Role of Vehicle Lifetime in Climate Change

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Role of Vehicle Lifetime in Climate Change

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Ph.D. in Economics

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Chapter 1: Introduction

1.1 Climate impact of automobiles

Human activities have already caused global warming of 1.0 °C above pre-industrial levels (Figure 1.1). If we were to maintain today's mass-production and mass-consumption society, the global warming would reach 1.5 °C between 2030 and 2052 (IPCC, 2018). By current accelerated global warming, there is concern over the unprecedented climate change and loss of biodiversity. For this reason, global warming is an urgent issue to address through effective CO_2 emission reduction policies. Achieving the Paris Agreement goals as adopted at COP21 will require highly transparent climate change countermeasures (UNFCCC, 2016).

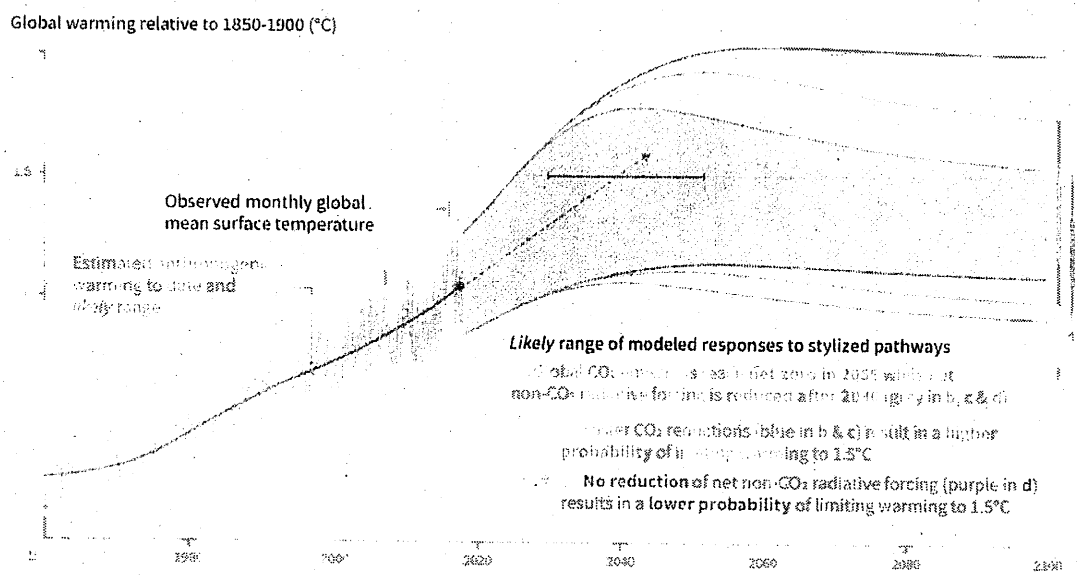

Figure 1.1: Human-induced global warming change above pre-industrial levels

Source: Summary for Policymakers. In Global Warming of 1.5°C (IPCC, 2018)

Considering global CO_2 emissions in 2017 by sector, the transportation sector accounts for 25% of the global CO_2 emissions, which is the second largest volume after power generation sector (Figure 1.2). In 2017, global petroleum demand by road vehicles and the number of car stock in the world are increased in 1.3 times and 1.6 times in comparison with 2000 (IEA, 2018). These facts indicate that the automotive sector is of particular concern.

Automotive CO_2 emissions come both directly, from driving vehicles, and indirectly, from various industries in each country through a massive global supply chain of the materials and parts required for automotive manufacturing. Each country has an obligation to lead initiatives mitigating the human contributions to climate change by reigning in the CO_2 incidental to vehicle life-cycles: the carbon footprint of vehicles (Pavlínek and Ženka, 2011; Timmer *et al.*, 2015; Kagawa *et al.*, 2015a; Tokito, 2018).

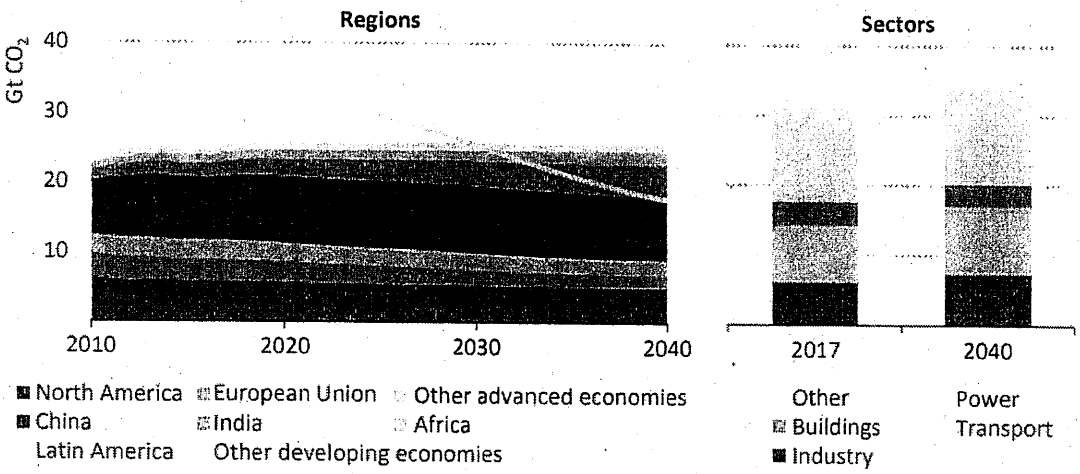

Figure 1.2: Global CO_2 emissions in 2017 by regions and sector (Gt CO_2)

Source: World Energy Outlook 2018 (IEA, 2018)

Recently, the situation around the automobile has been changing greatly. In Japan, for example, technological breakthroughs in the internal combustion engine, development of next-generation vehicles such as hybrid vehicle and fuel cell vehicle, and distribution streamlining are driving down CO_2 emissions from vehicle driving (Japan Automobile Manufacturers Association: JAMA, 2016).

Although the diffusion of next-generation vehicles contribute to reduction of direct CO_2 emission at driving phase, the indirect CO_2 emissions (e.g., parts manufacturing and production) from a next-generation vehicle larger than that from a gasoline vehicle (Toyota, 2015). The reason for this, states Toyota (2015), is that reduction in the environmental burden of product lifecycle does not override the quality of product, in an early stage of product development (e.g., the commercial release of the fuel cell vehicle is within 5 years in Japan). The production number of next-generation vehicles will surely increase in the future (IEA, 2018). For this reason, it is the pressing issue that reduction of the indirect CO_2 emissions from next-generation vehicles.

1.2 Circular economy: prolonger use of durable goods

In action plan for the circular economy (EC, 2019), EC are getting more attention in life-cycle assessments of products as follows:

> 'The circular economy should be made a backbone of the EU industrial strategy, enabling circularity in new areas and sectors, life-cycle assessments of products should become a norm and the eco-design framework should be broadened as much as possible.'

With this kind of background, it is essential in debating policy to analyze CO_2 emissions for the entire product life-cycle, from resource mining to vehicle disposal, and not just the product usage phase (Ou *et al.*, 2010; Melaina and Webster, 2011; Pauliuk *et al.*, 2011). There is particularly great interest in how product lifetime extension would impact CO_2 emissions across the full product life-cycle (Cooper, 2005). Previous studies on Switzerland, Germany, and Japan (Spielmann and Althaus 2007; Wursthorn *et al.* 2010; Kagawa *et al.* 2011) have concluded that extending vehicle lifetime will reduce overall life-cycle CO_2 emissions and be beneficial for the environment.

Generally, a longer product lifetime means that consumers buy new products less often (Serrenho and Allwood 2016; Nishijima 2017; Nakamoto 2017), in turn helping to reduce the CO_2 incidental to manufacturing new products (Bobba *et al.* 2016; Bakker *et al.* 2014; Emmenegger *et al.* 2006). However, slowing the pace of product replacement will leave many older, less energy-efficient products in society, which will increase CO_2 emissions incidental to product usage(Yu *et al.* 2010; Ardente and Mathieux 2014). If we were to achieve higher standards in energy efficiency, maybe disseminating a larger numbers of energy-efficient new products by shortening product lifetime would make the CO_2 reduction effects for product usage exceed the CO_2 increasing effect from product manufacturing (Rüdenauer and Gensch, 2005; Spitzley *et al.*, 2005; Truttmann and Rechberger, 2006; Cooper, 2010; Skelton *et al.*, 2013). Thus, it is important to analyze the role of the vehicle lifetime extension of countries in CO_2 emissions for the entire product life-cycle at globe.

1.3. Structure of this dissertation

This Ph.D. dissertation comprises six chapters (Figure 1.3). Chapter 2 provides a comprehensive review of relevant existing articles, identifies the contributions and problems of the existing research, and describes the significance and objectives of the present study.

Chapter 3 spatially extended the vehicle life-cycle analysis of a single country and developed a new method for vehicle life-cycle analysis by combining a 15-country automotive stock-flow model based on the 15-country automotive lifetime distribution with global multi-regional input-output analysis. From the results, I revealed that roles of changes in vehicle lifetime and fuel efficiency on global CO_2 emissions are vastly different between countries where vehicle lifetimes are longer and those where lifetimes are shorter.

Chapter 4 estimated the carbon footprint associated with the global final demand of automobiles and auto-related petroleum of the U.S.A., Germany, and Japan, which account for 31% of the stock of passenger cars in the world in 2009, during 1995 to 2009. This chapter further developed a comprehensive new method that offers a deeper understanding of the structural change in the global final demand of automobiles and discussed how the lifetime of automobiles of a specific country has contributed to their carbon footprints. Based on the results, I discuss what role change in the lifetime of automobiles has contributed to their carbon footprints.

Chapter 5 developed an integrated assessment framework by combining dynamic discrete choice analysis with life-cycle environmental accounting analysis based on a dynamic stock model. From the empirical results, I suggest the modifying the regulation policy with a focus on the car inspection system to induce car owners to keep their automobiles longer.

Chapter 6 summarizes the analysis results obtained from Chapters 3 to 5, and presents the conclusions of this dissertation.

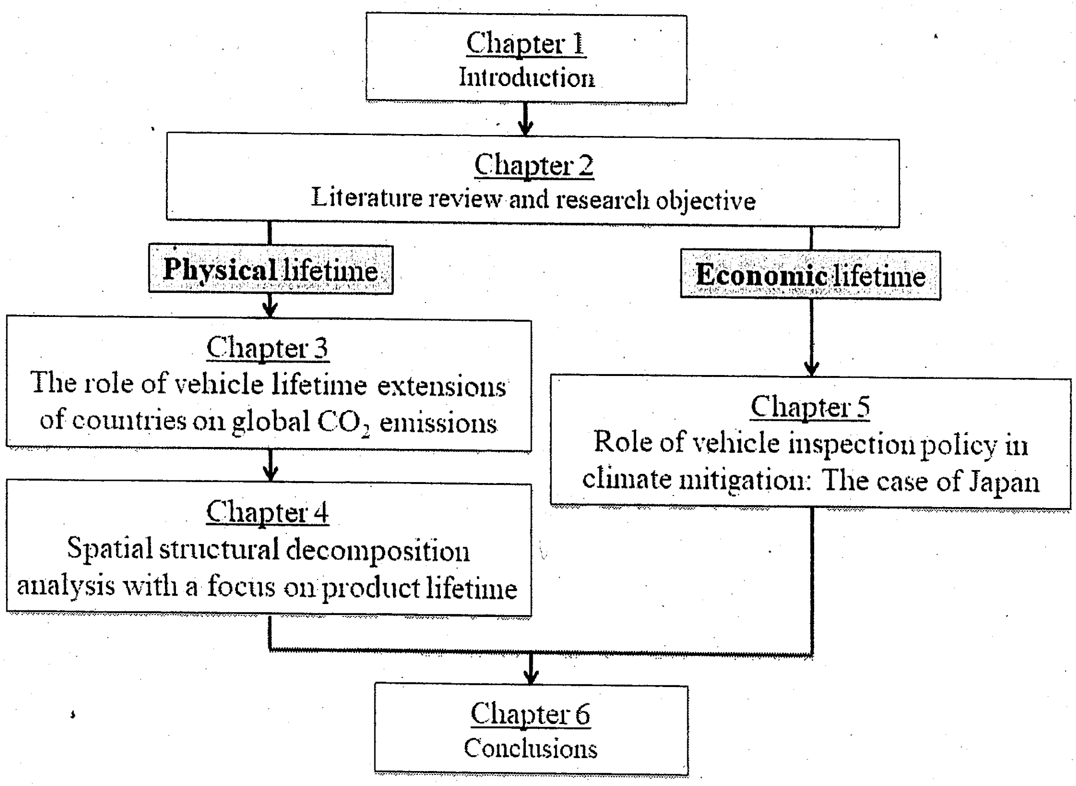

Figure 1.3: Structure of this Ph.D. dissertation

The contents of Chapters 3, 4, and 5 in this dissertation have been published in the following peer-reviewed journals as follows.

Chapter 3:

Nakamoto, Y., Nishijima, D. and Kagawa, S. (2019) 'The Role of Vehicle Lifetime Extensions of Countries on Global CO_2 Emissions', *Journal of Cleaner Production*, 207, 1040-1046.

Chapter 4:

Nakamoto, Y. (2019) 'Spatial Structural Decomposition Analysis with a Focus on Product Lifetime', *Economic Systems Research*, *Provisionally Accepted.*

Chapter 5:

Nakamoto, Y. and Kagawa, S. (2018) 'Role of vehicle inspection policy in climate mitigation: The case of Japan', *Journal of Environmental Management*, 224, 87–96.

Chapter 2: Literature review and research objectives

2.1. Life-cycle assessment: Process model and IO model

Life-Cycle Assessment (LCA, ISO14040/44) was adopted as one of the international standard for environmental management systems, known as ISO 14000 series, by International Organization for Standardization (ISO) in 1997 (Klüppel, 1999). In action plan for the circular economy (EC, 2019), LCA is clearly written as 'life-cycle assessments of products should become a norm'. Even though about 20 years have passed since LCA was adopted in ISO, there is considerable attention being paid to LCA (Hellweg and Canals, 2014; Mattila *et al.*, 2012; Canals *et al.*, 2011).

LCA can be divided broadly into two approaches: Process model (physical base) and Input-Output (IO) model (monetary base). Process model is a bottom-up approach, that sums up the environmental burden from resource mining to product disposal (from cradle to grave). On the other hand, IO model is a top-down approach, that is based on the input-output tables (Hawkins *et al.*, 2007; Hendrickson *et al.*, 1998, 1997). In IO model, by using the CO_2 emission intensities per industry and the direct and indirect inputs of required for unit production of a product, we can estimate the environmental impacts of the product. The properties of Process model and IO model are explained below.

Process model is featured by the detailed assessment of emissions from each life-stages and inventories of a specific product. Due to this characteristic, companies are applying LCA for the cleaner production of their products (Heijungs, 1994; Reich, 2005). For instance, (Yokokawa *et al.*, 2019) demonstrated environmental impacts of packaging-derived changes, comparing a refrigerated milk witch have a polyethylene (PE) laminated carton with a refrigerated milk witch have an aluminum and PE laminated carton.

However, in Process model, the selection of system boundaries is arbitrary. If the assessment cannot take all environmental burdens from relevant supplies into account, the life-cycle CO_2 emission of the product will be underestimated. (Lenzen, 2000; Suh *et al.*, 2004). Raynolds *et al.* (2000) states that the identification the entire life-cycle emissions is impossible in Process model. Thus, it should be noted that the life-cycle CO_2 emission have systematic errors estimated by Process model. Moreover, Process model relatively requires enormous amount of inventory data, cost, and time.

Meanwhile, the input-output table used in IO model, is a matrix that broad monetary aggregates industries and commodities in a single country, showing the linkages of goods and services, and regularly updated by statistical bureaus (once in a five-year period in Japan). Thereby, in theory, IO model specifies all of the direct and indirect inputs required for unit production of a product. In other words, we can completely estimate carbon footprint of product in IO model. In addition, IO model relatively requires small amount of data, cost, and time (Lenzen, 2000).

On the other hand, as the average industrial technology and broadly aggregated input-output structure are used in IO model, the result of LCA is relatively rough (Hertwich, 2005; Peters, 2008). Accordingly, the products that has the same price and belongs to the same industry (e.g., a \$20,000 car of motor company A and a \$20,000 car of motor company B), even if the design and functionality are different from each other (e.g., fuel efficiency, horse power, and riding capacity), has the same input-output structures and the same life-cycle emissions. Additionally, in IO model, system boundary is upstream of production stages, and so the assessments cannot cover the emissions from downstream of production stages (i.e., product use by the consumer or wastes by disposal activity) (Lave *et al.*, 1995).

This section will close by introducing the hybrid LCA model, that employing characteristics of both Process model and IO model, and complementing respective faults (Kagawa and Inamura, 2001; Shao and Chen, 2013; Strømman *et al.*, 2009; Suh and Huppes, 2005). At first, the hybrid LCA model analyzes detailed physical inventories of a specific product based on Process model. Next, based on IO model, the hybrid LCA model calculates life-cycle emissions that could not cover by the Process model. This comprehensive life-cycle analysis was proposed by Joshi (1999). As a case study, he also estimated the CO_2 emissions of the automotive fuel tank through the entire life-cycle such as tank manufacturing phase, use phase, and waste and recycling phase. In this dissertation, the estimation procedure of the carbon footprint of vehicles is based on the hybrid LCA model.

2.2. Studies on Environmentally Extended Input–Output Analysis

Environmentally extended input–output analysis (EEIOA), which is an application of input–output analysis to environmental impact assessment, was pioneered by Wassily Leontief (1971) and has been widely adopted in environmental impact assessment (see, for example, (Hamilton, 1997) on deforestration, (Lange, 1998) on air pollution, water use, and land use, (Wier and Hasler, 1999) on nitrogen, (Lenzen and Murray, 2001) on land use, (Dixon *et al.*, 2003; Emmerson *et al.*, 1995; Roson and Sartori, 2015; Zhang *et al.*, 2012) on water use, and (Feng *et al.*, 2015; Hoekstra *et al.*, 2016) on GHG). By using the inputs for the product of each industry, and the CO_2 emission intensity of the relevant industry (e.g., CO_2/ a million yen), we can estimate the direct and indirect environmental burdens associate with the final demand of the product.

Furthermore, EEIOA has been widely employed not only in life-cycle footprint analysis, but also in material and energy demand analysis, and in stock-flow analysis in many countries and regions, and global. (see, for example, material: (Weinzettel and Kovanda, 2011; Wiedmann *et al.*, 2015; Wood *et al.*, 2009), energy: (Liao *et al.*, 2007; Sun, 1998; Weber, 2009; Zhang and Lahr, 2014), waste: (Beylot, 2015; Liao *et al.*, 2015; Nakamura and Kondo, 2006, 2002)). Wiedmann *et al.*, (2015) estimated the material use that is induced by the consumption of nations (material footprint: MF) and the raw material equivalents (RMEs) of imports and exports of 186 countries. As a result, they pointed out that the current material use of nations is grave situation, since there is great difference domestic material consumption (DMC) that is used in many countries in policy making and consumption based MF.

Static EEIOA is used for measuring economic impact, productivity, or environmental burden from a relatively normative and short-term perspective, while structural decomposition analysis (SDA) is aimed at breaking changes of components down into certain driving forces from a relatively positivistic and long-term perspective. Index decomposition analysis (IDA) uses regional-level or national-level aggregated data. On the other hand, SDA is based on input–output tables and so enables the analyst to include indirect demand effects induced by certain direct demand effects (Ang, 1994; Dietzenbacher and Los, 1998; Hoekstra and van der Bergh, 2003; Lenzen, 2016; Su and Ang, 2012).

Especially in the energy and environment field, SDA has been conducted for multiple regions (Alcántara and Duarte, 2004; de Nooij *et al.*, 2003; Unander *et al.*, 1999) by using multi-regional input-output tables (MRIO) as well as for the regional level by using the national input-output tables of many countries (Baiocchi and Minx, 2010; Cao *et al.*, 2010; Lim *et al.*, 2009; Munksgaard *et al.*, 2000; Peters *et al.*, 2007). Some analyses have focused on consumption (final demand) versus technology (production structure and emission intensity) over time (Baiocchi and Minx, 2010; De Haan, 2001; Roca and Serrano, 2007). The general findings of these studies is that GHG emissions have increased due to the expansion of consumption but that the emissions were mitigated by improvements in technology and efficiency over the study period.

2.3. Product lifetime analysis

Product lifetime can be divided broadly into two categories: *physical* lifetime that denotes the survival (failure) rate during production stage and final waste stage, and *economic* lifetime that represents the possession (replacement) rate during purchase of a product and replace the product (Murakami *et al.*, 2010; Oguchi *et al.*, 2010, 2006; Tasaki *et al.*, 2001) (see Figure 2.1).

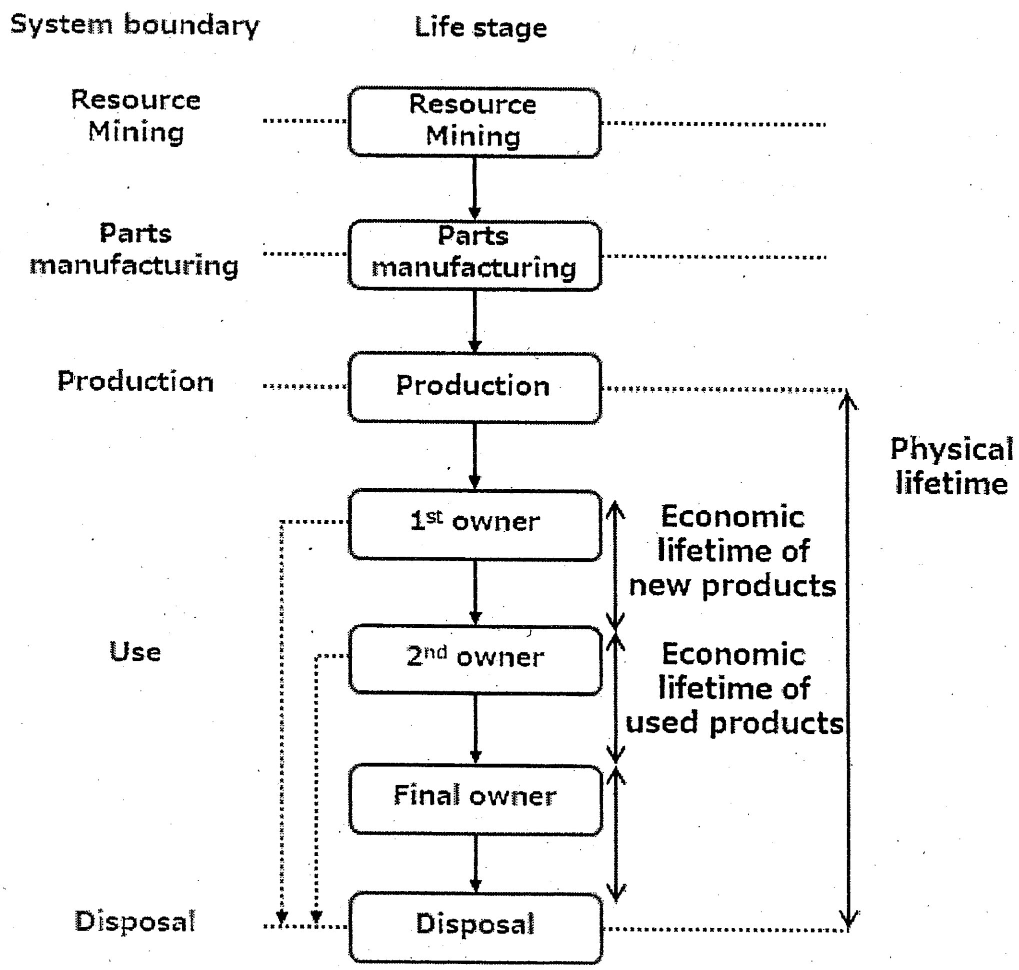

Figure 2.1: definitions of product lifetime for durable goods.

Note: Modified from Murakami *et al.* (2010).

Kagawa *et al.* (2011), for example, estimated the average *physical* lifetime of gasoline passenger cars in Japan (number of years of survival from the time of new car purchase to the time of disposal) to be 11.5 years. In contrast, according to a survey on passenger car market trends (Japan Automobile Manufacturers Association; JAMA, 2016), the *economic* lifetime of the average gasoline passenger car in Japan (number of years of ownership from the time of new car purchase to the time of car replacement) is 6.9 years. Thus, the economic lifetime of vehicles is approximately only half the physical lifetime of vehicles in Japan.

The *physical* lifetime distribution analysis has been applied in a wide range of durable goods or material such as personal computers, TV, air conditioner, refrigerator, and buildings (Babbitt *et al.*, 2009; Bayus L. B., 1988; Cox *et al.*, 2013; Echegaray, 2016; Islam and Meade, 2000; Kim *et al.*, 2003; Nomura and Momose; 2008; Miller *et al.*, 2016; Petridis *et al.*, 2016; Tasaki *et al.*, 2013; Weymar and Finkbeiner, 2016). When we estimate the number of surviving (failing) products in the product lifecycle analysis, the relevant product lifetime is an important parameter. Hence, the product lifetime enables us to do dynamic LCA, or LCA that considering with aging of the product, based on stock-flow analysis of the product.

In vehicle life-cycle analysis that is based on product lifetime, by controlling lifetime distribution of vehicles, the analyst can estimate the reduction potentials through the more diffusion of the greener vehicles and change in the energy mix as a result of short-term replacement of older cars (see (Hao *et al.*, 2011; Zhao and Heywood, 2017) in China, (Wursthorn *et al.*, 2010) in Germany, (Alam *et al.*, 2017) in Ireland, (Singh and Strømman,

2013) in Norway, (Baptista *et al.*, 2012) in Portugal, and (Kromer *et al.*, 2010) in USA).

Furthermore, *physical* lifetime distributions (e.g., Weibull distribution) have been employed widely in studies on material flow analysis (e.g., Nakamura *et al.*, 2014; Pauliuk *et al.*, 2017) and on estimating the amount of stock of various materials (e.g., iron (Daigo *et al.*, 2007), aluminum (Chen and Graedel, 2012), and copper (Spatari *et al.*, 2005)). Regarding to electrical appliances (particularly ICT products such as laptop and mobile phone), there is particularly great interest in material flow and stock analysis of *E-waste*, or electronic and electrical wastes, based on the product lifetime. (Araújo *et al.*, 2012; Dwivedy and Mittal, 2010; Jain and Sareen, 2006; Leigh *et al.*, 2007; Nguyen *et al.*, 2009; Pant, 2013; Polák and Drápalová, 2012; Steubing *et al.*, 2010; Wang *et al.*, 2013; Yoshida *et al.*, 2009). Yoshida *et al.* (2009) analyzed of material flow for the laptop and desktop PCs in Japan. From the results, they found that an increase of domestic use and exports of used PCs has decreased the disposal rate of PCs in Japan.

