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Environmental Input-Output Analyses of Global Supply Chain Restructuring

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https://hdl.handle.net/2324/7182285

出版情報:Kyushu University, 2023, 博士(経済学), 課程博士

バージョン: 権利関係:

Environmental Input Output Analyses of Global Supply Chain Restructuring

A Dissertation Submitted in Partial Fulfillment of the Requirement for the Degree of Ph.D. in Economics

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by

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Chapter 1: Introduction

1.1 Research background

1.1.1 Global warming and greenhouse gas emissions associated with human activity

Since the Industrial Revolution, the world has experienced rapid growth in greenhouse gas (GHG) emissions, such as CO₂, owing to human activities, increasing by approximately 150% by 2021 (WDCGG, 2023). Over the past few decades, the global consequences of climate change resulting from substantial GHG emissions have become increasingly evident. The Intergovernmental Panel on Climate Change (IPCC), established by the United Nations, announced strict warnings about the negative impacts of climate change (IPCC, 2018, 2023). Specifically, the IPCC expects a global temperature increase of 4°C by 2100 compared to the pre-industrial era in scenarios where the world relies heavily on fossil fuels. In addition, the IPCC has reported various risks triggered by climate change, such as rising sea levels and intense precipitation events (IPCC, 2021). They argue that the world must realize the sustainable society scenario, which limits temperature increase below 2°C in 2100 to protect the ability of future generations to satisfy their demands and interests.

As a sustainable society scenario is recognized as a common global target, 194 countries have ratified the Paris Agreement, an international alliance for achieving climate goals (United Nations, 2023). Under the Paris Agreement, these countries must

submit their "nationally determined contribution: NDC" for GHG reductions. Furthermore, in line with this commitment, over 150 countries have declared a net-zero GHG emissions goal by 2070 (IEA, 2021; Ministry of Economy, Trade, and Industry: METI of Japan (in Japanese), 2023). Given this background, climate change mitigation is an essential challenge as social demands increase.

1.1.2 Need for CO₂ reductions from industrial production activities including those global supply chains

The total GHG emissions worldwide were 34Gt-CO₂ in 2019, 44% higher than in 2000 (IEA, 2022). Figure 1-1 shows the GHG emissions in the United States of America: USA, Japan, Germany, China, and India between 2000 and 2019. As shown in Fig. 1-1, GHG emissions in the USA, Japan, and Germany decreased by 13%, 9%, and 21%, respectively, during this period. Moreover, the Group of Seven (G7), comprising advanced countries that include these nations, achieved a 14% reduction in GHG emissions during this period (IEA, 2022). However, GHG emissions in China and India increased significantly to 40% of total global GHG emissions in 2019. The growth of these emissions in developing countries has contributed to a net increase in global GHG emissions.

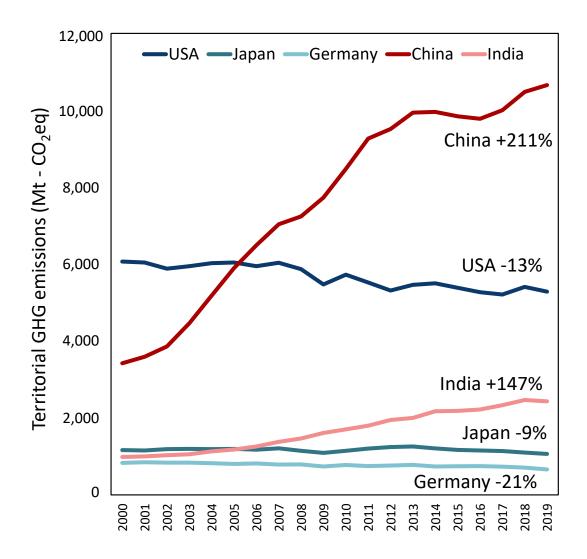


Figure 1-1. GHG emissions in USA, Japan, Germany, China and India during 2000 and 2019 (Source: GHG emissions from Energy Highlights 2022 (IEA)).

In addition to economic growth, one of the main drivers behind the increase in CO₂ emissions in developing countries is their role as manufacturing bases for producing goods and services for advanced countries, originating from the development of the global supply chain (GSC) structure (Wiedmann, 2009a; Peters *et al.*, 2011; Davis *et al.*, 2011). As the development of the international fragmentation system (i.e., the GSC)

structure) has evolved over the past few decades, industries in advanced countries have transferred their production locations to developing countries with a cost advantage (Baldwin, 2011). Therefore, CO₂ emissions resulting from industrial production activities are simultaneously transferred to developing countries, which often prioritize economic development at the expense of environmental protection; this phenomenon is known as carbon leakage or CO₂ emission transfers (e.g., Peters *et al.*, 2011; Feng *et al.*, 2013; Nakamoto *et al.*, 2023). Peters *et al.* (2011) revealed that CO₂ emission transfers from advanced to developing countries reached 1.6Gt, four times larger than those in 1990, driven by the expansion of the global supply chain structure.

As represented by CO₂ emission transfers, consumption-based CO₂ emissions from global supply chains induced by final consumption have attracted significant research attention. Using global multi-regional input-output (MRIO) analysis, numerous previous studies have estimated consumption-based CO₂ emissions and demonstrated their significance in designing appropriate climate policies to mitigate climate change (e.g., Munksgaard and Pedersen, 2001; Lenzen *et al.*, 2007; Peters, 2008; Peters and Hertwich, 2008, 2009; Wiedmann, 2009a; Davis and Caldeira, 2010; Hubacek *et al.*, 2014, 2016; Wiedmann and Lenzen, 2018). As a consequence of these contributions in the last two decades, the IPCC reported consumption-based CO₂ emissions and emphasized their importance, as stated in the sixth assessment report (IPCC, 2022). "A wider system boundary going beyond territorial emissions is important to avoid pollution outsourcing and achieve global decarbonization."

Based on this background, industries worldwide must reduce CO₂ emissions

associated with their production activities and global carbon footprints (GSCs) for climate change mitigation. For example, the Japanese government offers guidelines for firms to estimate their global carbon footprints and encourages them to participate in international initiatives such as TCFD or CDP to reduce CO₂ emissions from the GSC structure (Ministry of the Environment of Japan, 2017; METI, 2022c). In addition, TOYOTA, Japan's largest company, has committed to achieving carbon neutrality throughout its production activities, including global supply chains, by 2050. This ambitious goal was pursued by promoting a 3% annual reduction in CO₂ emissions among suppliers, in line with "the TOYOTA Environmental Challenge 2050" (TOYOTA, 2016).

1.1.3 Research objective of this thesis

As industries aim to reduce CO₂ emissions from GSCs, the circumstances surrounding the global GSC structure have changed. Recent international events, such as the COVID-19 pandemic and the Russia/Ukraine conflict, have highlighted the vulnerability and disruption risk in the existing GSC structure (Baldwin and Freeman, 2022; OECD, 2022; IMF, 2022). Consequently, several major countries are promoting strategies to restructure existing GSCs to mitigate disruption risks and enhance resilience (e.g., Business Europe, 2022; The White House, 2022; METI, 2022a, 2022b). Thus, in this context, industries need to transition their existing GSCs into environmentally friendly GSCs with a low-carbon structure (i.e., low-carbon GSC restructuring).

Based on this background, this thesis aims to develop a novel analytical framework to estimate the impact of restructuring a specific GSC on CO₂ emissions from the relevant

GSC. The proposed framework can offer valuable insights for policymaking toward low-carbon GSC restructuring by providing useful evidence, such as proof of the change in CO₂ emissions triggered by a structural shift in the GSC, that relevant stakeholders might consider. To the best of my knowledge, few attempts have been made to quantify the relationship between a hypothetical structural change in GSCs based on a specific scenario and the corresponding change in CO₂ emissions. This thesis conducts case studies focusing on the restructuring of automobile GSCs, which are one of the main targets of GSC restructuring (METI, 2022a, 2022b; Germany Trade and Investment, 2022) and often identified as significant CO₂ emissions from their upstream suppliers (Kagawa *et al.*, 2015; Tokito, 2018).

1.2 Structure of this thesis

This thesis comprises five chapters, as shown in Figure 1-2. Chapter 2 provides a comprehensive literature review focusing on two crucial research fields related to this thesis: environmentally extended input-output analysis and hypothetical extraction analysis. This chapter identifies the research questions and objectives based on previous studies. Furthermore, it describes the novelty and contributions of this thesis.

Chapter 3 develops an integrated analysis framework using four input-output methods— unit structure analysis, cluster analysis, extended global extraction analysis, and structural decomposition analysis—to model GSC restructuring targeting CO₂ emission hotspots in a relevant GSC. Applying the framework to the World Input-Output Database (WIOD) in 2014, this chapter presents a case study to quantify the CO₂ reduction potential of the restructuring of the Japanese automotive GSC, targeting its CO₂ emission hotspot, and identify the main factors contributing to CO₂ reductions. Finally, based on the findings of this analysis, appropriate policies for CO₂ mitigation through the GSC restructuring are discussed.

Chapter 4 focuses on the practical CO₂ reduction potential of GSC restructuring, reflecting the differences in the reasonable scale of relevant GSC restructuring by a target supplier. As in Chapter 3, this chapter presents a case study of the restructuring of the Japanese and German automotive GSC. Specifically, applying a hybrid HEM framework that combines the partial HEM and the global extraction method to WIOD, this chapter identifies key sectors for low-carbon GSC restructuring based on CO₂ change effects

caused by "a unit" of relevant GSC restructuring (i.e., a marginal GSC restructuring). Furthermore, this chapter reveals the practical potential for CO₂ reduction based on a reasonable scale of relevant GSC restructuring defined by the revealed comparative advantage (RCA) index, indicating a specific sector's substitutability.

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

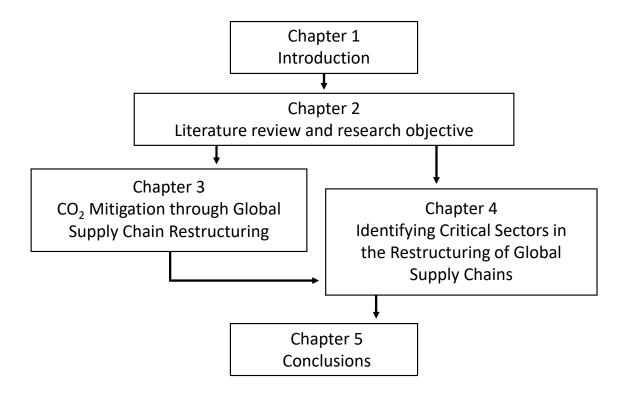


Figure 1-2. Structure of this thesis

The contents of Chapters 3 and 4 have been published as articles in peer-reviewed journals as follows.

Chapter 3:

Maeno, K., Tokito, S., Kagawa, S. (2022) CO₂ mitigation through global supply chain restructuring, *Energy Economics*, 105, 105768.

Chapter 4:

Maeno, K. (2023) Identifying critical sectors in the restructuring of low-carbon global supply chains, *Energy Economics*, 127, 107025.

Chapter 2: Literature Review

2.1 Environmentally extended input-output analysis (EEIOA)

2.1.1 History of EEIOA for estimating consumption-based CO2 emissions

In the late 1960s, the environmentally-extended input-output analysis (EEIOA) was developed, which integrates external factors (e.g., environmental pollution) associated with industrial production activities into an input-output table (IOT) formulated by Leontief (1936, 1941) (Daly, 1968; Isard et al., 1968; Ayres and Kneese, 1969). As the important previous studies, Leontief (1970), Leontief and Ford (1972) developed the EEIOA framework that incorporated industrial pollution emissions and "pollution abatement activities" that had not been considered in previous analyses into IOT, and they modeled relationships between production activities and environmental pollutant emissions/abatements in an economic system. These crucial contributions in the early 1970s formed the basis of the EEIOA archetype, which remains relevant today (Suh and Kagawa, 2005; Wiedmann, 2009b). Furthermore, EEIOA has been employed in industrial ecology research, focusing on resource production and consumption structures and their environmental impacts across different industries through production supply chains (Duchin, 1990, 1992; Suh and Kagawa, 2005).

Since the United Nations Framework Convention on Climate Change (UNFCCC) was established at the Earth Summit in 1992, the urgent need to mitigate global warming

has become widely recognized as a common goal for the planet. With the development of the global supply chain structure, the production and consumption locations of products have become more divergent, leading to discussions on the allocation of responsibility for the environmental impacts and CO₂ emissions stemming from industrial production activities (Rees, 1992; Forssell and Polenske, 1998). In the early 1990s, EEIOA began to be applied to the analysis of CO₂ emissions associated with industrial production activities (Common and Salma, 1992; Gay and Proops, 1993; Gale, 1994; Wyckoff and Roop, 1994; Imura and Moriguchi, 1995; Schaeffer and Sa, 1996; Proops et al., 1996). In relevant early work, Gay and Proops (1993) estimated direct and indirect CO₂ emissions from each industry in the UK economy to satisfy final demands for fossil fuels. Wyckoff and Roop (1994) estimated the direct and indirect CO₂ emissions associated with imports of goods by advanced countries. They found that approximately 13% of the total CO₂ emissions in developed countries were emitted outside the countries by importing goods. Although it was common to allocate responsibilities to emitting countries/sectors at that time, EEIOA provided new insight into which responsibilities should be allocated to consumers of goods that induce such emissions (i.e., consumption-based CO₂ emissions).

During the 1990s and the 2000s, numerous studies developed EEIOA models for the quantification of consumption-based CO₂ emissions and demonstrated their significance through empirical analysis (Lenzen, 1998; Kondo *et al.*, 1998; Munksgaard *et al.*, 2000; Machado *et al.*, 2001; Wier *et al.*, 2001; Munksgaard and Pedersen, 2001; Sanchez-Choliz and Duarte, 2004; Gallego and Lenzen, 2005; Hoekstra and Janssen, 2006; Lenzen *et al.*, 2007). Specifically, using a unit-hybrid IO table, Lenzen (1998) showed a more accurate energy balance and various GHG (i.e., CO₂, CH₄, N₂O, CF₄, and

C₂F₆) emission structures induced by final demand in Australia, including imports and exports. Lenzen (1998) indicated that indirect CO₂ emissions, which attracted less attention at that time, accounted for a large part of GHG emissions in Australia and recommended that governments change consumers' behavior toward climate change mitigation. Considering domestic or outsourced CO₂ emissions induced by final demands for industries in Denmark, Munksgaard and Pedersen (2001) developed the critical concept of the "CO₂ trade balance of a country" by taking differences between production- and consumption-based CO₂ emissions in the relevant country. They pointed out that the emission reduction goals defined by the Kyoto Protocol, which considered only territorial CO₂ emissions, were inappropriate in the rapidly globalizing world. Gallego and Lenzen (2005) proposed a novel model to quantify the distribution of emission responsibilities among supply chain stakeholders. They argued that it was essential for all supply chain stakeholders, rather than just producers or consumers, to address CO₂ reduction based on quantified emission responsibilities.

Since the 2000s, EEIOA analysis has been applied to the quantification of total CO₂ emissions embodied in a "global" supply chain structure, which is directly and indirectly required to satisfy consumptions in a particular country or sector (Ahmad and Wyckoff, 2003; Lenzen *et al.* 2004; Wiedmann *et al.*, 2007; Peters and Hertwich, 2006a, 2006b, 2006c). As an early attempt to conduct global supply chain analysis, Lenzen *et al.* (2004) constructed a multi-regional input-output table (MRIOT) involving Denmark and its three main trading partners. They incorporated the national energy statistics of each country into their MRIOT to reveal the relationships of CO₂ emission structure among the relevant countries. Traditional approaches focusing on the CO₂ trade balance of a country (e.g.,

Wyckoff and Roop, 1994; Munksgaard and Pedersen, 2001) mainly estimated CO₂ emissions in foreign countries under the assumption that imported goods were produced domestically. Lenzen *et al.* (2004) overcame this assumption by integrating the MRIOT with the energy statistics of each country, clarifying the CO₂ trade balance of an open economy with trading partner countries. Several important studies with a similar approach (Lenzen *et al.*, 2004; Nijidam *et al.*, 2005; Munksgaard *et al.*, 2005) made significant contributions to the development of global carbon footprint analysis in the late 2000s.

With the enrichment of international industrial trade and energy consumption databases, the capacity of MRIO analysis to depict the entire global economic system and global carbon footprint has greatly advanced (Peters and Hertwich, 2008, 2009; Wiedmann, 2009a, Peters et al., 2011; Davis et al., 2011; Kanemoto et al., 2012; Moran et al., 2018). Peters and Hertwich (2008) created a global MRIOT, which had a considerably high spatial resolution at that time, covering 87 regions and 57 sectors, based on the Global Trade Analysis Project (GTAP database ver. 6 (Dimaranan, 2006), revealing the CO₂ emissions embodied in international trade and the CO₂ trade balances of each country in 2001. Furthermore, using the above-mentioned MRIO database, Peters and Hertwich (2009) revealed the per capita consumption-based global CO₂ emissions, the compositions of emission sources (i.e., countries and industries) and the carbon footprint elasticities for expenditure categories in each county. During that period of limited data availability, these previous studies had a substantial interdisciplinary impact, raising awareness of the significance of CO2 emissions from GSCs and triggering numerous subsequent studies on CO2 emissions in GSC structures worldwide. Based on these contributions to global MRIO analysis, Peters (2008) provided a comprehensive overview

and explanation of the methodologies for estimating production- and consumption-based CO₂ emissions embodied in trade using MRIOT while emphasizing the importance of introducing consumption-based CO₂ emissions accounting into climate policies involving multiple countries.

