters in a global economy, *Economic Development Quarterly*, vol. 14, pp. 15–34.

135) Rand, W.M. (1971) Objective criteria for the evaluation of clustering methods, *Journal of the American Statistical Association*, vol. 66, pp. 846–850.

136) Raupach, M. R., Marland, G., Ciais, P., Le Quéré, C., Canadell, J. G., Klepper, G., and Field, C. B. (2007) Global and regional drivers of accelerating CO_2 emissions, *Proceedings of the National Academy of Sciences*, vol. 104, pp. 10288–10293.

137) Raynolds, M., Fraser, R., Checkel, D. (2000) The relative mass-energy-economic (RMEE) method for system boundary selection Part 1: A means to systematically and quantitatively select LCA boundaries, *The International Journal of Life Cycle Assessment*, vol. 5, pp. 37–46.

138) Reich, M.C. (2005) Economic assessment of municipal waste management systems—case studies using a combination of life cycle assessment (LCA) and life cycle costing (LCC), *Journal of Cleaner Production*, vol. 13, pp. 253–263.

139) Rodrigues, J., Domingos, T., Giljum, S., Schneider, F. (2006) Designing an indicator of environmental responsibility, *Ecological Economics*, vol. 59, pp. 256–266.

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

141) Rogner, H. H., Zhou, D., Bradley, R., Crabbé, P., Edenhofer, O., Hare, B., Kuijpers, L., Yamaguchi, M. (2007) Introduction, in Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (eds.), *Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

142) Rothman, D.S. (1998) Environmental Kuznets curves—real progress or passing the buck?: A case for consumption-based approaches, *Ecological Economics*, vol. 25, pp. 177–194.

143) Shahbaz, M., Mutascu, M., Azim, P. (2013) Environmental Kuznets curve in Romania and the role of energy consumption, *Renewable and Sustainable Energy Reviews*, vol. 18, pp. 165–173.

144) Shao, L., Chen, G.Q. (2013) Water footprint assessment for wastewater treatment: Method, indicator and application, *Environmental Science & Technology*, vol. 47, pp. 7787–7794.

145) Shao, L., Chen, G.Q., Chen, Z.M., Guo, S., Han, M.Y., Zhang, B., Hayat, T., Alsaedi, A., Ahmad, B. (2014) Systems accounting for energy consumption and carbon emission by building, *Communications in Nonlinear Science and Numerical Simulation*, vol. 19, pp. 1859–1873.

146) Shapley, L.S. (1953) A value for n-person games, in Kuhn, H.W., Tucker, A.W. (eds.), *Contributions to the Theory of Games*, *vol. 2*., Princeton University Press.

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

148) Sinden, G.E., Peters, G.P., Minx, J., Weber, C.L. (2011) International flows of embodied CO_2 with an application to aluminium and the EU ETS, *Climate Policy*, vol. 11, pp. 1226–1245.

149) Smith, D.M., Cusack, S., Colman, A.W., Folland, C.K., Harris, G.R., Murphy, J.M. (2007) Improved Surface Temperature Prediction for the Coming Decade from a Global Climate Model, *Science,* vol. 317, pp. 796–799.

150) Sonis, M., Hewings, G.J.D., Guo, J. (2000) A new image of classical key sector analysis: minimum information decomposition of the Leontief inverse, *Economic Systems Research*, vol. 12, pp. 401–423.

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

152) Stott, P.A., Kettleborough, J.A. (2002) Origins and estimates of uncertainty in predictions of twenty-first century temperature rise, *Nature*, vol. 416, pp. 723–726.

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

154) Strømman, A.H., Peters, G.P., Hertwich, E.G. (2009) Approaches to correct for double counting in tiered hybrid life cycle inventories, *Journal of Cleaner Production*, vol. 17, pp. 248–254.

155) Suh, S., Lenzen, M., Treloar, G., Hondo, H., Horvath, A., Huppes, G., Jolliet, O., Klann, U., Krewitt, W., Moriguchi, Y., Munksgaard, J., Norris, G. (2004) System boundary selection in life-cycle inventories using hybrid approaches, *Environmental Science & Technology*, vol. 38, pp. 657‑664.

156) Suh, S., Huppes, G. (2005) Methods for life cycle inventory of a product, *Journal of Cleaner Production*, vol. 13, pp. 687–697.

157) Suh, S. (2006) Are services better for climate change?, *Environmental Science & Technology*, vol. 40, pp. 6555–6560.

158) Suh, S., Nakamura, S. (2007) Five years in the area of input-output and hyrbid LCA, *The International Journal of Life Cycle Assessment*, vol. 12, pp. 351–352.

159) Suh, S. (eds.) (2009) *Handbook of Input–Output Economics in Industrial Ecology*, Springer, New York, USA.