Previous studies that have modeled product replacement purchases based on *physical* lifetime distribution have not evaluated *economic* lifetime. In other words, such studies have not adequately described the *economic* lifetime of products based on the choice behavior of consumers—that is, how consumers decide every term to either continue using the same product or to make a replacement purchase. Thus, studies to date have been unable to make effective policy proposals in relation to product demand policy. Numerous studies have been carried out on commodity markets using discrete choice models based on consumer theory (random utility theory)—e.g., Rust (1987), Chevalier and Goolsbee (2005), Gordon (2009), Schiraldi (2011), and Gavazza *et al.* (2014)—but thus far few studies have tried to assess the influence of adopting or modifying demand policy for durable goods on global warming.

By applying EEIOA to the environmental impacts, and material and energy problems, there has been much discussion on the policies to achieve the sustainable development. In particular, there is great interest in product lifetime extension as a circular strategy, that is a policy to establish the circular economy (EC, 2015). Current life-cycle studies based on product lifetime have concluded that, we can receive more environmental benefits through the extending lifetime of older products with less energy-efficient, than disseminating a larger numbers of energy-efficient new products by shortening lifetime. (see, for example, (Bakker *et al.*, 2014) on refrigerator and laptop, (Bobba *et al.*, 2016) on vacuum cleaner, (Emmenegger *et al.*, 2006; Yu *et al.*, 2010) on mobile phone, (Ardente and Mathieux, 2014) on washing machine, and (Aktas and Bilec, 2012) on buildings). Aguilar-Hernandez *et al.* (2018) states that, a lifetime extension of a product reduces the demand of consumers for that product, and hence reductions of intermediate input and energy input for the production of the product can be achieved.

Based on the case of automobiles, the indirect CO_2 emissions (e.g., parts manufacturing and production) accounted for about 20%, 30%, and 70% of the overall life-cycle CO_2 emissions from a gasoline vehicle, a hybrid vehicle, and a fuel cell vehicle, respectively (Toyota, 2015). Since increasing of indirect energy and material inputs through enhance the value added (advanced functions, safety measures, etc.) on the vehicles, environmental management systems of automobile industry have to change the direction from the improving fuel efficiency to reducing the indirect emissions associate with the global supply chains of products (Carbon trust, 2016). In this context, the vehicle lifetime extension will expand of the scale of the indirect impacts on the environment.

2.4. Contribution of this dissertation

To the best of my knowledge, previous studies on automobile lifetime analysis have the following issues:

(1) There are no international comparisons of what impact changes in product lifetime have on the product's carbon footprint.
(2) It is unclear what impact changes in product lifetime in a country have on the structure of final demand through the global supply chain and carbon footprint associated with the global final demand.
(3) There are no life-cycle analysis that have modeled vehicle replacement purchases based on *economic* lifetime of vehicles.
(4) There are no highly transparent policies to achieve a lifetime extension of vehicles.

To address these issues, this Ph.D. dissertation conducted environment input-output life-cycle analysis focusing on changes in the global final demand for automobiles and auto-related petroleum induced by the automobile lifetime changes of countries.

First, I spatially extended the vehicle life-cycle analysis of a single country and developed a novel method for vehicle life-cycle analysis by combining a 15-country automotive stock-flow model with global multi-regional input-output analysis (e.g., Lenzen *et al.*, 2012; Kagawa *et al.*, 2015a). Specifically, this dissertation focuses on passenger vehicles sold and owned from 1995 to 2008 in the 15 countries (Australia, Austria, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, South Korea, Spain, U.K., and U.S.A.). Using the World Input-Output Database (WIOD) (Timmer *et al.*, 2015), I estimated the impact of changes in lifetime and fuel efficiency for vehicles owned in these countries on the carbon footprint associated with global vehicle supply-chains in 2008. From the results, I argue that roles of changes in vehicle lifetime and fuel efficiency on global CO_2 emissions are vastly different between countries where vehicle lifetimes are longer and those where lifetimes are shorter.

Second, this dissertation estimated the carbon footprint associated with the global final demand of automobiles and auto-related petroleum of the U.S.A., Germany, and Japan, which account for 31% of the stock of passenger cars in the world in 2009, during 1995 to 2009. Furthermore, I developed a comprehensive new method that offers a deeper understanding of the structural change in the global final demand of automobiles and discussed how the lifetime of automobiles of a specific country has contributed to their CFs.

Finally, I develop an integrated assessment framework by combining dynamic discrete choice analysis with life-cycle environmental accounting analysis based on a dynamic stock model. In particular, to achieve a product lifetime extension, I focused on vehicle safety inspection system and this system has an effect of shortening the *economic* lifetimes of automobiles and increasing CO_2 emissions associated with vehicle life-cycle. From the empirical results, I found that modifying the regulation policy with a focus on the car inspection system to induce car owners to keep their automobiles longer would have environmental benefits.

Chapter 3: The Role of Vehicle Lifetime Extensions of Countries on Global CO_2 Emissions

3.1. Introduction

Achieving the Paris Agreement goals as adopted at COP21 will require highly transparent climate change countermeasures (UNFCCC, 2018). Looking at the worldwide greenhouse gas (GHG) emissions by sector for 2010, the transportation sector, at approximately 14% bears much of the responsibility for emissions (IPCC, 2014). The automotive sector is of particular concern. Automotive CO_2 emissions come both directly, from driving vehicles, and indirectly, from various industries in each country through a massive global supply chain of the materials and parts required for automotive manufacturing. Each country has an obligation to lead initiatives mitigating the human contributions to climate change by reigning in the CO_2 incidental to vehicle life-cycles: the carbon footprint of vehicles (Pavlínek and Ženka, 2011; Timmer *et al.*, 2015; Kagawa *et al.*, 2015a; Tokito, 2018).

Given the above situation, in Japan, for example, technological breakthroughs in the internal combustion engine, development of next-generation vehicles, and distribution streamlining are driving down CO_2 emissions from vehicle driving (Japan Automobile Manufacturers Association: JAMA, 2016). The world greatly needs a shift from linear economies to circular economies (European Commission, 2015). In action plan for the circular economy, EC are getting more attention in closing supply chains and resource efficiency. With this kind of background, it is essential in debating policy on this shift to analyze CO_2 emissions for the entire product life-cycle, from resource mining to vehicle disposal, and not just the product usage phase (Ou *et al.*, 2010; Melaina and Webster, 2011; Pauliuk *et al.*, 2011).

There is particularly great interest in how product lifetime extension would impact CO_2 emissions across the full product life-cycle (Cooper, 2005). Previous studies on Switzerland and Japan (Spielmann and Althaus, 2007; Kagawa *et al.*, 2011) have concluded that extending vehicle lifetime will reduce overall life-cycle CO_2 emissions and be beneficial for the environment.

Generally, a longer product lifetime means that consumers buy new products less often (Serenho and Allwood, 2016), in turn helping to reduce the CO_2 incidental to manufacturing new products. However, slowing the pace of product replacement will leave many older, less energy-efficient products in society, which will increase CO_2 emissions incidental to product usage. It is possible that Switzerland and Japan as mentioned above are special cases. Perhaps the reductions in CO_2 from product manufacturing with extended product lifetimes would not exceed the increases in CO_2 from product usage. If we were to achieve higher standards in energy efficiency, maybe disseminating a larger numbers of energy-efficient new products by shortening product lifetime would make the CO_2 reduction effects for product usage exceed the CO_2 increasing effect from product manufacturing (Rüdenauer and Gensch, 2005; Spitzley *et al.*, 2005; Truttmann and Rechberger, 2006; Cooper, 2010; Skelton *et al.*, 2013).

To the best of our knowledge, we found the following issues: (1) there are no international comparisons of what impact changes in product lifetime have on the product's carbon footprint; and (2) there are no estimates of what impact changes in product lifetime in a relevant country have on carbon footprint of the global supply chain. To address these two important issues, in this study, we used the automotive lifetime distributions as estimated by Oguchi and Fuse (2015) for 15 countries. Based on this 15-country automotive lifetime distribution, we developed a novel method for vehicle life-cycle analysis by combining a 15-country automotive stock-flow model with global multi-regional input-output analysis (e.g., Lenzen *et al.*, 2012; Kagawa *et al.*, 2015a).

Specifically, this study focuses on passenger vehicles sold and owned from 1995 to 2008 in the 15 countries (Australia, Austria, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, South Korea, Spain, U.K., and U.S.A.). Using the World Input-Output Database (WIOD) (Timmer *et al.*, 2015), we estimated the impact of changes in lifetime and fuel efficiency for vehicles owned in these countries on the carbon footprint associated with global vehicle supply-chains in 2008. From the results, we argue that roles of changes in vehicle lifetime and fuel efficiency on global CO_2 emissions are vastly different between countries where vehicle lifetimes are longer and those where lifetimes are shorter.

The remainder of this paper is organized as follows: Section 3.2 provides the methodology; Section 3.3 describes the data used in this study; Section 3.4 discusses the results; and finally Section 3.5 concludes this chapter.

3.2. Methodology

3.2.1 Stock-flow analysis for passenger cars based on the lifetime distributions

In this study, we focused on passenger cars newly registered from 1995 to 2008 in 15 countries. Firstly, this study models the cumulative scrappage rate of new passenger cars as a cumulative distribution function. Specifically, the cumulative scrappage rate for new passenger cars of a specific country c that are newly registered in year 0 and deregistered in year t follows the Weibull distribution function described by Eq. (3.1) (e.g., Kagawa *et al.*, 2011; McCool, 2012; Oguchi and Fuse, 2015).

$$F_c(t) = 1 - \exp\left\{-\left(\frac{t}{\eta_c}\right)^{m_c}\right\} \quad (t \geq 0) \tag{3.1}$$

$$\mu_c = \eta_c \Gamma\left(1 + \frac{1}{m_c}\right) \tag{3.2}$$

Here, m_c represents a shape parameter and η_c represents a scale parameter. μ_c in Eq. (3.2) represents average vehicle lifetime of specific country c derived from the Weibull distribution function and Γ in Eq. (3.2) is the gamma function (McCool, 2012). The cumulative *survival* rate at year t for new cars newly registered at year 0 is also easily obtainable as $\varphi_c(t) = 1 - F_c(t)$. It should be noted that we have $\varphi_c(0) = 1$; in other words, all new cars purchased in year 0 survive in year 0.

As in previous studies (Kagawa *et al.*, 2015b; Nishijima, 2017; Nakamoto, 2017), using the cumulative survival rate of new cars with baseline average lifetime of country c, $\bar{\mu}_c$, the stock of passenger cars of country c in year t, $S_c(t;\bar{\mu}_c)$, can be estimated as follows:

$$S_c(t;\bar{\mu}_c) = B_c(t;\bar{\mu}_c) + \sum_{i=1}^{t-1} \varphi_c(t-i;\bar{\mu}_c) B_c(i;\bar{\mu}_c) \tag{3.3}$$

where $B_c(t;\bar{\mu}_c)$ represents the number of new cars purchased in country c in year t and $\varphi_c(t-i;\bar{\mu}_c)$ is the cumulative survival rate for new cars in country c in year t that are newly registered in year i, when the average lifetime of passenger cars of country c is the baseline.

Subsequently, we explain how to solve the stock dynamic equation, Eq. (3.3), by assuming that passenger cars are newly registered in initial year 1. In addition, we assume that all vintages of passenger cars sold in country c follow the same cumulative survival distribution. We have the following dynamic system of equations for each country:

$$\begin{cases} S_c(1;\bar{\mu}_c) = B_c(1;\bar{\mu}_c) \\ S_c(2;\bar{\mu}_c) = B_c(2;\bar{\mu}_c) + \varphi_c(1;\bar{\mu}_c) B_c(1;\bar{\mu}_c) \\ S_c(3;\bar{\mu}_c) = B_c(3;\bar{\mu}_c) + \varphi_c(1;\bar{\mu}_c) B_c(2;\bar{\mu}_c) + \varphi_c(2;\bar{\mu}_c) B_c(1;\bar{\mu}_c) \\ \vdots \end{cases} \tag{3.4}$$

In this study, the stock of passenger cars in each year $S_c(t;\bar{\mu}_c)$ is taken to be steady state. Thus, if the stock proportion of a vintage of passenger cars (cumulative survival rate) shifts from $\varphi_c(t;\bar{\mu}_c)$ to $\varphi_c(t;\mu_c)$ in accordance with the average lifetime of passenger cars shifting from $\bar{\mu}_c$ to μ_c, then the number of new passenger cars sold can be estimated sequentially as follows:

$$\begin{cases} B_c(1;\mu_c) = S_c(1;\bar{\mu}_c) \\ B_c(2;\mu_c) = S_c(2;\bar{\mu}_c) - \varphi_c(1;\mu_c)B_c(1;\mu_c) \\ B_c(3;\mu_c) = S_c(3;\bar{\mu}_c) - \varphi_c(1;\mu_c)B_c(2;\mu_c) - \varphi_c(2;\mu_c)B_c(1;\mu_c) \\ \vdots \end{cases} \tag{3.5}$$

The amount of newly purchased cars in country c in year t can be estimated as $B_c(t;\mu_c)$.

3.2.2 Direct CO_2 emissions associated with driving passenger cars

Annual gasoline consumption in liters of i-vintage cars in country c in year t, $g_c(t;\bar{\lambda}_c(i))$ $(i = 1,2,\cdots,t)$ was calculated by dividing the annual average travel distance in country c in year t, defined as $d_c(t)$ (km), by the fuel efficiency of i-vintage cars in country c, denoted by $\bar{\lambda}_c(i)$ (km/L), where the bar indicates the baseline fuel efficiency of i-vintage cars in country c in year t.

$$g_c(t;\bar{\lambda}_c(i)) = \frac{d_c(t)}{\bar{\lambda}_c(i)} \tag{3.6}$$

Here, it is assumed that the annual average travel distance of passenger cars in year t is same irrespective of their vintage. From Eq. (3.6), we can estimate the gasoline consumption generated by all vintages of vehicles on the road in country c in year t as follows:

$$q_c\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)=g_c\left(t;\bar{\lambda}_c(t)\right)B_c\left(t;\bar{\mu}_c\right)+\sum_{i=1}^{t-1}g_c\left(t;\bar{\lambda}_c(i)\right)\varphi_c\left(t-i;\bar{\mu}_c\right)B_c\left(i;\bar{\mu}_c\right) \tag{3.7}$$

where $\varphi_c\left(t-i;\bar{\mu}_c\right)B_c\left(i;\bar{\mu}_c\right)$ denotes the number of i-vintage passenger cars in use and $q_c\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)$ denotes the total annual gasoline consumption of passenger cars in use in country c in year t. The direct CO_2 emissions of a passenger car associated with car driving is calculable by multiplying the direct CO_2 emission intensity (i.e., direct CO_2 generated per unit of gasoline combustion on the road), e_{petro} (kt-CO_2/L), by the annual gasoline consumption, $q_c\left(t;\mu_c,\lambda_c\right)$.

3.2.3 Indirect CO_2 emissions associated with the life-cycle of passenger cars

We can estimate the number of new passenger car sales in country c in year t, $B_c\left(t;\bar{\mu}_c\right)$, by using the stock-flow model formulated in section 3.2.1. By multiplying the average sales price (including domestic cars and imported cars) per vehicle in country c, $p_{c,\,auto}(t)$, by the number of new passenger car sales, $B_c\left(t;\bar{\mu}_c\right)$, we can obtain the domestic final demand for passenger cars in value terms as $p_{c,\,auto}(t)B_c\left(t;\bar{\mu}_c\right)$.

Now, by using the WIOD, we can estimate the ratio of the final demand for imported cars from country b to country c, $f_{t,\,auto}^{bc}$, to the domestic final demand for passenger cars (including domestic cars and imported cars) in country c (the Trade coefficient of the

"Transport Equipment" sector), $\sum_{b=1}^{N} f_{t,\ auto}^{bc}$, for year t as follows:

$$\tau_{t,\ auto}^{bc} = \frac{f_{t,\ auto}^{bc}}{\sum_{b=1}^{N} f_{t,\ auto}^{bc}} \quad (c = 1, 2, \cdots, N) \tag{3.8}$$

where N denotes the number of countries in the WIOD. Note that $f_{t,\ auto}^{cc}\ (b = c)$ represents the final demand for *domestic* passenger cars in country c, and that $\sum_{b=1}^{N} \tau_{t,\ auto}^{bc} = 1$.

Similarly, we can estimate the following trade coefficient of the "Refined petroleum" sector.

$$\tau_{t,\ petro}^{bc} = \frac{f_{t,\ petro}^{bc}}{\sum_{b=1}^{N} f_{t,\ petro}^{bc}} \quad (c = 1, 2, \cdots, N) \tag{3.9}$$

where $f_{t,\ petro}^{bc}$ represents the final demand for imported petroleum products from country b to country c in year t and $\sum_{b=1}^{N} f_{t,\ petro}^{bc}$ represents the domestic final demand for petroleum products in country c in year t. Similar to above, $f_{t,\ petro}^{cc}\ (b = c)$ represents the final demand for *domestic* petroleum products in country c and $\sum_{b=1}^{N} \tau_{t,\ petro}^{bc} = 1$.

From Eqs. (3.8) and (3.9), the global final demand for passenger cars and petroleum products in country c in year t can be formulated as follows:

$$
\mathbf{f}_c\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)=\left[\begin{array}{c}
\mathbf{0}\\
f^{1c}_{c,\,auto}\left(t;\bar{\mu}_c\right)\\
f^{1c}_{c,\,petro}\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)\\
\mathbf{0}\\ \hdashline
\mathbf{0}\\
f^{2c}_{c,\,auto}\left(t;\bar{\mu}_c\right)\\
f^{2c}_{c,\,petro}\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)\\
\mathbf{0}\\ \hdashline
\vdots\\ \hdashline
\mathbf{0}\\
f^{Nc}_{c,\,auto}\left(t;\bar{\mu}_c\right)\\
f^{Nc}_{c,\,petro}\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)\\
\mathbf{0}
\end{array}\right]=\left[\begin{array}{c}
\mathbf{0}\\
\tau^{1c}_{t,\,auto}p_{c,\,auto}(t)B_c\left(t;\bar{\mu}_c\right)\\
\tau^{1c}_{t,\,petro}p_{c,\,petro}(t)q_c\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)\\
\mathbf{0}\\ \hdashline
\mathbf{0}\\
\tau^{2c}_{t,\,auto}p_{c,\,auto}(t)B_c\left(t;\bar{\mu}_c\right)\\
\tau^{2c}_{t,\,petro}p_{c,\,petro}(t)q_c\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)\\
\mathbf{0}\\ \hdashline
\vdots\\ \hdashline
\mathbf{0}\\
\tau^{Nc}_{t,\,auto}p_{c,\,auto}(t)B_c\left(t;\bar{\mu}_c\right)\\
\tau^{Nc}_{t,\,petro}p_{c,\,petro}(t)q_c\left(t;\bar{\mu}_c,\bar{\lambda}_c\right)\\
\mathbf{0}
\end{array}\right] \quad (3.10)
$$

It should be noted that the global final demand vector of Eq. (3.10) is also considered as a function of average lifetime of passenger cars μ and fuel efficiency of passenger cars λ. Therefore, we can assess the influence by the change in both average vehicle lifetime and fuel efficiency of a *specific* country on the *global* final demand vector.

The indirect CO_2 emissions associate with the global final demand of passenger cars and auto-related petroleum products in country c in year t can be estimated as follows:

$$
Q_{c,\,indirect}\left(t;\mu_c,\lambda_c\right)=\mathbf{e}_t\left(\mathbf{I}-\mathbf{A}_t\right)^{-1}\mathbf{f}_c\left(t;\mu_c,\lambda_c\right) \quad (3.11)
$$

Based on a multi-regional input-output analysis, $\mathbf{e}_t=\left(\mathrm{e}_{t,i}\right)$ is the CO_2 emissions coefficient row vector indicating the direct CO_2 emissions per unit production of industry i in year t. $\mathbf{I}$ is the identity matrix, $\mathbf{A}_t=\left(a_{t,ij}\right)$ is the input coefficient matrix expressing the input of industry i required for unit production of industry j in year t. $\mathbf{L}_t=\left(\mathbf{I}-\mathbf{A}_t\right)^{-1}$

is the Leontief inverse matrix based on the multi-regional input-output table in year t. Therefore, the life-cycle CO_2 emissions including the direct and indirect emissions in the pre-consumer, production, and driving phases can be finally estimated as follows:

$$Q_c(t;\mu_c,\lambda_c) = Q_{c,\,indirect}(t;\mu_c,\lambda_c) + e_{petro}q_c(t;\mu_c,\lambda_c) \tag{3.12}$$

In this study, life-cycle CO_2 emissions directly and indirectly caused by the scrapping phase of end-of-life passenger cars were neglected. It should be noted that the life-cycle CO_2 emissions caused by the scrapping phase of end-of-life passenger cars are very small (Kagawa *et al.*, 2011).

3.3. Data

We collected and aggregated the data for the number of passenger car sales B_c for 15 countries (Australia, Austria, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, South Korea, Spain, the U.K., and the U.S.A.) for the study period of 1995 to 2008 provided by Japan Automobile Manufacturers Association, FOURIN, which is a Japanese research company, the Australian Bureau of Statistics, and Statistics Canada.

Using the vehicle database provided by the Japan Automobile Manufacturers Association, the Australian Bureau of Statistics, Statistics Canada, and EnerData, which is a French research company, we estimated the annual average travel distance $d_c(t)$ by dividing the annual national distance driven by all vehicles in kilometers by the number of cars in use for each country. Although the annual average travel distance might differ depending on the vehicle type, auto manufacturer, and attributes of the car owner, we assumed that all passenger cars in use in a country have the same annual average travel distance.

The data source for the gasoline price $p_{c, petro}$ (USD/L) and the passenger car fuel efficiency normalized to U.S. CAFE λ_c (km/L) are from the International Energy Agency (IEA, 2014) and the International Council on Clean Transportation (ICCT, 2018), respectively. It should be noted that we assumed that the fuel efficiencies of 1995-vintage to 1999-vintage cars follow that of 2000-vintage cars and that the fuel efficiency for Australia follows that of the E.U. due to a lack of data.

By using the consumer price index (World Bank, 2017), we adjusted a dataset for passenger car sales price in 2015 from IHS Markit (Cuenot and Fulton, 2011) to obtain the sales price during 1995 to 2008. We adopted the 'average' passenger car sales price in OECD countries (29,000 USD in 2015) for the sales prices for Canada, Finland, Ireland, and South Korea since those data were not available. The direct industrial CO_2 emission coefficient vector of countries $\mathbf{e}_t$ and the direct CO_2 emission intensity for gasoline consumptions $e_{petro} = 0.00231$ (t-CO_2/L) are respectively those provided by Timmer *et al.* (2015) and the National Institute for Environmental Studies, Japan (2010). The 15 countries were selected due to the availability and reliability of the above data and the two parameters for the Weibull distribution in Table 3.1.

An important study is to estimate lifetime of wide variety of vehicles of hybrid vehicles, diesel vehicles, and others of countries, however the lifetime database has not been well estimated due to the lack of reliable panel data of vehicles of countries. Therefore, we focused on the 'average' vehicles and treated diesel vehicles that have large market share in the Europe and Korea as petro vehicles in this study due to the data limitation. This expanded analysis with a focus of wide variety of vehicle models is an important and challenging future work.

3.4. Results

3.4.1 Effects of changes in average vehicle lifetime on stock and flow of passenger cars

First, using the passenger vehicle lifetime distribution of the 15 countries, we analyzed the impacts of change in average vehicle lifetime for each country (namely, the average service life from new vehicle registration to scrapping) on the amounts of vehicle stock and flow in that country. Table 3.1 gives the average passenger vehicle lifetimes in 2008 for the 15 countries studied as estimated by Oguchi and Fuse (2015) and the two parameters for the Weibull distribution, shape parameter m_c and scale parameter η_c. On the longer end, the average passenger vehicle lifetimes were 22.6 in Australia and 22.0 years in Finland; on the shorter end, the same periods for Ireland, Japan, and South Korea were all approximately 13 years (Table 3.1). Thus, average passenger vehicle lifetimes are widely dispersed. (Table 3.1).

Table 3.1: Lifetime parameter used in this study

Country	Average lifetime (years)	Shape parameter	Scale parameter	Passenger cars per 1000 people
Australia	22.6	3.0	25.3	553
Austria	15.4	4.2	16.9	514
Canada	15.4	4.4	16.9	587
Germany	13.7	3.1	15.3	509
Denmark	16.7	3.5	18.6	383
Spain	18.0	4.7	19.7	481
Finland	22.0	2.9	24.7	460
France	15.2	4.2	16.7	495
United Kingdom	13.5	3.9	14.9	503
Ireland	13.0	4.0	14.3	429
Italy	14.1	4.0	15.6	607
Japan	13.3	3.4	14.8	450
Korea	13.0	2.7	14.6	513
Netherlands	15.1	3.7	16.7	468
United States	16.2	2.8	18.2	448
Average	15.8	3.6	17.6	493.4
Variance	9.0	0.4	11.5	3,470
Standart deviation	3.0	0.6	3.4	59

Source: Oguchi and Fuse, 2015; OICA; UN Department of Economic and Social Affairs

In this study, we emulated Kagawa *et al.* (2011), fixing the Weibull distribution shape parameter m_c from Table 3.1 and changing the scale parameter η_c to shift average lifetime $\bar{\mu}_c$ of passenger vehicles newly registered between 1995 and 2008 from −5 years to +5 years. Figure 3.1 shows the 2008 passenger car stock in Australia for vehicles newly registered between 1995 and 2008 in each of the average lifetime change scenarios estimated using Eq. (3.5). According to these results, changes in average lifetime (extension and shortening) in Australia, where the average passenger vehicle lifetime is very long, has an extremely limited impact upon the vehicle stock of each vintage (older models held onto) and thus new vehicle units sold. In Finland, where the average passenger vehicle lifetime is also long, the effects of changes in lifetime are similar (see Figure S3.1 in the Appendix).

In contrast, change in lifetime has an outsized impact in the U.S.A., where the average passenger vehicle lifetime is exactly at the world average, 15.8 years: shortening average passenger vehicle lifetime by 5 years increases the share of newly purchased 2008 vehicles from 6.7% to 9.8% and, conversely, reduces the share of vehicle stock from 93.3% to 90.2% (Figure 3.2). Meanwhile, extending passenger vehicle lifetime by 5 years in the U.S.A reduces the share of newly purchased 2008 vehicles from 6.7% to 5.4% and, conversely, expands the share of older vehicles purchased before 2008 from 93.3% to 94.6% (Figure 3.2).