During the 2010s, with the growing demand for a global carbon footprint analysis, several projects were conducted to build a global MRIOT that captured a wide range of international intermediate transactions in each sector of each country. This section lists the global MRIOTs that are widely used in Table 2-1. The MRIOTs in Table 2-1 were published as open access, leading to numerous studies on various environmental loads such as CO₂ emissions (e.g., Peters *et al.*, 2011; Kanemoto *et al.*, 2012; Liu *et al.*, 2015; Mi *et al.*, 2017; Moran *et al.*, 2018; Meng *et al.*, 2018; Lenzen *et al.*, 2020; Lamb *et al.*, 2021; Zheng *et al.*, 2022), air pollution (e.g., Guan *et al.*, 2014; Meng *et al.*, 2015; Moran and Kanemoto, 2016; Nagashima *et al.*, 2017; Nansai *et al.*, 2021; Mitoma *et al.*, 2021), biodiversity losses (e.g., Lenzen *et al.*, 2012; Moran and Kanemoto, 2017; Marquardt *et al.*, 2019), forest losses (e.g., Hoang and Kanemoto, 2021; Sun *et al.*, 2023), and natural resource consumption (e.g. Galli *et al.*, 2012; Wiedmann *et al.*, 2015; Plank *et al.*, 2018) from the perspective of GSCs.

Table 2-1. The list of MRIOTs widely used in the literatures.

Global multi regonal input-ouput tables	Year covered	Number of countries	Number of sectors
Eora (Lenzen et al., 2012, 2013)	1990-2022	190	26
Exiobase (Tukker et al., 2013; Stadler et al., 2018)	1995-2022	49	163
GTAP (Peters et al., 2011; Aguiar et al., 2022)	2004-2017	141	65
GLORIA (Lenzen et al., 2017, 2022)	1990-2027	164	120
OECD/ICIO (OECD, 2021)	1995-2018	66	45
WIOD (Dietzenbacher et al., 2013; Timmer et al., 2015)	2000-2014	44	56

As the data availability for global MRIOTs improved, methods for quantifying CO₂ emission responsibilities, in addition to production- and consumption-based CO₂ emissions, were developed in the 2010s. Kander *et al.* (2015) pointed out that consumption-based accounting could not assess the contributions of exporting sectors to CO₂ reductions in a specific country. To address this limitation, they proposed a new emissions accounting framework called technology-adjusted consumption-based accounting (TCBA), which incorporated the differences in CO₂ emissions intensities between a specific sector and the global average into consumption-based accounting. Furthermore, Dietzenbacher *et al.* (2020) expanded TCBA into emission responsibility allotment, the ERA framework, focusing on bilateral trade relationships between countries rather than using the global average CO₂ emission intensities. Marques *et al.* (2012) developed an income-based CO₂ emissions accounting that could capture CO₂ emissions from value-added in a specific country. Liang *et al.* (2016) formulated betweenness-based CO₂ emissions accounting and identified key sectors in the middle of the GSC network where CO₂ emissions were transmitted.

2.1.2 CO₂ emission hotspot analysis based on EEIOA

Since the late 2000s, many previous studies have used EEIOA to identify CO₂ emission hotspots, often pointing out a large room for emission reductions in a domestic or global supply chain structure. Applying structural path analysis (Defourny and Thorbecke, 1984; Peters and Hertwich, 2006a; Wood and Lenzen, 2009; Oshita, 2012) to an MRIO database, Peters and Hertwich (2006a) identified CO₂-intensive transactions in GSCs induced by the final demands of Norway. Kagawa et al. (2013a, 2013b) developed a new framework to identify CO₂ emission hotspots in a specific supply chain "network" using a spectral clustering approach. Kagawa et al. (2015) applied this framework to the global MRIOT (WIOD). They found CO₂-intensive clusters (i.e., CO₂ emission hotspots) of developing countries in the GSC network, triggered by the final demands of advanced countries, expanding the betweenness-based emission accounting proposed by Liang et al. (2016), Hanaka et al. (2017) revealed CO2 emission hotspots in the GSC network based on a high "vertex" centrality, important "sectors" transmitting a large amount of CO₂ emissions, and those based on a high "edge" centrality, critical "supply chain path" transmitting a large amount of CO2 emissions. Through various EEIOA-based analyses, previous studies have demonstrated the importance of identifying CO₂ emission hotspots within GSCs for industries to reduce CO₂ emissions from their GSCs.

2.2 Hypothetical extraction analysis

2.2.1 History of the hypothetical extraction method

In the history of input-output analysis, a key sector analysis was developed to measure the interdependency or importance of a relevant sector in a complex economic system based on linkages of the relevant sector with other sectors. In the late 1950s, several studies (Rasmussen, 1956; Chenery and Watanabe, 1958) proposed a new framework for quantifying sectoral linkages using an input-output table. Specifically, these studies measured "forward" or "backward" links of a specific sector by summing a row or column vector for a relevant sector in an input coefficient matrix (Chenery and Watanabe, 1958) and a Leontief inverse matrix (Rasmussen, 1956), respectively. A forward linkage effect indicates how much production activities are generated by the outputs of a specific sector, while a backward linkage effect measures how much production activities are required to satisfy the demand for a specific sector (Lenzen, 2003; Miller and Blair, 2009). Based on Rasmussen (1956), Hirschman (1958) developed a new indicator to identify key sectors in an economic system. The proposed indicator can be calculated by dividing a sector's forward or backward linkage effect by an "average" effect of all sectors, indicating more than one value as a relatively larger linkage effect. Industries with larger forward and backward linkage effects are considered key sectors in the relevant economic system.

The HEM was developed to identify key sectors in an economic system (Miller and Lahr, 2001). The HEM measures the importance of a specific sector by estimating the

decrease in the total output of an economy by extracting a relevant sector from an economic system; in other words, it replaces all elements of a relevant sector in the IOT with zero. Although the original concept of the HEM was developed in the late 1960s (Paelinck *et al.*, 1965; Strassert, 1968), Shultz (1977) first formulated the HEM in English (Miller and Lahr, 2001) and conducted an empirical study focusing on the importance of the British agricultural sector. HEM had an advantage in its ability to estimate a specific sector's "total" influences, which the Hirschman's indicator failed to capture.

In a fundamental early work, Cella (1984) developed the traditional HEM to measure industrial linkage effects. Specifically, Cella (1984) divided the total influence of a specific sector into forward and backward linkage effects by partitioning and rearranging an input-output table. Based on Cella's work, several studies have developed the HEM as an industrial linkage measurement tool (Milana, 1985; Cella, 1988; Clement, 1990; Dietzenbache et al., 1993, 1997). For example, Clement (1990) pointed out an issue in the division of linkage effects developed by Cella (1984), proposing a new method for overcoming the problem while attempting to estimate "normalized" linkage effects. Using MRIOT for the European community, Dietzenbacher et al. (1993) quantified a specific region's "regional" linkage effects by applying HEM not to a specific sector but to a relevant region. Moreover, Dietzenbacher et al. (1997) proposed a second-stage HEM framework to measure forward and backward linkage effects at regional/sectoral stages. In addition, they first applied the Gosh model, which considered output-oriented (i.e., supply-driven) spillovers through an economic system, rather than the Leontief model, which considered input-oriented (i.e., demand-pull) spillovers, for the measurement of forward linkage effects of a specific sector to exclude biases for forward linkage effects

stemming from the volume of final demand for a relevant sector. Miller and Lahr (2001) reviewed the development of HEM as a tool for linkage effect measurement and offered practitioners helpful guidelines for HEM.

Since the 2000s, the HEM has been applied to measure industrial linkage effects for environmental loads, such as water use (Duarte et al., 2002; Fang and Cheng, 2018), energy use (Guerra and Sancho, 2010), and CO₂ emissions (Wang et al., 2013; Zhao et al., 2015; Tokito et al., 2022). In the first application of HEM to environmental analysis, Duarte et al. (2002) demonstrated the forward/backward/internal linkage effects of industries weighted by water use in the Spanish economy. While they found that the agricultural sector had the largest linkage effects, they demonstrated the usefulness of HEM for analyzing environmental loads other than water use. Guerra and Sancho (2010) investigated the backward linkage effects of the Spanish energy sectors (e.g., mining of the energy resources, electricity, and gas sectors) and the forward linkage effects of the Spanish non-energy sectors on the energy sectors to identify key sectors that should improve energy efficiency considering spillover in an economic system. Tokito et al. (2022) compared the total linkage effects (i.e., importance) of industries based on betweenness centrality (Liang et al., 2016; Hanaka et al., 2017) and the HEM and clarified the advantages of each method in identifying environmentally important sectors in complex supply chains.

2.2.2 Development of HEM for scenario analysis

As a key development of the HEM for this thesis, its application has been extended to analyze the impacts of a particular economic event on a relevant economy or environment. Specifically, Dietzenbacher and Lahr (2013) formulated the HEM as a method for assessing the impact of a particular event in a relevant sector (e.g., a production disruption due to a disaster) on the overall economy, in other words, the importance of the phenomenon and its economic impact. Furthermore, they illustrated the difference between the results obtained using a full extraction approach, the conventional method, and a "partial extraction" approach, highlighting that the latter can offer valuable insights into policymaking.

In this context, Dietzenbacher *et al.* (2019) expand the HEM as a simulation tool for structural change scenarios of global economic systems that were not considered in the single-country IOT model developed in a previous study (Dietzenbache and Lahr, 2013). They modeled a hypothetical structural change by extracting a specific sector in a particular country from a global MRIOT and substituting those in the same sectors in other countries. Moreover, in the latest research, Guerra and Sancho (2023) refined the HEM model proposed by Dietzenbacher *et al.* (2019) to capture a change in the price equilibrium of the Spanish economy originating from extraction and substitution of a specific sector by integrating the Armington treatment, which considered elasticities between domestic and imported goods, into the HEM model. Using HEM as a simulation tool, several studies have conducted empirical analyses to investigate the impacts of particular events causing structural changes in the GSC, such as Brexit (Chen *et al.*, 2018;

Giametti *et al.*, 2020), the US-China trade war (Wu *et al.*, 2021; Yuan *et al.*, 2023), the COVID-19 pandemic (Sajid and Gonzalez, 2021; Wen *et al.*, 2022), and the Russia/Ukraine conflict (Mardons, 2022; Haddad *et al.*, 2022).

2.3 Contribution of this thesis

Previous studies on EEIOA have revealed the CO₂ emission structures of GSCs induced by the final demand for goods and services. In addition, by developing EEIOA techniques, previous studies have illustrated CO₂ emission hotspots in GSCs, which should be prioritized to implement effective climate policies. However, although CO₂ emission hotspots have been identified, previous studies have not quantified the CO₂ reduction effects of eliminating such CO₂ emission hotspots from existing GSC structures. Furthermore, while previous studies have pointed out where industries have issues with their GSCs (i.e., CO₂ emission hotspots), how industries should improve their GSC structures to reduce CO₂ emissions from their production activities, including GSC, remains unclear.

The HEM, developed to measure inter-industry linkage effects, has been used as a tool for the scenario analysis of structural changes in economic systems caused by relevant events. Using this method, practitioners can estimate the impacts of hypothetical production ceases in a specific sector (i.e., extractions of a specific sector from the IOT) on a relevant economy or environment. The HEM has not yet been employed to estimate the impacts of structural change in the "upstream parts" of a relevant GSC on CO₂ emissions (i.e., the GSC restructuring of a relevant sector). Moreover, the HEM assumes complete replacement and substitution of a relevant sector as a premise for analysis; therefore, a "reasonable scale" of structural change targeting a relevant sector cannot be considered.

Based on the above, this Ph.D. thesis addresses the following two research questions: How much CO₂ reduction potential is generated by eliminating CO₂ emission hotspots in the GSC structure of a relevant sector? Considering a reasonable scale of a relevant GSC restructuring, which sector included in a relevant GSC (i.e., supplier) can reduce most CO₂ emissions by being targeted for GSC restructuring? Or, put differently, which sector should be a policy target for low-carbon GSC restructuring?

To answer the first research question, Chapter 3 develops a novel analysis framework integrating four input-output methods to model GSC restructuring, targeting CO₂ emission hotspots in a relevant GSC. Applying the framework to a global MRIOT, this chapter conducts a case study to quantify the CO₂ reduction potential of the GSC restructuring of the Japanese automotive GSC targeting its CO₂ emission hotspot and to identify the main factors contributing to these CO₂ reductions.

To answer the second research question, Chapter 4 focuses on the practical CO₂ reduction potential of GSC restructuring, reflecting differences in the reasonable scale of relevant GSC restructuring by a target supplier. As in Chapter 3, this chapter presents a case study of the restructuring of the Japanese and German automotive GSC. Specifically, applying a hybrid HEM framework that combines the partial HEM and the global extraction method to WIOD, this chapter identifies key sectors for low-carbon GSC restructuring based on CO₂ change effects caused by "a unit" of relevant GSC restructuring (i.e., a marginal GSC restructuring). Furthermore, this chapter reveals the practical potential for CO₂ reduction based on a reasonable scale of relevant GSC restructuring defined by the revealed comparative advantage (RCA) index, indicating a

specific sector's substitutability.

This thesis expands the application of the HEM as a simulation tool. It develops an integrated analysis framework that can quantify the relationships between a hypothetical structural change in GSCs based on a specific scenario and a corresponding change in CO₂ emissions.

Chapter 3: CO₂ Mitigation through Global Supply Chain Restructuring

3.1 Introduction

The global supply chain (GSC) structure has seen considerable development over the past few decades and has stimulated international trade worldwide (Baldwin, 2011). Due to the expansion of GSCs, large CO₂ emissions are embodied in international trade (Davis *et al.*, 2011; Wiedmann and Lenzen, 2018). Researchers have warned policymakers about growing CO₂ emissions embodied in trade using input-output (IO) methodologies (Wiedmann *et al.*, 2009; Serrano and Dietzenbacher, 2010; Xu and Dietzenbacher, 2014; Duarte *et al.*, 2018; Bolea *et al.*, 2020). One of the most important issues related to CO₂ emissions embodied in trade is the transfer of these emissions from developed to developing countries (Peters *et al.*, 2011; Wood *et al.*, 2020).

The development of GSC structures between 1990 and 2008 increased the transfer of CO₂ emissions from developed to developing countries by 1.2 Gt-CO₂, leading to a 39% increase in global CO₂ emissions over an 18-year period (Peters *et al.*, 2011). Hoekstra *et al.* (2016) conducted the structural decomposition analysis to quantify the effect of international production sourcing from high-wage countries to medium- or low-wage countries on global CO₂ emissions and estimated the emission cost of sourcing (ECS) defined by net change in CO₂ emissions at global level. They found that the ECS from high-wage group to low-wage group accounts for about 18% of the overall increase in global CO₂ emissions during 1995-2007 and this type of sourcing significantly

contributes to the increase in global CO₂ emissions. Moreover, the future expansion of GSCs is expected to further increase global CO₂ emissions (Jiang and Green, 2017). This rapid growth of CO₂ emission transfer needs to be urgently reduced (Peters *et al.*, 2011; Hoekstra *et al.*, 2016; Jiang and Green, 2017; Intergovernmental Panel on Climate Change [IPCC], 2014; Wood *et al.*, 2020). Green supply chain management can be used to reduce the environmental impact of products throughout their life cycle. The creation of green supply chains is expected to reduce the transfer of CO₂ emissions from developed to developing countries (Sarkis, 2012; Tseng *et al.*, 2019). To implement green supply chain management, it is important to identify CO₂ emission hotspots that play a critical role in reducing the CO₂ emissions of supply chains in each industry from every country (Wiebe, 2018).

As a related study analyzing CO₂ emission hotspots in GSCs, Kagawa *et al.* (2015) identified CO₂ intensive manufacturing processes using the World Input–Output Database (WIOD; Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015). They found that the US construction and Japanese automotive supply chains contributed significantly to CO₂ emissions owing to the Chinese materials industry between 1995 and 2008. Duan and Jiang (2018) visualized the network structure of the CO₂ emissions embodied in international trade using WIOD and found the major flows of CO₂ emission transfer. Wang *et al.* (2018) identified important sectors and paths for controlling CO₂ emissions in China's interregional supply chain networks in 2010 and 2012 by combining IO analysis and structural path analysis. Hanaka *et al.* (2017) and Jia *et al.* (2019) identified key industries that have high betweenness centrality¹ in supply chain networks to reduce

¹ The betweenness centrality of a relevant sector in an IO network is the amount of environmental

life-cycle CO₂ emissions. Tokito (2018) found that Chinese sectors were important hubs of developed countries' GSCs for transport equipment in 2013 using the Eora database (Lenzen *et al.*, 2012, 2013), which offers a higher spatial resolution compared to other global multi-regional input output databases.