160) Sun, J. W. (1998) Changes in energy consumption and energy intensity: A complete decomposition model, *Energy Economics*, vol. 20, pp. 85–100.

161) Sun, J. W. (1999) Decomposition of aggregate CO_2 emissions in the OECD: 1960-1995, *The Energy Journal*, vol. 20, pp. 147–155.

162) ten Raa, T., Rueda-Cantuche, J.M. (2013) The problem of negatives generated by the commodity technology model in input–output analysis: A review of the solutions, *Journal of Economic Structures*, vol. 2, pp. 1–14.

163) Tétreault, H.I., Jolliet, O., Deschênes, L., Ralph, K. (2013) Analytical propagation of uncertainty in life cycle assessment using matrix formulation, *Journal of Industrial Ecology*, vol. 17, pp. 485–492.

164) Treloar, G.J. (1997) Extracting embodied energy paths from input-output tables: towards an input-output-based hybrid energy analysis method, *Economic Systems Research*, vol. 9, pp. 375–391.

165) Treloar, G.J., Love, P.E.D., Faniran, O.O., Iyer-Raniga, U. (2000) A hybrid life cycle assessment method for construction, *Construction Management and Economics*, vol. 18, pp. 5–9.

166) Turner, K., Lenzen, M., Wiedmann, T., Barrett, J. (2007) Examining the global

environmental impact of regional consumption activities — Part 1: A technical note on combining input–output and ecological footprint analysis, *Ecological Economics*, vol. 62, pp. 37–44.

167) UNEP (2010) Assessing the Environmental Impacts of Consumption and Production: Priority Products and Materials, in Hertwich, E., van der Voet, E., Suh, S., Tukker, A., Huijbregts, M., Kazmierczyk, P., Lenzen, M., McNeely, J., Moriguchi, Y. (eds.) *, A Report of the Working Group on the Environmental Impacts of Products and Materials to the International Panel for Sustainable Resource Management*, United Nations Environmental Programme, Paris, France.

168) von Luxburg, U. (2007) A tutorial on spectral clustering, *Statistics and Computing*, vol. 17, pp. 395–416.

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

170) von Luxburg, U. (2010) Clustering stability: an overview, Foundations and Trends in Machine Learning, 2, 235–274.

171) Vringer, K., Benders, R., Wilting, H., Brink, C., Drissen, E., Nijdam, D., Hoogervorst, N. (2010) A hybrid multiregion method (HMR) for assessing the environmental impact of private consumption, *Ecological Economics*, vol. 69, pp. 2510–2516.

172) Weber, C.L., Matthews, H.S. (2007) Embodied emissions in U.S. international trade: 1997–2004, *Environmental Science & Technology*, vol. 41, pp. 4875–4881.

173) White, H.C., Breiger, R.L. (1975) Pattern across networks, *Society*, vol. 12, pp. 68–73.

174) Wiedmann, T., Lenzen, M., Turner, K., Barrett, J. (2007) Examining the global environmental impact of regional consumption activities — Part 2: Review of input–output models for the assessment of environmental impacts embodied in trade, *Ecological Economics*, vol. 61, pp. 15–26.

175) Wiedmann, T. (2009) A review of recent multi-region input–output models used for consumption-based emission and resource accounting, *Ecological Economics*, vol. 69, pp. 211–222.

176) Wood, R., Lenzen, M. (2006) Zero-value problems of the logarithmic mean divisia index decomposition method, *Energy Policy*, vol. 34, pp. 1326–1331.

177) Wood, R., Lenzen, M. (2009) Structural path decomposition, *Energy Economics*, vol. 31, pp. 335–341.

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

179) Xia, X.H., Huang, G.T., Chen, G.Q., Zhang, B., Chen, Z.M., Yang, Q. (2011) Energy security, efficiency and carbon emission of Chinese industry, *Energy Policy*, vol. 39, pp. 3520–3528.

180) Yabe, N. (2004) An analysis of CO_2 emissions of Japanese industries during the period between 1985 and 1995, *Energy Policy*, vol. 32, pp. 595–610.

181) Yu, S.X., Shi, J. (2003) Multiclass Spectral Clustering, *Proceedings of 2003 Ninth IEEE International Conference on Computer Vision*, vol. 1, pp. 113–119.

182) Zhang, Z., Jordan, M.I. (2008) Multiway spectral clustering: a margin-based perspective, *Statistical Science*, vol. 23, pp. 383–403.

183) Zhang, Y. (2009) Structural decomposition analysis of sources of decarbonizing economic development in China; 1992–2006, *Ecological Economics*, vol. 68, pp. 2399–2405.

184) Zhang, B., Chen, G.Q., Xia, X.H., Li, S.C., Chen, Z.M., Ji, X. (2012) Environmental emissions by Chinese industry: Exergy-based unifying assessment, *Energy Policy*, vol. 45, pp. 490–501.