If we assume that technological breakthroughs will improve fuel efficiency in newer vehicles, then shortening the buying cycle by shortening the average vehicle lifetime will put more relatively fuel-efficient vehicles on the road. Conversely, when fewer new vehicles are purchased due to longer average lifetimes, more vehicles with relatively poor fuel efficiencies will be driving the streets. Accordingly, extending the average lifetime should contribute to increasing the CO_2 emissions attributed to the fuel consumption of vehicles on the streets, as shown in the second term on the right-hand side of Eq. (3.12), and decreasing the CO_2 emissions attributed to new vehicle sales, which is included in the first term on the right-hand side of Eq. (3.12). As shown in Figure 3.2, it is possible that, in countries such as the U.S.A., where change in passenger vehicle lifetime clearly impacts vehicle ownership, changing passenger vehicle lifetime will help to reduce global CO_2 emissions.

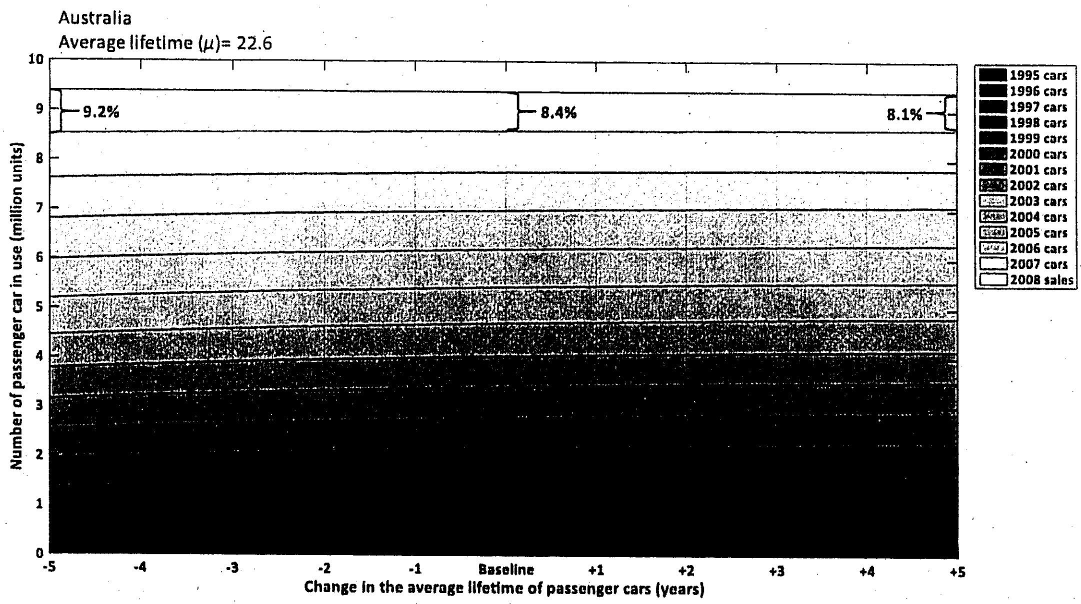

Figure 3.1: Passenger car stock in 2008 under the lifetime scenarios (Australia)

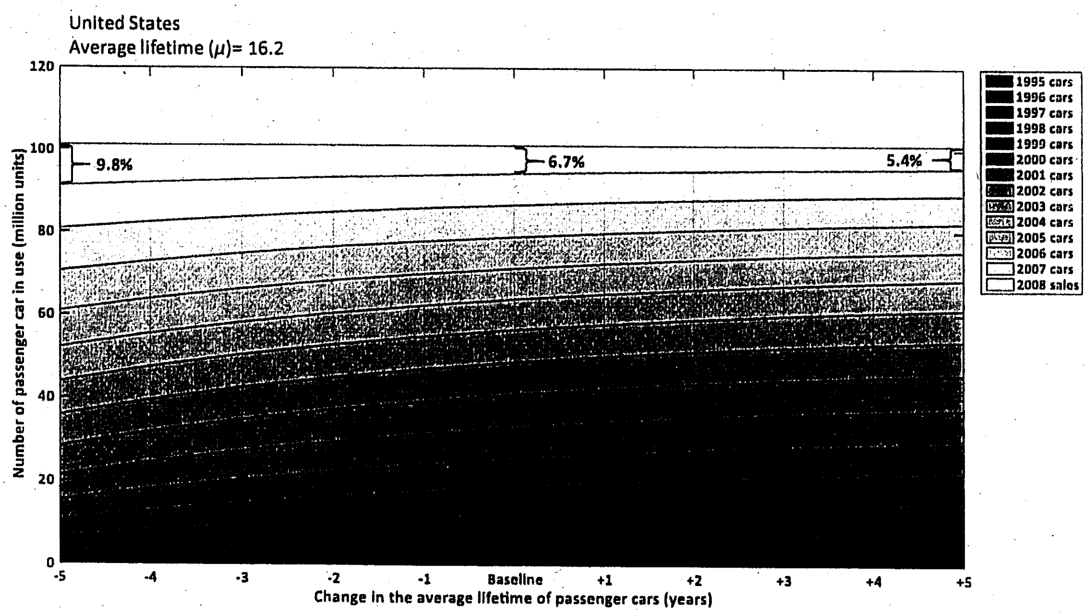

Figure 3.2: Passenger car stock in 2008 under the lifetime scenarios (U.S.A.)

3.4.2 CO_2 reduction potentials under the combined scenarios

Figure 3.3 shows carbon footprints in vehicle lifetime scenarios for the countries in terms of life-cycle CO_2 emissions for 2008 associated with the final demand of passenger vehicles and gasoline consumptions of countries (see Eq. (3.12)). Looking at country's carbon footprints in the baseline analysis as estimated using the average lifetimes for each country from Table 3.1, we can see in Figure 3.3 that the U.S.A., Germany, and Japan lead in CO_2 emissions at 555 Mt-CO_2-eq., 187 Mt-CO_2-eq., and 146 Mt-CO_2-eq., respectively. The fact that passenger vehicle carbon footprints in these three countries, the world's recognized automotive giants, have reached a combined 889 Mt-CO_2-eq. absolutely cannot be ignored in climate change mitigation policies. The overall carbon footprint for all 15 countries is 1.6 Gt-CO_2-eq, accounting for 4.9% of the 31.6 Gt of global CO_2 emissions for 2008 (IPCC, 2014).

One important finding from these results is that, in all 15 countries studied, shortening the average passenger vehicle lifetime increased the carbon footprint of passenger vehicles and, conversely, lengthening the average passenger vehicle lifetime decreased the carbon footprint of passenger vehicles. The carbon footprint of passenger vehicles associated with the final demand of passenger cars, or vehicle production phase substantially decrease due to lengthening the average passenger vehicle lifetime, even though carbon footprint associated with fuel combustion, or driving phase increase (see Figure S3.2). The major reason for this is that a lengthening the average passenger vehicle lifetime contributes to reducing the number of new car sold. Particularly for the U.S.A., Germany, and Japan, where vehicle stock and flow are high, extending passenger vehicle lifetime by 5 years compared to the baseline footprints reduced the passenger vehicle carbon footprints by 13.3 Mt-CO_2-eq. (−2%), 8.1 Mt-CO_2-eq. (−4%), and 7.2 Mt-CO_2-eq. (−5%), respectively (Figure 3.3). Conversely, shortening the lifetime by 5 years in the three countries increased their passenger vehicle carbon footprints by 31.2 Mt-CO_2-eq. (+6%), 17.6 Mt-CO_2-eq. (+9%), and 14.6 Mt-CO_2-eq. (+10%), respectively.

In Australia and Finland, however, two countries with extremely long average vehicle lifetimes, the same extension to vehicle lifetime had a very limited effect toward reducing CO_2 emissions at 0.31 Mt-CO_2-eq. (−1%) and 0.05 Mt-CO_2-eq. (0%), respectively. Interestingly, in the U.K., Ireland, and South Korea, where average vehicle lifetimes are shorter, extending the vehicle lifetime 5 years compared to baseline footprint had a relatively large effect on reducing emissions at 5.50 Mt-CO_2-eq. (−4%), 0.42 Mt-CO_2-eq. (−4%), and 3.37 Mt-CO_2-eq. (−5%), respectively. Thus, these results illustrate that countries with shorter average vehicle lifetimes can reduce their vehicle carbon footprints more by keeping their vehicles in service longer.

Ten of the 15 countries studied had vehicle lifetimes shorter than the average of 15.8 years: Austria, Canada, Germany, France, the U.K., Ireland, Italy, Japan, South Korea, and the Netherlands (Table 3.1). We calculated that by increasing the average vehicle lifetimes of passenger cars registered during 1995 to 2008 of these 10 countries to the global average of 15.8 years, a reduction of 17 Mt-CO_2-eq. from the total baseline footprint of the 10 countries could be realized. Accordingly, extending the average vehicle lifetime for those countries with shorter average vehicle lifetimes up to at least the global average would definitely help in mitigating climate change.

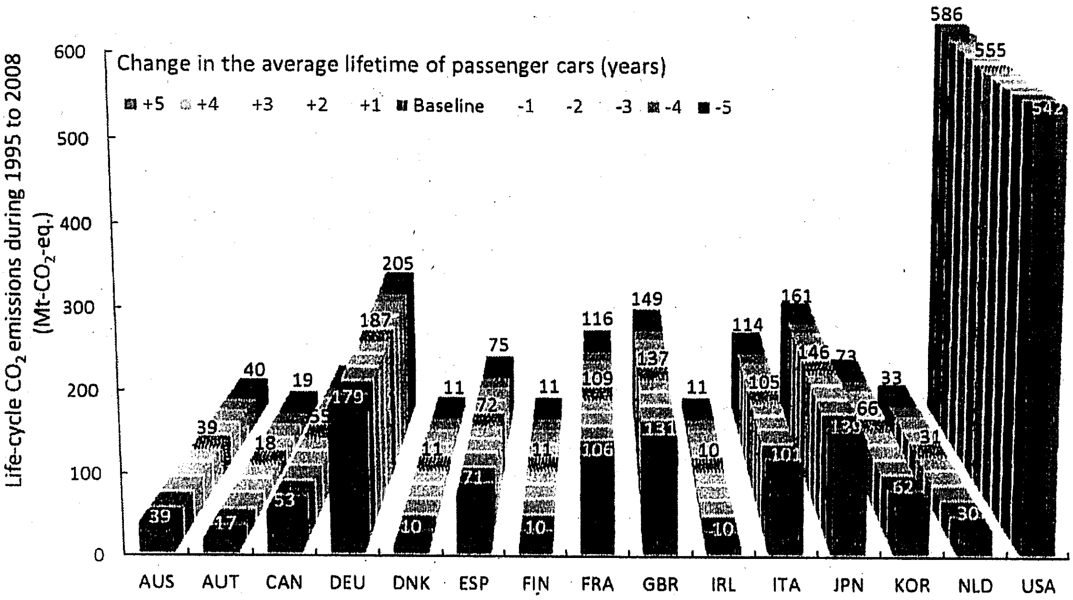

Figure 3.3: Life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under lifetime scenarios

Policymakers may oppose policies for mitigating climate change by extending vehicle lifetimes. After all, they reason, extending average lifetimes would mean fewer consumers purchasing more fuel efficient vehicles and increase the number of less fuel efficient vehicles, in turn increasing CO_2 emissions from driving. Maybe further improvements in average fuel efficiency for new vehicles, even as vehicle lifetimes are shortened, will stem the increases in CO_2 emissions. This line of thinking forms the basis for the current emissions reduction policies of many countries.

To analyze these two opposing positions for this study, we conducted a combined scenario analysis uniting the vehicle lifetime change scenarios and vehicle fuel efficiency change scenarios. Specifically, we estimated the emission reductions when the fuel efficiencies (at purchase and over time) for passenger vehicles sold in the relevant countries between 1995 and 2008 increased uniformly by 10%, 20%, and 30% from the baseline fuel efficiency of $\bar{\lambda}_c(i)(i=1995,1996,\cdots,2008)$ (km/L).

In Figure 3.4 to Figure 3.7, we can see the potential for reducing the vehicle carbon footprints in four countries under the combined scenario: Australia, where vehicle lifetimes are longer; the U.S.A., where vehicle lifetimes are close to the global average; and Germany and Japan, where vehicle lifetimes are shorter. According to the results in the Figure 3.6 and Figure 3.7, extending vehicle lifetime would be effective in reducing CO_2 emissions in countries like Germany and Japan where average lifetimes are relatively short. It is also important to note here that, in Germany and Japan, any reductions in CO_2 emissions from fuel efficiency improvements will largely be negated by shortening vehicle lifetime (Figure 3.6 and Figure 3.7). For Germany and Japan, these results illustrate that the increases in indirect emissions associated with new vehicle manufacturing from shortening average lifetimes will exceed the decreases in direct emissions from driving due to fuel efficiency improvements. In contrast, in Australia and the U.S.A., shortening the average vehicle lifetime in the fuel efficiency improvement scenarios increases the number of vehicles with relatively good fuel efficiencies, resulting in decreases in direct emissions from reduced fuel consumption that outpaced the increases in indirect emissions associated with increased vehicle manufacturing (Figure 3.4 and Figure 3.5). Focusing on Australia, where vehicle lifetime is longer, the reductions from further extending vehicle lifetime would be small compared to reductions from improving fuel efficiency. There are some countries (e.g., Australia and Finland) that has little or no domestic automobile makers. Achieving fuel efficiency improvement in such countries, the policymakers need to focus their efforts on importing new vehicles with higher fuel efficiency within the country.

We should note here that, realistically, fuel efficiency improvement measures can only be applied to new vehicles; they are exceedingly difficult to apply to currently owned older models. On the other hand, measures to extend vehicle lifetime can be applied to all currently owned vehicles. In Germany and Japan, where hopes are high for these emission reductions associated with vehicle lifetimes, policymakers need to pivot toward policies centered on extending vehicle lifetimes. We also conclude that, in order to realize the higher levels of CO_2 emission reductions needed for us to achieve our GHG emissions reduction goals under the Paris Agreement, it is crucial that those countries with shorter vehicle lifetimes concurrently extend their average vehicle lifetimes and improve their fuel efficiencies. A large-scale shift to electric motorization, which is planned in many countries, would enhance the emission intensity of driving phase. On the contrary, additional materials needed for electric systems and for batteries increase the emission intensity of pre-consumer phase (Toyota, 2017; Nakamoto and Kagawa,2018). Following the result of this study, we can conclude that lifetime extensions of electric vehicles have relatively great potential to reducing not only the demand for additional materials for next-generation cars but also the carbon footprint of transportation sector.

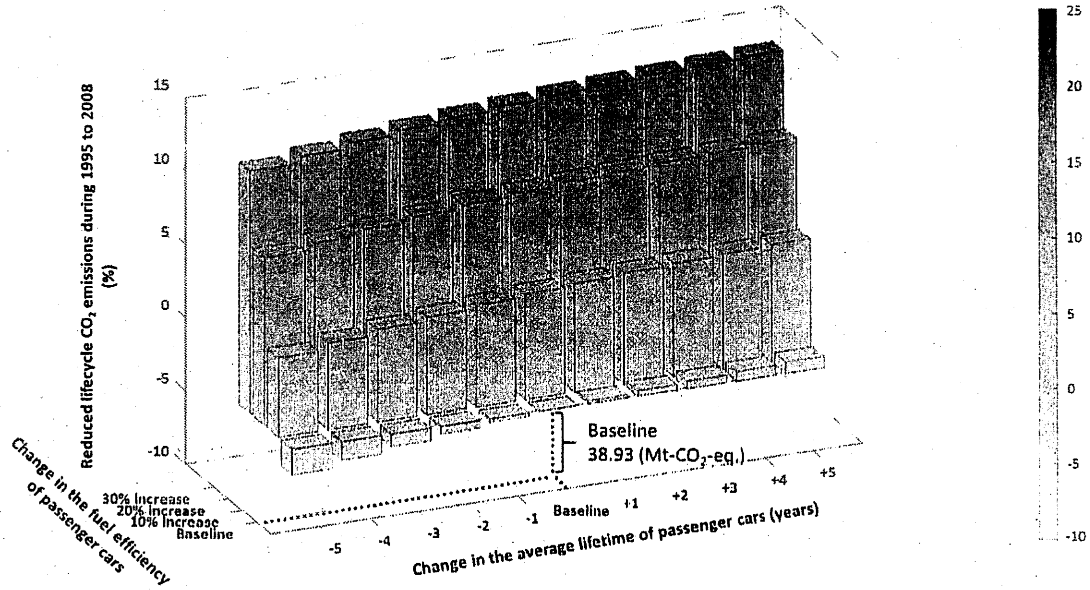

Figure 3.4: Reduced life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under combined scenarios (Australia)

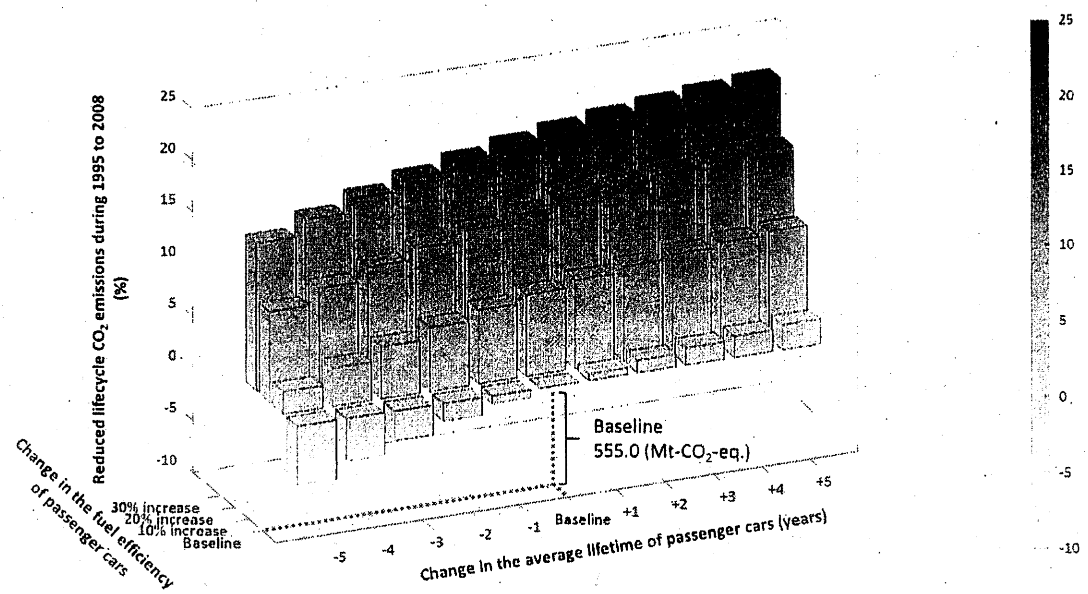

Figure 3.5: Reduced life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under combined scenarios (U.S.A.)

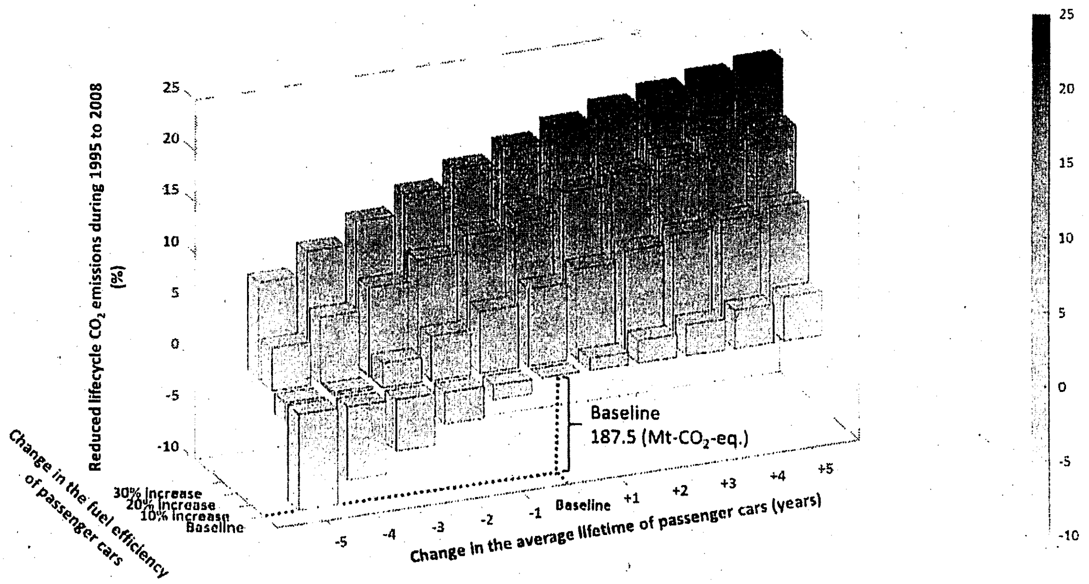

Figure 3.6: Reduced life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under combined scenarios (Germany)

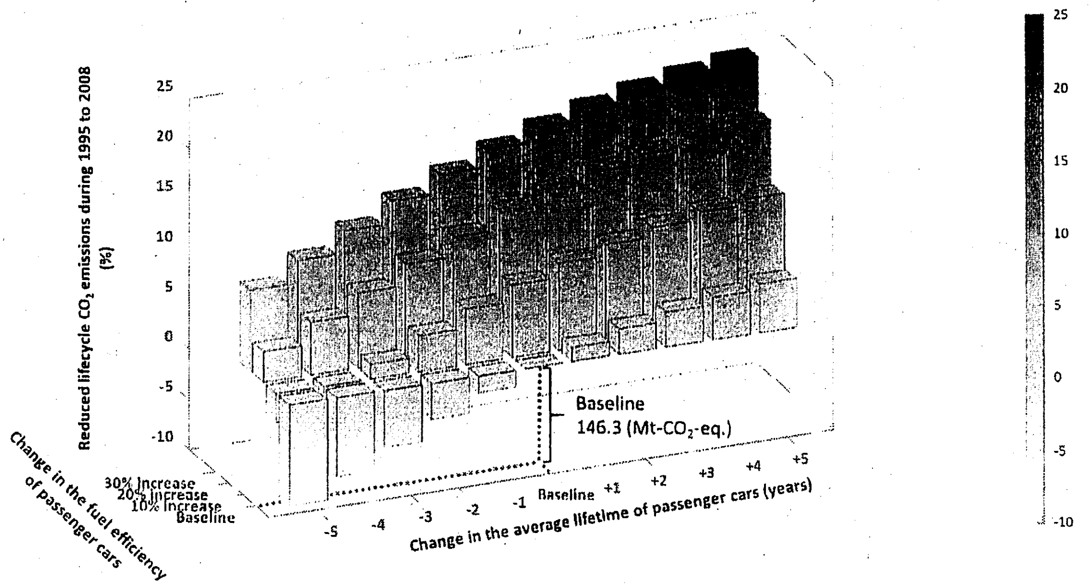

Figure 3.7: Reduced life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under combined scenarios (Japan)

3.5. Conclusion

In this study, we analyzed the impacts that changing the passenger vehicle lifetimes of 15 countries worldwide would have on vehicle stock and flow in those countries by using a vehicle lifetime distribution model. The results showed that, for countries with relatively short average passenger vehicle lifetimes, changing the average lifetimes greatly impacted passenger vehicle stock (older models held onto) and flow (new vehicle units sold).

Next, by combining the 15-country stock-flow model and a multi-regional input-output analysis, we estimated the impact of changes in vehicle lifetime and fuel economy for a country upon that country's vehicle-derived carbon footprint. According to the results, extending vehicle lifetime has a very limited effect in reducing the carbon footprint in countries where vehicle lifetimes are longer, such as Australia and Finland, but is expected to greatly reduce emissions in countries where vehicle lifetimes are shorter, such as Germany and Japan.

Whereas fuel economy improvement strategies only apply to new vehicles, lifetime extension strategies can be widely applied to both new vehicles and vehicles bought in previous years, which are nearly 90 percent of all vehicles owned. In the interest of reducing vehicle-derived CO_2 emissions, it is crucial to promote vehicle lifetime extension into conventional technical policy along with elements such as fuel efficiency improvements and next-generation vehicle development. And it is also important to build incentives for vehicle owners to keep their vehicles longer. In terms of possible owner incentives, we need to make ownership of older model vehicles easier by vitalizing the used car sales, maintenance, and repair markets, re-manufacture (Seitz, 2007; Gutowski *et al.*, 2011; European Commission, 2015; Matsumoto, Chinen and Endo, 2017).

Chapter 4: Spatial Structural Decomposition Analysis with a Focus on Product Lifetime

4.1. Introduction

In the EU action plan for the circular economy, which establishes low-carbon and sustainable development of the economy, it is important to shed light on the 'closing-loop' of the product life-cycle through designing products with longer lifetimes and achieving greater re-use and recycling (European Commision, 2015). Such circular strategies for products have impacts on both the economy and the environment through the global supply chains of the products. Thus, it is crucial to analyze the carbon footprint (CF) for the entire product life-cycle.

Environmentally extended input–output analysis (EEIOA), which is an application of input–output analysis to environmental impact assessment, was pioneered by Wassily Leontief (1971) and has been widely employed in life-cycle footprint analysis (Horvath and Hendrickson, 1998; Kagawa *et al.*, 2008; Wiedmann and Minx, 2008; Hertwich and Peters, 2009) and material flow analysis (Nakamura *et al.*, 2014; Ohno *et al.*, 2017; Pauliuk *et al.*, 2017). Aguilar-Hernandez *et al.* (2018) reviewed current EEIOA studies of circular strategies and categorized them into four groups: residual waste management, closing supply chains, product lifetime extension, and resource efficiency.

Static EEIOA is used for measuring economic impact, productivity, or environmental burden from a relatively normative and short-term perspective, while structural decomposition analysis (SDA) is aimed at breaking changes of components down into certain driving forces from a relatively positivistic and long-term perspective. Index decomposition analysis (IDA) uses regional-level or national-level aggregated data. On the other hand, SDA is based on input–output tables and so enables the analyst to include indirect demand effects induced by certain direct demand effects (Ang, 1994; Dietzenbacher and Los, 1998; Hoekstra and van der Bergh, 2003; Lenzen, 2016; Su and Ang, 2012). Especially in the energy and environment field, SDA has been conducted for multiple regions (Alcántara and Duarte, 2004; de Nooij *et al.*, 2003; Unander *et al.*, 1999) by using multi-regional input-output tables (MRIO) as well as for the regional level by using the national input-output tables of many countries (Baiocchi and Minx, 2010; Cao *et al.*, 2010; Lim *et al.*, 2009; Munksgaard *et al.*, 2000; Peters *et al.*, 2007).

Some analyses have focused on consumption (final demand) versus technology (the Leontief production structure and emission intensity) over time (Baiocchi and Minx, 2010; De Haan, 2001; Roca and Serrano, 2007). The general findings of these studies is that GHG emissions have increased due to the expansion of consumption but that the emissions were mitigated by improvements in technology and efficiency over the study period.