These studies revealed the structure of CO₂ emissions in GSCs and identified CO₂ emission hotspots; however, they did not demonstrate an effective supply chain management for CO₂ emission hotspots. More specifically, they did not answer the important question of how global CO₂ emissions would be affected if supply chains were structured to exclude CO₂ emission hotspots. In other words, the effects on global CO₂ emissions, caused by structural changes in GSCs that stakeholders might consider, remain unclear. In recent times, numerous attempts to decentralize industries' GSC structures have been identified in major countries across the world (United States Department of State, 2020; The Federal Government, 2020; Cabinet Office, 2020). As decentralized supply chains are reestablished, the above question must be answered to create green supply chains.

To implement effective supply chain management for greener supply chain restructuring, it is important to identify the impact of structural changes on the global carbon footprint of an industrial supply chain. The hypothetical extraction method (HEM) was developed to estimate the decrease in the output of an economy in the event that a sector is removed from that economy (Paelinck *et al.*, 1965; Schultz, 1977; Cella, 1984;

pressure generated by all supply chain paths passing through the sector. The betweenness centrality of a sector indicates the importance of the sector in a supply chain network as a transmission center (Liang *et al.*, 2016; Hanaka *et al.*, 2017; Jia *et al.*, 2019).

Miller and Lahr, 2001; Duarte *et al.*, 2002; Guerra and Sancho, 2010; Tokito *et al.*, 20210; Hanaka *et al.*, 2022). Expanding this HEM, Dietzenbacher and Lahr (2013) developed an analytical framework to estimate the impact of a scenario-based supply chain on a national economy, including additional supply chains to supplement the removed IO structures of an industrial sector. Dietzenbacher *et al.* (2019) applied this analytical framework to a multi-region IO table and proposed a global hypothetical extraction method (GEM), thus enabling analysis at the global level.

To elaborate, Dietzenbacher *et al.* (2019) created a scenario in which the automotive industries of the major automotive-producing countries (the United States, Germany, and China) cease production entirely, based on which they estimated the impact of hypothetical structural changes on the value added associated with global final demand. To manage GSCs at the industry level, we must focus on the GSC structures associated with the final demand of a sector in a country. As in the studies of Ozaki (1980) and Kagawa *et al.* (2013), this study constructed a GSC network structure associated with the final demand of a particular sector. Based on the GSC network data, the GEM developed by Dietzenbacher *et al.* (2019) can be extended to analyze the environmental impacts of hypothetical structural changes in the upstream industries (raw materials and components industries) that constitute the GSC of a particular sector.

This study aims to develop a framework to help supply chain managers design policies needed for greener supply chain restructuring by extending the GEM. First, this study used the latest 2014 WIOD data to model the GSC network structure induced by the final demand for one relevant industry in one relevant country. Specifically, this study

applies this approach to the Japanese automobile industry. Tokito (2018) showed that the global CO₂ emissions induced by the final demand of transport equipment manufactured in Japan was 106 Mt-CO₂ in 2013, accounting for 7.5% of Japan's total CO₂ emissions. In addition, more than 90% of the CO₂ emissions were indirectly emitted through its global supply chains (Tokito, 2018). It is important to note that Japan should reduce this large carbon footprint through automobile supply chain engagements. Therefore, this study focuses on Japan's automobile industry. Second, this study created an adjacency matrix by weighting the CO₂ emissions embedded in transactions between each sector. Third, this study applied cluster analysis (Kagawa *et al.*, 2013; Tokito, 2018) to the adjacency matrix to identify supply chain groups with overconcentrated CO₂ emissions (CO₂ emission clusters) outside of Japan in the GSC network.

This study then estimated the impact of the newly formed automotive supply chain structure on global CO₂ emissions by extracting sectors found in CO₂ emission clusters, endogenously determined by cluster analysis (i.e., overconcentrated upstream sectors of the Japanese automotive supply chain), from the automotive supply chain. The novelty of this study is the development of an integrated analysis framework based on four different IO methods—unit structure model (Ozaki, 1980; Kagawa *et al.*, 2013), cluster analysis (Kagawa *et al.*, 2013, 2015), extended global extraction analysis (Dietzenbacher *et al.*, 2019), and structural decomposition analysis (Miller and Blair, 2009). The integrated analysis framework can provide the results on how GSC restructuring with a focus on CO₂ emission hotspots contributes to CO₂ mitigation and the effects of restructuring elements on changes in CO₂ emissions. This study calls this integrated analysis framework the scenario—based extraction method (SEM) in this study. To the best of our

knowledge, this study is the first to quantify the relationship between restructuring GSC structures and CO₂ emissions.

The remainder of this chapter proceeds as follows. In Section 3.2, this study proposes a new SEM method based on the unit structure model and cluster analysis. Section 3.3 describes the data used, Section 3.4 presents the results and a discussion, and Section 3.5 presents the conclusions and the policy implications derived from the results.

3.2 Methodology

3.2.1 Carbon footprint based on multi-regional input-output table

Using a multi-regional input-output table consisting of N countries and M industries, from the intermediate input matrix $\mathbf{Z} = \left(Z_{ij}^{rs}\right)$, which represents the intermediate inputs from industry i in country r to industry j in country s, and the output vector $\mathbf{x} = (x_i^r)$ of industry i in country r, the input coefficient matrix, which represents the input coefficients from industry i in country r to industry j in country s, is obtained as $\mathbf{A} = \mathbf{Z}\{\operatorname{diag}(\mathbf{x})\}^{-1}$. Here, $\operatorname{diag}(\mathbf{x})$ is a diagonal matrix with x_i^r , the output of industry i in country i in country i as its diagonal component.

Following the basic Leontief model (Leontief, 1953; Miller and Blair, 2009), CO₂ emissions from industry i in country r induced by the final demand for industry m in country c, $\mathbf{q} = (q_i^r)(i = 1, \dots, M; r = 1, \dots, N)$, can be estimated using Equation (3.1):

$$\mathbf{q} = \operatorname{diag}(\mathbf{e})(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}_m^c = \operatorname{diag}(\mathbf{e})\mathbf{L}\mathbf{f}_m^c, \quad (3.1)$$

where diag(**e**) is the diagonal matrix of the direct CO₂ emissions coefficient, representing direct CO₂ emissions per unit of output for every industry in every country; $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse matrix (Leontief, 1953; Miller and Blair, 2009); and \mathbf{f}_m^c denotes a vector that takes a value only for the component corresponding to the final demand of industry m in country c and in all other cases, takes 0. The Leontief

inverse matrix $\mathbf{L} = \begin{pmatrix} l_{ij}^{rs} \end{pmatrix}$ presents the output of industry i in country r directly and indirectly required to produce one unit of final demand for industry j in country s (Miller and Blair, 2009). Since the Leontief inverse matrix can be expanded as the infinite series $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \cdots$, Equation (3.1) can be expressed as

$$\mathbf{q} = \operatorname{diag}(\mathbf{e})(\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \cdots)\mathbf{f}_m^c.$$
 (3.2)

The unit structure model (Ozaki, 1980; Kagawa *et al.*, 2013) can be formulated as per Equation (3.3):

$$\mathbf{Q} = \operatorname{diag}(\mathbf{e})\operatorname{diag}(\mathbf{f}_{m}^{c}) + \operatorname{diag}(\mathbf{e})\mathbf{A}\operatorname{diag}(\mathbf{f}_{m}^{c}) + \operatorname{diag}(\mathbf{e})\mathbf{A}\operatorname{diag}(\mathbf{A}\mathbf{f}_{m}^{c}) + \operatorname{diag}(\mathbf{e})\mathbf{A}\operatorname{diag}(\mathbf{A}^{2}\mathbf{f}_{m}^{c}) + \cdots, \quad (3.3)$$

Where $\mathbf{Q} = \left(q_{ij}^{rs}\right)$ is a matrix that shows the CO₂ emissions embedded in inter-industry deliveries from industry i in country r to industry j in country s that are indirectly needed to satisfy the final demand for a particular sector m in country c. In this study, this matrix is defined as an inter-industrial CO₂ emission matrix. In Equation (3.3), diag(\mathbf{e})diag(\mathbf{f}_m^c) in the first term on the right-hand side represents CO₂ emissions from the production of final goods in industry m in country c; diag(\mathbf{e})Adiag(\mathbf{f}_m^c) represents the CO₂ emissions from the production of intermediate goods in the corresponding industry in the corresponding country, which is directly required for the production of finished goods by industry m in country c (i.e., CO₂ emissions from first-stage production fragmentation); and diag(\mathbf{e})Adiag(\mathbf{Af}_m^c) expresses CO₂ emissions from second-stage production fragmentation. In line with Kagawa $et\ al.$ (2013), Equation (3.3) can be further

transformed as

$$\mathbf{Q} = \operatorname{diag}(\mathbf{e})\operatorname{diag}(\mathbf{f}_m^c) + \operatorname{diag}(\mathbf{e})\operatorname{A}\operatorname{diag}(\mathbf{L}\mathbf{f}_m^c), \quad (3.4)$$

where the second term of Equation (3.4) is a unit structure of industry m in country c that represents the *indirect* CO₂ emissions for inter-industry deliveries triggered by the final demand of industry m in country c. It should be noted that the matrix computed as \mathbf{L} diag($\mathbf{f}_{\mathbf{m}}^{\mathbf{c}}$) in the standard Leontief model has figures in the column of industry m in country c and otherwise 0. The matrix, \mathbf{L} diag($\mathbf{f}_{\mathbf{m}}^{\mathbf{c}}$) indicates the total amount of industrial production from every industry that is directly and indirectly needed to satisfy the final demand for a particular sector m in country c. On the other hand, since the vector computed as $\mathbf{L}\mathbf{f}_{\mathbf{m}}^{\mathbf{c}}$ has figures showing the total amount of industrial production from every industry that is directly and indirectly needed to satisfy the final demand for a particular sector m in country c, the matrix computed as \mathbf{A} diag($\mathbf{L}\mathbf{f}_{\mathbf{m}}^{\mathbf{c}}$) in the unit structure model has figures in the matrix elements showing inter-industry deliveries that are indirectly needed to satisfy the final demand for a particular sector m in country c (i.e., unit production structure).

3.2.2 Supply chains' clustering analysis

This study created a symmetric adjacency matrix $\mathbf{G} = (g_{ij}^{rs})$ from the interindustry CO₂ emissions matrix (**Q**) estimated by Equation (3.4) as follows:

$$\mathbf{G} = \begin{cases} g_{ij}^{rs} = q_{ij}^{rs} + q_{ji}^{rs} \ (i \neq j, \forall r, \forall s) \\ g_{ij}^{rs} = 0 \ (i = j, \forall r, \forall s) \end{cases}$$

Subsequently, a cluster analysis of supply chains was applied to the adjacency matrix (**G**) based on nonnegative matrix factorization (see Kagawa *et al.*, 2013, 2015; Tokito *et al.*, 2016). As in Kagawa *et al.* (2013, 2015), the optimal number of clusters was determined by the maximized modularity index (Newman and Girvan, 2004). The cluster analysis yields K industry groups that contribute to CO₂ emissions through strong interindustry relationships (Kagawa *et al.*, 2013, 2015). The K industry groups are represented as K clusters of $\{C_1, C_2, \dots, C_K\}$, where cluster C_k ($k = 1, 2, \dots, K$) includes $\binom{j_0^k, s_0^k}{j_0^k}$, representing the industry code and country code belonging to the kth cluster group, respectively.

3.2.3 Extended global extraction analysis

This study proposes an HEM based on a unit structure model. This section focuses on the sectors belonging to the k^{th} CO₂ emission-intensive cluster identified in the previous section. Here, in line with Dietzenbacher *et al.* (2019), this study assumes that the products of industry j_0^k in country s_0^k belonging to the k^{th} cluster are not sold to other countries. In this hypothetical world economy, the production activities of industry j_0^k in country s_0^k are directly extracted from the GSC network. Note, however, that the production activities of industry j_0^k in country s_0^k are indirectly included in the GSC network through the production of goods and services by other industries in country s_0^k .

The input coefficient matrix in this hypothetical world economy, $\bar{\mathbf{A}} = (\bar{a}_{ij}^{rs})$, is modified as per Dietzenbacher *et al.* (2019):

$$\bar{a}_{j_0^k j}^{s_0^k s} = 0 (\forall j, \forall s \neq s_0^k), \quad (3.5)$$

$$\bar{a}_{j_0^k j}^{rs} = a_{j_0^k j}^{rs} + a_{j_0^k j}^{s_0^k s} \frac{a_{j_0^k j}^{rs}}{\sum_{r \neq s_0^k s} a_{j_0^k j}^{rs}} (\forall j, \forall r \neq s_0^k, \forall s \neq s_0^k), (3.6)$$

where Equation (3.5) shows that industry j_0^k in country s_0^k does not export products to other countries (i.e., they are extracted). Equation (3.6) shows that industry j in country sis complemented by additionally imported intermediate goods from industry j_0^k in country r outside country s_0^k , obtained by multiplying the import procurement ratio of industry j_0^k in country r extracting country s_0^k , $a_{j_0^k j}^{rs}/\sum_{r \neq s_0^k, s} a_{j_0^k j}^{rs}$, by imports from industry j_0^k in country s_0^k , $a_{j_0^k j}^{s_0^k s}$. Equation (3.6) explicitly assumes that imported intermediate goods from industry j_0^k in country s_0^k cannot be sourced domestically (Dietzenbacher et al., 2019). In addition, Equation (3.6) indicates that the stakeholder tends to import the intermediate product to a greater extent from trade partners that have a stronger trade relation with the stakeholder. This study provides a simple example of the global extraction analysis of four countries and one industry (Figure 3-1). Figure 3-1 reveals the input coefficient vectors for country 1 in the actual and hypothetical cases and concisely explains Equations (3.5) and (3.6). From Figure 3-1, it can be understood that imports from country 2 (i.e., CO₂ emission hotspot) are extracted and substituted by other countries (i.e., countries 3 and 4) following their import procurement ratios of two-thirds and one-third, respectively.

	Actual case		Hypothetical case
	Country 1		Country 1
Country 1	0.2	→	0.2 (Domestic input)
Country 2 (Hotspot)	0.3	→	0 (Extracted imports)
Country 3	0.2	→	$0.2 + 0.3 \times \frac{0.2}{0.2 + 0.1}$ (Additional imports)
Country 4	0.1	→	$0.1 + 0.3 \times \frac{0.1}{0.2 + 0.1}$ (Additional imports)

Figure 3-1. A simple example of the global extraction analysis.

In the hypothetical GSC network in which the production activities of industry j_0^k in country s_0^k are extracted, the direct and indirect CO₂ emissions (i.e., the carbon footprint) originating from the final demand for finished goods produced by the corresponding industry m in the corresponding country c can be formulated using the following equation:

$$\overline{\mathbf{q}} = \operatorname{diag}(\mathbf{e})(\mathbf{I} - \overline{\mathbf{A}})^{-1}\mathbf{f}_{m}^{c} = \operatorname{diag}(\mathbf{e})\overline{\mathbf{L}}\mathbf{f}_{m}^{c}$$
 (3.7)

Thus, the difference between direct and indirect CO2 emissions in the real and

hypothetical worlds $\Delta \mathbf{q}$, can be expressed using the following equation:

$$\Delta \mathbf{q} = \overline{\mathbf{q}} - \mathbf{q} = \operatorname{diag}(\mathbf{e})\overline{\mathbf{L}}\mathbf{f}_{m}^{c} - \operatorname{diag}(\mathbf{e})\mathbf{L}\mathbf{f}_{m}^{c}$$
$$= \operatorname{diag}(\mathbf{e})(\overline{\mathbf{L}} - \mathbf{L})\mathbf{f}_{m}^{c} = \operatorname{diag}(\mathbf{e})\Delta\mathbf{L}\mathbf{f}_{m}^{c}. \quad (3.8)$$

Equation (3.8) enables us to estimate the extent to which the carbon footprint associated with final goods produced by industry m in country c is affected by the structural shift ($\Delta \mathbf{L}$) when the production activities of industry j_0^k in country s_0^k are extracted from the GSC network.

3.2.4 Structural decomposition analysis

Finally, this study describes the structural decomposition analysis of ΔL . Since $\bar{L} = (I - \bar{A})^{-1}$ and $L = (I - A)^{-1}$, the following equations hold:

$$\bar{\mathbf{L}}(\mathbf{I} - \bar{\mathbf{A}}) = \mathbf{I} = \bar{\mathbf{L}} - \bar{\mathbf{L}}\bar{\mathbf{A}},$$
 (3.9)

$$(\mathbf{I} - \mathbf{A})\mathbf{L} = \mathbf{I} = \mathbf{L} - \mathbf{AL}. \quad (3.10)$$

By arranging Equations (3.9) and (3.10), this study can obtain the equations for $\bar{\mathbf{L}} - \mathbf{I} = \bar{\mathbf{L}}\bar{\mathbf{A}}$ and $\mathbf{L} - \mathbf{I} = \mathbf{A}\mathbf{L}$, respectively. By multiplying both sides of Equation (3.9) by $\bar{\mathbf{L}}$ from the right, and similarly multiplying both sides of Equation (3.10) by $\bar{\mathbf{L}}$ from the left, this study can rewrite these equations as follows (Miller and Blair, 2009):

$$(\bar{\mathbf{L}} - \mathbf{I})\mathbf{L} = \bar{\mathbf{L}}\bar{\mathbf{A}}\mathbf{L} \implies \bar{\mathbf{L}}\mathbf{L} - \mathbf{L} = \bar{\mathbf{L}}\bar{\mathbf{A}}\mathbf{L},$$
 (3.11)

$$\bar{\mathbf{L}}(\mathbf{L} - \mathbf{I}) = \bar{\mathbf{L}}\mathbf{A}\mathbf{L} \implies \bar{\mathbf{L}}\mathbf{L} - \bar{\mathbf{L}} = \bar{\mathbf{L}}\mathbf{A}\mathbf{L}.$$
 (3.12)

By subtracting Equation (3.12) from (11), this study obtains

$$\Delta \mathbf{L} = \bar{\mathbf{L}} - \mathbf{L} = \bar{\mathbf{L}} \bar{\mathbf{A}} \mathbf{L} - \bar{\mathbf{L}} \mathbf{A} \mathbf{L} = \bar{\mathbf{L}} (\bar{\mathbf{A}} - \mathbf{A}) \mathbf{L} = \bar{\mathbf{L}} \Delta \mathbf{A} \mathbf{L}. \tag{3.13}$$

From Equation (3.13), $\Delta \mathbf{L}$, which expresses the change in the GSC structure, can be interpreted in terms of the change in the input coefficient matrix, $\Delta \mathbf{A}$. Here, the change in the intermediate input coefficient from the corresponding sector i_0 in the corresponding country r_0 to corresponding sector j_0 in country s_0 , $\Delta \mathbf{A}_{i_0j_0}^{r_0s_0}$, can be defined as follows:

$$\Delta \mathbf{A}_{i_0j_0}^{r_0s_0} = \left\{ \Delta a_{ij}^{rs} \right\} = \left\{ \begin{matrix} \overline{a}_{ij}^{rs} - a_{ij}^{rs} \ (i = i_0, j = j_0, r = r_0, s = s_0) \\ 0 & Otherwise \end{matrix} \right..$$

In this case, ΔA can be decomposed as follows (Miller and Blair, 2009):

$$\Delta \mathbf{A} = \Delta \mathbf{A}_{11}^{11} + \dots + \Delta \mathbf{A}_{ij}^{rs} + \dots + \Delta \mathbf{A}_{MM}^{NN} = \sum_{r=1}^{N} \sum_{s=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{M} \Delta \mathbf{A}_{ij}^{rs}.$$
 (3.14)

Substituting Equation (3.14) into the right-hand side of Equation (3.13), this study obtains Equation (3.15):

$$\Delta \mathbf{L} = \sum_{r=1}^{N} \sum_{s=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{M} \Delta \mathbf{L}_{ij}^{rs} = \sum_{r=1}^{N} \sum_{s=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{M} \bar{\mathbf{L}} \Delta \mathbf{A}_{ij}^{rs} \mathbf{L}.$$
(3.15)

where $\Delta \mathbf{L}_{ij}^{rs} = \bar{\mathbf{L}} \Delta \mathbf{A}_{ij}^{rs} \mathbf{L}$ represents the change in the GSC structure caused by the change in the intermediate input coefficient from sector i in country r to sector j in country s.

The variation in the impact on the GSC structure of the extraction of the production activity of industry j_0^k in country s_0^k belonging to the k^{th} CO₂ cluster, $\Delta \mathbf{L}^e$, and the variation in the impact on the GSC structure of the substitution of production activities by industry j_0^k in country r except country s_0^k resulting from the extraction of production activities j_0^k in country s_0^k , $\Delta \mathbf{L}^s$, can be, respectively, expressed as

$$\Delta \mathbf{L}^{e} = \sum_{s=1}^{N} \sum_{j=1}^{M} \bar{\mathbf{L}} \Delta \mathbf{A}_{j_{0}^{k} j}^{s_{0}^{k} s} \mathbf{L}, \tag{3.16}$$

$$\Delta \mathbf{L}^{s} = \sum_{r=1, r \neq s_{0}^{k}}^{N} \sum_{s=1}^{N} \sum_{j=1}^{M} \bar{\mathbf{L}} \Delta \mathbf{A}_{j_{0}^{k} j}^{rs} \mathbf{L}.$$
 (3.17)

Finally, from Equation (3.8), the impact of structural changes in the GSC on the carbon footprint associated with final goods produced by industry m in country c can be decomposed using Equations (3.16) and (3.17) as follows:

$$\Delta \mathbf{q} = \Delta \mathbf{q}^e + \Delta \mathbf{q}^s = \operatorname{diag}(\mathbf{e}) \Delta \mathbf{L}^e \mathbf{f}_m^c + \operatorname{diag}(\mathbf{e}) \Delta \mathbf{L}^s \mathbf{f}_m^c. \tag{3.18}$$

Vector $\Delta \mathbf{q}^e$ in Equation (3.18) shows the variation in the impact on the carbon footprint of the structural change in the GSC due to the extraction of the production activities of industry j_0^k in country s_0^k . This study refers to this as the extraction effect. Vector $\Delta \mathbf{q}^s$

expresses the variation in the impact on the carbon footprint of structural changes in the GSC resulting from the substitution of production activities by industry j_0^k in country r outside country s_0^k . This study refers to this as the substitution effect.

Figure 3-2 presents a brief outline of the integrated analysis framework proposed in this study.

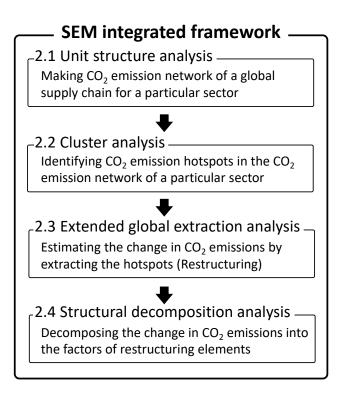


Figure 3-2. The brief outline of the integrated analysis framework proposed in this study.

3.3. Data

This study uses the latest multi-regional industrial IO tables (covering 43 countries/regions plus 56 industries in the Rest of the World (RoW)) from 2014 (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015) published by WIOD (www.wiod.org/home). In addition, this study uses direct CO₂ emissions data by industry and country (Corsatea *et al.*, 2019) from the environmental impact data published by the WIOD as supplementary tables. The WIOD includes the manufacturing industry of motor vehicles, trailers, and semi-trailers that this study wants to focus on. As in previous studies (Kagawa *et al.*, 2015; Hanaka *et al.*, 2017), this study decided to use the WIOD to describe the GSC network data centered around the sector that manufactures motor vehicles, trailers, and semi-trailers in Japan.

3.4. Results

3.4.1 Cluster analysis

The carbon footprint of Japan's automotive supply chain was 74,575 kt-CO₂ in 2014. Of these, the direct CO₂ emissions from the manufacture of Japanese automobiles was 1,007 kt-CO₂, while about 99% was indirect CO₂ emissions from the GSC, indicating that the Japanese automobile industry induces a large amount of CO₂ emissions through its indirect production processes.

This study conducted a clustering analysis of the carbon footprint of the Japanese automobile industry to identify CO₂ emission-intensive clusters (Table 3-1).

Table 3-1. CO₂ emission clusters in Japan's automotive supply chain and CO₂ emissions from industries included in those clusters.

Cluster Number	CO ₂ Emissions (kt-CO ₂)	Number of Industries Included in the Cluster
7	42200	18
12	8950.1	12
1	7946.6	1990
6	7581.9	5
18	2082.4	11
19	1657.3	23
17	936.2	36
2	904	14
9	803	9
16	733.8	23
5	669.4	79
15	74	24
20	14.9	25
4	9.2	7
14	8.1	1
13	2	14
8	1.9	1
11	0.4	1
10	0.1	2
3	0	2

Twenty CO₂ emission clusters in the GSC were associated with the final demand for Japan's automotive industry (see S3.1 and S3.2 in Supplementary materials). Table 3-1 shows that cluster #7 is the largest CO₂ emitting cluster (42,200 kt-CO₂), and it primarily includes 13 industries in Japan, including electricity, gas, steam, and air conditioning supply (JPN); basic metals (JPN); non-metallic mineral products (JPN); and motor vehicles (JPN). Cluster #7 is a group of industries that play an extremely important role in production by the Japanese automobile industry.

Table 3-2. Industries composing the largest CO₂ emission cluster outside of Japan.

No.	No. Code	Name	Contents
П	В	B Mining and quarrying (CHN)	Mining, quarrying
2	C19	C19 Manufacture of coke and refined petroleum products (CHN)	Coke, petroleum products
က	C20	C20 Manufacture of chemicals and chemical products (CHN)	Chemical products
4	C22	C22 Manufacture of rubber and plastic products (CHN)	Rubber, plastic products
2	C23	Manufacture of other non-metallic mineral products (CHN)	Non-metallic mineral products
9	C24	Manufacture of basic metals (CHN)	Basic metals
7	C25	C25 Manufacture of fabricated metal products, except machinery and equipment (CHN)	Fabricated metal products
∞	C26	C26 Manufacture of computer, electronic, and optical products (CHN)	Computer, electronic products
6	6	Manufacture of electrical equipment (CHN)	Electrical equipment
10	C28	C28 Manufacture of machinery and equipment n.e.c. (CHN)	Machinery and equipment
11	C29	C29 Manufacture of motor vehicles, trailers, and semi-trailers (CHN)	Motor vehicles
12	D35	12 D35 Electricity, gas, steam, and air conditioning supply (CHN)	Electricity, gas

Note: Codes are presented according to ISIC rev. 4.

The largest cluster outside of Japan is the Chinese manufacturing industry cluster #12², which includes electricity, gas, steam, and air conditioning supply (CHN); basic metals (CHN); chemical products (CHN); and electrical equipment (CHN), together with eight other industries (see Table 3-2). The CO₂ emissions from cluster #12 accounted for approximately 27% of the total CO₂ emissions from overseas clusters. This result implies that the Japanese automotive GSC induces a significant amount of CO₂ emissions, particularly in cluster #12, which consists of Chinese industries.

Next, this study can observe that the CO₂ emissions produced by clusters #1 and #6 are large. Cluster #1 comprises small groups of weakly interrelated industries, totaling 1,990 industries, while cluster #6 consists of only five industries in RoW. This makes it difficult to perform a detailed analysis of these clusters. Thus, this study focuses on cluster #12, which has a significantly higher quantity of CO₂ emissions than the other clusters, except for clusters #1 and #6.

3.4.2 SEM based on the clustering results.

This study estimates the extent to which the carbon footprint of the CO₂ emissionintensive cluster of Chinese industries (cluster #12) would change to be extracted from

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² As in Kagawa *et al.* (2013, 2015), we used the industrial cluster analysis based on the non-negative matrix factorization and estimated the feature vectors of sectors. Subsequently, we applied a rounding method (i.e., *K*-means method) to the feature vectors. It is important to note that the *K*-means method starts with a random initial cluster assignment and always contains uncertainty. Therefore, we conducted the *K*-means analysis 100 times. As a result, we found that though the optimal number of clusters lies between 5 and 31, the Chinese manufacturing cluster #12, shown in Table 2, is always identified in the uncertainty analysis. Therefore, we argue that the Chinese manufacturing cluster shown in Table 2 should be highlighted as a robust CO₂ emission hotspot.

Japan's automotive supply chain. Accordingly, Table 3-3 demonstrates the extent to which each country's CO₂ emissions would change if cluster #12 was extracted from Japan's automotive supply chain, and the intermediate goods produced by the Chinese industry cluster #12 were instead produced by industries in other countries.

Table 3-3. CO₂ emissions of each country induced by the final demand for Japanese automobile in the actual and hypothetical world, and the impact of structural changes on CO₂ emissions.

No. Country Territorial CO₂ Emissions of the Emissions of the Emissions (kt-CO₂) Change in Emissions (kmissions (kt-CO₂) Change in Emissions (kmissions (kt-CO₂) Emissions (kt-CO₂) CO₂ CO₂ CO₂ (%) 1 Australia 32.9 992.8 70 7.6% 2 Austria 33.4 45.3 12 35.9% 3 Belgium 39.3 51.9 12.6 32.1% 4 Bulgaria 12 16.2 4.2 35.9% 6 Canada 276.2 318.4 42.2 15.3% 6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% <t< th=""><th></th><th></th><th></th><th></th><th></th><th></th></t<>						
No. Country						Change in
Emissions Hypothetical Emissions Emissions Kk-CO ₂ World (kk-CO ₂) (We)	No.	Country	-			-
1 Australia 922.9 992.8 70 7.6% 2 Austria 33.4 45.3 12 35.9% 3 Belgium 39.3 51.9 12.6 32.1% 4 Bulgaria 12 16.2 4.2 35.1% 5 Brazil 472.1 556.7 84.6 17.9% 6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 25.6 1.4 33.2% 10 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.16 39 Slovenia 4.3 6.16 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10		3331111				
2 Austria 33.4 45.3 12 35.9% 3 Belgium 39.3 51.9 12.6 32.1% 4 Bulgaria 12 16.2 4.2 35.1% 5 Brazil 472.1 556.7 84.6 17.9% 6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15.5 6.9 1.4			(kt-CO ₂)	World (kt-CO ₂)	(kt-CO ₂)	(%)
3 Belgium 39.3 51.9 12.6 32.1% 4 Bulgaria 12 16.2 4.2 35.1% 5 Brazil 472.1 556.7 84.6 17.9% 6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2 16 France	1	Australia	922.9	992.8	70	7.6%
4 Bulgaria 12 16.2 4.2 35.1% 5 Brazil 472.1 556.7 84.6 17.9% 6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United K	2	Austria	33.4	45.3	12	35.9%
5 Brazil 472.1 556.7 84.6 17.9% 6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18	3	Belgium	39.3	51.9	12.6	32.1%
6 Canada 276.2 318.4 42.2 15.3% 7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 33.2% 19 <t< td=""><td>4</td><td>Bulgaria</td><td>12</td><td>16.2</td><td>4.2</td><td>35.1%</td></t<>	4	Bulgaria	12	16.2	4.2	35.1%
7 Switzerland 11.6 15.2 3.6 30.9% 8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 21 I	5	Brazil	472.1	556.7	84.6	17.9%
8 China 9,547.50 506.2 -9,041.30 -94.7% 9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indone	6	Canada	276.2	318.4	42.2	15.3%
9 Cyprus 1.1 1.5 0.5 46.8% 10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India<	7	Switzerland	11.6	15.2	3.6	30.9%
10 Czech Republic 32.5 45.8 13.3 41.1% 11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ir	8	China	9,547.50	506.2	-9,041.30	-94.7%
11 Germany 374.6 499.7 125.1 33.4% 12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy	9	Cyprus	1.1	1.5	0.5	46.8%
12 Denmark 82.1 88.6 6.5 7.9% 13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan	10	Czech Republic	32.5	45.8	13.3	41.1%
13 Spain 80.8 111.1 30.2 37.4% 14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South	11	Germany	374.6	499.7	125.1	33.4%
14 Estonia 5.5 6.9 1.4 25.1% 15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27	12	Denmark	82.1	88.6	6.5	7.9%
15 Finland 38.8 45.9 7.1 18.2% 16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28	13	Spain	80.8	111.1	30.2	37.4%
16 France 110.2 145.7 35.6 32.3% 17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29	14	Estonia	5.5	6.9	1.4	25.1%
17 United Kingdom 184.2 229.7 45.5 24.7% 18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30	15	Finland	38.8	45.9	7.1	18.2%
18 Greece 13.4 17.5 4.2 31.2% 19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta	16	France	110.2	145.7	35.6	32.3%
19 Croatia 4.2 5.6 1.4 33.2% 20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Nether	17	United Kingdom	184.2	229.7	45.5	24.7%
20 Hungary 13 17.9 4.9 37.5% 21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 <td< td=""><td>18</td><td>Greece</td><td>13.4</td><td>17.5</td><td>4.2</td><td>31.2%</td></td<>	18	Greece	13.4	17.5	4.2	31.2%
21 Indonesia 947.3 1,194.10 246.8 26.1% 22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34	19	Croatia	4.2	5.6	1.4	33.2%
22 India 754.7 979 224.3 29.7% 23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal	20	Hungary	13	17.9	4.9	37.5%
23 Ireland 11.5 14.7 3.2 27.4% 24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania<	21	Indonesia	947.3	1,194.10	246.8	26.1%
24 Italy 88.1 125 36.8 41.8% 25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Re	22	India	754.7	979	224.3	29.7%
25 Japan 43,114.80 43,295.00 180.2 0.4% 26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 <	23	Ireland	11.5	14.7	3.2	27.4%
26 South Korea 1,756.30 2,219.00 462.7 26.3% 27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39	24	Italy	88.1	125	36.8	41.8%
27 Lithuania 6.6 8.4 1.8 27.5% 28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden	25	Japan	43,114.80	43,295.00	180.2	0.4%
28 Luxembourg 3.2 3.8 0.6 18.0% 29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey	26	South Korea	1,756.30	2,219.00	462.7	26.3%
29 Latvia 1.7 2.2 0.5 26.4% 30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan	27	Lithuania	6.6	8.4	1.8	27.5%
30 Mexico 91.9 125.8 34 37.0% 31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States	28	Luxembourg	3.2	3.8	0.6	18.0%
31 Malta 1 1.3 0.3 27.5% 32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	29	Latvia	1.7	2.2	0.5	26.4%
32 The Netherlands 76.3 97.6 21.2 27.8% 33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	30	Mexico	91.9	125.8	34	37.0%
33 Norway 50 59.6 9.6 19.2% 34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	31	Malta	1	1.3	0.3	27.5%
34 Poland 75.5 107.2 31.7 42.0% 35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	32	The Netherlands	76.3	97.6	21.2	27.8%
35 Portugal 9.8 13.8 3.9 40.0% 36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	33	Norway	50	59.6	9.6	19.2%
36 Romania 15.4 21.9 6.5 41.8% 37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	34	Poland	75.5	107.2	31.7	42.0%
37 Russia 2,146.90 2,436.80 289.9 13.5% 38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	35	Portugal	9.8	13.8	3.9	40.0%
38 Slovak Republic 12.9 19 6.1 47.1% 39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	36	Romania	15.4	21.9	6.5	41.8%
39 Slovenia 4.3 6 1.6 38.1% 40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	37	Russia	2,146.90	2,436.80	289.9	13.5%
40 Sweden 32.5 40.5 8 24.8% 41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	38	Slovak Republic	12.9	19	6.1	47.1%
41 Turkey 86.2 133.3 47.1 54.6% 42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	39	Slovenia	4.3	6	1.6	38.1%
42 Taiwan 975 1,198.30 223.4 22.9% 43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	40	Sweden	32.5	40.5	8	24.8%
43 United States 955.5 1,190.90 235.4 24.6% 44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	41	Turkey	86.2	133.3	47.1	54.6%
44 Rest of the World 11,102.50 12,712.60 1,610.10 14.5%	42	Taiwan	975	1,198.30	223.4	22.9%
	43	United States	955.5	1,190.90	235.4	24.6%
Total 74,575.30 69,724.40 -4,850.90 -6.5%	44	Rest of the World	11,102.50	12,712.60	1,610.10	14.5%
		Total	74,575.30	69,724.40	-4,850.90	-6.5%