An important problem is how circular strategies contributed to the climate mitigation. Such strategies may reduce consumption and/or promote the innovation of technology and efficiency improvements. For example, lifetime extension of automobiles in a particular country reduces car replacement (i.e., final demand). This primary effect would spread widely over the automotive parts required for their manufacture, the trade structure of the materials, the share of older model vehicles in the country, and gasoline consumption through the global supply chain of the product. Thus, a lifetime extension of a product reduces the demand of consumers for that product (Serrenho and Allwood, 2016), and hence reductions of intermediate input and energy input for the production of the product can be achieved (Kagawa *et al.*, 2008; Nishijima, 2017). Therefore, by uncovering the whole truth of the mechanisms of final demand, impact assessments of different strategies can be performed.

Since the supply chain for automotive manufacturing extends beyond the domestic industries into the global market (Kagawa *et al.*, 2015; Pavlínek and Ženka, 2011; Timmer *et al.*, 2015; Tokito, 2018), management of the global supply chain associated with automobiles is essential. Nevertheless, to the best of my knowledge, previous studies on automobile lifetime analysis have the following issues: (1) The scope of these automobile lifetime studies has been domestic, whereas the supply chain of automobiles is global in scale; and therefore (2) It is unclear what impact changes in product lifetime in a country have on the structure of final demand through the global supply chain and CF associated with the global final demand.

To address these issues, this study focused on changes in the global final demand for automobiles and auto-related petroleum induced by the automobile lifetime changes of countries. Using the World Input-Output Database (WIOD) (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015), I develop a comprehensive new method that offers a deeper understanding of the structural change in the global final demand of automobiles.

Specifically, I decomposed the final demand effects of automobile and petroleum induced by changes in automobile lifetime of countries into 6 drivers: New car demand, Petroleum demand, Car stock, Travel distance, International trade of cars, and International trade of petroleum products. Using an extended SDA (E-SDA) model, this study focused on the three major countries of the U.S.A., Germany, and Japan, which account for 31% of the stock of passenger cars in the world in 2009 (International Organization of Motor Vehicle Manufacturers: OICA, 2018), and estimated the CF associated with the global final demand of automobiles and petroleum of those three countries during 1995 to 2009. Based on the results, I discuss what role change in the lifetime of automobiles has contributed to their CFs.

4.2. Methodology

4.2.1 Stock dynamic system for passenger cars

I assumed that the cumulative scrappage rate for the new passenger cars of a specific country c that are newly registered in year 0 and deregistered in year t follows the Weibull distribution function described by Eq. (4.1) (e.g., Kagawa *et al.*, 2011; McCool, 2012; Oguchi and Fuse, 2015).

$$F^{c}(t)=1-\exp\left\{-\left(\frac{t}{\eta^{c}}\right)^{m^{c}}\right\} \quad (t\geq 0) \tag{4.1}$$

$$\mu^{c}=\eta^{c}\Gamma\left(1+\frac{1}{m^{c}}\right) \tag{4.2}$$

where m^c represents a shape parameter and η^c represents a scale parameter. In Eq. (4.2), μ^c represents the average vehicle lifetime derived from the Weibull distribution function and Γ is the gamma function (McCool, 2012). The cumulative survival rate at year t for new cars newly registered at year 0 can be formulated as $\varphi^{c}(t)=1-F^{c}(t)$. It should be noted that we have $\varphi^{c}(0)=1$; in other words, all new cars purchased in year 0 remain throughout year 0.

The stock of passenger cars of country c in year t, $S^{c}(t;\bar{\mu}^{c})$, can be obtained using the following equation as in (Nakamoto *et al.*, 2019):

$$S^c\left(t;\bar{\mu}^c\right)=B^c\left(t;\bar{\mu}^c\right)+\sum_{i=1}^{t-1}\varphi^c\left(t-i;\bar{\mu}^c\right)B^c\left(i;\bar{\mu}^c\right) \tag{4.3}$$

where $B^c\left(t;\bar{\mu}^c\right)$ represents the number of new cars purchased in country c in year t and $\varphi^c\left(t-i;\bar{\mu}^c\right)$ is the cumulative survival rate for new cars in country c in year t that are newly registered in year i, when the average lifetime of passenger cars of country c is the baseline.

In this study, I focused on passenger cars newly registered from 1987 to 2009 in the U.S.A., Germany, and Japan. I assumed that all vintages of passenger cars sold in country c follow the same cumulative survival distribution. When the passenger cars are newly registered in initial year 1, the number of cars in use for country c under the baseline average lifetime, $\bar{\mu}^c$, can be estimated by solving the stock dynamic system of equations for each country, Eq. (4.3):

$$\begin{cases} S^c\left(1;\bar{\mu}^c\right)=B^c\left(1;\bar{\mu}^c\right) \\ S^c\left(2;\bar{\mu}^c\right)=B^c\left(2;\bar{\mu}^c\right)+\varphi^c\left(1;\bar{\mu}^c\right)B^c\left(1;\bar{\mu}^c\right) \\ S^c\left(3;\bar{\mu}^c\right)=B^c\left(3;\bar{\mu}^c\right)+\varphi^c\left(1;\bar{\mu}^c\right)B^c\left(2;\bar{\mu}^c\right)+\varphi^c\left(2;\bar{\mu}^c\right)B^c\left(1;\bar{\mu}^c\right) \\ \vdots \end{cases} \tag{4.4}$$

In this study, the stock of passenger cars in each year $S^c\left(t;\bar{\mu}^c\right)$ is taken to be unchanged, even if cumulative survival rate changes from baseline $\varphi^c\left(t;\bar{\mu}^c\right)$ to lifetime scenario $\varphi^c\left(t;\mu^c\right)$. According to this assumption, if the stock proportion of a vintage of passenger cars (cumulative survival rate) shifts from $\varphi^c(t;\bar{\mu}^c)$ to $\varphi^c(t;\mu^c)$ along with the average lifetime of passenger cars shifting from $\bar{\mu}^c$ to μ^c, then the number of new passenger cars sold can be estimated sequentially as follows:

$$\begin{cases} B^c(1;\mu^c) = S^c(1;\bar{\mu}^c) \\ B^c(2;\mu^c) = S^c(2;\bar{\mu}^c) - \varphi^c(1;\mu^c)B^c(1;\mu^c) \\ B^c(3;\mu^c) = S^c(3;\bar{\mu}^c) - \varphi^c(1;\mu^c)B^c(2;\mu^c) - \varphi^c(2;\mu^c)B^c(1;\mu^c) \\ \vdots \end{cases} \tag{4.5}$$

In eq. (4.5), it is important to note that unless the number of car sales is smaller than the number of scrap cars, the stock of passenger cars will increase over time. The amount of newly purchased cars in country c in year t can be estimated as $B^c(t;\mu^c)$.

4.2.2 Annual gasoline consumption and direct CO_2 emissions

Annual gasoline consumption in liters of i-vintage cars in country c in year t, $d^c(t)\lambda^c(i)$ $(i = 1,2,\cdots,t)$, was calculated by multiplying the annual average travel distance in country c in year t, defined as $d^c(t)$ (100km), by the fuel efficiency of i-vintage cars in country c, denoted as $\lambda^c(i)$ (L/100km). Although the annual travel distance might differ depending on the vehicle type, automaker, and attributes of the car owner, I assumed that the annual average travel distance of passenger cars in year t is the same irrespective of their vintage. Subsequently, we can estimate the gasoline consumption generated by all vintages of the vehicle fleet on the road in country c in year t as follows:

$$
\begin{aligned}
q^c\left(t;\mu^c\right) &= d^c(t)\lambda^c(t)B^c\left(t;\mu^c\right)+\sum_{i=1}^{t-1} d^c(t)\lambda^c(i)\varphi^c\left(t-i;\mu^c\right)B^c\left(i;\mu^c\right) \\
&= q_{new}^c\left(t;\mu^c\right)+q_{stock}^c\left(t;\mu^c\right)
\end{aligned}
\tag{4.6}
$$

where $\varphi^c\left(t-i;\mu^c\right)B^c\left(i;\mu^c\right)$ represents the number of *i*-vintage passenger cars in use and $q^c\left(t;\mu^c\right)$ denotes the total annual gasoline consumption of passenger cars in use in country c in year t. In Eq. (4.6), $q_{new}^c\left(t;\mu^c\right)$ represents the gasoline consumption generated by cars newly put on the road in country c in year t and $q_{stock}^c\left(t;\mu^c\right)$ is defined as the gasoline consumption generated by 1-vintage to t-1-vintage vehicles in country c in year t. The direct CO_2 emissions of a passenger car in the driving phase, $G_{direct}^c\left(t;\mu^c\right)=e_{petro}q^c\left(t;\mu^c\right)$, is calculable by multiplying the direct CO_2 emission intensity (i.e., direct CO_2 emissions generated per unit of gasoline combustion on the road), e_{petro} (kt-CO_2/L), by the annual gasoline consumption, $q^c\left(t;\mu^c\right)$.

4.2.3 Indirect CO_2 emissions associated with the life-cycle of automobiles

In the WIOD (Dietzenbacher *et al.*, 2013; Timmer *et al.*, 2015), the final demand vector in country c for year t can be expressed as $\mathbf{f}^c(t)=\left\{f_j^{sc}(t)\right\}$ $(j=1,\ldots,M)$, where an element $f_j^{sc}(t)$ of $\mathbf{f}^c(t)$ represents the global final demand in country c for the products of industry j of country s, and M denotes the number of industries. Now, we can estimate the ratio of the final demand for imported cars from country s to country c,

$f^{sc}_{auto}(t)$, to the domestic final demand for all passenger cars (including domestic cars and imported cars) in country c (the Trade coefficient of the "Transport Equipment" sector), $\sum_{s=1}^{N} f^{sc}_{auto}(t)$, for year t as follows:

$$\tau^{sc}_{auto}(t) = \frac{f^{sc}_{auto}(t)}{\sum_{s=1}^{N} f^{sc}_{auto}(t)} \quad (c = 1, 2, \cdots, N) \tag{4.7}$$

where N denotes the number of countries and regions in the WIOD. Note that $f^{cc}_{auto}(t)\ (s = c)$ represents the final demand for *domestic* passenger cars in country c, and that $\sum_{s=1}^{N} \tau^{sc}_{auto}(t) = 1$. Similarly, we can estimate the trade coefficient of the "Refined petroleum" sector $\tau^{sc}_{petro}(t)$.

By multiplying the average sales price (including domestic cars and imported cars) of a vehicle in country c, $p^{c}_{auto}(t)$, by the number of new passenger car sales, $B^{c}(t; \mu^{c})$, we can obtain the domestic final demand for passenger cars in value terms as $p^{c}_{auto}(t) B^{c}(t; \mu^{c})$. In the same manner, the domestic final demand for auto-related petroleum products can be estimated as $p^{c}_{petro}(t) q^{c}(t; \mu^{c})$. From Eq. (4.7), the global final demand for passenger cars and auto-related petroleum products in country c in year t can be formulated as follows:

$$
\mathbf{f}^{c}\left(t;\mu^{c}\right)=
\overbrace{\begin{bmatrix} 0 \\ f_{auto}^{1c}\left(t;\mu^{c}\right) \\ f_{petro}^{1c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \\ \hdashline \vdots \\ \hdashline 0 \\ f_{auto}^{Nc}\left(t;\mu^{c}\right) \\ f_{petro}^{Nc}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix}}^{\text{Country } c}
=
\begin{bmatrix} 0 \\ f_{auto}^{1c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \hdashline \vdots \\ \hdashline 0 \\ f_{auto}^{Nc}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}
+
\begin{bmatrix} 0 \\ 0 \\ f_{petro}^{1c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \\ \hdashline \vdots \\ \hdashline 0 \\ 0 \\ f_{petro}^{Nc}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix}
=
\begin{bmatrix} 0 \\ \tau_{auto}^{1c}(t)\,p_{auto}^{c}(t)\,B^{c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \hdashline \vdots \\ \hdashline 0 \\ \tau_{auto}^{Nc}(t)\,p_{auto}^{c}(t)\,B^{c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}
+
\begin{bmatrix} 0 \\ 0 \\ \tau_{petro}^{1c}(t)\,p_{petro}^{c}(t)\,q^{c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \\ \hdashline \vdots \\ \hdashline 0 \\ 0 \\ \tau_{petro}^{Nc}(t)\,p_{petro}^{c}(t)\,q^{c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix}
\tag{4.8}
$$

Note that the global final demand vector of Eq. (4.8) is considered as a function of average lifetime of passenger cars μ^{c}. Therefore, we can assess the influence of changing the average vehicle lifetime of a *specific* country on the *global* final demand vector.

Following the EEIOA (e.g., Nakamoto *et al.*, 2019), the indirect CO_2 emissions associate with the global final demand of passenger cars and auto-related petroleum products in country c in year t can be estimated as follows:

$$
Q^{c}\left(t;\mu^{c}\right)=\mathbf{e}(t)\left(\mathbf{I}-\mathbf{A}(t)\right)^{-1}\mathbf{f}^{c}\left(t;\mu^{c}\right)=\mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^{c}\left(t;\mu^{c}\right) \tag{4.9}
$$

here $\mathbf{e}(t)=\left\{e_{i}^{r}(t)\right\}$ is the CO_2 emission coefficient row vector indicating the direct CO_2 emissions per unit production of industry i of country r in year t. $\mathbf{I}$ is the identity matrix, $\mathbf{A}(t)=\left\{a_{ij}^{rs}(t)\right\}$ is the technical coefficient matrix expressing the input of industry i of country r required for unit production of industry j of country s in year t. $\mathbf{L}(t)=(\mathbf{I}-\mathbf{A}(t))^{-1}=\{L_{ij}^{rs}(t)\}$ is called the Leontief inverse matrix based on the multi-regional input-output table in year t. Therefore, the life-cycle CO_2 emissions including the direct and indirect emissions in the pre-consumer, production, and driving phases can be finally estimated as follows:

$$CF^c(t;\mu^c)=Q^c(t;\mu^c)+G_{direct}^c(t;\mu^c) \tag{4.10}$$

It should be noted that life-cycle CO_2 emissions directly and indirectly caused by the scrapping phase of end-of-life passenger cars were negligibly small (Kagawa *et al.*, 2011).

4.2.4 Decomposition analysis of the life-cycle CO_2 emissions of automobiles

In additive decomposition, the change in the life-cycle CO_2 emissions of automobiles from year t-1 to year t in country c of Eq. (4.10) can be expressed as follows:

$$\begin{aligned}\Delta CF^c &= CF^c(t;\mu^c)-CF^c(t-1;\mu^c)\\ &= Q^c(t;\mu^c)+G_{direct}^c(t;\mu^c)-\{Q^c(t-1;\mu^c)+G_{direct}^c(t-1;\mu^c)\}\\ &= Q^c(t;\mu^c)-Q^c(t-1;\mu^c)+G_{direct}^c(t;\mu^c)-G_{direct}^c(t-1;\mu^c)\\ &= \Delta Q^c+\Delta G_{direct}^c\end{aligned} \tag{4.11}$$

Accordingly, the change in the indirect CO_2 emissions associate with the global final demand from year t-1 to year t in country c of Eq. (4.11) can be decomposed as follows:

$$\Delta Q^c = Q^c\left(t;\mu^c\right) - Q^c\left(t-1;\mu^c\right)$$
$$= \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c\left(t;\mu^c\right) - \mathbf{e}(t-1)\mathbf{L}(t-1)\mathbf{f}^c\left(t-1;\mu^c\right) \tag{4.12}$$

By using the Logarithmic Mean Divisia Index (LMDI) (Ang, 2015; Ang and Liu, 2007; Wood and Lenzen, 2006), Eq. (4.12) can be transformed as follows:

$$\Delta Q^c = \Delta E^c + \Delta L^c + \Delta F^c \tag{4.13}$$

where ΔE^c, ΔL^c, and ΔF^c represents the effect of technological changes in the industrial emission intensities, the effect of changes in the production structure, and the effect of changes in the final demand, respectively. The mathematical formula for estimating each effect is presented in Appendix 4.1. To handle zero values in the LMDI approach, the strategies presented by (Ang *et al.*, 1998; Ang and Liu, 2007; Wood and Lenzen, 2006) are applied.

4.2.5 Decomposition analysis of automobile gasoline consumption and its CO_2 emissions

Based on the decomposition model for automobile gasoline consumption (Kagawa *et al.*, 2012), I decompose the change in the gasoline consumption of vehicles. By using the LMDI, the change in the gasoline consumption generated by new cars on the road from year *t*-1 to year *t* in country *c* given in Eq. (4.6) can be expressed as follows:

$$\Delta q_{new}^{c} = \alpha_{new}^{LM,c} \ln \frac{d^{c}(t)}{d^{c}(t-1)} + \alpha_{new}^{LM,c} \ln \frac{\lambda^{c}(t)}{\lambda^{c}(t-1)} + \alpha_{new}^{LM,c} \ln \frac{B^{c}(t;\mu^{c})}{B^{c}(t-1;\mu^{c})} \\ = \Delta d_{new}^{c} + \Delta\lambda^{c} + \Delta S^{c} \tag{4.14}$$

Here, $\alpha_{new}^{LM,c} = \dfrac{q_{new}^{c}(t;\mu^{c}) - q_{new}^{c}(t-1;\mu^{c})}{\ln\{q_{new}^{c}(t;\mu^{c})\} - \ln\{q_{new}^{c}(t-1;\mu^{c})\}}$ is a weighting factor. Δd_{new}^{c}, $\Delta\lambda^{c}$, and ΔS^{c} represents the effect of changes in the travel distance of a new car, the effect of changes in the fuel efficiency of a new car, and the effect of changes in the number of new car sales, respectively. Note that when we have $q_{new}^{c}(t;\mu^{c}) = q_{new}^{c}(t-1;\mu^{c})$, then $\alpha_{new}^{LM,c} = q_{new}^{c}(t;\mu^{c}) = q_{new}^{c}(t-1;\mu^{c})$.

Next, I consider a decomposition analysis of the gasoline consumption generated by 1-vintage to t-1-vintage vehicles. The change in the gasoline consumption of older vehicles between year t-1 and year t in country c of Eq. (4.6) can be obtained as follows:

$$\Delta q_{stock}^{c} = q_{stock}^{c}(t;\mu^{c}) - q_{stock}^{c}(t-1;\mu^{c}) \\ = \sum_{i=1}^{t-1} d^{c}(t)\lambda^{c}(i)\varphi^{c}(t-i;\mu^{c})B^{c}(i;\mu^{c}) - \sum_{i=1}^{(t-1)-1} d^{c}(t-1)\lambda^{c}(i)\varphi^{c}(t-1-i;\mu^{c})B^{c}(i;\mu^{c}) \tag{4.15}$$

Then, referring to (Kagawa *et al.*, 2012), Eq. (4.15) can be transformed algebraically as follows:

$$
\begin{aligned}
\Delta q^{c}_{stock} &= d^{c}(t)\underbrace{\left[\lambda^{c}(1)\;\; \lambda^{c}(2)\;\; \cdots\;\; \lambda^{c}(t-2)\;\; \lambda^{c}(t-1)\right]}_{\boldsymbol{\lambda}^{c}(t)}\underbrace{\begin{bmatrix} \varphi^{c}(t-1;\mu^{c})B^{c}(1;\mu^{c}) \\ \varphi^{c}(t-2;\mu^{c})B^{c}(2;\mu^{c}) \\ \vdots \\ \varphi^{c}(2;\mu^{c})B^{c}(t-2;\mu^{c}) \\ \varphi^{c}(1;\mu^{c})B^{c}(t-1;\mu^{c}) \end{bmatrix}}_{\mathbf{k}^{c}(t;\mu^{c})} \\
&\quad -d^{c}(t-1)\underbrace{\left[\lambda^{c}(1)\;\; \lambda^{c}(2)\;\; \cdots\;\; \lambda^{c}(t-2)\;\; \lambda^{c}(t-1)\right]}_{\boldsymbol{\lambda}^{c}(t-1)}\underbrace{\begin{bmatrix} \varphi^{c}(t-2;\mu^{c})B^{c}(1;\mu^{c}) \\ \varphi^{c}(t-3;\mu^{c})B^{c}(2;\mu^{c}) \\ \vdots \\ \varphi^{c}(1;\mu^{c})B^{c}(t-2;\mu^{c}) \\ 0 \end{bmatrix}}_{\mathbf{k}^{c}(t-1;\mu^{c})}
\end{aligned}
\tag{4.16}
$$

where $\boldsymbol{\lambda}^{c}(t)$ denotes the fuel efficiency vector for older vintage vehicles in year t. $\mathbf{k}^{c}(t;\mu^{c})=\{k^{c}_{h}(t;\mu^{c})\}$ is the number of older cars vector, with h-th element expressing the number of h-vintage vehicles in year t. The important point is that the fuel efficiency for older vintage vehicles is assumed to remain at the initial value over time, $\boldsymbol{\lambda}^{c}(t)=\boldsymbol{\lambda}^{c}(t-1)$. This assumption leads to the result that the change in the gasoline consumption derived from a change in the fuel efficiency of older vehicles is zero. Using the LMDI approach, Eq. (4.16) can be rewritten as follows:

$$
\begin{aligned}
\Delta q^{c}_{stock} &= \sum_{h}\alpha^{LM,c}_{stock,h}\ln\frac{d^{c}(t)}{d^{c}(t-1)}+\sum_{h}\alpha^{LM,c}_{stock,h}\ln\frac{k^{c}_{h}(t;\mu^{c})}{k^{c}_{h}(t-1;\mu^{c})} \\
&= \Delta d^{c}_{stock}+\Delta K^{c}
\end{aligned}
\tag{4.17}
$$

Here, the first term on right-hand side represents the effect of changes in the travel distance of an older car, while the second term denotes the effect of changes in the number of older cars. In particular, $\alpha_{stock,h}^{LM,c} = \frac{q_{stock,h}^{c}(t;\mu^{c}) - q_{stock,h}^{c}(t-1;\mu^{c})}{\ln\{q_{stock,h}^{c}(t;\mu^{c})\} - \ln\{q_{stock,h}^{c}(t-1;\mu^{c})\}}$ represents the logarithmic mean weight of the annual gasoline consumption generated by h-vintage vehicles in years t-1 and t. If $q_{stock,h}^{c}(t;\mu^{c}) = q_{stock,h}^{c}(t-1;\mu^{c})$, then we have $\alpha_{stock,h}^{LM,c} = q_{stock,h}^{c}(t;\mu^{c}) = q_{stock,h}^{c}(t-1;\mu^{c})$.

Consequently, the change in the gasoline consumption of all vintages of vehicles between year t-1 and year t in country c can be decomposed as follows:

$$\begin{aligned}\Delta q^{c} &= \Delta q_{new}^{c} + \Delta q_{stock}^{c} \\ &= \Delta d_{new}^{c} + \Delta\lambda^{c} + \Delta S^{c} + \Delta d_{stock}^{c} + \Delta K^{c}\end{aligned} \tag{4.18}$$

From Eqs. (4.14)-(4.18), we can decompose the change in the direct emission associated with petroleum consumption ΔG_{direct}^{c} into factors as follows:

$$\begin{aligned}\Delta G_{direct}^{c} &= G_{direct}^{c}(t;\mu^{c}) - G_{direct}^{c}(t-1;\mu^{c}) \\ &= \Delta d_{direct,new}^{c} + \Delta\lambda_{direct}^{c} + \Delta S_{direct}^{c} + \Delta d_{direct,stock}^{c} + \Delta K_{direct}^{c}\end{aligned} \tag{4.19}$$

where $\Delta d_{direct,new}^{c}$, $\Delta\lambda_{direct}^{c}$, ΔS_{direct}^{c}, $\Delta d_{direct,stock}^{c}$, and ΔK_{direct}^{c} on the right-hand side are the direct gasoline emission changes owing to the travel distance of a new car, the fuel efficiency of a new car, the number of new car sales, the travel distance of an older car, and the number of older cars, respectively. Recalling the definition of direct CO_2 emissions in the driving phase, $G^{c}_{direct}(t;\mu^{c}) = e_{petro} q^{c}(t;\mu^{c})$, these effects were easily calculated by multiplying the effects of change in the gasoline consumption of all vintages of vehicles from Eq. (4.18) by the direct CO_2 emission intensity from gasoline combustion.

4.2.6 Extended structural decomposition analysis of the life-cycle CO_2 emissions of automobiles

To extend the decomposition analysis with a focus on product lifetime, I consider 6 elements that constitute global final demand vector of Eq. (4.8). The Hadamard product (or element-wise product) can be considered for detecting the elements in a global final demand vector as follows:

$$\mathbf{f}^c(t;\mu^c) = \mathbf{f}^c_{auto}(t;\mu^c) + \mathbf{f}^c_{petro}(t;\mu^c) = \begin{bmatrix} 0 \\ \tau^{1c}_{auto}(t)\, p^c_{auto}(t)\, B^c(t;\mu^c) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ \tau^{Nc}_{auto}(t)\, p^c_{auto}(t)\, B^c(t;\mu^c) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \tau^{1c}_{petro}(t)\, p^c_{petro}(t)\, q^c(t;\mu^c) \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ 0 \\ \tau^{Nc}_{petro}(t)\, p^c_{petro}(t)\, q^c(t;\mu^c) \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ \tau^{1c}_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ \tau^{Nc}_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \odot \begin{bmatrix} 0 \\ p^c_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ p^c_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \odot \begin{bmatrix} 0 \\ B^c(t;\mu^c) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ B^c(t;\mu^c) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \tau^{1c}_{petro}(t) \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ 0 \\ \tau^{Nc}_{petro}(t) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \odot \begin{bmatrix} 0 \\ 0 \\ p^c_{petro}(t) \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ 0 \\ p^c_{petro}(t) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \odot \begin{bmatrix} 0 \\ 0 \\ q^c(t;\mu^c) \\ 0 \\ \vdots \\ 0 \\ \hline \vdots \\ \hline 0 \\ 0 \\ q^c(t;\mu^c) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{4.20}$$

$$= \boldsymbol{\tau}^c_{auto}(t)\, p^c_{auto}(t)\, B^c(t;\mu^c) + \boldsymbol{\tau}^c_{petro}(t)\, p^c_{petro}(t)\, q^c(t;\mu^c)$$

where $\odot$ is the Hadamard product and $\boldsymbol{\tau}^c_{auto}(t)$ and $\boldsymbol{\tau}^c_{petro}(t)$ represent the trade coefficient vectors for passenger cars and petroleum products extracted from the corresponding final demand vectors.

Moreover, by combining Eqs. (4.18) and (4.20), we can extend the decomposition of the indirect emission associated with petroleum consumption (e.g., petroleum refining). Hence, the final demand effect ΔF^c underlying the change in CF from year t-1 to year

t in country c can be additionally decomposed as following separate effects: the trade coefficient of automobiles $\Delta\tau^c_{auto}$, the sales price of automobiles Δp^c_{auto}, the number of car sales ΔB^c, the trade coefficient of petroleum $\Delta\tau^c_{petro}$, the sales price of petroleum products Δp^c_{petro}, the travel distance of a new car $\Delta d^c_{indirect,\,new}$, the fuel efficiency of a new car $\Delta\lambda^c_{indirect}$, the number of new car sales $\Delta S^c_{indirect}$, the travel distance of an older car $\Delta d^c_{indirect,\,stock}$, and the number of older cars $\Delta K^c_{indirect}$:

$$
\begin{aligned}
\Delta F^c = & \underbrace{\Delta\tau^c_{auto} + \Delta p^c_{auto} + \Delta B^c}_{\mathbf{e}(t)\mathbf{L}(t)\Delta\mathbf{f}^c_{auto}(t;\mu^c)} \\
& + \underbrace{\Delta\tau^c_{petro} + \Delta p^c_{petro} + \Delta d^c_{indirect,\,new} + \Delta\lambda^c_{indirect} + \Delta S^c_{indirect} + \Delta d^c_{indirect,\,stock} + \Delta K^c_{indirect}}_{\mathbf{e}(t)\mathbf{L}(t)\Delta\mathbf{f}^c_{petro}(t;\mu^c)}
\end{aligned}
\tag{4.21}
$$

The mathematical formula for calculating each effect is presented in Appendix 4.2.

In this study, the new car demand effect consists of the number of car sales effect and the sales price of automobiles effect, $\Delta p^c_{auto} + \Delta B^c + \Delta S^c_{direct} + \Delta S^c_{indirect}$. On the other hand, the petroleum demand effect, or the demand for petroleum associated with travel by car in value terms, is defined as the summation of the sales price of petroleum products effect and the fuel efficiency of a new car effect, $\Delta p^c_{petro} + \Delta\lambda^c_{direct} + \Delta\lambda^c_{indirect}$. Finally, by reorganizing and consolidating some driving forces, the proposed Extended-Structural Decomposition Analysis (E-SDA) model with a focus on product lifetime obtains 8 factors, defined as follows: technological changes in the industrial emission intensities (E: ΔE^c), changes in the production structure (L: ΔL^c), changes in the new car demand (Car_demand: $\Delta p^c_{auto} + \Delta B^c + \Delta S^c_{direct} + \Delta S^c_{indirect}$), changes in the petroleum demand

(Petro_demand: $\Delta p^{c}_{petro} + \Delta \lambda^{c}_{direct} + \Delta \lambda^{c}_{indirect}$), changes in the number of older cars on direct and indirect gasoline emission (Car_stock: $\Delta K^{c}_{direct} + \Delta K^{c}_{indirect}$), changes in the travel distance on direct and indirect gasoline emission of new and vintage cars (Travel_dist.: $\Delta d^{c}_{direct,new} + \Delta d^{c}_{direct,stock} + \Delta d^{c}_{indirect,new} + \Delta d^{c}_{indirect,stock}$), changes in the international trade of cars (Car_trade: $\Delta \tau^{c}_{auto}$), and changes in the international trade in petroleum products (Petro_trade: $\Delta \tau^{c}_{petro}$) (Figure 4.1).

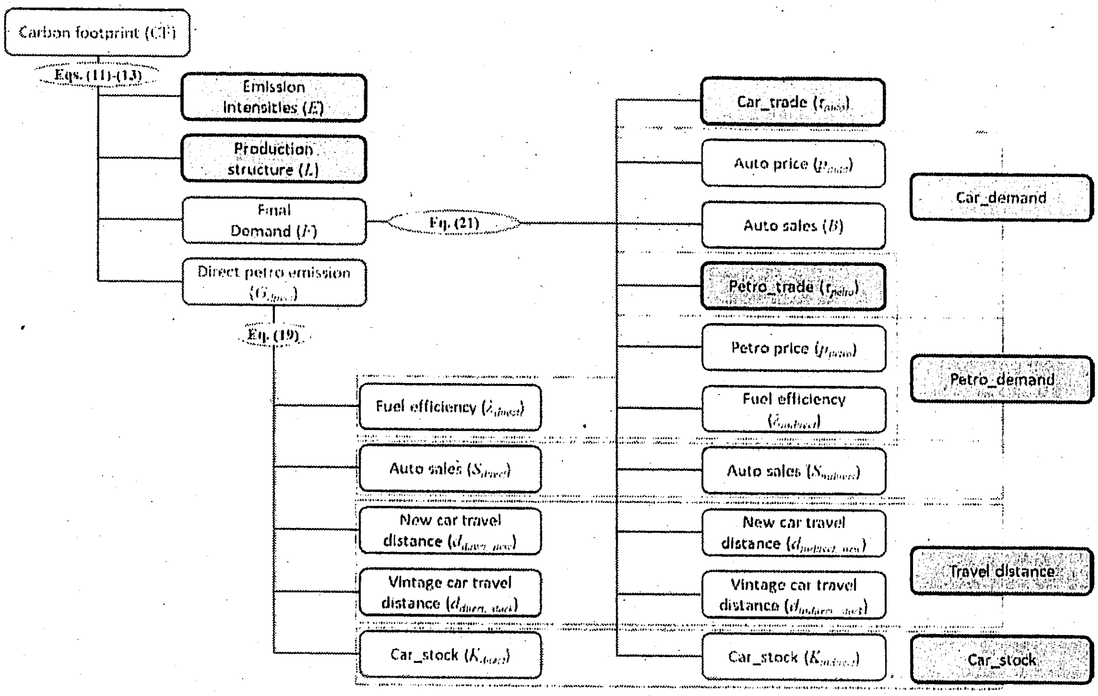

Figure 4.1: Structure of Extended-Structural Decomposition Analysis (E-SDA)

Rectangles denote the factors of changes in CF and the ovals express corresponding equation for the decomposition. The sum of factors surrounded by dotted lines denote the aggregation factor. The Rectangles with dark color denote the result of Extended-Structural Decomposition.

4.3. Data sources

I collected and aggregated the data for the number of passenger car sales, B^c, and the number of cars in use, S^c, for three countries (Germany, Japan, and the U.S.A.) for the study period of 1987 to 2009 provided by OICA, the Japan Automobile Manufacturers Association (JAMA), FOURIN, which is a Japanese research company, and EnerData, which is a French research company.

The total number of cars in use for the three countries (the U.S.A., Germany, and Japan) in 2009 was 232 million, which accounts for 31% of the stock of passenger cars in the world (OICA, 2018). As a case study, I focused on these three major countries that have highly reliable statistical data. We can obtain implications that are crucial for future global transport policies from the empirical results for these countries. I estimated the annual average travel distance, d^c, by dividing the annual national distance driven by all vehicles in kilometers by the number of cars in use for each country during the study period (Table S4.1 of the Supporting Information). Following Nakamoto *et al.* (2019), I assumed that all passenger cars in use in a country in a year have the same annual average travel distance. The data sources for the gasoline price p^c_{petro} (USD/L) and the passenger car fuel efficiency λ^c (L/100km) are the International Energy Agency (IEA, 2014) and statistical data for each country (United States Environmental Protection Agency (EPA), 2017; Das Umweltbundesamt (UBA), 2017; and Ministry of Land, Infrastructure, Transport and Tourism, Japan (MLIT), 2010), respectively (Table S4.1 and S4.2). It should be noted that I assumed for Germany that the fuel efficiencies of 1987-vintage to 1994-vintage cars follow that of 1995-vintage cars and for Japan that the fuel efficiencies of 1987-vintage to 1992-vintage cars follow that of 1993-vintage cars due to a lack of data.

By using the consumer price index (World Bank, 2017), I adjusted a dataset for passenger car sales price in 2015 from IEA (IEA, 2017) to obtain the sales price (constant 2009 prices) during 1995 to 2009. The direct industrial CO_2 emission coefficient vector of countries $\mathbf{e}$ and the direct CO_2 emission intensity for gasoline consumptions $e_{petro} = 0.00231$ (t-CO_2/L) are respectively those provided by Timmer *et al.* (2015) and the National Institute for Environmental Studies, Japan (2010). In this study, the data in value terms during 1995 to 2009 (WIOD, the gasoline price p^c_{petro} (USD/L), and the passenger car sales price p^c_{auto} (USD)) are normalized to constant 2009 prices (see Shironitta (2016) for a deflated WIOD).

4.4 Results and discussion

4.4.1 Carbon footprint of automobiles

The solid lines in Figure 4.2 represent change in CF of automobiles between 1995 and 2009 estimated using Eq. (10). In this study, the 14 years from 1995 to 2009 were divided into four periods: 1995–2000 (5 years), 2000–2005 (5 years), 2005–2008 (3 years), and 2008–2009 (1 year). Thus, the analysis results for 2008–2009, when the impact of the economic crisis was particularly great, were separated from the analysis results for 2005–2008. The estimation includes "indirect" CO_2 emissions generated by domestic final demand for cars in the relevant country (the U.S.A., Germany, or Japan) and "direct" CO_2 emissions associated with gasoline consumption in the relevant country. Note that in Figure 4.2, the footprint in 1995 is set to a reference value of 1. The CF of automobiles for the three countries shows an upward trend with an average rate of increase between 1995 and 2000 of 3.3%/yr, and an average rate of increase between 2000 and 2005 of 5.8%/yr (Figure 4.2). In addition, the rate of increase in CF was -12.4% between 2008 and 2009 due to stagnation of consumption associated with the economic crisis of 2009 (Figure 4.2). The CF in the U.S.A., in particular, increased dramatically to 1.5 times the 1995 value ahead of the other countries in 2003 (Figure 4.2). Meanwhile, due to sluggish growth in the number of new cars sold, the CF in Japan remained relatively steady, reaching a peak in 2004 (Figure 4.2).

The dashed lines in Figure 4.2 indicate the CF when the average lifetime of passenger cars in the relevant country is extended or shortened by just one year, in contrast to the baseline CF (solid lines). The lifetime scenarios can be set by fixing the Weibull distribution shape parameter m^c (see Eqs. (4.1) and (4.2)) and changing the scale parameter η^c (see Eqs. (4.1) and (4.2)) to shift average lifetime μ^c of passenger vehicles newly registered between 1987 and 2009 by −1 year or +1 year. It should be noted that the passenger vehicles newly registered between 1987 and 2009 follow the same lifetime distribution, irrespective of their vintage. When the average lifetime is shifted by −1 year or +1 year, the passenger vehicles follow the modified identical lifetime distribution. The dashed line above the solid line in Figure 4.2 indicates CF when average lifetime is shortened, and shows that in all three countries (the U.S.A., Germany, and Japan) the CF of automobiles increases as a result of a one-year shortening of average lifetime of passenger cars. Meanwhile, in all three countries, a one-year extension of average lifetime of passenger cars (dashed line below the solid line in Figure 4.2) has the effect of reducing emissions compared to the baseline.

In the U.S.A., where the increase in emissions was particularly large, focusing on the 5-year period from 2000 to 2005 when the increase in CF was striking, the average annual rate of increase in CF is reduced by 1.1%/yr as a result of a one-year extension of average lifetime of passenger cars. Past input–output life-cycle assessments (IO-LCAs) have revealed that extension of lifetime of passenger cars in a specific country contributes to CF reduction (e.g., Spielmann and Althaus, 2007; Kagawa *et al.*, 2008, 2011), and this study obtained similar results.

Using the E-SDA developed in this study, we can estimate the impact of changes in the stock and flow of passenger cars associated with changes in lifetime of passenger cars in the relevant country on global CF. Before that, the next section applies an SDA to changes in CF of automobiles in the U.S.A., Germany, and Japan.

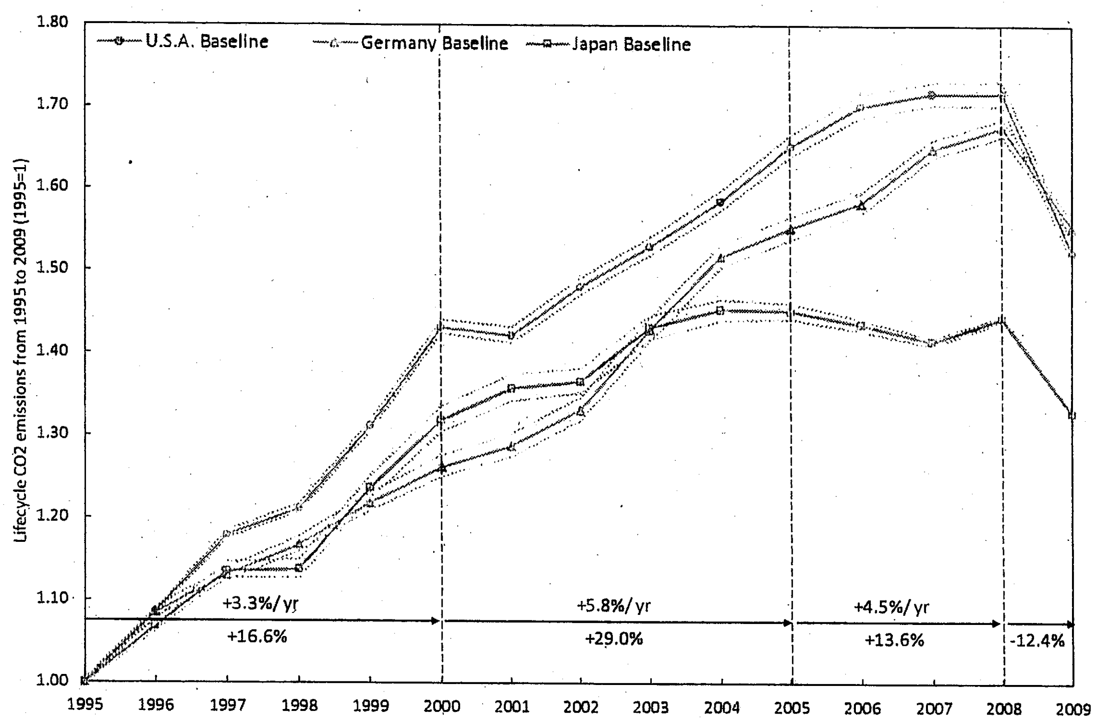

Figure 4.2: Life-cycle CO_2 emissions of automobiles during 1995 to 2009 (1995=1). The solid lines show the baseline emissions for each country. The upper dotted lines denote the -1 year lifetime scenario, whereas the lower dotted lines denote the +1 year lifetime scenario.

4.4.2 Decomposition results of carbon footprint of automobiles

In the U.S.A., CF increased by 212 Mt-CO_2-eq. between 1995 and 2000; however, the increase gradually diminished between 2000 and 2005 and between 2005 and 2008 (Figure 4.3). Meanwhile in Germany, CF gradually increased between 1995 and 2005, but the increase in CF between 2005 and 2008 was only 19 Mt-CO_2-eq. (Figure 4.4). Using an SDA, I analyzed the drivers of change in CF of automobiles, including indirect CO_2 emissions generated by domestic final demand for cars in the relevant country and direct CO_2 emissions associated with gasoline consumption in the relevant country, between 1995 and 2009. Using Eqs. (4.11) and (4.13), it is possible to decompose the drivers of change in CF from Year t-1 to Year t into the following: the effects of changes in production structure (L), the effects of changes in final demand (F), the effects of changes in direct emissions associated with petroleum consumption (Petro_direct), and the effects of technological changes in industrial emission intensities (E), (Figures 4.3, 4.4, and 4.5).

Looking at the drivers of change in CF of automobiles in the three countries, the effects of technological changes in emission intensities (E) of suppliers directly and indirectly involved in automotive manufacturing contribute to emissions reduction, and greener automotive manufacturing with less energy consumptions is advancing worldwide through technological innovation (Figures 4.3, 4.4, and 4.5). Importantly, between 1995 and 2008, the effects of changes in production structure (L) in the three countries contribute approximately 30% of the emissions increase in the three countries together, and completely canceled out the minus effects of technological changes in emission intensities (E) in the three countries together (Figures 4.3, 4.4, and 4.5).

The effects of changes in final demand of passenger cars and gasoline (F) in the three counties reached a peak between 2000 and 2005, and then declined due to stagnation of the new car market in the relevant country. On the other hand, the effects of changes in direct emissions associated with petroleum consumption (Petro_direct) in the three countries also contributed to the increase between 1995 and 2008, and contributed to the decrease in 2009.

From Figures 4.3, 4.4, and 4.5, obtained using an SDA, we were not able to identify a substantial difference in the drivers of change in CF of automobiles in the relevant countries. Furthermore, the decomposition results obtained from an SDA are lacking in specificity and must be interpreted carefully. This is because the results of an SDA conceal the effects of economic trends, improvements in product efficiency (e.g., internal combustion engines of cars), and introduction of government policies (e.g., policies to promote energy-saving products). The next section reveals the entire picture of the drivers of change in CF of automobiles through a detailed analysis using the E-SDA, which is proposed herein, to solve this problem.

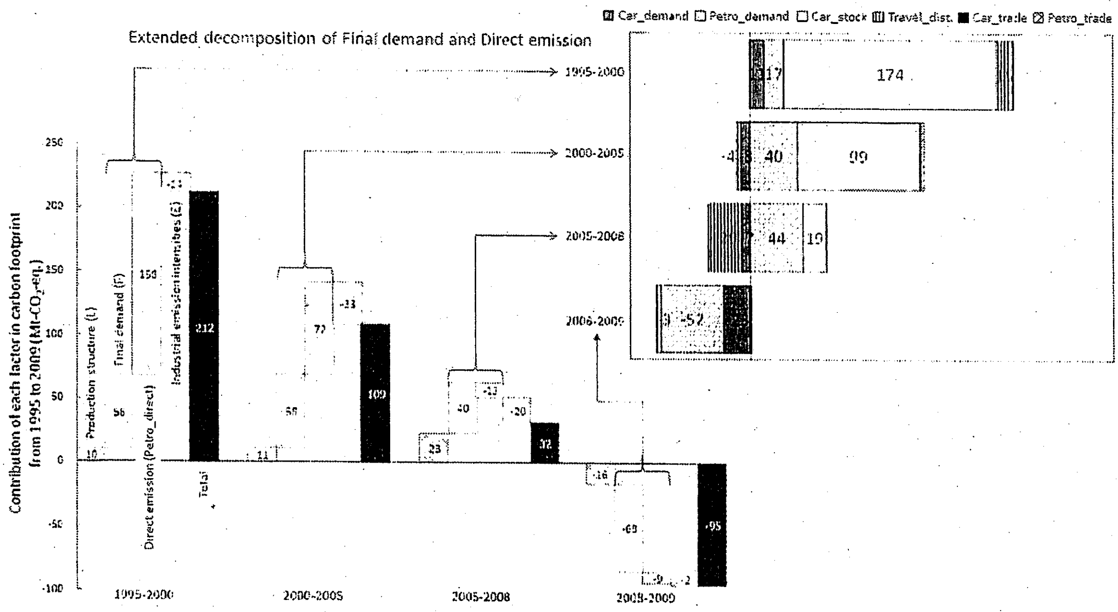

Figure 4.3: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 (U.S.A.).

The waterfall chart represents contributions of decomposition factors by SDA, whereas the bar chart shows the extended decomposition of final demand (F) and direct emissions from petroleum consumption (Petro_direct).

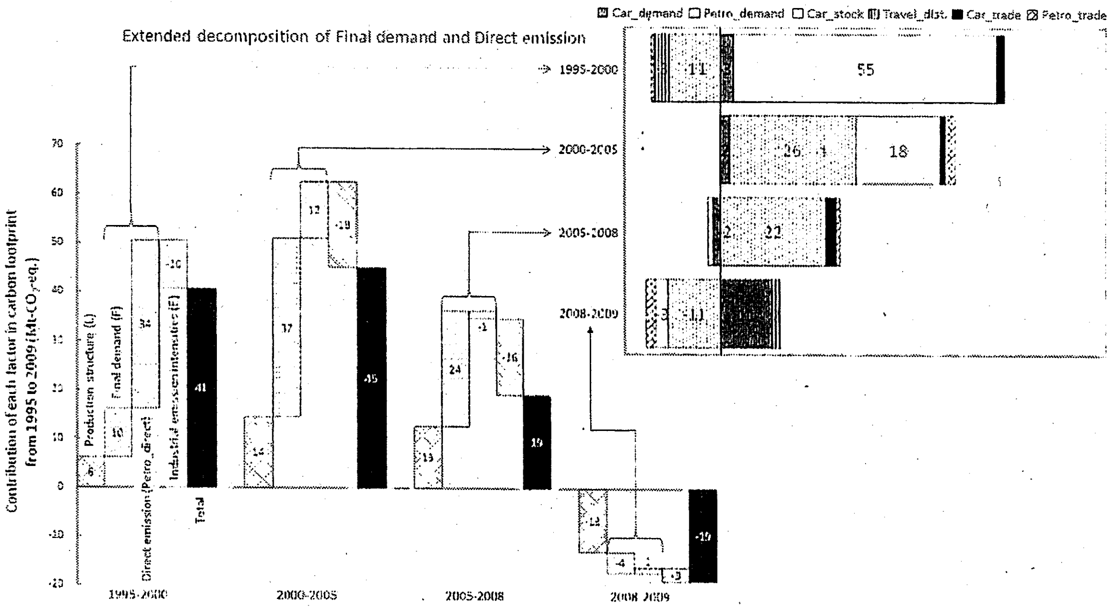

Figure 4.4: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 (Germany).

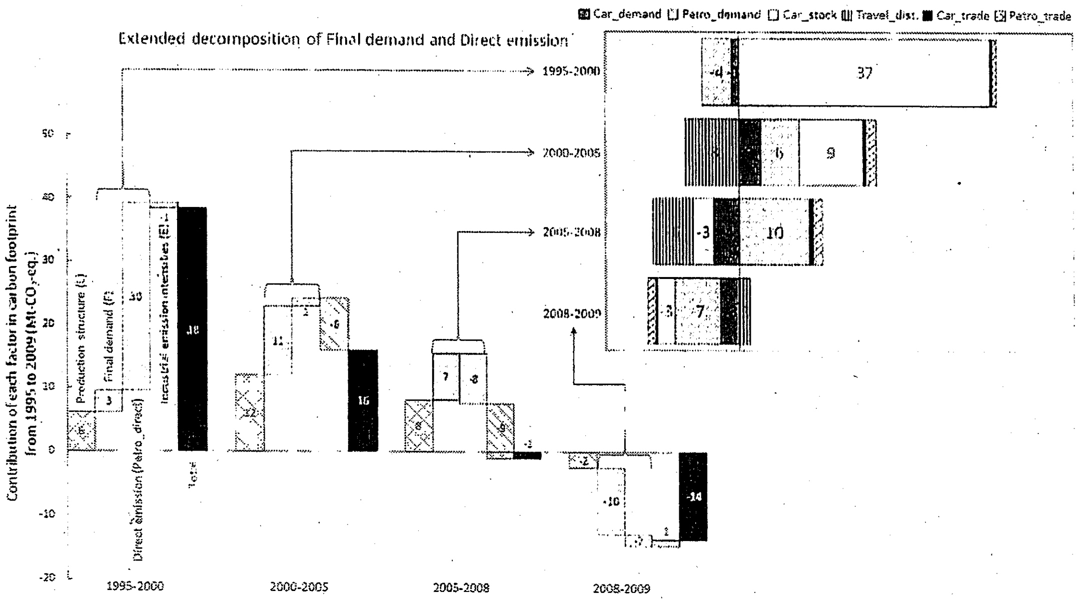

Figure 4.5: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 (Japan).

4.4.3 Decomposition results from the E-SDA

To analyze in detail the drivers of change in CF of automobiles, I applied the E-SDA formulated in Section 2. Using Eqs. (4.19) and (4.21), the effects of changes in final demand (F) and the effects of changes in direct emissions associated with petroleum consumption (Petro_direct) can be additively decomposed into 6 elements (Car_demand, Petro_demand, Car_stock, Travel_dist., Car_trade, and Petro_trade) (Figures 4.1, 4.3, 4.4, and 4.5).

Figures 4.3, 4.4, and 4.5 show that the effects of changes in new car demand (Car_demand) associated with new car sales have a limited influence on changes in CF of automobiles in the relevant country. According to each country's statistical data (FOURIN, 2010; Kraftfahrt-Bundesamt, 2010), the numbers of new cars sold in the U.S.A. and Japan reached their respective peaks in 2000 and 2004 (8.85 million in the U.S.A. and 4.77 million in Japan) and gradually decreased thereafter. The number of new cars sold in Germany was relatively stable at 3.30 million between 1995 and 2009 but increased greatly to 3.81 million in 2009. It is interesting that whereas the U.S.A. and Japan were hit hard by the economic crisis and the effects of changes in new car demand (Car_demand) contributed to decrease CF, in Germany, changes in new car demand (Car_demand) contributed greatly to increase CF between 2008 and 2009. This is because eco-car subsidy policies introduced by the German government in January 2009 were successful, and the number of new cars sold domestically in Germany greatly increased (Kraftfahrt-Bundesamt, 2010). The U.S.A. and Japan also introduced eco-car subsidy policies in the same period, but their effects on demand were not as immediate or as large as in Germany.

The effects of changes in petroleum demand (petro_demand) associated with driving new and old cars contributed greatly to decrease CF during 1995–2000 and 2008–2009 in Germany and Japan (but only during 2008–2009 in the U.S.A.), and surprisingly, these decreases were greater than the decreases due to the effects of technological changes in emission intensities (E) (Figures 4.4 and 4.5). However, the effects of changes in petroleum demand (petro_demand) between 2000 and 2008 in Germany and Japan (between 1995 and 2008 in the U.S.A.) constituted an important driver in increasing CF. In other words, the effects of changes in petroleum demand (petro_demand) have a large influence on changes in CF. During the analysis period, fuel efficiency in Germany and Japan improved substantially compared to in the U.S.A. (MLIT, 2010; UBA, 2017) and changes in the effects of changes in petroleum demand (petro_demand) stem largely from the price of gasoline rather than fuel efficiency (IEA, 2014).

The effects of changes in the number of older cars (Car_stock) led to the great increase of CF between 1995 and 2005 in Germany and Japan (until 2008 in the U.S.A.), and since then have contributed slightly to decrease CF (Figures 4.3, 4.4, and 4.5). This result shows that, since 2005 (since 2008 in the U.S.A.), the number of cars scrapped in accordance with their lifetime has been greater than the number of new cars sold. One feature of the effects of changes in travel distance (Travel_dist.) is a relatively strong contribution to decrease CF of automobiles in Japan (Figure 4.5). As for the influence of changes in trade structure of passenger cars, the effects of changes in the international trade of cars (Car_trade) and petroleum products (Petro_trade) were marginal (Figures 4.3, 4.4, and

4.5).

The results of the E-SDA show that the detailed drivers making up the effects of changes in final demand (F) and the effects of changes in direct emissions associated with petroleum consumption (Petro_direct) do not all decrease CF in the three countries. Instead, the effects of changes in petroleum demand (petro_demand) and the effects of changes in travel distance (Travel_dist.), in particular, contribute to emissions reduction, and they offset increases due to the effects of changes in the number of older cars in use (Car_stock) and the effects of changes in new car demand (Car_demand) (Figures 4.3, 4.4, and 4.5).