The total change in the carbon footprint, shown in the bottom row of Table 3-3, demonstrates that the change in direct and indirect CO₂ emissions following this restructuring is -4,850 kt, which is about 6.5% less than its carbon footprint before restructuring. The results indicate that Japan's current automotive supply chain has the potential to significantly reduce CO₂ emissions through structural reforms.

Additionally, observing the changes in the CO₂ emissions of each country resulting from the restructuring of Japan's automotive supply chain (Table 3-3), this study observes that China's CO₂ emissions will also significantly reduce by 9,041 kt-CO₂ (-94.7%) compared with the actual CO₂ emissions induced by the production of Japan's automobile industry. This decrease is attributed to the extraction of Chinese emissions cluster #12 from Japan's automotive supply chain. At the same time, restructuring will increase CO₂ emissions in all countries other than China, particularly in South Korea, Russia, and the United States by +462 kt-CO₂ (+26.3%), +289 kt-CO₂ (+13.5%), and +235 kt-CO₂ (+24.6%), respectively. This result indicates that these three countries are closely linked to Japan through international trade in intermediate goods and constitute important locations for the substitute production of intermediate goods manufactured by cluster #12 in China.

3.4.3 Decomposition results

This section describes the CO₂ reduction effect (i.e., the extraction effect) resulting from the extraction of one of the industries in the Chinses cluster #12 from the Japanese automobile supply chain, and the CO₂ increase effect (i.e., the substitution effect)

resulting from the substitution of intermediate goods manufactured by that industry in China with those manufactured in other countries. Chinese industries included in the CO₂ emission hotspot play an important role in creating a clean supply chain in the Japanese automotive industry when the structural change caused by the extraction and substitution of that Chinese industry reduces the net carbon footprint. Conversely, when structural changes involving a corresponding Chinese industry (i.e., extraction and substitution) produce an increase in the net carbon footprint, the restructuring of the supply chain is expected to increase greenhouse gas emissions and thus exacerbate climate change.

Figure 3-3 shows the impact of extraction and substitute production on the carbon footprint associated with Japanese automobiles for 12 Chinese industries included in cluster #12. The blue bars indicate the CO₂ reduction effect produced by extracting one of the relevant Chinese industries, that is, the extraction effect. The effect of extracting the electrical equipment (CHN) sector is the largest (-2,762 kt-CO₂), which is approximately 1.5 times greater than the extraction effect of the second largest sector, motor vehicles (CHN) (-1,835 kt-CO₂). This result demonstrates that the Chinese electrical equipment sector plays an important role in the Japanese automotive supply chain.

One key question is the extent to which substitute production in other countries, caused by the extraction of intermediate goods manufactured in the Chinese electrical equipment sector, will increase CO₂ emissions. The red bars in Figure 3-3 show the increase in CO₂ emissions for the entire Japanese automotive supply chain, resulting from the additional production substitution of intermediate goods manufactured by the

corresponding sectors (cluster #12), in countries other than China. The figure demonstrates that the substitution effect for the Chinese electrical equipment sector is +1,140 kt-CO₂. In other words, by summing the substitution and extraction effects, the impact on the carbon footprint of the extraction of the Chinese electrical equipment sector and the associated substitute production is estimated at -1,621 kt-CO₂ (see the corresponding circle in Figure 3-3). This reduction in emissions resulting from the restructuring of the GSC targeting the Chinese electrical equipment sector accounts for 2.2% of the carbon footprint of the Japanese automotive supply chain.

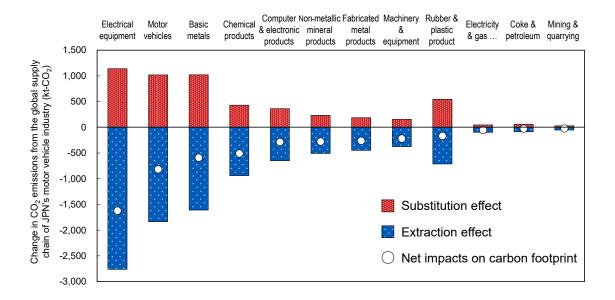


Figure 3-3. Extraction and substitution effects resulting from the restructuring where industries outside of China, included in the Japanese automobile supply chain, use products from countries other than China to substitute for the use of products made by the relevant Chinese industries that constitute cluster #12.

Table 3-4 presents the impact of the extraction and substitution of the electrical

equipment sector (CHN) in the Japanese automotive supply chain on its carbon footprint in each country. The table extracts CO₂ emissions from substitute production in RoW.

Table 3-4. Extraction and substitution effects in each country, where each country produces relevant products in lieu of China producing electrical equipment for Japan's automotive supply chain.

		Impacts on	Substitution Effect on	Extraction Effect on
Rank	Country	Carbon	Carbon	Carbon
	,	Footprint	Footprint	Footprint
		(kt-CO ₂)	(kt-CO ₂)	(kt-CO ₂)
1	South Korea	-300.5	222.8	-523.3
2	Germany	-281.1	51.9	-333
3	United States	-188.7	74.4	-263.1
4	Taiwan	-107.2	81.6	-188.8
5	Indonesia	-94.7	112.7	-207.3
6	France	-56.3	13	-69.3
7	United Kingdom	-56.3	13.8	-70.1
8	Italy	-35.3	10	-45.3
9	Switzerland	-30	5.5	-35.5
10	Spain	-27.2	9.6	-36.7
11	Mexico	-22.1	14.2	-36.3
12	Japan	-18.7	10.7	-29.4
13	Sweden	-18.5	3.9	-22.4
14	Belgium	-16.2	5.4	-21.6
15	Austria	-12.7	2.5	-15.2
16	Canada	-11.4	5	-16.4
17	Czech Republic	-10.5	4.4	-14.9
18	Brazil	-8.8	5.1	-13.9
19	The Netherlands	-8.2	2	-10.2
20	Denmark	-6.8	1.2	-8
21	Poland	-6.3	3.5	-9.9
22	Norway	-5.4	1.1	-6.5
23	Finland	-4.6	1	-5.6
24	Hungary	-3.2	1.4	-4.7
25	Ireland	-3.1	0.8	-3.8
26	Malta	-3	0.8	-3.8
27	Turkey	-2.9	2.1	-5.1
28	Australia	-2.8	1.2	-4
29	Romania	-1.8	0.9	-2.7
30	Portugal	-1.8	0.7	-2.4
31	Slovak Republic	-1.2	0.5	-1.7
32	Slovenia	-1.2	0.5	-1.6
33	Bulgaria	-0.5	0.6	-1.1
34	Croatia	-0.4	0.1	-0.5
35	Estonia	-0.3	0.1	-0.5
36	Lithuania	-0.2	0	-0.2
37	Greece	-0.2	0.1	-0.2
38	Luxembourg	-0.1	0	-0.1
39	Latvia	-0.1	0	-0.1
40	Cyprus	0		0
41	Russia	0	0	0
42	India	2.1	27.4	-25.4
	Total	-1,348.3	692.5	-2,040.8

Extracting the manufacture of electrical equipment in China decreased the carbon footprint by 523 kt-CO₂, while substituting this for the manufacture of products in South Korea increased the carbon footprint by 223 kt-CO₂. As a result, the substitution in South Korea for the manufacture of electrical equipment reduces the carbon footprint by 300kt-CO₂. This change, centered on the two countries, is very significant in reducing the carbon footprint associated with the final demand for Japanese automobiles.

Next, if Germany and the United States substitute for the manufacture of electrical equipment for the Japanese automotive supply chain, the carbon footprint associated with the final demand for Japanese automobiles is reduced by 281 kt-CO₂ and 188 kt-CO₂, respectively (see the rows for Germany and the United States in Table 3-4). Therefore, the impact of emission reductions from substitute production in the electrical equipment sector by three countries—South Korea, Germany, and the United States—is relatively significant, representing about 1% of the carbon footprint of the entire Japanese automotive supply chain.

In contrast, if India produced the relevant products in lieu of the electrical equipment sector in China, it would result in an increase in supply chain emissions of 2.1 kt-CO₂ compared to the factual case (Table 3-4). This is mainly because the average of the CO₂ emission coefficients of the relevant manufacturing sectors in India are approximately three times higher than those of China. In other words, the technology of the manufacturing industries in India that might be new trade partners of Japan's automobile supply chain is not environment- friendly compared to the original trade partners.

3.5. Discussion and Conclusions

It has become increasingly important to consider greenhouse gas (GHG) emissions from the perspective of the entire product supply chain (Hertwich and Wood, 2018). Estimating Scope 3 Category 1 GHG emissions, as defined in the GHG Protocol, is an important initiative in corporate green supply chain management. It should be noted that the Scope 3 category 1 GHG emissions include all upstream (i.e., cradle-to-gate) emissions from the production of products purchased or acquired by industries (World Resources Institute & World Business Council for Sustainable Development, 2013). The estimates allow companies to identify CO₂ emissions hotspots in their supply chains. In another approach, Science Based Targets, a downstream company, estimates their own life-cycle GHG emissions and provides their upstream suppliers with their GHG reduction targets applied to the 2°C or 1.5°C target set by the Paris Agreement (Science Based Target Initiative, 2020). This approach provides an incentive for supply chain stakeholders to reduce CO₂ emissions.

However, while the existing policy approaches, such as the two above, can contribute to reducing CO₂ emissions at hotspots within existing supply chains, they lack the comprehensive view required to evaluate the supply chain structure itself. This prevents policymakers from considering a lower-carbon GSC structure. The integrated analysis framework developed in this study, SEM (Figure 3-2), focuses on the supply chain structure itself and can provide policymakers concerned about greener supply chain restructuring with useful information, that is, the change in CO₂ emissions caused by the structural change (i.e., the restructuring with a focus on CO₂ emission hotspots) that

stakeholders might consider. Using this information, policymakers will be aware of where regional and/or sectoral CO₂ emissions will increase through GSC restructuring. In addition, from the decomposition results, they can determine which restructuring elements will contribute most to the net change in CO₂ emissions. Based on this, they can further design appropriate climate policies and priorities for greener restructuring. In this study, this study demonstrates the case of Japan's automotive industry.

As a case study, the elements required by the Japanese automotive industry to create a supply chain with lower CO₂ emissions were analyzed. A One of the key findings is that in 2014, there was a large CO₂ emission cluster in the Japanese automotive supply chain that included Chinese manufacturing sectors. This reveals that Japan's automotive supply chain structure has a significant concentration of CO₂ emissions in China, that is, a CO₂ emission hotspot. The SEM-based results demonstrated that a change from overconcentrated CO₂ emissions of the current automobile industry to a supply chain structure with decentralized CO₂ emissions has the potential to reduce the carbon footprint of automobiles by 6.5%. Japanese automotive companies should, therefore, extend their CO₂ emissions management to include not only their direct supply chain, but also the supply chains of their material suppliers (i.e., up to the life-cycle level), and decentralize supply chain groups with overconcentrated CO₂ emissions.

Japanese automotive companies such as Toyota and Nissan are supply chain members in the carbon disclosure project (CDP) in Japan, and they have conducted hybrid life-cycle assessments to report their life-cycle CO₂ emissions to stakeholders (CDP, 2021; Toyota, 2020; Nissan, 2021). It is important to note that few material suppliers

outside of Japan (especially in China: CO₂ emission hotspot in this study) are participating in the CDP (CDP Companies scores, 2021). Based on the CDP website, the number of Chinese steel companies participating in the CDP is half of that of Japanese steel companies (CDP Companies scores, 2021). In addition, the Chinese steel companies have the lowest score of "F" implying that the effort for climate change is not enough (CDP Companies scores, 2021). This study suggests the following greener supply chain strategy. For the first step, the Japanese automotive companies should motivate material suppliers in the "CO₂ emission hotspot" identified in this study to participate in the CDP and report their life-cycle CO₂ emissions to stakeholders including the auto company. In the second step, the Japanese automotive companies should contract under the agreement that the material suppliers must reduce the life-cycle CO₂ emissions by a certain percentage (e.g., 30%) during a certain period (e.g., five years). If the material suppliers cannot achieve the reduction target during the period, the automotive companies should not contract with them, and should find greener partners to contract with. Thus, Japanese automotive companies can gradually restructure their GSCs and decarbonize them.

Moreover, through structural decomposition analysis, this study found that within CO₂ emission clusters, structural changes in the electrical equipment (CHN) sector contributed the most to reducing the carbon footprint of the Japanese automotive industry. The most effective supply chain management policy, therefore, would be to prioritize eliminating the dependence of industries in Japan's automotive supply chain on the electrical equipment (CHN) sector and to distribute the sector across other countries.

Specifically, this study proposes that Japanese automotive companies should not

use the products of specific sectors of upstream companies belonging to the CO₂ emission clusters (i.e., electrical equipment (CHN)). The Japanese government should restructure a low-carbon automotive supply chain by strengthening trade agreements for intermediate goods (e.g., electrical equipment and basic metals in this study) with existing and new trading partners, apart from China (South Korea, Germany, and the United States, in this study). Using these strengthened trade agreements, the stakeholders of Japanese automotive companies could procure materials from green companies to reduce CO₂ emissions from a life-cycle perspective (i.e., green procurement) for certain intermediate goods in the GSC.

Post-COVID society must achieve annual global reductions in CO₂ emissions in the range of 9%–10% to apply the 1.5°C target (IPCC, 2018) set by the Paris Agreement (United Nations Framework Convention on Climate Change, 2015; Lenzen *et al.*, 2020). Considering the Japanese automotive supply chain, the -6.5% reduction in CO₂ emissions resulting from changes to the supply chain structure estimated in this study will be insufficient in isolation to attain this goal. To achieve the target set by the Paris Agreement, the government must ambitiously reduce industrial supply chain CO₂ emissions by adopting comprehensive policies based on two perspectives: technology and structure. As the restructuring of the GSC is promoted, the framework proposed in this study would help policymakers to rebuild greener supply chains from the perspective of structure in particular.

It is important to note that our results include sectoral aggregation biases. As in previous studies (Su et al., 2010; Olsen et al., 2014; Koning et al., 2015), the global

carbon footprint at the country level estimated in this study is not significantly biased because of the sectoral aggregation biases in environmental IO analysis. However, there exists uncertainty in substitution between highly aggregated sectors, which might yield unrealistic results. In future follow-up studies, it is necessary to focus on the proportion of substituting a specific commodity produced in other countries for that produced in the CO₂ emission hotspot country (i.e., China) based on the trade database with higher sectoral resolution.