The final demand sector is sensitive to policies to promote consumer demand (e.g., policies to shorten automobile lifetime along with the introduction of subsidies for eco-cars) and policies to inhibit demand for new materials and products (e.g., promoting a circular economy associated with extending automobile lifetime). A conventional SDA can only evaluate the effect of policies by changes in final demand. By decomposing the final demand sector into additional drivers with E-SDA, we can analyze the influence of policies such as those mentioned above on the relevant country's production volume, energy consumption, and CF in more detail. Indeed, an increase in new car demand expected as a result of the eco-car subsidy policy in Germany is indisputably reflected in the analysis results (Figure 4.4).

4.4.4 E-SDA under the automobile lifetime scenarios

The influence of changes in lifetime of passenger cars (dashed lines in Figure 4.2) on changes in CF in the relevant country were estimated by applying the E-SDA developed in this study, which takes into account product lifetime. Figures, 4.6, 4.7, and 4.8 show the E-SDA results for the relevant country under the lifetime change scenario during the analysis period, which was divided into four periods. In all of the target countries, demand for cars was induced by shortening lifetime, and CF increased (Figures, 4.6, 4.7, and 4.8). The eco-car subsidy system in Germany during the economic crisis of 2009 greatly increased new car demand (Kraftfahrt-Bundesamt, 2010). Thus, the scenario analysis results show that shortening automobile lifetime stimulates economic activity. If we choose lifetime shortening (for example, an eco-car subsidy system) as a measure to stimulate the economy, we must accept an increase in CF.

On the other hand, extension of lifetime resulted in an increase in old cars with relatively poor fuel efficiency and increased the effects of changes in the number of older cars (Car_stock) and the effects of changes in petroleum demand (petro_demand), but these were exceeded by a decrease due to the effects of changes in new car demand (Car_demand), and therefore CF decreased (Figures, 4.6, 4.7, and 4.8). This reduction effect was particularly large in Germany and Japan.

The E-SDA results for Japan between 2000 and 2005 in Figure 4.8 show that the effects of technological changes in the industrial emission intensities (E) and the effects of changes in new car demand (Car_demand) are -8.3 Mt-CO_2-eq. and 3.2 Mt-CO_2-eq., respectively, in the baseline CF, but -8.2 Mt-CO_2-eq. and -12.6 Mt-CO_2-eq. in the +1 year lifetime extension scenario. The important point here is that a similar or greater reduction in CF as the reduction due to the effects of technological changes in industry (E) can be achieved by suppressing new car demand through lifetime extension (Figures 4.6, 4.7, and 4.8). This indicates that not only a decrease of the emission intensities of product manufacturing through technological innovation but the creation of a circular economy (for example, automobile lifetime extension) are required for climate mitigation.

A lifetime extension of automobiles reduces the direct global and domestic demand of consumers for automobiles, whereby reductions of intermediate input and energy input (i.e., indirect global and domestic demand) for the production of the product can be achieved. On the supply side, as these indirect demands disappear, the relevant suppliers of the product will face economical loss. In contrast, on the demand side, a shift in consumption expenditures from the product to other goods and services may cause an overall increase in emissions in the country (Kagawa *et al.*, 2011). I do not address these rebound effects (of both the supply and the demand sides), but instead I focus on the impact of changes in vehicle lifetimes on the life-cycle footprint of automobiles through the global supply chain. An expanded analysis considering the rebound effects (of both the supply and the demand sides) is important and challenging future work.

Conventional SDA using IO-LCA focuses on the effects of technological changes in industrial emission intensities (E) and the effects of changes in production structure (L). Final demand, which creates economic ripple effects, is a "black box," and the dynamism of demand is not explicitly considered. In scenario analysis by controlling product lifetime (Kagawa *et al.*, 2008; Nakamoto, 2017; Nishijima, 2017), the final demand sector that causes those ripples (or, the primary ripple) is notable, as well as the effects of technological changes in industrial emission intensities (E) and the ripple effects associated with the effects of changes in production structure (L). Now, using the E-SDA developed in this study, we have gained a new perspective in IO-LCAs.

The case study in this research looked at changes in lifetime, but it is applicable to other policies and strategies. Reducing average annual travel distance by promoting the use of public transport could result in the effects of changes in travel distance (Travel_dist.) contributing negatively. Alternatively, the introduction of gasoline tax and measures to improve fuel efficiency, such as Corporate Average Fuel Economy (CAFE) standards, could have a large impact on the effects of changes in petroleum demand (petro_demand).

I found that although the automotive supply chains have been spread globally (Kagawa *et al.*, 2015; Timmer *et al.*, 2015), the impact of changes in trade structure of passenger cars on the CF was very small (Figure 4.3-4.5). Further, combining structural path analysis (Defourny and Thorbecke, 1984; Lenzen, 2003; Strømman, Peters and Hertwich, 2009) or structural path decomposition (Oshita, 2012; Owen *et al.*, 2016; Wood and Lenzen, 2009) with E-SDA could provide useful clues in explaining the influence that changes in trade structure (trade agreements such as the North American Free Trade Agreement, Trans-Pacific Partnership, and EU) and supply chain associated with final demand have on the effects of changes in production structure (L), the effects of changes in the international trade of cars (Car_trade), and petroleum products (Petro_trade).

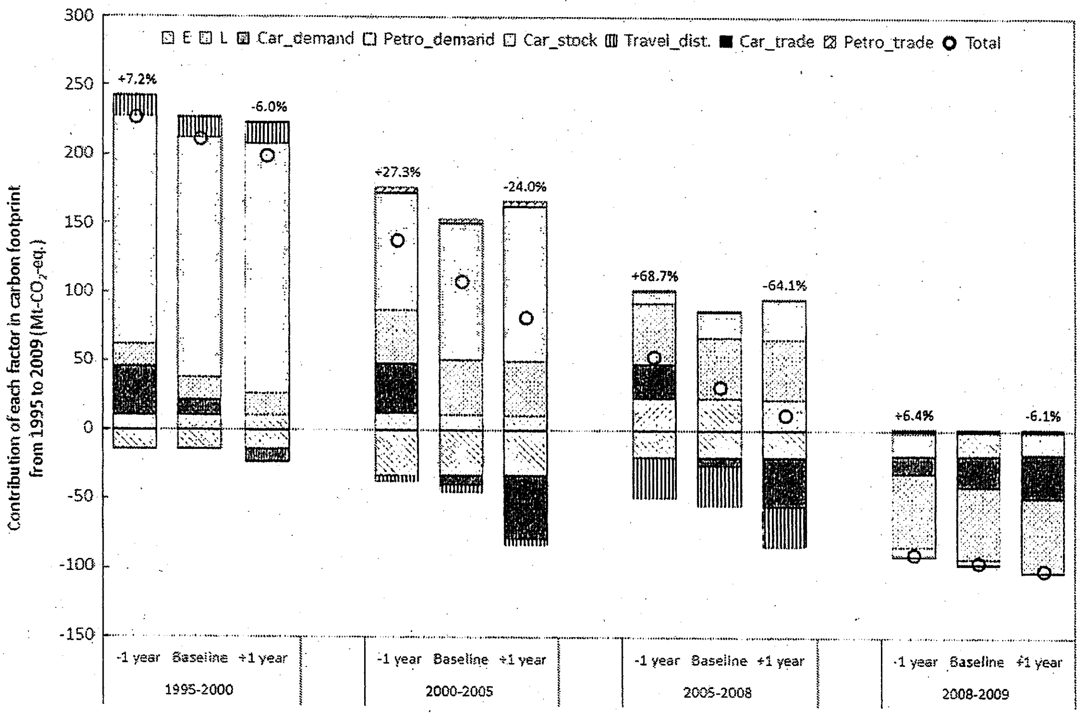

Figure 4.6: E-SDA of the carbon footprint of automobiles during 1995 to 2009 under the automobile lifetime scenario (U.S.A.).

Left bars: -1 year lifetime scenario. Center bars: baseline scenario.

Right bars: +1 year lifetime scenario.

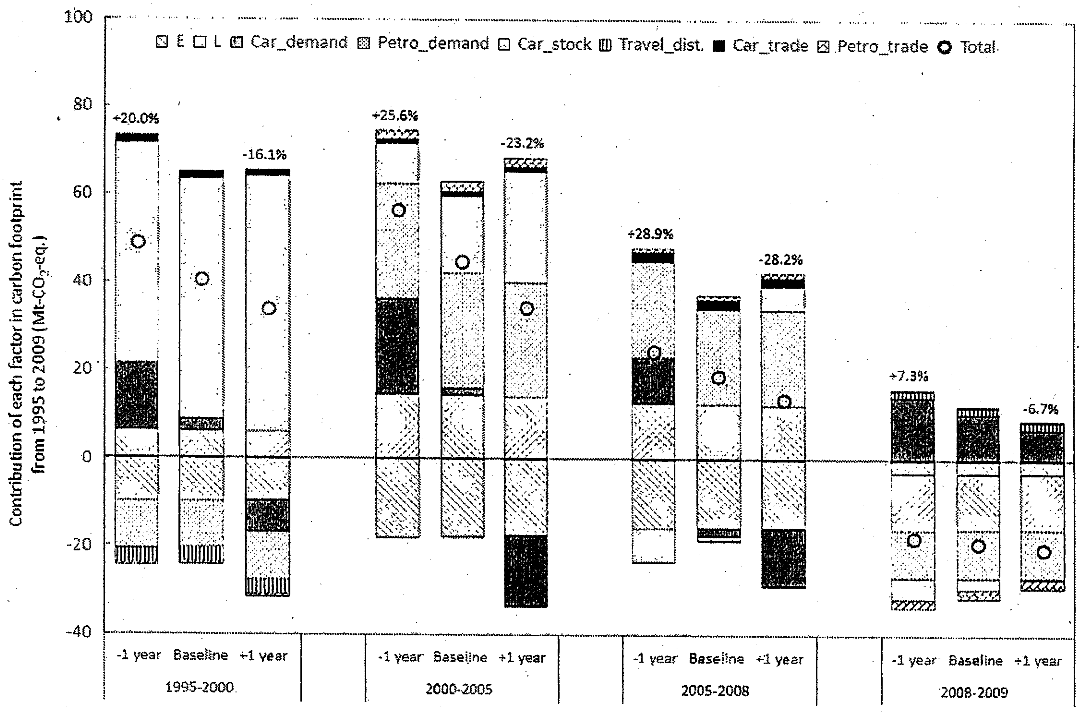

Figure 4.7: E-SDA of the carbon footprint of automobiles during 1995 to 2009 under the automobile lifetime scenario (Germany).

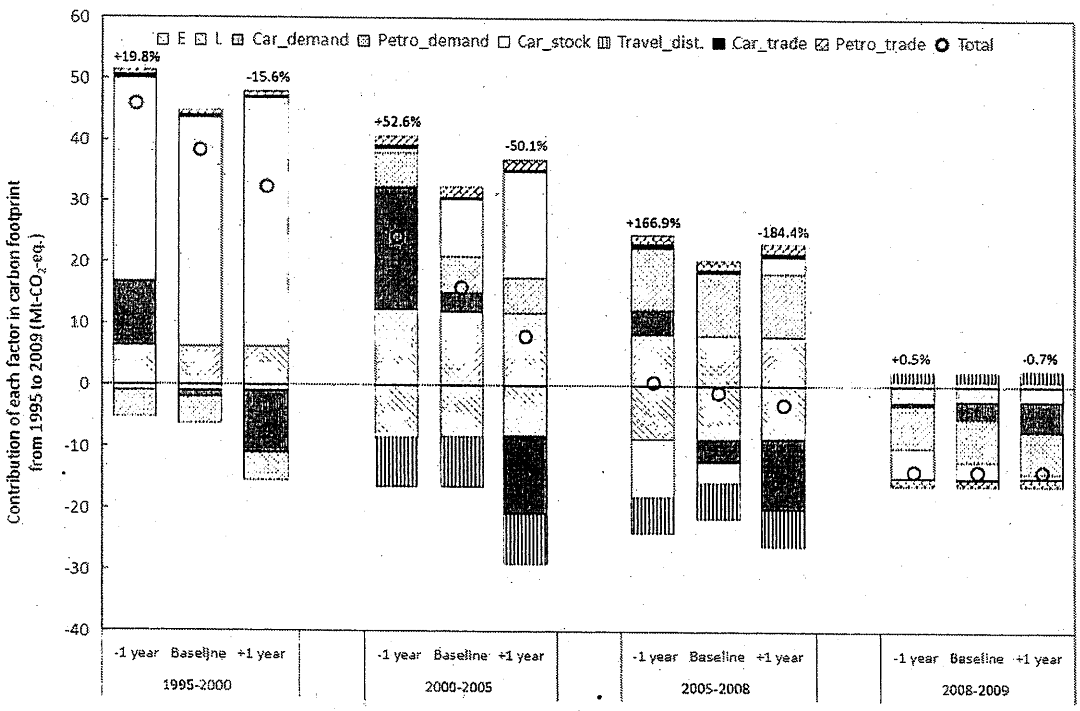

Figure 4.8: E-SDA of the carbon footprint of automobiles during 1995 to 2009 under the automobile lifetime scenario (Japan).

4.5. Conclusion

In this study, I carried out a life-cycle analysis that combined a multi-regional input–output analysis and a stock-flow model based on a lifetime distribution model of cars in the U.S.A., Germany, and Japan. I also analyzed the influence of changes in automobile lifetime in the relevant country on global CF by changing the average lifetime of passenger cars. Additionally, I applied an extended SDA (namely, E-SDA) to changes in CF in the relevant country.

The SDA results showed that the effects of technological changes in emission intensities (E) of suppliers directly and indirectly involved in automotive manufacturing contributed to a reduction in emissions in the three countries between 1995 and 2009. While the environmental burden on automobile manufacturing has decreased globally, the Leontief production structure (L) runs counter to carbon reduction and completely canceled out the effects of technological changes in emission intensities (E).

The E-SDA increased the transparency of dynamism of demand in the final demand sector, which causes economic ripples, and made detailed discussion possible. The benefits of integrating the lifetime scenario analyses with the E-SDA method is to not only clarify a more detailed structure of the impacts of product lifetime changes but connect the impacts of product lifetime changes with more concrete 'effects' as described by the E-SDA method. Although a structure of the effects of product lifetime changes on environment had been unclear and vague yet, the methodology developed in this study can quantitatively identify the impacts of circular strategies (in this study product lifetime extension) in more direct and detail level such as 'effects' of SDA methods. Therefore, we can understand the structure of environmental impacts of product lifetime changes more clearly.

Surprisingly, suppressing demand for new cars through lifetime extension greatly reduced CF, and had a similar or greater effect than changes in industrial technology. I conclude that lifetime extension aimed at creating a circular economy is important, as well as decarbonization of automobile manufacturing, in future policymaking in the transport sector directed toward implementation of the Paris Agreement. System design aimed at allowing car owners to drive their cars for longer is critically important in extending automobile lifetime. In Japan, the expensive vehicle inspection program encourages owners to replace their cars and shortens their economic lifetime (Nakamoto and Kagawa, 2018). Designing incentives to keep cars longer invariably requires policy proponents to review existing policies/systems and to create better environments around old cars by stimulating the market for secondhand cars and the repair/maintenance market.

Chapter 5: Role of Vehicle Inspection Policy in Climate Mitigation: The Case of Japan

5.1. Introduction

Vehicle safety inspection systems have been introduced in many countries, among them Japan, which introduced such a system in 1951 (Hirota and Minato, 2001). Under the Japan's car inspection system, testing for conformity to strict exhaust regulations and many other maintenance regulations are conducted three years after initial purchase and every two years thereafter, and the cost of such comprehensive inspections is a big burden on car owners (National Agency for Automobile and Land Transport Technology, 2016). Car owners would like to avoid the burden of car inspections and sell currently owned vehicles with higher market values before their next inspection and replace them with new vehicles. The cost burden motivates car owners having 'greener' current cars with good fuel economy to frequently replace them with new cars. As a result, the car inspection system hinders long-term use of the 'greener' cars and contributes to the increase in CO_2 emissions associated with the vehicle life-cycle, including manufacturing and disposal (Kagawa *et al.*, 2011). Therefore, it is important to determine to what extent the car inspection system has increased CO_2 emissions over time, as well as how we can modify the current car inspection system in keeping with a climate mitigation policy.

Previous life-cycle studies focused on the motor vehicle sector have successfully specified the lifetime distribution of vehicles, both in Japan and overseas (Oguchi and Fuse, 2015), and demonstrated that extending vehicle lifetime contributes to CO_2

emissions reduction (Kagawa *et al.*, 2011). To show the environmental benefit of introducing a subsidy system, Kagawa *et al.* (2013) compared the amount of life-cycle CO_2 emissions from vehicles (only new vehicles) under a subsidy system in which all vehicles are simultaneously replaced to the amount of life-cycle CO_2 emissions without a subsidy system, whereby vehicles are replaced slowly in accordance with a normal vehicle lifetime distribution. Lenski *et al.* (2010) showed the environmental benefit of the 'cash for clunkers' policy introduced in the United States in 2009. In this kind of life-cycle study focused on the motor vehicle sector, vehicle replacement purchase has been modeled according to the physical lifetime distribution of vehicles (e.g., Weibull distribution). Typically, physical lifetime distributions have been employed widely in studies on material flow analysis (e.g., Nakamura *et al.*, 2014; Pauliuk *et al.*, 2017) and on estimating the amount of stock of various materials (e.g., iron (Daigo *et al.*, 2007), aluminum (Chen and Graedel, 2012), and copper (Spatari *et al.*, 2005)).

However, previous studies that have modeled vehicle replacement purchases based on physical lifetime distribution have not evaluated social lifetime influences on the reasons of the owner and economic lifetime influences on maintenance costs, such as gasoline, property tax, and car inspections of vehicles. Kim *et al.* (2003, 2006) and De Kleine *et al.* (2011) estimated the lifetime of durable goods using life-cycle optimization analysis, to minimize the environmental burden, but they did not consider consumer behavior, which maximizes utility level over time. In other words, such studies have *not* adequately described the social lifetime or economic lifetime of vehicles based on the choice behavior of consumers—that is, how consumers decide every term to either continue driving the same vehicle or to make a replacement purchase. Thus, studies to date have been unable to make effective policy proposals in relation to vehicle demand policy. Numerous studies have been carried out on commodity markets using discrete choice models based on consumer theory (random utility theory)—e.g., Rust (1987), Chevalier and Goolsbee (2005), Gordon (2009), Schiraldi (2011), and Gavazza *et al.* (2014)—but thus far few studies have tried to assess the influence of adopting or modifying demand policy for durable goods on global warming.

In this study, we set out to estimate the impact of a car inspection system on CO_2 emissions derived from vehicles and to propose a vehicle life-cycle analysis using a dynamic discrete choice (DDC) model based on optimal consumer behavior. In the dynamic discrete choice model proposed in this study, the probability of a consumer choosing to continue driving the same vehicle without making a replacement purchase, versus making a replacement purchase of a new vehicle, depends on the expected cost (utility level). Incorporating the vehicle replacement purchase rate estimated by the DDC model into a vehicle life-cycle CO_2 emissions analysis based on the dynamic stock accounting model (Müller, 2006; Kagawa *et al.*, 2006; Nishijima, 2016), we conducted a scenario analysis of the impact of a car inspection system on the amount of CO_2 emissions derived from vehicles.

By estimating the economic lifetime of vehicles based on consumer behavior that maximizes utility level over time, we were able not only to specify the replacement purchase rate based on a DDC model but also to quantitatively analyze the environmental impact of changes in consumer behavior due to the adoption of policies—e.g., a car inspection system. The proposal of this new integrated analysis framework is expected to be quite useful in formulating a CO_2 emissions reduction policy targeted at the transport sector. We also clarified the role of policy change for a car inspection system in achieving Japan's emissions reduction. Finally, we discuss further policies that may be effective in achieving the target for CO_2 emissions reduction in the transport sector.

5.2. Methodology

5.2.1 Definition of utility function

Rust (1987), Chevalier and Goolsbee (2005), and Rapson (2014) all formulated durable goods replacement purchase consumer behavior (e.g., for automobiles or household air conditioners) that considers expected utility (in this study, expected cost) as a DDC model. Based on these earlier studies, we formulated a dynamic replacement purchase behavior model for specific motor vehicles, based on a maximization of expected utility. In period t, a single motor vehicle owner makes a decision whether to continue owning their current vehicle or to replace it by purchasing a new vehicle. The replacement purchase choice of a car owner in period t is formulated using the control variable i_t as follows (Rust, 1987):

$$i_t = \begin{cases} 1 & \text{if a car owner replaces in period } t \\ 0 & \text{otherwise.} \end{cases} \tag{5.1}$$

In this study, we focused on one particular model of car, a relatively green car, the Toyota Prius, that has rapidly established a large market presence over the past 10 years. Prius cars are assumed to be homogeneous and independent in the sense that the choice to make a replacement purchase of a Prius i is not influenced by the replacement purchase choice of a Prius j.

As in Rust (1987), in accordance with random utility theory (McFadden and Train, 2000), the utility of a car owner in period t can be formulated as a parametric function:

$$u(x_t, d_t, \varepsilon_{it}, i_t; \theta_{11}, \theta_{12}, \theta_{13}) = u(x_t, d_t, \varepsilon_{it}, i_t; \boldsymbol{\theta}_1) = (1-i_t)(\theta_{11}x_t + \theta_{12}d_t) + i_t\theta_{13} + \varepsilon_{it} \quad (5.2)$$

x_t is the cumulative travel distance of a car from the new car purchase at the start of period 1 to the end of period *t*. Dummy variable d_t takes value 1 in the third period after the new car purchase (i.e., $d_3 = 1$), after which it takes the value 1 every two further periods (e.g., $d_5 = 1$ and $d_7 = 1$); for all other periods, $d_t = 0$. Under Japan's *shaken* car inspection system, testing for conformity to strict exhaust regulations is conducted three years after purchase and then every two years thereafter, and the cost of such inspections is a big burden on car owners. For this reason, the car inspection system induces consumers to replace their cars (Clerides, 2008). ε_{it} is an unobservable error that influences the utility of consumers in making choice *i* in period *t*. In this study, this variable is assumed to follow a type I extreme value distribution with independent and identically distributed (i.i.d.) characteristics (Train, 2003). One interpretation of why we are unable to observe the error is that the replacement choice when there is no error is $i_t = i^*(x_t, d_t; \boldsymbol{\theta}_1)$, from the state variable that we obtained. This shows that the replacement purchase behavior of a single car owner must be explained completely by the cumulative travel distance and car inspection dummy in period *t*. However, since it is not necessarily the case that a single car owner follows an optimal solution when guided by this model, in most cases the behavior cannot be explained only by observed state variables.

In Eq. (5.2), when a car owner chooses not to make a replacement purchase in period t (i.e., $i_t = 0$), we obtain $u_t = \theta_{11}x_t + \theta_{12}d_t + \varepsilon_{0t}$, and the cumulative travel distance and car inspection dummy influence utility. In this case, utility decreases not only because of cumulative travel distance but because of the additional costs incurred at car inspection time. Therefore, the values of θ_{11} and θ_{12}, which represent utility function parameters, can be expected, in theory, to be negative. On the other hand, when a car owner chooses to purchase a new car in period t (i.e., $i_t = 1$), we get $u_t = \theta_{13} + \varepsilon_{1t}$. In this case, θ_{13} represents the consumer's replacement purchase cost, including opportunity cost, and if replacement cost increases then utility decreases. As a result, the parameter θ_{13} can be expected to be negative in theory.

Car owners (i.e., consumers) make replacement purchase choices $\{i_1, i_2, i_3, \cdots, i_T, i_{T+1}, \cdots\}$ so as to maximize the expected discounted value of the (infinite) series of periods $(t = 1, 2, 3, \cdots, T, T+1, \cdots)$:

$$\max_{\{i_1, i_2, \cdots\}} E\left[\sum_{t=1}^{\infty} \beta^{t-1} u(x_t, d_t, \varepsilon_{it}, i_t; \boldsymbol{\theta}_1)\right] \tag{5.3}$$

where β is the discount rate, which takes a value between 0 and 1, and the state variables in Eq. (5.3) are observable travel distance x_t, car inspection dummy d_t, and unobservable error ε_{it}.

The corresponding value function of this maximization problem (3) is formulated as:

$$V(x_t, d_t, \varepsilon_{it}; \boldsymbol{\theta}_1) = \max_{\{i_{t+1}, i_{t+2}, \cdots\}} E_{x,\varepsilon}\left[u(x_t, d_t, \varepsilon_{it}, i_t; \boldsymbol{\theta}_1) + \left\{\sum_{\tau=t+1}^{\infty} \beta^{\tau-t} u(x_\tau, d_\tau, \varepsilon_{i\tau}, i_\tau; \boldsymbol{\theta}_1) | x_{\tau-1}\right\}\right] \tag{5.4}$$

where $E_{x,\varepsilon}$ indicates expected value with respect to the two random variables, cumulative travel distance x and error term ε.

Thus, the Bellman equation based on the value function defined in Eq. (5.4) is as follows:

$$\begin{aligned}
V(x_t, d_t, \varepsilon_{it}; \boldsymbol{\theta}_1) &= \max_{i=\{0,1\}}\left\{u(x_t, d_t, \varepsilon_{it}, i_t; \boldsymbol{\theta}_1) + \beta E_{x,\varepsilon}\left[V(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1)\right]\right\} \\
&= \max\left\{u(x_t, d_t, \varepsilon_{0t}, 0; \boldsymbol{\theta}_1) + \beta E_{x,\varepsilon}\left[V(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1)\right], u(x_t, d_t, \varepsilon_{1t}, 1; \boldsymbol{\theta}_1) + \beta E_{\varepsilon}\left[V(0, 0, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1)\right]\right\} \\
&= \max\left\{\tilde{V}(x_t, d_t, \varepsilon_{0t}, 0; \boldsymbol{\theta}_1), \tilde{V}(x_t, d_t, \varepsilon_{1t}, 1; \boldsymbol{\theta}_1)\right\}
\end{aligned} \tag{5.5}$$

where $\tilde{V}(x_t, d_t, \varepsilon_{it}, i_t; \boldsymbol{\theta}_1)$ is the choice-specific value function dependent on choice i_t. In the DDC model expressed in Eq. (5.5), the discount rate β is generally given rather than estimated. In the extremely myopic case of the DDC model with β equal to zero, the car owner's replacement purchase choice is decided purely based on the utility in period t. In contrast, in the DDC model with a forward-looking perspective, in which the value of β is close to 1, the choice i_t in period t is influenced by the expected discounted utility in the future $E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]$. Chevalier and Goolsbee (2005), for example, investigated the question of whether the choice of students to buy a textbook at the present time depends on the expected utility that might be obtained from the future sale of a revised edition of the textbook. The results indicated that students purchased textbooks with a forward-looking perspective (Chevalier and Goolsbee, 2005).

5.2.2 Markov transition probabilities of additional annual travel distance

As per Rust (1987), we hypothesized that under conditions in which a replacement purchase is not made, the transition probability from x_t, the cumulative travel distance in period *t*, to x_{t+1}, the cumulative travel distance in period $t+1$, corresponds to the following conditional probability:

$$p\left(x_{t+1}, \varepsilon_{i,t+1} \middle| x_t, \varepsilon_{it}, i_t\right) = p\left(\varepsilon_{i,t+1} \middle| x_{t+1}, x_t, \varepsilon_{it}, i_t\right) \cdot p\left(x_{t+1} \middle| x_t, \varepsilon_{it}, i_t\right) = p\left(\varepsilon_{i,t+1}\right) \cdot p\left(x_{t+1} \middle| x_t, i_t\right) \tag{5.6}$$

where x_t and ε_{it} are assumed to be independent of each other. Furthermore, when the cumulative travel distance x_t at time *t* and the replacement purchase choice i_t are given, the cumulative travel distance x_{t+1} in the next period is also assumed to be independent of error term ε. Since ε is assumed to follow an i.i.d. Type I extreme value distribution for all of x_t, we obtain $p\left(\varepsilon_{t+1} \middle| x_{t+1}, x_t, \varepsilon_t, i_t\right) = p\left(\varepsilon_{t+1}\right)$.

Furthermore, from assuming conditional probability, a Markov property is assigned to additional travel distance in the dynamic optimization problem. The increase in the cumulative travel distance between period t and period $t+1$, $\Delta x_{t+1} = x_{t+1} - x_t$, is assumed to have probabilistic transitions and the transition probability can be formulated as follows:

$$p\left(x_{t+1} \middle| x_t, i_t\right) = f\left(x_{t+1} \middle| x_t\right) \tag{5.7}$$

where $f\left(x_{t+1} \middle| x_t\right)$ represents the conditional probability of the increase in cumulative travel distance Δx_{t+1} during the period $t+1$ for cumulative travel distance at time t x_t. Note that $f\left(x_{t+1} \middle| x_t\right)$ depends solely on the x_t of the previous period, not on the earlier values $x : x_{t-1}, x_{t-2}, \cdots$.

It is also assumed that the replacement purchase choice does not influence the travel distance transition probability. Note that if $i_t = 1$, then the cumulative travel distance x_t is set to zero, since the choice is made to purchase a new car, so the increase in cumulative travel distance becomes $\Delta x_{t+1} = x_{t+1}$.

If a car owner chooses not to make a replacement purchase at time t (i.e., $i_t = 0$), then the transition probability of the increase in the cumulative travel distance from period t to period $t+1$ (Markov transition probability) is given by the conditional probability density function $f(x_{t+1}|x_t)$. In this study, the probability density function $f(x_{t+1}|x_t)$ is discretized and converted to the discrete probability distribution $\boldsymbol{\theta}_2 = [\theta_{21}\ \theta_{22}\ \theta_{23}]$ as follows:

$$\Delta x_t = x_{t+1} - x_t = \begin{cases} [0, r_1) & \text{with probability of } \theta_{21}, \\ [r_1, r_2) & \text{with probability of } \theta_{22}, \\ [r_2, r_3) & \text{with probability of } \theta_{23}, \\ [r_3, \infty) & \text{with probability of } 1-\theta_{21}-\theta_{22}-\theta_{23}. \end{cases} \tag{5.8}$$

where $\boldsymbol{\theta}_2 = [\theta_{21}\ \theta_{22}\ \theta_{23}]$ satisfies both $0 < \theta_{21}, \theta_{22}, \theta_{23} < 1$ and $\theta_{21} + \theta_{22} + \theta_{23} \leq 1$. $[0, r_1)$, $[r_1, r_2)$, $[r_2, r_3)$, and $[r_3, \infty)$ express the discretized increase in cumulative travel distance as a fourfold grid. For example, if $r_1 = 5{,}000$, $r_2 = 10{,}000$, and $r_3 = 15{,}000$, and the car owner decides not to make a replacement purchase in period *t*, then the transition probability of the increase in cumulative travel distance from period *t* to period $t+1$ being less than 5,000 km is θ_{21}, the transition probability of it being at least 5,000 but less than 10,000 km is θ_{22}, and the transitional probability of it being at least 10,000 but less than 15,000 km is θ_{23}, meaning that the transition probability of it being 15,000 km or greater is $1-\theta_{21}-\theta_{22}-\theta_{23}$.

5.2.3 Estimation method: likelihood function

The likelihood function pertaining to the replacement purchase choice of a single car owner from period 1 through the end of period T can be formulated as follows:

$$\begin{aligned} L(\boldsymbol{\theta}) &= L(x_1,\ldots,x_T,d_1,\ldots,d_T,i_1,\ldots,i_T;\boldsymbol{\theta}) \\ &= \prod_{t=1}^{T} \mathrm{Prob}(i_t,x_t,d_t | x_t,x_{t-1},i_{t-1};\boldsymbol{\theta}) \\ &= \prod_{t=1}^{T} \mathrm{Prob}(i_t | x_t,d_t;\boldsymbol{\theta}_1)\,\mathrm{Prob}(x_t | x_{t-1},i_{t-1};\boldsymbol{\theta}_2) \end{aligned} \tag{5.9}$$

By taking the logarithm of Eq. (5.9), we can divide the likelihood function into two separate items:

$$\log L(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log \mathrm{Prob}(i_t | x_t,d_t;\boldsymbol{\theta}_1) + \sum_{t=1}^{T} \log \mathrm{Prob}(x_t | x_{t-1},i_{t-1};\boldsymbol{\theta}_2) \tag{5.10}$$

In this way, the likelihood can be determined in two steps. In the first step, we can straightforwardly calculate the discretized transition probability (Markov transition probability) $\hat{\boldsymbol{\theta}}_2 = \left[\hat{\theta}_{21},\hat{\theta}_{22},\hat{\theta}_{23}\right]$ of the increase in cumulative travel distance, under the condition that a replacement purchase is not made. In the second step, we estimate the parameter $\boldsymbol{\theta}_1 = [\theta_{11},\theta_{12},\theta_{13}]$ of the utility function. $\mathrm{Prob}(i_t = 1 | x_t,d_t;\boldsymbol{\theta}_1)$, based on the assumption on ε, is equivalent to the following:

$$
\begin{aligned}
&\text{Prob}\left(i_t = 1 \middle| x_t, d_t; \boldsymbol{\theta}_1\right) \\
&= \text{Prob}\Big(u\left(x_t, d_t, \varepsilon_{1t}, 1; \boldsymbol{\theta}_1\right) + \beta E_\varepsilon\left[V\left(0, 0, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right] > u\left(x_t, d_t, \varepsilon_{0t}, 0; \boldsymbol{\theta}_1\right) + \beta E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\Big) \\
&= \text{Prob}\Big(\theta_{13} + \varepsilon_{1t} + \beta E_\varepsilon\left[V\left(0, 0, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right] > \theta_{11} x_t + \theta_{12} d_t + \varepsilon_{0t} + \beta E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\Big) \\
&= \text{Prob}\Big(\varepsilon_{1t} - \varepsilon_{0t} > \theta_{11} x_t + \theta_{12} d_t - \theta_{13} + \beta E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}\right) - V(0)\right]\Big).
\end{aligned}
\tag{5.11}
$$

Then, based on the assumption that ε_{1t} and ε_{0t} each follow an i.i.d. Type I extreme value distribution, $\varepsilon_{1t} - \varepsilon_{0t}$ follows a logistic distribution. Therefore, the probability of a replacement purchase in period t and the probability of continued ownership can each be formulated according to a binomial logit model (BLM), as follows:

$$
\begin{cases}
\text{Prob}\left(i_t = 1 \middle| x_t, d_t; \boldsymbol{\theta}_1\right) = \dfrac{\exp\left\{\theta_{13} + \beta E_\varepsilon\left[V\left(0, 0, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\right\}}{\exp\left\{\theta_{11} x_t + \theta_{12} d_t + \beta E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\right\} + \exp\left\{\theta_{13} + \beta E_\varepsilon\left[V\left(0, 0, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\right\}} \\[2ex]
\text{Prob}\left(i_t = 0 \middle| x_t, d_t; \boldsymbol{\theta}_1\right) = \dfrac{\exp\left\{\theta_{11} x_t + \theta_{12} d_t + \beta E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\right\}}{\exp\left\{\theta_{11} x_t + \theta_{12} d_t + \beta E_{x,\varepsilon}\left[V\left(x_{t+1}, d_{t+1}, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\right\} + \exp\left\{\theta_{13} + \beta E_\varepsilon\left[V\left(0, 0, \varepsilon_{i,t+1}, i_{t+1}; \boldsymbol{\theta}_1\right)\right]\right\}}
\end{cases}
\tag{5.12}
$$

The second step for maximizing the likelihood function expressed in Eq. (5.10) is the procedure of estimating the utility function parameter $\hat{\boldsymbol{\theta}}_1$ defined in Eq. (5.2), which is done by means of a nested fixed-point algorithm (NFPA), as proposed in Rust (2000). (see Appendix 5.1)

5.2.4 Cumulative life-cycle CO_2 emissions based on a stock and flow analysis

The DDC model formulated in the previous section explicitly includes θ_{11}, the maintenance and repair costs in the utility function when the car is retained or replaced, θ_{12}, the car inspection cost, and θ_{13}, the replacement purchase cost (cost of buying a new car). This makes it possible to estimate the environmental impact of changes in the consumer behavior due to the introduction of measures such as car inspection systems and eco-car subsidies.

Using the BLM of Eq. (5.12) and the estimated expected value function EV, $\phi_\tau(x_\tau, d_\tau; \boldsymbol{\theta}_1)$, the probability that a car owner who purchased a new car in the first period (period 1) chooses to purchase a new replacement car in period τ (instead of retaining the same car) can be expressed as follows:

$$\phi_\tau(x_\tau, d_\tau; \boldsymbol{\theta}_1) = \begin{cases} \mathrm{Prob}(i_\tau = 1 | x_\tau, d_\tau; \boldsymbol{\theta}_1) & (\tau = 1) \\ \mathrm{Prob}(i_\tau = 1 | x_\tau, d_\tau; \boldsymbol{\theta}_1) \left\{ \prod_{t=1}^{\tau-1} \mathrm{Prob}(i_t = 0 | x_\tau, d_\tau; \boldsymbol{\theta}_1) \right\} & (\tau = 2, 3, 4, \cdots) \end{cases} \tag{5.13}$$

Note that the probability of a replacement purchase rate in period 0 is $\phi_0(x_0, d_0; \boldsymbol{\theta}_1) = 0$. From Eq. (5.13), the probability that a car purchased in period 1 is retained in period τ (cumulative survival probability), $H_\tau(x_\tau, d_\tau; \boldsymbol{\theta}_1)$, is

$$H_t\left(x_\tau, d_\tau; \boldsymbol{\theta}_1\right) = 1 - \sum_{\tau=1}^{t} \phi_\tau\left(x_\tau, d_\tau; \boldsymbol{\theta}_1\right) \tag{5.14}$$

Note that the cumulative survival probability in period 0 is $H_0\left(x_0, d_0; \boldsymbol{\theta}_1\right) = 1$.

Based on Kagawa *et al.* (2013), Nishijima (2016), and Nakamoto (2017), the car replacement purchase rate $\phi_\tau\left(x_\tau, d_\tau; \boldsymbol{\theta}_1\right)$ and cumulative survival probability $H_\tau\left(x_\tau, d_\tau; \boldsymbol{\theta}_1\right)$ in Eqs. (5.13) and (5.14), respectively, can be used to formulate a stock flow estimation model for cars.

Using the replacement probability of new cars, the stock of passenger cars in year *t*, $S(t)$, can be estimated as follows:

$$S(t) = B(t) + \sum_{i=1}^{t-1} H_{t-i}\left(x_{t-i}, d_{t-i}; \boldsymbol{\theta}_1\right) B(i) \tag{5.15}$$

where $B(t)$ represents the number of new cars purchased in year *t*, and $H_{t-i}\left(x_{t-i}, d_{t-i}; \boldsymbol{\theta}_1\right)$ is the replacement probability for new cars in year *t* that are newly registered in year *i*.

Next we explain how to solve the stock dynamic equation by assuming that passenger cars are newly registered in year 1 (i.e., $i = 1$ in Eq. (5.15)). In addition, we assume that all new passenger cars follow the same replacement probability, irrespective of their vintage. We have the following dynamic system of equations.

$$\begin{cases} S(1) = B(1) \\ S(2) = B(2) + H_1(x_1, d_1; \boldsymbol{\theta}_1) B(1) \\ S(3) = B(3) + H_1(x_1, d_1; \boldsymbol{\theta}_1) B(2) + H_2(x_2, d_2; \boldsymbol{\theta}_1) B(1) \\ \vdots \end{cases} \tag{5.16}$$

In this study, stock of passenger cars in each year $S(t)$ is taken to be steady state. Then, when the stock of passenger cars at steady state is given as S', the number of new passenger cars sold can be estimated sequentially as follows:

$$\begin{cases} B(1) = S'(1) \\ B(2) = S'(2) - H_1(x_1, d_1; \boldsymbol{\theta}_1) B(1) \\ B(3) = S'(3) - H_1(x_1, d_1; \boldsymbol{\theta}_1) B(2) - H_2(x_2, d_2; \boldsymbol{\theta}_1) B(1) \\ \vdots \end{cases} \tag{5.17}$$

Here, it should be noted that in this study we assumed that once car owners release the vintage Prius focused in this study, they do not purchase other car models and used Prius but new Prius. The amount of newly-purchased Prius in year t can be estimated as $B(t)$. Thus, we analyzed the replacement cycle of a specific greener car model (i.e., TOYOTA Prius). This is a limitation of this study.

Based on Nakamoto (2017), the life-cycle CO_2 emissions of new cars registered in year t can be formulated as follows:

$$q(t)=f_mB(t)+f_w\sum_{s=1}^{t}\phi_{t-s}(x_{t-s},d_{t-s};\boldsymbol{\theta}_1)B(s)+\sum_{s=1}^{t}f_g(s)H_{t-s}(x_{t-s},d_{t-s};\boldsymbol{\theta}_1)B(s) \quad (5.18)$$

where f_m, f_w, and $f_g(s)(s=0,1,\cdots,S)$ represent the life-cycle CO_2 emission intensity for, respectively, producing a new passenger car, scrapping an end-of-life passenger car, and driving an s vintage passenger car. Accordingly, the terms on the right-hand side of eq. (5.18) denote the life-cycle CO_2 emissions in, respectively, the pre-consumer phase, the scrapping phase of end-of-life passenger cars, and the driving phase of passenger cars newly registered in year s.

Note that the right-hand side of Eq. (5.18) is clearly a function of cumulative travel distance x and car inspection dummy d for a given time period. Thus, we have shown that we are able to assess the influence of car inspection systems (through the effect of car inspection dummy θ_{12} on the utility function in Eq. (5.2)) and subsidy systems (through the effects of maintenance cost θ_{11} due to cumulative travel distance and of replacement purchase cost θ_{13}, which includes consumers' opportunity cost, in Eq. (5.2)) on cumulative life-cycle CO_2 emissions (in manufacturing, driving, and disposal).

In addition, the economic lifetime of cars, based on consumer behavior directed to maximizing utility level over time, can be defined as follows:

$$\text{Economic lifetime} \equiv \sum_{t=1}^{T} \left\{ \phi_t \left(x_t, d_t; \boldsymbol{\theta}_1 \right) \times \text{Motor vehicle age}_t \right\} \tag{5.19}$$

where *motor vehicle age* expresses the age of the car, that is, the number of years from the time of first registration in year 0 to year t. This basically means the length of time that the car owner who purchased a new car in period 1 has continued to drive the car, which can be interpreted as the number of years of ownership.

5.3. Setting data

In this study, for the samples for new car replacement purchases, we utilized used car sales data for 1,195 vehicles, obtained from the web site kakaku.com (kakaku.com, 2017). This used car sales dataset provides various kinds of data: sales price for each relevant vehicle (¥), year of first registration, cumulative travel distance (km), need of car inspection (yes/no), repair history, and engine displacement (cc). Data on the year of re-registration as a used car are also included. The number of years calculated by subtracting the initial year of registration from the year of re-registration can be understood as the total time during which an original owner has continued to drive a particular vehicle, or in other words, the number of years of ownership. The maximum value of the cumulative travel distance was 188,000 km, and the maximum value of years of ownership was 12 years. The annual average travel distance value was 10,000 km (see Full sample in Table 5.1).

Table 5.1: Summary of sample data

Generation	Vintage	Cumulative mileage (10,000 km)			Annual mileage (10,000 km)			Length of ownership (years)			Price (10,000 yen)			Number of samples
		Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	
1st	1997/12-2003/08	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
2nd	2003/09-2009/04	18.8	0.8	7.0	2.7	0.1	0.9	12.0	3.0	8.1	198.0	30.0	97.6	119
3rd	2009/05-2015/11	17.4	0.0	5.1	4.5	0.0	1.1	7.0	0.0	5.0	319.0	53.7	138.4	949
4th	2015/12-current	2.6	0.0	0.6	2.6	0.0	0.6	1.0	0.0	0.6	418.0	199.0	278.6	127
Full sample		18.8	0.0	4.8	4.5	0.0	1.0	12.0	0.0	4.9	178.0	30.0	149.2	1195

Since being released as the world's first mass-production hybrid vehicle (HV) in December 1997, the Toyota Prius has sold a total of nearly 4 million units worldwide (approximately 1.80 million units in Japan) as of January 2017 (Toyota, 2017). To date, three full model changes (generation changes) have occurred in September 2003, May 2009, and December 2015, with each change bringing increased fuel efficiency, engine displacement, and horsepower, even though the price has remained almost constant over this time (Autoc one, 2017) (see descriptive statistics for the four generations shown in Table 5.1). Analyzing price data for car models sold in Japan in terms of a price index based on 1997 prices for the period from 1997 to 2016 during which the Prius was sold, we find that the car price indices reached a maximum of 100.4 (in 1998 and 2016) and a minimum of 97.3 (2013) (Ministry of Internal Affairs and Communications, 2017). This means that the average car price remained almost unchanged for the whole period from 1997 to 2016. For the reason above, in this study, we treat the Prius as homogeneous and independent, that is, assume that a replacement purchase choice of a Prius i is not influenced by the replacement purchase choice of a Prius j.

In the calculation of life-cycle CO_2 emissions in Eq. (5.18), based on a 2005 environmental input–output table (National Institute for Environmental Studies, 2010) and Kagawa *et al.* (2011), we set the CO_2 emission intensity in Table 5.2. Specifically, the CO_2 emission intensity in manufacturing per passenger car f_m was taken to be 6.42 t-CO_2 and the CO_2 emission intensity associated with waste disposal per passenger car f_w was taken to be 0.0574 t-CO_2 (Table 5.2).

Annual gasoline consumption $g(s)$ was calculated by dividing the annual average travel distance, 10,000 km (from sample data), by the fuel efficiency of a Prius of vintage s, $e(s)$ (Toyota, 2017). Then by multiplying the annual gasoline consumption $g(s)$ by the CO_2 emissions per liter of gasoline burned during car travel, r_g (t-CO_2), and by the CO_2 emissions per liter of gasoline generated during refining, r_c (t-CO_2), we calculated the annual unit CO_2 emissions associated with travel per passenger car of vintage s, $f_g(s)(s = 0,1,\cdots,S)$ (Table 5.2).

Table 5.2: Parameter settings used in this analysis

Generation	Vintage	Variable and parameter settings		
		$e(s)$ (km/L)	$g(s)$ L	$f_g(s)$ (t CO_2-eq./car)
1st	1997/12-2003/08	29.0	344.8	1.014
2nd	2003/09-2009/04	33.0	303.0	0.891
3rd	2009/05-2015/11	35.5	281.7	0.829
4th	2015/12-current	40.8	245.1	0.721
			r_g= 0.00231 (t CO_2-eq./l)	
			r_c= 0.00063 (t CO_2-eq./l)	
			f_m= 6.426 (t CO_2-eq./car)	
			f_w= 0.057 (t CO_2-eq./car)	

Data sources: Toyota, Japan (2010) and National Institute for Environmental Studies, Japan (2010).

5.4. Results and discussion

5.4.1 Estimating DDC model

To calculate EV as expressed in Eq. (A5.1) (see Appendix 5.1), we discretized the increase in cumulative travel distance from period t to period $t+1$, Δx_{t+1}. More specifically, we used cumulative travel distance data for each of the automobiles included in our source data on used car sales. Assuming that the annual travel distance per car is constant from year to year, it can be calculated by dividing the total cumulative travel distance of the car by the number of years of car ownership. Using a histogram for additional yearly average travel distance from the 1,195 data samples, we estimated a discrete distribution $\boldsymbol{\theta}_2$. If the grid width in Eq. (5.8) is 5,000 km (i.e., $r = 5{,}000$) and we consider that the maximum cumulative travel distance of a Prius from the obtained data was 188,000 km, then the grid size of the state variable x is $n = 38$. Similarly, for grid widths 3,000, 7,000, and 10,000 km (i.e., $r = 3{,}000$, $r = 7{,}000$, and $r = 10{,}000$), the grid sizes of the state variable x are respectively $n = 63$, $n = 27$, and $n = 19$.

In this study, when $\beta = 0$ with the above grid sizes and annual average travel distances, we obtained the following discrete distributions $\boldsymbol{\theta}_2$:

Case of n=63

$$\Delta x_t = x_{t+1} - x_t = \begin{cases} [0,3,000) & \text{with probability of } 0.063, \\ [3,000,6,000) & \text{with probability of } 0.164, \\ [6,000,9,000) & \text{with probability of } 0.241, \\ [9,000,\infty) & \text{with probability of } 0.532. \end{cases}$$

Case of n=38

$$\Delta x_t = x_{t+1} - x_t = \begin{cases} [0,5,000) & \text{with probability of } 0.163, \\ [5,000,10,000) & \text{with probability of } 0.380, \\ [10,000,15,000) & \text{with probability of } 0.271, \\ [15,000,\infty) & \text{with probability of } 0.186. \end{cases}$$

Case of n=27

$$\Delta x_t = x_{t+1} - x_t = \begin{cases} [0,7,000) & \text{with probability of } 0.308, \\ [7,000,14,000) & \text{with probability of } 0.462, \\ [14,000,21,000) & \text{with probability of } 0.168, \\ [21,000,\infty) & \text{with probability of } 0.061. \end{cases}$$

Case of n=19

$$\Delta x_t = x_{t+1} - x_t = \begin{cases} [0,10,000) & \text{with probability of } 0.544, \\ [10,000,20,000) & \text{with probability of } 0.385, \\ [20,000,30,000) & \text{with probability of } 0.065, \\ [30,000,\infty) & \text{with probability of } 0.006. \end{cases}$$

Tables 5.3 and 5.4 list the estimated values of utility function parameters. We analyzed the utility function based on two scenarios: a forward-looking scenario ($\beta = 0.99$) and a myopic scenario ($\beta = 0$). The values of the estimated parameters $\boldsymbol{\theta}_1 = [\theta_{11}, \theta_{12}, \theta_{13}]$ are all negative, so in the sense that the utility to the car owner decreases due to increasing cumulative travel distance, car inspection cost, and replacement purchase cost, this result is consistent with economic theory (Tables 5.3 and 5.4). In other words, this result seems to be in accordance with car replacement purchase behavior of a car owner who aims at maximizing utility while taking into consideration future maintenance and repair costs and car inspection costs, as well as car trade-in value. Note here that cumulative travel distance has a relatively big impact on the utility of consumers in the myopic model ($\beta = 0$) compared to the case of the forward-looking model ($\beta = 0.99$) (Tables 5.3 and 5.4).

In these results, even as the grid width changes, there is no significant influence on the likelihood, or economic lifetime, so we chose $r = 5,000$ as the benchmark value (Tables 5.3 and 5.4). Thus, in this study, by assuming that car owners behave with a forward-looking perspective, we adopted the estimated parameters when $\beta = 0.99$ and $r = 5,000$ as benchmark values.

Table 5.3: Logit estimates for utility function ($\beta = 0$)

Grid interval	3,000	5,000	7,000	10,000
Number of grids	63	38	27	19
θ_{11}	-1.732*	-1.039*	-0.742*	-0.520*
	(0.068)	(0.041)	(0.029)	(0.021)
θ_{12}	-3.778*	-3.778*	-3.778*	-3.778*
	(0.102)	(0.102)	(0.102)	(0.102)
θ_{13}	-0.626*	-0.626*	-0.626*	-0.626*
	(0.074)	(0.074)	(0.074)	(0.074)
θ_{21}	0.063	0.163	0.308	0.544
θ_{22}	0.164	0.380	0.462	0.385
θ_{23}	0.241	0.271	0.168	0.065
Log-likelihood	-2361.88	-2361.88	-2361.88	-2361.88
Economic lifetime	5.08	5.08	5.08	5.08

Number of obs.=1,195

Standard error in parentheses.

* Statistically significant ($p < 0.01$).

Table 5.4: Logit estimates for utility function ($\beta = 0.99$)

Grid interval	3,000	5,000	7,000	10,000
Number of grids	63	38	27	19
θ_{11}	-0.853*	-0.420*	-0.252*	-0.139*
	(0.052)	(0.025)	(0.015)	(0.003)
θ_{12}	-3.709*	-3.691*	-3.681*	-3.670*
	(0.110)	(0.110)	(0.112)	(0.149)
θ_{13}	-0.009*	-0.008*	-0.007*	-0.007*
	(0.001)	(0.001)	(0.001)	(0.001)
θ_{21}	0.063	0.163	0.308	0.544
θ_{22}	0.164	0.380	0.462	0.385
θ_{23}	0.241	0.271	0.168	0.065
Log-likelihood	-2378.13	-2382.71	-2387.91	-2396.87
Economic lifetime	5.07	5.07	5.07	5.06

Number of obs.=1,195

Standard error in parentheses.

* Statistically significant ($p < 0.01$).

5.4.2 Economic lifetime, hazard functions, and car inspection system

'Physical' lifetime distribution is widely used in material flow analysis and material stock analysis (e.g., Kagawa *et al.*, 2011; Chen and Graedel, 2012; Nakamura *et al.*, 2014). Kagawa *et al.* (2011), for example, estimated the average physical lifetime of 'average' gasoline passenger cars in Japan (number of years of survival from the time of new car purchase to the time of disposal) to be 11.5 years. In contrast, according to a survey on passenger car market trends (Japan Automobile Manufacturers Association; JAMA, 2016), the economic lifetime of the average gasoline passenger car in Japan (number of years of ownership from the time of new car purchase to the time of car replacement) is 6.9 years. Thus, the economic lifetime is approximately only half the physical lifetime.