Chapter 4: Identifying Critical Sectors in the Restructuring of Low-Carbon Global Supply Chains

4.1 Introduction

Many governments worldwide have set targets to achieve net-zero CO₂ emissions by 2050 with the goal of climate change mitigation (IEA, 2021). To adapt to this ambitious target, industries worldwide urgently need to reduce the CO₂ emissions associated with their production activities, including their global supply chains (GSCs). Over the past two decades, the development of the GSC industry structure has significantly increased global CO₂ emissions based on CO₂ emission transfers and carbon leakage. Peters *et al.* (2011) found that with the development of global GSC structures, CO₂ emissions from international trade grew by approximately 1.8 times between 1990 and 2008. Additionally, they revealed that CO₂ emission transfers through international trade from developing to developed countries rapidly increased from 0.4 Gt to 1.6 Gt during this period.

Environmentally extended input-output (EEIO) analysis has been developed as a useful tool for evaluating environmental pressures, including greenhouse gas emissions, from the perspective of consumption-based accounting (Wiedmann, 2009; Serrano and Dietzenbacher, 2010; Kander *et al.*, 2015; Dietzenbacher *et al.*, 2020). Using EEIO techniques, many previous studies focused on the CO₂ emission structures of GSCs with empirical analysis (Duarte *et al.*, 2018; Zhang *et al.*, 2020; Zheng *et al.*, 2020), cluster analysis (Kagawa *et al.*, 2015; Bolea *et al.*, 2020), decomposition analysis (Xu and

Dietzenbacher, 2014), and footprint analysis (Meng *et al.*, 2018; Meng *et al.*, 2018; Hertwich, 2021). They revealed that reducing CO₂ emissions in a relevant GSC (i.e., global carbon footprint) is a crucial policy target for climate change mitigation.

Although industries need to reduce the CO₂ emissions from their GSCs, they face the risk of GSC disruption based on recent events such as the COVID-19 pandemic and Russia/Ukraine conflict (Baldwin and Freeman, 2022; OECD, 2022; IMF, 2022). For industries around the world, GSC restructuring is a critical solution for mitigating risk, and many major countries are implementing policies to promote GSC restructuring. (e.g., Business Europe, 2022; The White House, 2022; METI, 2022a; 2022b; 2022d). Importantly, while GSC restructuring can mitigate the risk of uncertainty in GSCs, it can provide an excellent opportunity for industries to transform their existing GSCs into green GSCs with a low-carbon structure and reduce their global carbon footprint (i.e., low-carbon restructuring) (Maeno *et al.*, 2022).

In this situation, the key questions that should be made clear for industries worldwide to restructure a low-carbon GSC are as follows. First, which sector (i.e., supplier) included in a relevant GSC can achieve the greatest CO₂ emission reduction through GSC restructuring? In short, which sector should be a policy target for relevant low-carbon GSC restructuring? Second, to what extent can the CO₂ emissions of a relevant GSC be reduced through GSC restructuring?

The hypothetical extraction method (HEM), which is an input-output (IO) model, has been developed to highlight the importance of a relevant sector in the world economy

by extracting all activities of a particular sector (Schultz, 1977; Cella, 1984; Miller and Lahr, 2001; Duarte *et al.*, 2002; Guerra and Sancho, 2010; Dietzenbacher and Lahr, 2013; Hertwich, 2021; Tokito *et al.*, 2022). Dietzenbacher *et al.* (2019) proposed the global extraction method (GEM) by expanding the HEM to estimate the impacts of a hypothetical structural change in a GSC triggered by the suspension of the production activities of a relevant sector on global GDP. Maeno *et al.* (2022) developed an integrated analytical framework using an extended GEM to estimate the impact of GSC restructuring on a relevant sector's global CO₂ emissions.

By integrating IO cluster analysis (Kagawa *et al.*, 2013) with the GEM (Dietzenbacher *et al.*, 2019), Maeno *et al.* (2022) modeled a restructuring scenario of a relevant GSC in which its intermediate trades with specific industries identified as CO₂ emission hotspots were completely extracted and substituted with corresponding sectors outside the hotspot countries. By applying this GSC restructuring scenario to the Japanese automobile GSC, Maeno *et al.* (2022) demonstrated that restructuring the Japanese automobile GSC would have a significant CO₂ reduction potential of 6.5% of its global carbon footprint. The main contributions of their study were modeling the restructuring of a relevant GSC and attempting to quantify the relationship between GSC restructuring and CO₂ emissions for the first time.

However, previous studies have only analyzed a specific scenario, such as the restructuring of the Japanese automobile GSC targeting CO₂ emission hotspots, and have not revealed the impact of restructuring targeting every sector included in relevant GSCs on CO₂ emissions. In other words, the target sector that can achieve the greatest reduction

in CO₂ emissions through relevant restructuring is unclear. This impact can be estimated by applying an extended HEM (Dietzenbacher *et al.*, 2019; Maeno *et al.*, 2022) to every sector included in a relevant GSC. However, the restructuring scenario defined by the existing HEM is based on extracting all intermediate trade transactions with a target sector (i.e., suspension of intermediate trade with a target sector). This makes the existing model exaggerated and unrealistic for general application to every sector included in a relevant GSC. Additionally, although the practical scale of GSC restructuring differs among target sectors, complete extraction does not consider these differences. Therefore, previous studies (Dietzenbacher *et al.*, 2019; Maeno *et al.*, 2022) have not answered the key question of the extent to which the CO₂ emissions of a relevant GSC can be reduced through reasonable GSC restructuring.

To answer these research questions, this study empirically investigated the impact of relevant GSC restructuring targeting every sector using a practical HEM model. Specifically, this study applied a hybrid HEM model called partial and global HEM (Dietzenbacher and Lahr, 2013; Dietzenbacher *et al.*, 2019) to estimate the impact of "a unit" of relevant GSC restructuring targeting every sector (i.e., marginal restructuring of a relevant GSC). Furthermore, this study incorporated an indicator of the comparative advantage of a target sector into the hybrid HEM framework to describe the practical scale of relevant GSC restructuring and estimate the CO₂ emission reduction potential of practical GSC restructuring. Following the previous studies (Dietzenbacher *et al.*, 2019; Maeno *et al.*, 2022), this study conducted a case study applying practical HEM analysis to major automobile GSCs (i.e., Japanese and German automobile GSCs), which are at the center of attention for GSC restructuring (METI, 2022a; Germany Trade and

Investment, 2022); these induce significant CO₂ emissions from upstream suppliers (Kagawa *et al.*, 2015; Tokito, 2018; Maeno *et al.*, 2022).

The main contribution of this study is the provision of intuitive and certain evidence for the relationship between GSC restructuring and CO₂ reduction to policymakers who are willing to implement low-carbon GSC restructuring by enhancing the practicality and flexibility of scenario-based HEM as a simulation tool for the real world.

The remainder of this paper is organized as follows. Section 2 details this research methodology. Section 3 discusses the data used in this study. Section 4 presents the results of an empirical analysis. Finally, Section 5 discusses the implications of the findings of this study and concludes the paper.

4.2 Methodology

4.2.1 Partial and global extraction analysis

From a multi-regional IO table (MRIOT) with M industries in N countries, this study obtained the intermediate input matrix $\mathbf{Z} = \left(Z_{ij}^{RS}\right)$, which represents the intermediate inputs from industry i in country R to industry j in country S, the final demand vector $\mathbf{f} = (f_i^R)$ of industry i in country R, and the total output vector $\mathbf{x} = (\mathbf{x}_i^R)$ of industry i in country R, the input coefficient matrix, which represents the input coefficients from industry i in country R to industry I in country I

calculated as $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$. Here, $\hat{\mathbf{x}}^{-1}$ is a diagonal matrix with x_i^R , which represents the outputs of industry i in country R, as its diagonal elements. Following the basic Leontief model (Miller and Blair, 2009), the total output vector \mathbf{x} can be expressed as follows.

$$x = Ax + f$$

$$(I - A)x = f$$

$$x = (I - A)^{-1}f = Lf$$

where $(\mathbf{I} - \mathbf{A})^{-1} = \mathbf{L} = (l_{ij}^{RS})$ is the Leontief inverse matrix (Miller and Blair, 2009), representing the output of industry i in country R directly and indirectly required to produce one unit of final demand for industry j in country S. According to the environmentally extended IO model (Miller and Blair, 2009), the direct and indirect CO_2 emissions induced by the final demand for industry m in country C, which is denoted as q_m^C , can be estimated using equation (4.1).

$$q_m^{\mathcal{C}} = \mathbf{e}(\mathbf{I} - \mathbf{A})^{-1} \mathbf{f}_m^{\mathcal{C}} = \mathbf{e} \mathbf{L} \mathbf{f}_m^{\mathcal{C}}$$
 (4.1)

Here, \mathbf{e} is the row vector of the direct CO₂ emission coefficients, representing the direct CO₂ emissions per unit of production for each industry in each country. \mathbf{f}_m^C represents a vector with a value only for the component corresponding to the final demand of industry m in country C (the automotive sector in Japan or Germany for the case studies in this study) for all other cases, which is zero.

Although, originally, GSC structure based on the MRIOT is ultimately determined

to satisfy the final demands of an entire global economy, this study defines all production spillovers triggered by final demands for industry m in country C (i.e., it is calculated as \mathbf{Lf}_{m}^{C}) as an independent GSC structure for industry m in country C, and assumes that the GSC is restructured in its upstream parts.

This study applied a hybrid HEM model called the partial and global HEM (Dietzenbacher and Lahr, 2013; Dietzenbacher *et al.*, 2019). This model assumes a hypothetical GSC structure in which a marginal unit of the trade coefficient γ (1% in this study) of industry k in country k with other sectors is extracted and substituted with industry k in other countries. The input coefficient matrix in this hypothetical world, which is denoted as $\overline{\bf A} = (\overline{a}_{ij}^{RS})$, is defined as

$$\bar{a}_{kj}^{HS} = a_{kj}^{HS} - \sum_{R} a_{kj}^{RS} \left(\frac{a_{kj}^{HS}}{\sum_{R} a_{kj}^{RS}} \gamma \right) = a_{kj}^{HS} - a_{kj}^{HS} \gamma \ (\forall j, \ \forall S \neq H), (4.2)$$

$$\bar{a}_{kj}^{TS} = a_{kj}^{TS} + a_{kj}^{HS} \gamma \frac{a_{kj}^{TS}}{\sum_{R \neq H.S} a_{kj}^{RS}} (\forall j, \forall S, \forall T \neq H). \tag{4.3}$$

Equation (2) indicates that the trade coefficient of industry k in country H with the other industries in all countries except for country H drops by 1% (i.e., extracted marginally). Equation (3) indicates that industry j in country S requires additional imports of intermediate goods from industry k in country R outside country H, which are calculated by multiplying the import procurement ratio of industry k in country R (excluding country H as $a_{kj}^{TS}/\sum_{R \neq H,S} a_{kj}^{RS}$) by the extracted imports from industry k in country H ($\sum_{R} a_{kj}^{RS} \left(\frac{a_{kj}^{HS}}{\sum_{R} a_{kj}^{RS}} \gamma\right)$). Equation (4.3) also indicates that the imports of

intermediate goods from industry k in country H cannot be substituted by the domestic sector. As defined in previous studies (Dietzenbacher $et\ al.$, 2019; Maeno $et\ al.$, 2022), this study assumed that countries import products for reasons such as high costs, regional availability, or preferences for a variety of suppliers. Additionally, equation (4.3) indicates that industry j in country S imports more intermediate products from trading partners with stronger trade relationships. This allocation system is based on the economic implication that stakeholders who implement GSC restructuring tend to select partners who already have strong trade relationships with them as new trade partners (Maeno $et\ al.$, 2022). A brief explanation of these processes is presented in Figure 4-1.

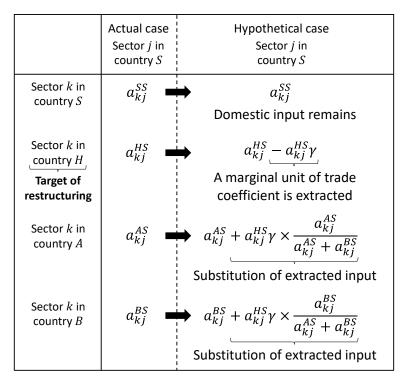


Figure 4-1. Brief explanation of the partial and global extraction methods.

In the hypothetically restructured GSC, where the international intermediate trade of industry k in country H is partially extracted, the direct and indirect CO₂ emissions (i.e., carbon footprint) stem from the final demand for sector m in country C, which is denoted as \overline{q}_m^c and can be estimated using the following equation:

$$\bar{q}_m^C = \mathbf{e}(\mathbf{I} - \overline{\mathbf{A}})^{-1} \mathbf{f}_m^C = \mathbf{e} \overline{\mathbf{L}} \mathbf{f}_m^C.$$
 (4.4)

Here, the direct CO₂ emissions from industry m in country C do not change. Therefore, the difference between the indirect CO₂ emissions in the actual and hypothetical worlds Δq_m^C can be expressed by the following equation:

$$\Delta q_m^C = \bar{q}_m^C - q_m^C = \mathbf{e}\bar{\mathbf{L}}\mathbf{f}_m^C - \mathbf{e}\mathbf{L}\mathbf{f}_m^C. (4.5)$$

Equation (4.5) captures the impact of marginal GSC restructuring originating from the partial extraction of the international intermediate trade of industry k in country H on the global carbon footprint of industry m in country C.

4.2.2 Practical scale of GSC restructuring

In the real world, based on differences in the substitutability of relevant intermediate goods, there are large differences in the reasonable scale of supply chain restructuring between target sectors. However, the traditional HEM does not have a framework for considering this difference. Therefore, this study combined the partial HEM described above with an index reflecting the substitutability of a specific product to define the limits of reasonable extraction for each target sector. Furthermore, because the substitutability of a product in international trade depends on its competitiveness in the global market, this study applied the revealed comparative advantage (RCA) index (Balassa, 1965) as a proxy index representing the substitutability of a relevant target sector.

The RCA index is a well-known indicator of a relevant sector's international competitiveness or product specialization and is widely used in the field of international economic study (Timmer *et al.*, 2018). The RCA index of sector k in country H, which is denoted as RCA_k^H , is calculated using the following equation:

$$RCA_k^H = \frac{E_k^H / \sum_i E_i^H}{\sum_W E_k^W / \sum_W \sum_i E_i^W}, (4.6)$$

where E_k^H is the added value generated directly by products of sector k in country H, which are exported from country H to the world as intermediate or final products. The numerator represents the share of the added value generated by the exports of sector k in country H among the added value of the total exports of country H. The dominator represents the share of the added value generated by the exports of sector k that add value to the total global exports. A higher RCA index indicates that sector k in country k has relatively high international competitiveness, implying that intermediate goods from that sector cannot be easily substituted.

First, this study calculated the RCA index of every sector based on the added value of exports. The RCA indices of all sectors are listed in Table S2.3 in Supplementary materials 4.2. To ensure the robustness of the RCA indices, this study calculated the average RCA indices for five years (2010 to 2014). Second, this study compared the RCA indices of a particular sector by country, and based on the results, this study defined the interquartile range of the RCA index of a relevant sector. Based on the interquartile ranges, which reflect relative substitutability, the relevant sectors in a country were classified into six groups, as shown in Figure 4-2. These groups were then used to determine the partial extraction ratios (Figure 4-2).

Interquartile range of the RCA index of a relevant sector

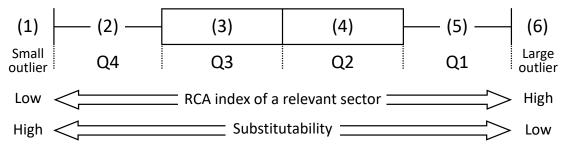


Figure 4-2. Group separation based on the interquartile range of the RCA index of a relevant sector.

Although the RCA index is a simple indicator of a product's competitiveness, the RCA index does not consider other external factors such as regional or political backgrounds (e.g., trade agreements). This study considered relevant GSC restructuring targeting all sectors (i.e., suppliers) independent of a specific scenario. Therefore, to reduce uncertainty caused by external factors, this study assumed that sectors belonging to a specific group determined by the interquartile ranges mentioned above have uniformly convergent substitutability. This assumption simplifies a complex international trade market involving external factors and fairly defines the reasonable extraction and substitution of all sectors, which reflects the competitiveness of a product.

This study also considered the assumption of the original HEM regarding complete extraction as a standard for determining the limits of partial extraction. Therefore, this study assumed that a relevant sector could be restructured to limits of (1)100%, (2)90%, (3)75%, (4)50%, (5)25%, and (6)10% according to the distributions of the interquartile ranges as shown in Fig. 4-2. By applying the limits of partial extraction based on the

substitutability of a relevant product to the HEM framework (i.e., Eqs. (2) to (5)), this study estimated the practical CO₂ emission reduction potentials of relevant GSC restructuring on a reasonable scale.

4.3 Data

For the case study, this study used the world input-output database (WIOD) (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015), which is also used in the previous studies with the context that this study follows (i.e., Dietzenbacher *et al.*, 2019; Maeno *et al.*, 2022). The latest WIOD covered the production activities of 56 industries in 43 countries/regions and the rest of the world in 2014, and the data is published at www.wiod.org/home. WIOD includes a sector of "the manufacturing industry of motor vehicles, trailers, and semi-trailers," which this study focuses on, and it has sufficient sector disaggregation to demonstrate the case study for the GSC restructuring targeting every sector included in the automotive GSCs.

As for the other main MRIO databases, such as Eora (Lenzen *et al.*, 2013), Exiobase (Stadler *et al.*, 2018), for example, Eora does not include a specific sector as an automotive sector despite its high spatial resolution. While Exiobase has current data with a high sectoral resolution, the up-to-date database should be taken care of in use for its uncertainty based on a lack of consistent primary data (Stadler *et al.*, 2021), and the substantial sectoral disaggregation in Exiobase is not necessary for demonstrating the HEM framework, which focuses on every intermediate product rather than a specific product within the automotive GSCs because it makes calculations and results too

complex and enormous. These are the reasons why this study selected WIOD³.

This study used direct CO₂ emission data by industry and country from the environmental impact data (Corsatea *et al.*, 2019) consistent with the WIOD.

4.4 Results

4.4.1 Impacts of the marginal restructuring of Japanese and German automotive GSCs

In 2014, the carbon footprints of the automobile supply chains in Japan and Germany were 74,575 kt-CO₂ and 66,304 kt-CO₂, respectively. In both cases, indirect CO₂ emissions from the corresponding GSCs accounted for more than 95% of the total emissions. This finding indicates that automobile industries generate large amounts of CO₂ emissions through production activities in their global supply chains.

This study focused on 2464 sectors (56 industrial sectors in 44 countries and regions) using the practical HEM described in Section 2. This study estimated the CO₂ emission changing effects of the marginal restructuring of Japanese and German automotive GSCs targeting a particular sector in a particular country. All results are presented in Tables S2.1 and S2.2 in Supplementary materials 4.2. A positive change in CO₂ emissions indicates that the marginal restructuring of a sector increases the CO₂ emissions associated with

³ This study applied the HEM framework described in the section 2 to another MRIO database (i.e., Exiobase (Stadler *et al.*, 2021)) to check the difference in results between the databases. The results are shown in Supplementary materials 4.1.

automobile GSCs. Therefore, a sector with positive CO₂ emission change should not be restructured in an automobile GSC. Conversely, a negative change in CO₂ emissions indicates that the marginal restructuring of a sector reduces CO₂ emissions (i.e., CO₂ reduction effect). To mitigate CO₂ emissions, it is important to promote GSC restructuring to reduce CO₂ emissions. Therefore, this study focused on sectors with significant CO₂ reduction effects.

Table 4-1. Sectors with large CO₂ reduction effects based on the marginal restructuring of the Japanese automobile GSC.

			CO ₂ reduction effect
Rank	Country	Industry	by marginal
			restructuring (kt-CO ₂)
1	China	Electrical equipment	-15.3
2	China	Motor vehicles, trailers, and semi-trailers	-7.6
3	China	Basic metals	-5.7
4	Russia	Basic metals	-5.5
5	China	Chemicals and chemical products	-5.0
6	China	Other non-metallic mineral products	-2.7
7	Russia	Mining and quarrying	-2.6
8	China	Fabricated metal products, except machinery and equipme	-2.5
9	China	Computer, electronic, and optical products	-2.5
10	China	Machinery and equipment n.e.c.	-2.1
11	China	Rubber and plastic products	-1.5
12	India	Basic metals	-1.1
13	Russia	Land transport and transport via pipelines	-1.1
14	Korea	Basic metals	-1.1
15	Taiwan	Basic metals	-1.0

Table 4-1 lists the top 15 sectors with large CO₂ reduction effects based on relevant marginal restructuring in the Japanese automobile GSC. The CO₂ reduction effect of electrical equipment (China: CHN) is the largest (-15.3 kt-CO₂), and it accounts for 0.02% of the total CO₂ emissions from the Japanese automobile GSC. The reduction effect is over two times greater than the effects of the other sectors (Table 4-1). This result indicates that marginal restructuring of the Japanese automobile GSC targeting this sector can reduce its global carbon footprint by 0.02%. This CO₂ reduction can be achieved directly and indirectly through a 1% marginal decrease in the intermediate input from the electrical equipment (CHN) sector and substitution from the corresponding sectors in other countries. The electrical equipment (e.g., engine parts) made in China, on which the Japanese automobile GSC depends, includes CO₂-intensive material sectors (e.g., basic

metals (CHN), electricity, and gas (CHN)) in its supply chain. Because the marginal restructuring of this sector can replace the CO₂-intensive production process of electrical equipment (CHN) with other countries, it has significant CO₂ emission reduction potential in the Japanese automobile GSC.

The marginal restructuring of the Chinese and Russian basic metal sectors exhibits larger CO₂ reduction effects than many other sectors (-5.7 kt-CO₂ and -5.5 kt-CO₂, respectively). Although the production of basic metals is relatively CO₂ intensive, the results indicate that a large technology gap still exists between countries from the perspective of partial extraction analysis. This result indicates that the CO₂ reduction effects in the Japanese automobile GSC can be directly generated by substituting the basic metal sectors with production technology cleaner than that found in the Chinese and Russian basic metal sectors.

Table 4-2. Sectors with large CO₂ reduction effects based on the marginal restructuring of the German automobile GSC.

Rank	Country	Industry	CO ₂ reduction effect by marginal
-			restructuring (kt-CO ₂)
1	Russia	Basic metals	-19.0
2	China	Electrical equipment	-6.1
3	China	Machinery and equipment n.e.c.	-5.6
4	China	Fabricated metal products, except machinery and equipme	-4.5
5	China	Motor vehicles, trailers, and semi-trailers	-4.4
6	Russia	Mining and quarrying	-4.3
7	China	Basic metals	-4.3
8	China	Chemicals and chemical products	-4.2
9	China	Legal and accounting activities	-3.8
10	China	Computer, electronic, and optical products	-3.7
11	China	Rubber and plastic products	-3.2
12	Russia	Chemicals and chemical products	-2.6
13	Slovakia	Basic metals	-2.5
14	India	Basic metals	-2.4
15	Poland	Basic metals	-2.2

Table 4-2 indicates that the top 15 sectors have a large CO₂ reduction effect based on marginal restructuring in the German automobile GSC. One can see that marginal restructuring targeting basic metals (Russia: RUS) can reduce the CO₂ emissions of the German automobile GSC significantly (-19.0 kt-CO₂, accounting for 0.03% of total GSC CO₂ emissions). In the German automobile GSC, the CO₂ reduction effect of basic metals (RUS) is more than 3.5 times greater than those of the Japanese case (Tables 4-1 and 4-2). German automobile GSC inputs include many intermediate goods from the basic metals (RUS) sector, which has the highest direct CO₂ emission coefficient of the relevant sectors in the WIOD. Therefore, the extraction of Russian basic metals and their substitution from other countries (mainly EU countries) can generate a significant CO₂ reduction effect.

Similar to the Japanese automobile GSC, the marginal restructuring of the Chinese manufacturing sectors (e.g., electrical equipment (CHN), machinery and equipment (CHN), and fabricated metal products (CHN)) in the German automobile GSC has a relatively large CO₂ reduction effect (Table 4-2). The CO₂ reduction effects of these manufacturing sectors range from -3.2 kt-CO₂ to -6.1 kt-CO₂, which are smaller than those of Japan (-1.5 kt-CO₂ to -15.3 kt-CO₂) (Tables 4-1 and 4-2). This result indicates that the German automobile GSC depends not only on a specific Chinese material but widely depends on Chinese manufacturing materials. This implies that eliminating dependence on this region through GSC restructuring can mitigate the global CO₂ emissions of the German automobile GSC.

4.4.2 Practical CO₂ reduction potentials of restructuring Japanese and German automotive GSCs

This study revealed the CO₂ reduction effects of the marginal restructuring of automobile GSCs through partial extraction analysis. These effects can be interpreted as the impact of GSC restructuring itself on the global carbon footprint when targeting specific suppliers in automobile GSCs. This section describes the practical CO₂ reduction potential of a reasonable scale of GSC restructuring considering the substitutability of each target sector.

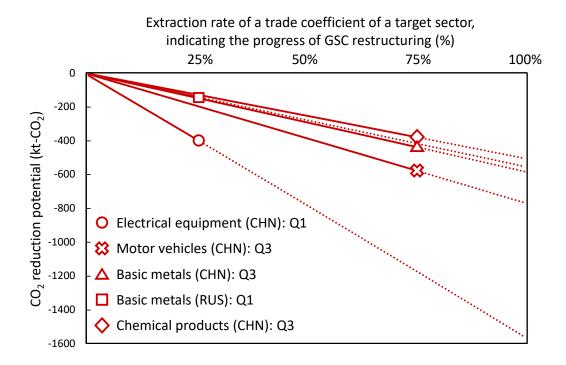


Figure 4-3. CO₂ reduction potentials according to the progress of Japanese automobile GSC restructuring considering the substitutability of a relevant sector based on the RCA index.

Figure 4-3 presents the CO₂ reduction potentials of the top five sectors that exhibit the largest CO₂ reduction effects based on the marginal restructuring of the Japanese automobile GSC considering the substitutability of relevant sectors based on the RCA index. The RCA indices of all sectors are listed in Table S2.3 in Supplementary materials 4.2. The horizontal axis represents the extraction rate of the trade coefficient of the target sector, indicating the progress of GSC restructuring as a percentage. The point at 100% indicates a scenario in which all international trade in a relevant sector is extracted from the automobile GSC and substituted by a corresponding sector in other countries (i.e., complete restructuring). The vertical axis represents the CO₂ reduction potential (kt-CO₂),

and the slope of the lines nearly indicates the CO₂ reduction effect of marginal restructuring of the sectors estimated by the partial and global extraction analysis⁴. The practical CO₂ reduction potential at the restructuring limit determined by groups (1) to (6), as defined in Figure 4-2, is represented by the markers. The CO₂ reduction potentials, according to the progress of restructuring up to the limit, are expressed by solid lines, and the dotted lines represent those above the limits.

As shown in Figure 4-3, in the case of the Japanese automobile GSC, the restructuring of motor vehicles (CHN) has the largest practical CO₂ reduction potential (-575 kt-CO₂, accounting for 0.8% of the global CO₂ emissions of the Japanese automobile GSC). This potential is 1.5 times greater than that of the electrical equipment (CHN) sector, which exhibited the greatest CO₂ reduction effect under marginal restructuring. However, because the electrical equipment (CHN) sector plays an important role in international trade, its RCA index is relatively high (RCA index: 2.2 (Table S2.3), belonging to Q1 group (5)). Therefore, while the CO₂ reduction effect of marginal restructuring in this sector is the greatest, the practical CO₂ reduction potential based on the promotion of restructuring in this sector is smaller than that of restructuring other sectors with high substitutability (i.e., motor vehicles (CHN), RCA index: 0.4, belonging to Q3 group (3)).

When this type of reversal occurs, the optimal restructuring strategy depends on the attitude of supply chain managers in the Japanese automobile GSC. Ambitious supply

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⁴ The curves in Fig. 4-3 are not linear, but very close to linear. This result is in accordance with the findings of a previous study based on the partial extraction analysis (Dietzenbacher and Lahr, 2013).

chain managers who conduct drastic GSC restructuring that overcomes the difficulties of substitution should strongly promote the restructuring of the electrical equipment (CHN) sector, which yields the greatest environmental benefits when complete restructuring is achieved. Otherwise, supply chain managers considering restructuring within a plausible scale should promote the restructuring of the motor vehicle (CHN) sector, which has the greatest practical CO₂ reduction potential.

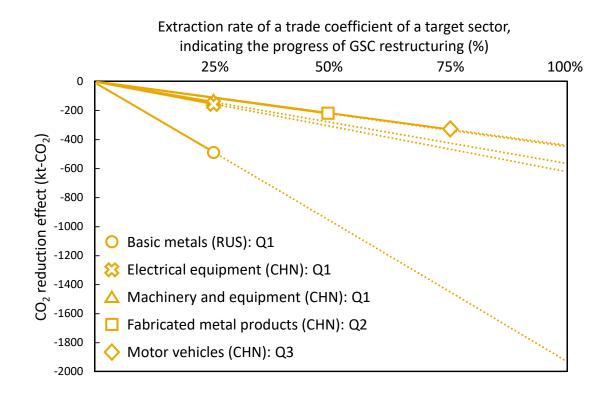


Figure 4-4. CO₂ reduction potentials according to the progress of German automobile GSC restructuring considering the substitutability of a relevant sector based on the RCA index.

Figure 4-4 presents the CO₂ reduction potentials of the top five sectors that exhibit

the greatest CO₂ reduction effects based on the marginal restructuring of the German automobile GSC considering the substitutability of relevant sectors based on the RCA index. In this case, the practical CO₂ reduction potential of the Russian basic metals sector, which exhibited the greatest CO₂ reduction effect based on marginal restructuring, is the greatest (-477 kt-CO₂, accounting for 0.7% of the global CO₂ emissions of the German automobile GSC). In Figure 4-4, this practical CO₂ reduction potential is greater than the others (1.5 times greater than the second-largest CO₂ reduction potential (-330 kt-CO₂) based on the restructuring of motor vehicles (CHN)). Therefore, compared to the Japanese case, the optimal restructuring strategy for the German automotive GSC is relatively simple. The promotion of restructuring the basic metals (RUS) sector in the German automobile GSC will yield the greatest benefit from the starting point of action. Therefore, it should be a top priority in policy strategies for the low-carbon supply chain restructuring of the German automotive GSC.

4.5 Discussion and Conclusions

This study focused on automotive GSCs in Japan and Germany and estimated the impacts of GSC restructuring in relevant sectors on their carbon footprints. To this end, this study extended the scenario-based HEM analysis framework developed by Maeno *et al.* (2022) into a more practical and flexible framework focusing on the scale of relevant GSC restructuring. This study applied the practical HEM analysis framework to the latest WIOD in 2014 and identified target sectors in which supply chain managers in the automobile sectors in Japan and Germany should prioritize low-carbon restructuring with substitutability for importing relevant intermediate products (e.g., basic metals) produced by other countries.

Recently, supply chain disruption shocks caused by the COVID-19 pandemic and the Russia/Ukraine conflict have stimulated global GSC restructuring (European Commission, 2020; OECD, 2022). Based on the above results, many significant opportunities exist to reduce CO₂ emissions by restructuring global supply chains. However, policies for global GSC restructuring mainly focus on reinforcing resilience based on the risk of uncertainty caused by foreign supply chains and disruptions (Business Europe, 2022; The White House, 2022; METI, 2022a; 2022b; 2022d). For example, considering existing policies in Japan, although the METI has implemented GSC restructuring policies such as developing new trade agreements in Quadrilateral Security Dialogue countries (i.e., Japan, The US, Australia, and India) or providing subsidies for the de-centralization of GSCs to firms, the impact of GSC restructuring on CO₂ emissions has been ignored. As a result, there are no incentives to reduce CO₂ emissions through

GSC restructuring (METI, 2022a; 2022d). The METI should promote supply chain restructuring by considering not only the economic but also environmental aspects. This study provides important insights for policymaking in this field, which has received little attention.

Following the evidence from the practical HEM analysis, policymakers and supply chain managers can decide on regulations or trade policies for GSC restructuring. As a policy implication for automobile GSCs based on the case studies, policymakers should strengthen trade agreements for excluding relevant target sectors with large CO₂ reduction potentials (i.e., electrical equipment (CHN), motor vehicles (CHN), and basic metals (RUS) in the case studies). Another effective policy implication is that policymakers should give firms incentives to reduce CO₂ emissions to a certain extent (e.g., practical CO₂ reduction potential) when they promote GSC restructuring.

Furthermore, policymakers can use evidence from the analytical framework developed in this study to implement trade-related climate policies such as the carbon border adjustment mechanism (European Commission, 2021) for low-carbon GSC restructuring. For example, a critical CO₂ reduction strategy for low-carbon GSC restructuring is that policymakers impose carbon costs on firms depending on the differences between the marginal CO₂ reduction effects of relevant target sectors (e.g., basic metals sectors around the world). To elaborate, by using the marginal CO₂ reduction effect of a relevant sector in a specific country that can reduce most CO₂ emissions through marginal restructuring (e.g., the Russian basic metals sector) as a benchmark, firms can be penalized for carbon costs if their CO₂ reductions based on marginal GSC

restructuring for the relevant sectors in other countries (e.g., South Korean basic metals sector) do not satisfy this benchmark. Through this process, the results of this study can provide firms with incentives to restructure the optimal target sectors for CO₂ reduction based on quantitative evidence. Additionally, by including the due diligence guidelines provided by the OECD (OECD, 2018) in policies for low-carbon GSC restructuring, firms can be motivated to reduce CO₂ emissions through GSC restructuring. In the shift toward the "new normal" conditions in the post-pandemic era, low-carbon GSC restructuring will play a crucial role in achieving a decarbonized society considering recent global events.

As a limitation, it is important to note that GSC restructuring defined in this study might implicitly have an unpractical aspect because the restructuring scenarios are based on the MRIOT, which follows the aggregated industrial classification. In the real world, it should be noted that the same industries in different countries might produce different products. Moreover, since this study defines GSC restructuring only in a monetary unit, GSC restructuring based on "a physical quantity" is not considered. Therefore, this study cannot reflect unit-cost information of a specific product on the GSC restructuring scenario. Potential future studies are expected to address these limitations.

Chapter 5: Conclusions

This Ph.D. dissertation reports on the design and execution of comprehensive analyses focusing on the relationship between the GSC restructuring and industrial CO₂ emissions. Integrating the EEIOA models with the HEM, this thesis develops an analysis framework that can estimate the impact of restructuring a specific GSC on CO₂ emissions from the relevant GSC to provide the necessary basis for effectively reducing CO₂ emissions through GSC restructuring (i.e., low-carbon GSC restructuring).

In Chapter 3, this thesis develops an integrated analysis framework based on the four IO methods called SEM. It models the relationships between hypothetical structural changes in the GSC, which eliminate CO₂ emission hotspots in the relevant GSC and CO₂ emissions. The results indicate that the GSC restructuring focusing on the CO₂ emission hotspot in the Japanese automotive GSC has a CO₂ reduction potential of 6.5% of its global carbon footprint. Furthermore, the replacement of the Chinese electrical equipment sector with the Japanese automotive GSC exhibits the most significant contribution to CO₂ reduction compared to other sectors included in the CO₂ emission hotspot. Concerning production locations in the newly formed GSC, while substitutions by South Korea and Germany decrease net CO₂ emissions, those by India show the opposite trend. Based on these results, this section discusses the policy implications of CO₂ mitigation through the GSC restructuring.

Chapter 4 develops the HEM framework into a practical and flexible one, focusing on the reasonable scale of relevant GSC restructuring by combining the partial HEM and

the RCA index. Based on the study's results, this chapter identifies the Chinese electrical equipment and Russian basic metals sectors, both of which relevant automotive GSCs are key sectors (i.e., key suppliers) for low-carbon GSC restructuring. These sectors exhibit the largest CO₂ reduction effects when targeted at the relevant GSC restructuring unit. This chapter also highlights the practical potential for CO₂ reduction based on a reasonable scale of relevant GSC restructuring, considering the substitutability of each target sector. Finally, based on these findings, this chapter discusses how policymakers should formulate trade policies prioritizing intermediate products to promote GSC restructuring toward low-carbon practices. It proposes an effective approach to utilize the results as benchmarks for setting CO₂ reduction targets or incentives in the context of GSC restructuring.

Through these analyses, this thesis provides science-based evidence for designing effective policies on how industries worldwide should promote GSC restructuring to reduce global carbon footprints. From the findings of Chapters 3 and 4, this thesis concludes that the GSC restructuring of industries has significant CO₂ reduction potential and suggests that stakeholders of a relevant GSC implement restructuring targeting key sectors that have the most significant reduction potential.

In this thesis, using the developed analytical frameworks, generalized case studies targeting all sectors included in the automotive GSCs are conducted to reveal the key sectors for the relevant industry to reduce its global carbon footprint. However, with detailed scenarios of target sectors of GSC restructuring based on MRIOTs, which have a high sectoral resolution, these frameworks can also be applied to assess the impacts of

specific events, such as the COVID-19 pandemic or Russia/Ukraine conflict, on the CO₂ emissions of a relevant GSC. Furthermore, these frameworks may be generalized for analyzing diverse environmental loads that have gained increasing importance in recent years, such as air pollution, natural resource consumption, forest and land use, and biodiversity losses.

Finally, it is essential to note that the frameworks developed in this thesis cannot capture the differences in the unit cost of a specific product across the producing countries. Additionally, these frameworks do not reflect changes in the price equilibrium of a specific product resulting from GSC restructuring. These factors could lead to underestimation or overestimation of the impact of GSC restructuring. This limitation represents significant room for improvement in future studies.

Supplementary materials

S.3.1 Modularity index

Following the relevant previous studies (Kagawa *et al.*, 2013, 2015; Tokito *et al.*, 2016; Tokito, 2018), this study applied the modularity index (Newman and Girvan, 2004) to determine the optimal number of clusters. The modularity index is an indicator of the validity of division of clustering and a higher score of the modularity index means a better result of division (Newman and Girvan, 2004; Yu and Ding, 2010; Kagawa *et al.*, 2013b, 2015). Figure S3-1 shows the modularity index of each number of clustering. This study found the maximum score, 0.33 which was obtained when the number of clusters is 20. Thus, this study identified 20 clusters in this case.

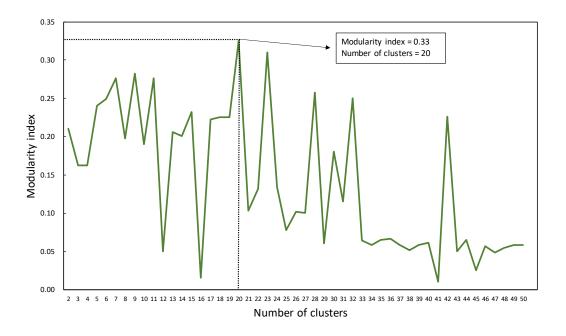


Figure S3-1. The modularity index of each number of clustering.

S.3.2 Clustering results

The complete clustering results for 2464 sectors in WIOD are shown in Table S2 at URL: https://ars.els-cdn.com/content/image/1-s2.0-S0140988321006101-mmc2.zip.

S.4.1 Checking the results based on another MRIO database: Exiobase

Table S4-1. Sectors with large CO₂ reduction effects (i.e., less than -0.1kt-CO₂) by a unit of restructuring of the Japanese automobile GSC based on Exiobase (2014).

CO ₂ reduction effect by a unit of restructuring of the Japanese automotive GSC based on Exiobase (2014)						
Rank	Country	Acronym	Industry	No_EXIO	No_WIOD	CO ₂ reduction effect (kt-CO ₂)
1	China	CHN	18	1698	410	-10.96
2	China	CHN	13	1693	405	-6.72
3	China	CHN	20	1700	412	-6.52
4	China	CHN	17	1697	409	-5.95
5	China	CHN	16	1696	408	-4.81
6	China	CHN	15	1695	407	-4.67
7	China	CHN	11	1691	403	-2.91
8	Russia	RUS	4	2020	2020	-2.84
9	China	CHN	19	1699	411	-2.02
10	China	CHN	14	1694	406	-1.78
11	India	IND	15	1919	1191	-0.77
12	China	CHN	6	1686	398	-0.54
13	Germany	DEU	32	312	592	-0.43
14	Taiwan	TWN	13	2253	2309	-0.43
15	China	CHN	4	1684	396	-0.36
16	China	CHN	32	1712	424	-0.36
17	Canada	CAN	4	1740	284	-0.29
18	China	CHN	10	1690	402	-0.29
19	India	IND	4	1908	1180	-0.29
20	Taiwan	TWN	4	2244	2300	-0.28
21	China	CHN	22	1702	414	-0.24
22	India	IND	20	1924	1196	-0.22
23	Korea	KOR	32	1824	1432	-0.21
24	Taiwan	TWN	11	2251	2307	-0.19
25	Indonesia	IDN	4	2356	1124	-0.18
26	China	CHN	27	1707	419	-0.17
27	Greece	GRC	32	648	984	-0.16
28	China	CHN	8	1688	400	-0.15
29	Brazil	BRA	15	1863	239	-0.15
30	Taiwan	TWN	32	2272	2328	-0.12
31	Japan	JPN	32	1656	1376	-0.11
32	India	IND	16	1920	1192	-0.11
33	China	CHN	21	1701	413	-0.11
34	India	IND	10	1914	1186	-0.11
35	India	IND	14	1918	1190	-0.11
Larger than -0.1	China	CHN	47	1727	439	-0.1

Table S4-2. Sectors with large CO₂ reduction effects (i.e., less than -0.1kt-CO₂) by a unit of restructuring of the Japanese automobile GSC based on WIOD (2014).

CO ₂ reduction effect by a unit of restructuring of the Japanese automotive GSC based on WIOD (2014)					
Rank	Country	Acronym	Industry	No_WIOD	CO ₂ reduction effect (kt-CO ₂)
1	China	CHN	18	410	-15.32
2	China	CHN	20	412	-7.6
3	China	CHN	15	407	-5.74
4	Russia	RUS	15	2031	-5.51
5	China	CHN	11	403	-4.97
6	China	CHN	14	406	-2.74
7	Russia	RUS	4	2020	-2.6
8	China	CHN	16	408	-2.54
9	China	CHN	17	409	-2.49
10	China	CHN	19	411	-2.09
11	China	CHN	13	405	-1.55
12	India	IND	15	1191	-1.12
13	Russia	RUS	31	2047	-1.11
14	Korea	KOR	15	1415	-1.06
15	Taiwan	TWN	15	2311	-0.96
16	India	IND	4	1180	-0.75
17	Taiwan	TWN	11	2307	-0.69
18	Brazil	BRA	15	239	-0.69
19	India	IND	20	1196	-0.67
20	China	CHN	24	416	-0.53
21	Taiwan	TWN	32	2328	-0.5
22	India	IND	11	1187	-0.45
23	India	IND	10	1186	-0.4
24	Russia	RUS	29	2045	-0.39
25	Japan	JPN	32	1376	-0.39
26	Russia	RUS	11	2027	-0.26
27	China	CHN	10	402	-0.25
28	China	CHN	6	398	-0.22
29	China	CHN	4	396	-0.22
30	China	CHN	29	421	-0.2
31	China	CHN	45	437	-0.18
32	Korea	KOR	32	1432	-0.18
33	Korea	KOR	14	1414	-0.17
34	Indonesia	IDN	4	1124	-0.17
35	Taiwan	TWN	33	2329	-0.16
36	China	CHN	8	400	-0.16
37	India	IND	16	1192	-0.14
38	China	CHN	7	399	-0.14
39	China	CHN	21	413	-0.13
40	India	IND	14	1190	-0.12
41	Taiwan	TWN	20	2316	-0.11
42	Russia	RUS	10	2026	-0.11
43	Taiwan	TWN	10	2306	-0.11
Larger than -0.1	India	IND	32	1208	-0.1

Table S4-1 and Table S4-2 show the sectors with large CO₂ reduction effects (i.e., less than -0.1kt-CO₂) by a unit of restructuring of the Japanese automobile GSC based on Exiobase and WIOD, respectively. The sectors overlapped in both tables are colored by red, and the others are colored by gray. In Table S4-1, the sectors with larger CO₂ reduction effects are described in darker red, and the corresponding sectors in Table S4-2 are described in the same color in Table S4-1.

From both tables, more than half of the sectors with large CO₂ reduction effects are overlapped in the results based on Exiobase and WIOD. In addition, the sectors colored by the darker red in Table S4-1 are more likely to place in the higher rank in Table S4-2. For example, the electrical equipment sector in China (number of WIOD: 410) had the largest CO₂ reduction effect based on both databases, and the automotive sector in China (number of WIOD: 412) had the third largest CO₂ reduction effect based on Exiobase while it had the second largest effect based on WIOD. This implicates that the results based on the different databases show a close tendency.

As for the effects of all sectors, the results are shown in Table S2.4 at URL: . https://ars.els-cdn.com/content/image/1-s2.0-S0140988323005236-mmc1.zip

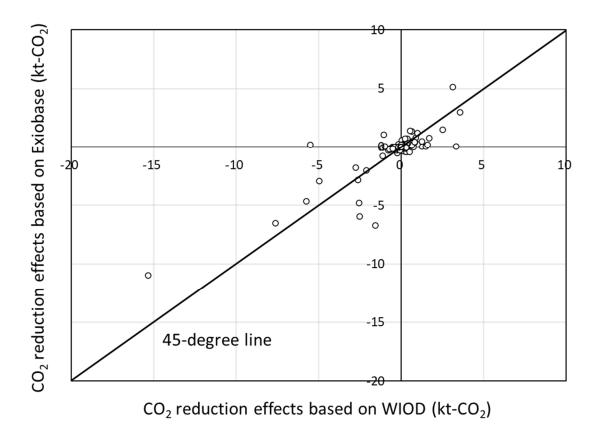


Figure S4-1. The convergence of the results (i.e., CO₂ reduction effect by a unit of restructuring of the Japanese automotive GSC targeting every sector) based on Exiobase and WIOD.

Figure S4-1 shows the CO₂ reduction effects by a unit of restructuring of the Japanese automotive GSC targeting every sector based on both databases. The vertical axis shows the CO₂ reduction effect based on Exiobase and the horizontal axis shows that based on WIOD. The results on the 45-degree line means that the CO₂ change effect based on both databases are the same value. From the figure, many cases (i.e., dots) are close to the 45-degree line, which means that the results based on the different databases also show a close tendency in the scale of the effects. These results can support the application and the results of WIOD in this study.

S.4.2 CO₂ emission change effect by marginal restructuring of every sector in Japanese and German automobile GSCs

The CO₂ emission change effects of all sectors included Japanese and German automobile GSCs are shown in Table S2.1, Table S2.2, respectively. The results are available at URL: https://ars.els-cdn.com/content/image/1-s2.0-S0140988323005236-mmc1.zip

S.4.3 RCA index of every sector in WIOD

The RCA index of every sector in WIOD is calculated based on the value added generated by exports. To ensure robustness of the RCA index, this study applied the average RCA value on five years of 2010-2014, which are shown in Table S2.3. The results are available at URL: https://ars.els-cdn.com/content/image/1-s2.0-S0140988323005236-mmc1.zip

Acknowledgement

First of all, I extend my deepest gratitude to my supervisor, Professor Shigemi Kagawa of Kyushu University. When I first joined his laboratory as a third-year undergraduate student, I was lazy and lethargic about everything because I did not have anything I wanted to do at the university. However, he did not abandon me and provided me with continuous encouragement for my seminar activities for seven years. Especially in research, he always told me "Take it easy, enjoy!" and supported me with deep knowledge and insightful ideas. The experiences he gave me not only ignited my passion for research but also propelled me to pursue a career as a researcher. Looking backward, I believe that belonging to his laboratory was the most fortunate event in my life. Again, I would like to express my sincere appreciation for Prof. Kagawa, who completely changed my life and gave me a lot of love throughout my university days as a laboratory member.

I am very thankful to Professors Hidemichi Fujii and Toshiyuki Fujita of the Faculty of Economics, Kyushu University. This Ph.D. thesis benefited greatly from critical questions and constructive comments from them. Additionally, Prof. Fujii kindly gave me advice and suggestions when he stepped in my lab room 406, which was shared by his laboratory members. His comments have also been used in my research. I would like to express my appreciation for this.

I would also like to express my appreciation to researchers at external institutions.

Dr. Masaharu Motoshita of the National Institute for Advanced Industrial Science and

Technology kindly supported me when I organized a young researcher's event at a conference. Furthermore, he gave me a lot of feedback on my research, leading to a research collaboration with him. Dr. Keisuke Nansai of the National Institute for Environmental Studies provided constructive comments on my research and he always motivated me with encouraging messages. Prof. Seiji Hashimoto of Ritsumeikan University, Prof. Hiroki Tanikawa of Nagoya University, and Assoc. Prof. Yosuke Shigetomi of Nagasaki University provided critical feedback on my research during the annual joint seminars. Dr. Shunichi Hienuki of Yokohama National University also provided valuable comments on my research at the conference. Dr. Norihiko Yamano of the OECD and Dr. Heran Zheng of University College London provided valuable advice on my research and helped me easily join the IIOA community. My scientific expertise has continuously advanced during my research.

Importantly, I extend my sincere gratitude to the members of the Kagawa Laboratory. Dr. Hirotaka Takayabu of Kindai University kindly accepted me as a mentor when I was a third-year undergraduate student. He protected me when I was lazy and controlled my motivation to move forward. He always expected me to perform better, which made me feel confident. The starting point of my academic career was to work with him. Dr. Shohei Tokito of Yamagata University taught me a lot of knowledge of not only input-output analysis but also how to write an academic paper. The discussion with him was always critical and deepened my research. Dr. Tomoaki Nakaishi of Kyushu University has always helped and motivated me as a good friend or sometimes colleague. His passion and hungry spirit for research always stimulated me. Dr. Shogo Eguchi of Fukuoka University, Dr. Fumiya Nagashima of Kindai University, Dr. Mitsuki Kaneko

of Mie University, and Dr. Minami Kito of Fukuoka Institute of Technology are kind and greatly supported me.

I would also like to thank the junior students at the laboratory. Haruka Mitoma has been of the same grade as me and is a good friend. She always entertained everyone around her, and I was helped by her affability and ability to break ice many times. Sora Matsushima, Taiga Shimotsuura, Seiya Imada, and Yusuke Oga shared a lot of time with me as they proceeded to the Ph.D. course, giving me enjoyable memories. Their growth always led to my own growth, and the relationship with them made my studies harder as a senior student in the laboratory. I am very grateful to all the members of the Kagawa laboratory with whom I have met for seven years.

Finally, I express my sincere gratitude to my family for their support and understanding. I am grateful for their patients' trust in me, who wasted much time at university. I do not thank you further.

October, 2023

Klitaw Maeno

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