In this study, we were able to estimate the replacement purchase rate ϕ_τ over time in our benchmark model ($\beta = 0.99$ and $r = 5{,}000$) by plugging the relevant parameters $(\theta_{11} = -0.420,\ \theta_{12} = -3.691,\ \theta_{13} = -0.008)$ into Eq. (5.13). By substituting ϕ_τ into Eq. (5.18), it is possible to estimate the economic lifetime of the passenger car (in the case of this study, a Toyota Prius). From Table 5.2, we find that the economic lifetime of a Prius in this benchmark model is surprisingly short, 5.07 years.

To clearly show what influence a car inspection system has on the replacement purchase behavior of car owners, we analyzed a scenario in which Japan has no car inspection system by setting the value of the car inspection dummy parameter θ_{12} to zero in the utility function of the benchmark model (Eq. (5.2)). Economic lifetime in the case of no car inspection system is approximately 0.5 years (6 months) longer than in the case of a car inspection system (Figure 5.2). This finding shows that the high cost burden a car inspection system imposes on consumers has the effect of inducing car replacement purchases, which also shortens the economic lifetime of cars.

Figure 5.1 shows the car replacement purchase rates according to the sample data and based on the benchmark DDC model. The horizontal axis is with respect to the number of years since the car was purchased (year 0). The estimated replacement purchase rate according to the benchmark model quite accurately captures the change in the observed replacement purchase rate (Figure 5.1). The car replacement purchase rate increases in the 3rd, 5th, and 7th years, when inspections[1] are due. The costs of car inspection and car maintenance/repair faced by car owners in Japan are substantially higher than in most other countries (Ministry of Land, Infrastructure, Transport and Tourism, 2016). In other words, the car owners tend to replace their cars according to the timing of obligatory car inspections in order to avoid paying the high cost of the inspection (Figure 5.1).

Figure 5.2 shows the replacement purchase rates in the benchmark model and in the scenario in which there are no mandatory inspections. Compared to the benchmark model, the car replacement purchase rate in the "no car inspection system" scenario is significantly less, 6% in the 3rd year and 5th year, when inspections are due (Figure 5.2). In other words, it seems that for a short period after car owners purchase a new vehicle, the car inspection system is an important factor in replacement purchases. In contrast, the

[1] Under Japan's passenger car inspection system, cars must be inspected three years after they are first registered and then every two years after that, regardless of the vehicle's age.

replacement purchase rate in the “no car inspection system” scenario is higher than that in the benchmark model from the 8th year onwards (Figure 5.2). This suggests that the abolition of the car inspection system would contribute to extending the economic lifetime of cars by deterring the replacement purchase behavior of car owners to some extent.

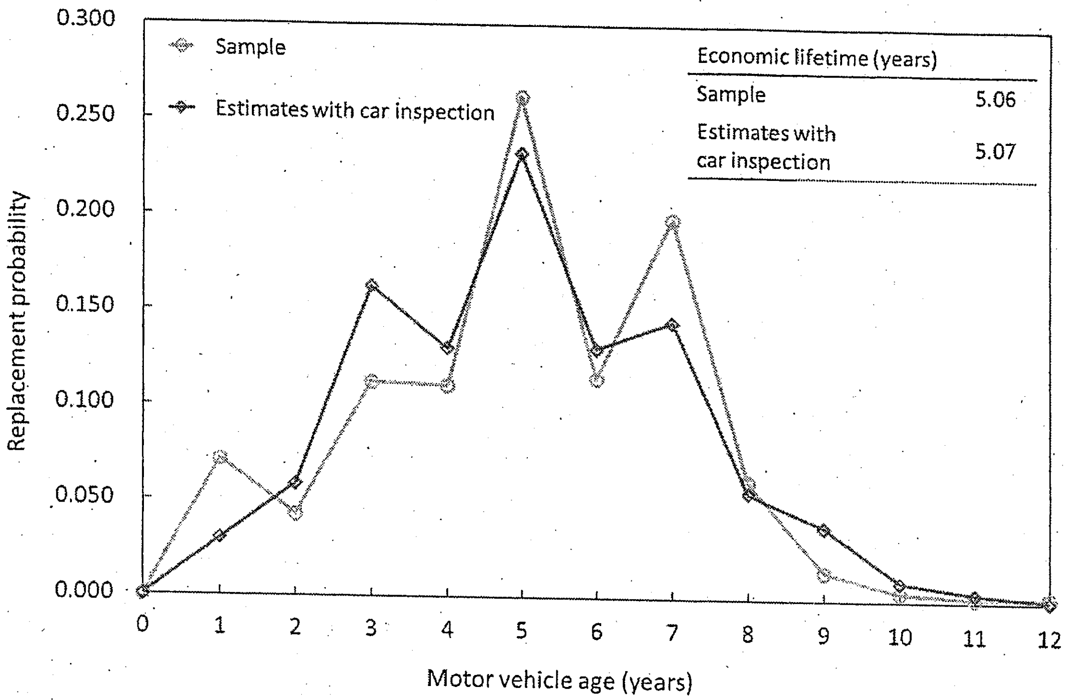

Figure 5.1: Motor vehicle replacement probability

(Sample / Estimates with car inspection scenario)

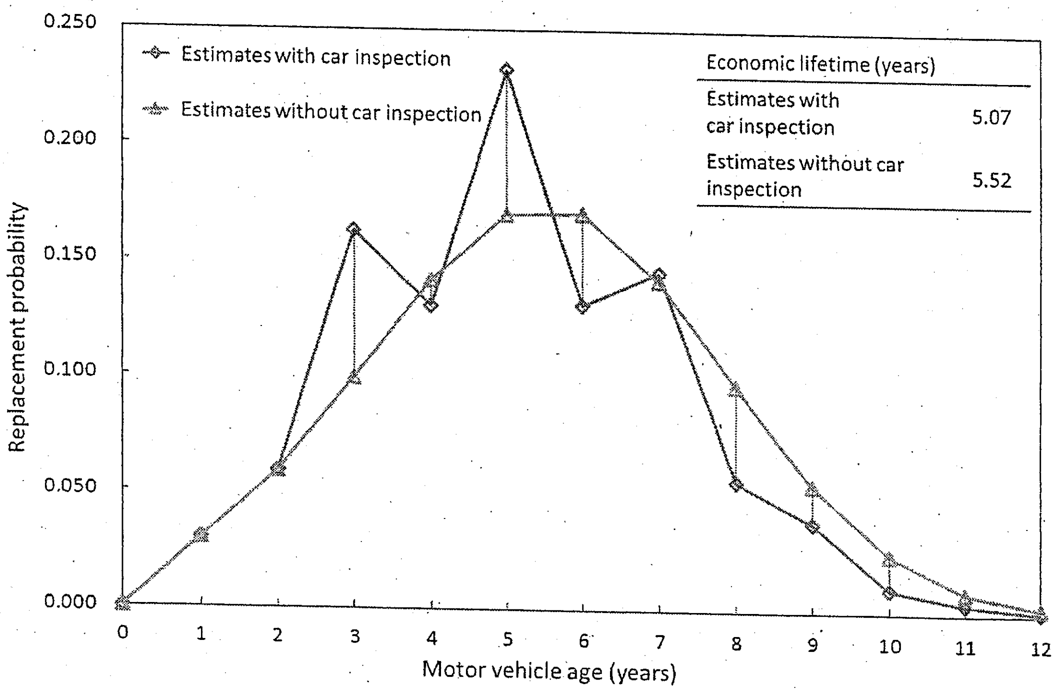

Figure 5.2: Motor vehicle replacement probability

(Estimates with car inspection scenario / Estimates without car inspection scenario)

5.4.3 CO_2 reduction potentials for the car inspection system

We inserted the replacement purchase rates and hazard rates based on the specified DDC model, as given in Eqs. (5.13) and (5.14), into a dynamic stock model for durable goods. Furthermore, from the car stock and flow determined from Eqs. (5.15), (5.16), and (5.17), we were able to estimate the cumulative life-cycle CO_2 emissions of cars, as given by Eq. (5.18). The important point here is that we now have the ability to assess the impact on cumulative life-cycle CO_2 emissions (in manufacturing, driving, and disposal) both when there is a car inspection system and when there is not.

It should be noted that the reduction in life-cycle CO_2 emissions associated with vehicles can be achieved by completely abolishing the car inspection system or modifying the system. The integrated analysis framework formulated in this study can provide the CO_2 emission reduction effects in the modified car inspection policies by controlling the car inspection dummy variables included in the DDC model. In this study, we estimated the cumulative life-cycle CO_2 emissions (in manufacturing, driving, and disposal) of passenger cars registered between 1997 and 2016 for our benchmark model and for the following four scenarios: "No car inspection system", "Without car inspection at third year", "Without car inspection at fifth year", and "Without car inspections at third and fifth years".

Figure 5.3 shows the effect that completely abolishing the car inspection system would have on decreasing cumulative life-cycle CO_2 emissions, calculated by subtracting the cumulative life-cycle CO_2 emissions in the case of no car inspection system from the cumulative life-cycle CO_2 emissions in the case that there is a car inspection system (see "No car inspection system" in Figure 5.3). From Figure 5.3, we can also see that abolishing the car inspection system would lead to increased CO_2 emissions from the vehicle fleet on the road but reduced CO_2 emissions at the stages of disposal and of manufacturing, particularly the latter (see "No car inspection system" in Figure 5.3). That is, by reducing the incentive of car owners to make replacement purchases (thereby increasing the economic lifetime of cars), abolishing the car inspection system would lead to reduced car production and therefore reduced CO_2 emissions in manufacturing. Reducing the number of cars produced would not only reduce the CO_2 emissions generated in manufacturing but would also, in turn, result in savings of energy and materials resources, e.g., the iron and steel needed for additional cars, and the rare-earth metals needed for electric motors and batteries. One factor tending to increase CO_2 emissions in the driving phase is that large numbers of the old-model Prius cars with relatively poor fuel efficiency would continue to drive on the roads, as the economic lifetime of cars would increase due to the complete abolition of the car inspection system.

As a result, the cumulative life-cycle CO_2 emissions derived from Prius cars registered during the 20-year period from 1997 to 2016 was found to be approximately 31 million tons, or some 1.55 million tons per year. The potential reduction in CO_2 emissions that can be achieved by completely abolishing the car inspection system is 1.11 million tons over 20 years. This means that abolishing the car inspection system to extend the economic lifetime of cars would serve to reduce CO_2 emissions by approximately 4%—a potential contribution that cannot be ignored (Figure 5.3).

If we consider that in comparison to 87 million cars in Japan between 1997 and 2016

(JAMA, 2017), cumulative total sales of Prius cars over the same period amounted to approximately 1.80 million (2% of the total) (Toyota, 2017), the analysis results point to a huge potential for reducing emissions. In other words, abolishing the car inspection system could make a big contribution towards meeting the CO_2 emissions reduction target set for Japan under the Paris Agreement.

In reality, it is very difficult to completely abolish the car inspection system due to the problem of the safety of car operation. Therefore, we need to consider a modified car inspection system. Figure 5.3 also shows that the emission reduction effects in the two scenarios "Without car inspection at third year" and "Without car inspection at fifth year" are 50% and 37%, respectively, that of the scenario "No car inspection system". Furthermore, the reduction effect in the scenario "Without car inspections at third and fifth years" is 88% that of the scenario "No car inspection system", i.e., nearly equal (Figure 5.3). These results imply that even if the car inspection system is not completely abolished, the modified car inspection framework without car inspections at the third and fifth years could have enough of an emission reduction effect.

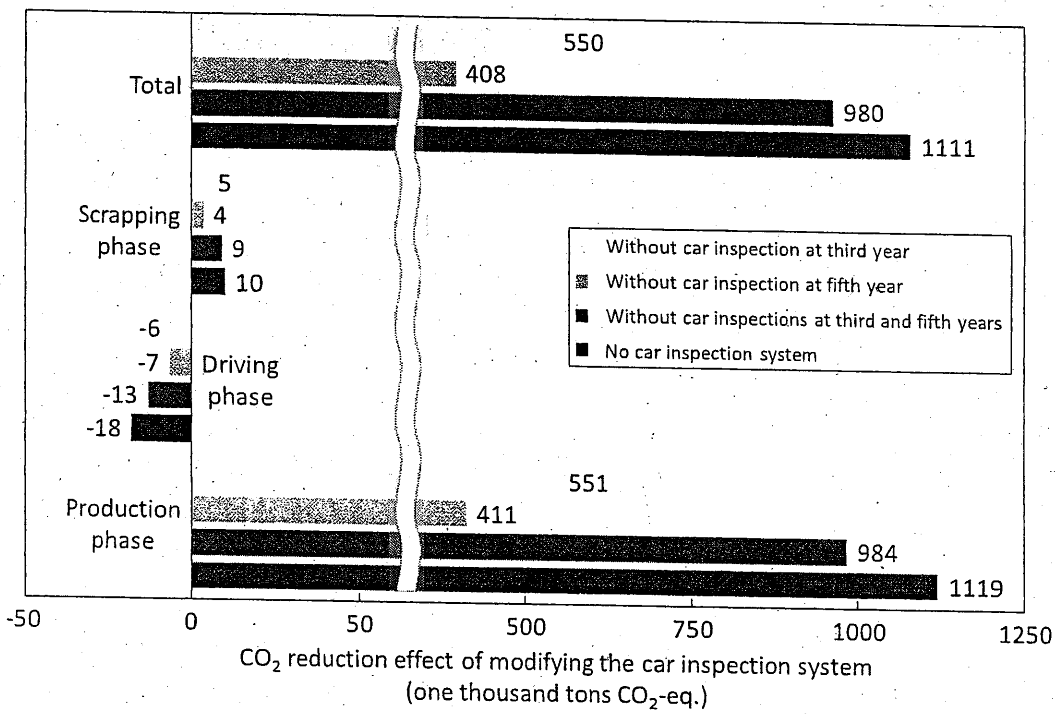

Figure 5.3: CO_2 reduction effect of modifying the car inspection system in Japan

5.5. Discussion and conclusion

In this study, we used a DDC model to estimate car replacement purchase rates based on consumer behavior aimed at maximizing utility levels over time. By combining replacement purchase rates specified from source data with life-cycle CO_2 emissions analysis, we demonstrated the impact of Japan's car inspection system on CO_2 emissions derived from cars. The parameter estimate results obtained from our DDC model are robust, showing that car owners behave with a forward-looking perspective. In addition, it is clear that abolishing the car inspection system can be expected to have a substantial effect on cutting CO_2 emissions associated with the transport sector because it would dampen car replacement purchase behavior and thereby increase the average economic lifetime of cars.

The results of this study show that revising Japan's car inspection system has the potential to cause a major turnaround in the replacement purchase behavior of the nation's car owners, thereby contributing to cutting CO_2 emissions. However, in practice, completely scrapping the current car inspection system would be very difficult. This is because, although abolishing inspections would relieve car owners of a painful cost burden, it might also put the safety of car operation at risk, due to the failure to detect problems that a car inspection would ordinarily detect. In view of this reality, we propose a modified car inspection system to relieve car owners of some of the cost burden of inspection.

Although demand management policies such as tax breaks and subsidies for eco-cars are certainly important to promote the diffusion and sale of next-generation cars, relaxing the current car inspection system could have a crucial CO_2 reduction effect through the expanding the economic lifetime of cars. Thus, to meet the greenhouse gas emission targets set under the Paris Agreement, it is vital to mitigate the climate change through the longer use of environment-friendly cars.

Chapter 6: Conclusions

In this Ph.D. dissertation, I proposed a comprehensive method for estimating how changes in *physical* lifetime of passenger vehicles affect global carbon footprints of vehicle. Moreover, this dissertation developed an integrated assessment framework by combining dynamic discrete choice analysis with life-cycle analysis, considering the vehicle replacement purchases based on *economic* lifetime of vehicles.

Chapter 3 spatially extended the vehicle life-cycle analysis of a single country and developed a new method for vehicle life-cycle analysis by combining a 15-country automotive stock-flow model based on the 15-country automotive *physical* lifetime distribution with global multi-regional input-output analysis. From the results, considering that ten of the 15 countries had vehicle lifetimes shorter than the average of 15.8 years: Austria, Canada, Germany, France, the U.K., Ireland, Italy, Japan, South Korea, and the Netherlands, I found that by increasing the average vehicle lifetimes of these 10 countries to the global average of 15.8 years, a reduction of 17 Mt-CO_2-eq. from the carbon footprint of the 10 countries could be achieved. In addition, I also revealed that roles of changes in vehicle lifetime and fuel efficiency on global CO_2 emissions are vastly different between countries where vehicle lifetimes are longer and those where lifetimes are shorter.

Chapter 4 estimated the carbon footprint associated with the global final demand of automobiles and auto-related petroleum of the U.S.A., Germany, and Japan, which account for 31% of the stock of passenger cars in the world in 2009, during 1995 to 2009.

This chapter further developed a comprehensive new method that offers a deeper understanding of the structural change in the global final demand of automobiles and discussed how the *physical* lifetime of automobiles of a specific country has contributed to their carbon footprints. While environmentally conscious automobile manufacturing through technological innovation has advanced globally, the industry's production structure runs counter to carbon reduction and completely canceled out the effects of technological changes in emission intensities. Suppressing demand for new cars through *physical* lifetime extension greatly reduced carbon footprint, and had a similar or greater effect than technological changes in emission intensities of suppliers directly and indirectly involved in automotive manufacturing.

Chapter 5 developed an integrated assessment framework by combining dynamic discrete choice analysis with life-cycle environmental accounting analysis based on a dynamic stock model. From the empirical results, I found that (1) the *economic* lifetime of a Prius in the benchmark model is surprisingly short, 5.07 years, due to the strict car inspection system, and this replacement cycle has contributed to increasing CO_2 over time; and (2) abolishing car inspections at the third and fifth years would considerably contribute to reducing life-cycle CO_2 emissions associated with Prius sold during the study period, 1997 to 2016, accounting for approximately one million tons-CO_2 eq. over 20 years. Thus, I conclude that modifying the regulation policy with a focus on the car inspection system to induce car owners to keep their automobiles longer would have environmental benefits.

An important study is to estimate lifetime of wide variety of vehicles of hybrid vehicles, diesel vehicles, and others of countries, however the lifetime database has not been well estimated due to the lack of reliable panel data of vehicles of countries. Therefore, I focused on the 'average' vehicles and treated diesel vehicles that have large market share in the Europe and Korea as petro vehicles in this study due to the data limitation. In addition, since this dissertation at the present time did not consider vehicle lifetimes and the market for *used cars*, the assessment frameworks in this dissertation should be adopted to include the environmental impacts of re-registering older cars as used cars. This expanded analysis with a focus of wide variety of vehicle models and used cars is an important and challenging future work.

In conclusion, I have shown the critical importance of the fact that *physical* and *economic* lifetime extension of vehicles can contribute towards a low-carbon transition society. And it is also important to build incentives for vehicle owners to keep their vehicles longer. In terms of possible owner incentives, this dissertation suggested policies that review existing systems and create better environments around old cars by stimulating the market for secondhand cars and the maintenance market.

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Jun 2019

Yuya Nakamoto

Appendex

Chapter 3

S3.1. Supplementary results

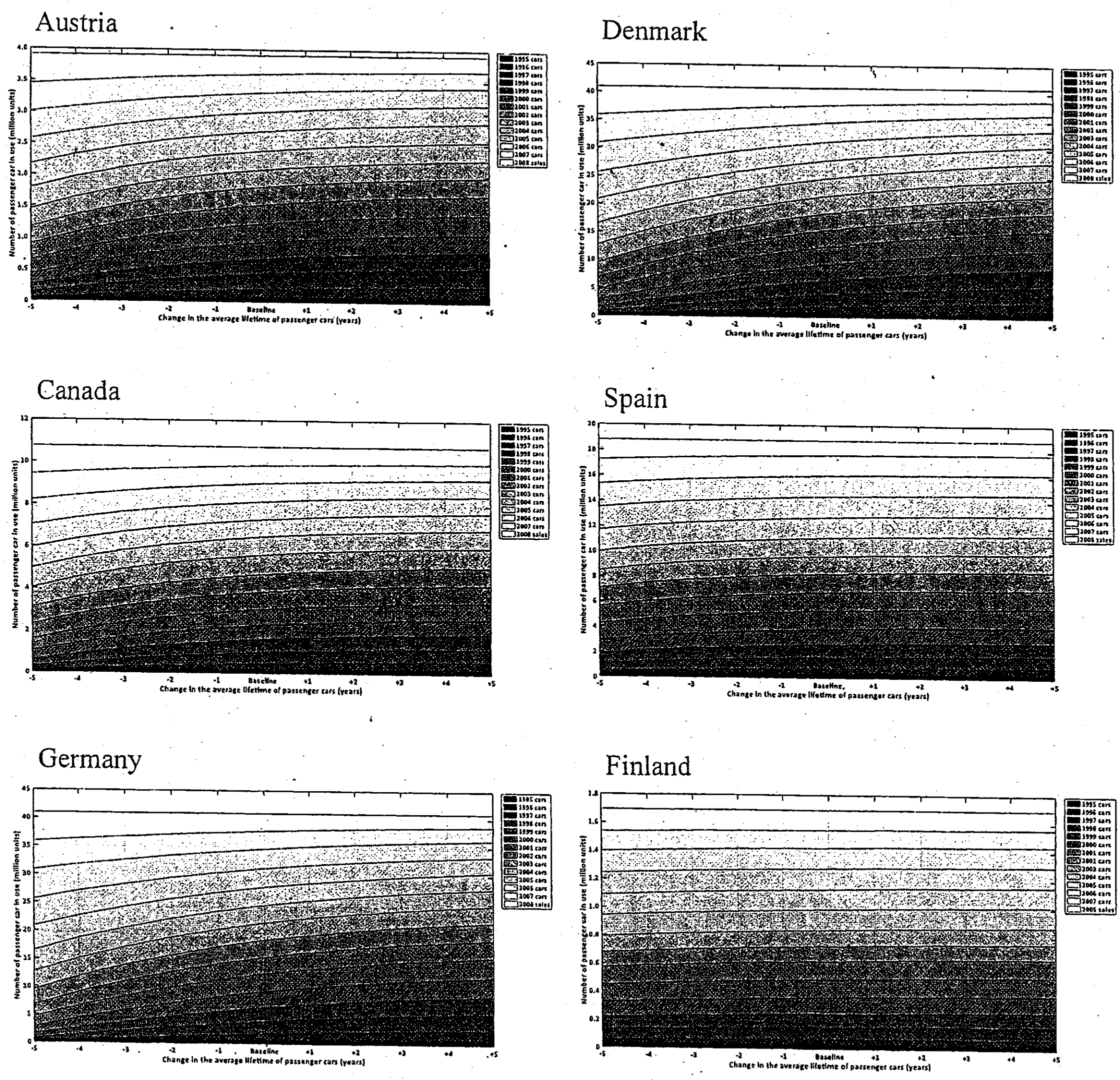

Figure S3.1: Passenger car stock in 2008 under the lifetime scenarios

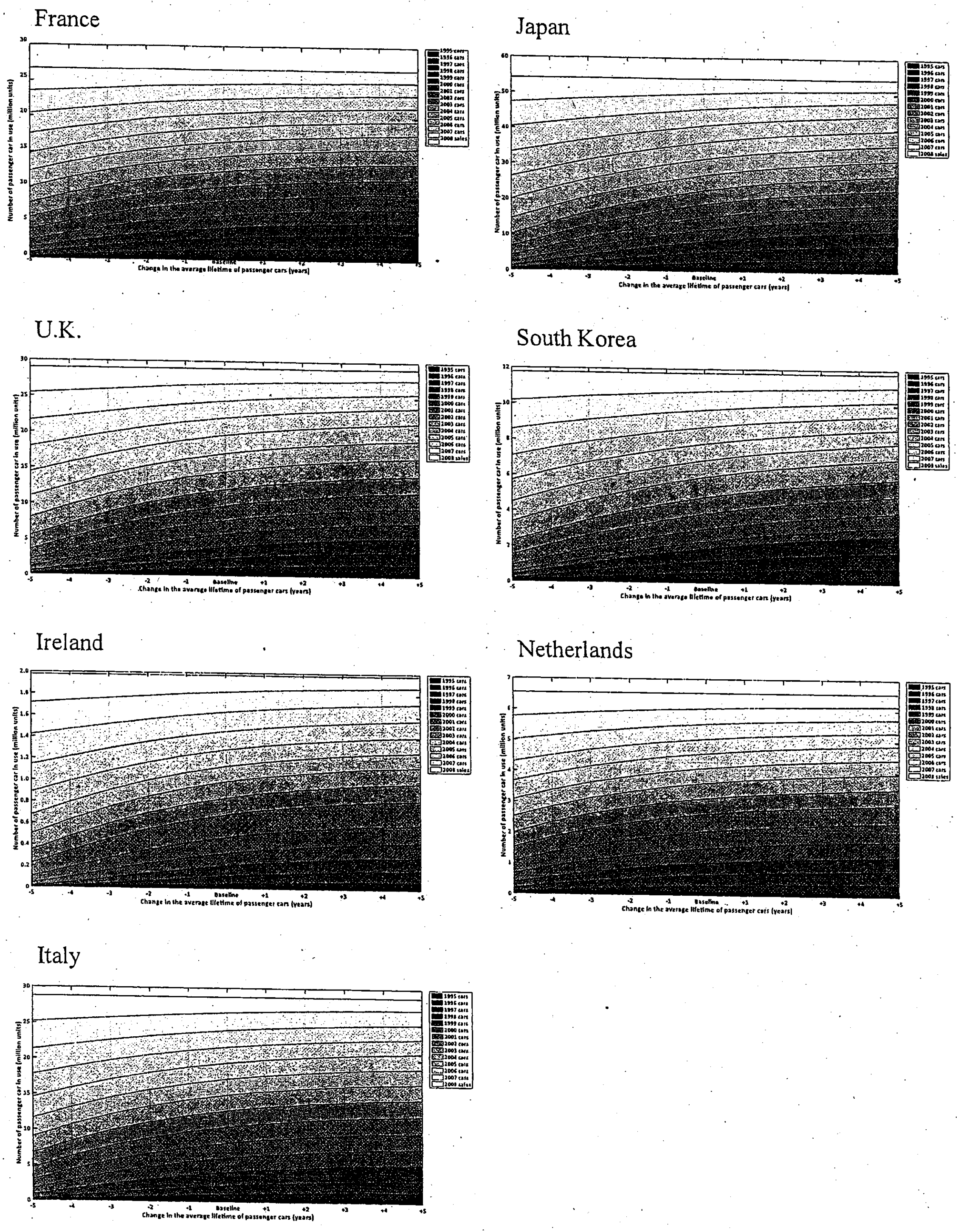

Figure S3.1: Passenger car stock in 2008 under the lifetime scenarios

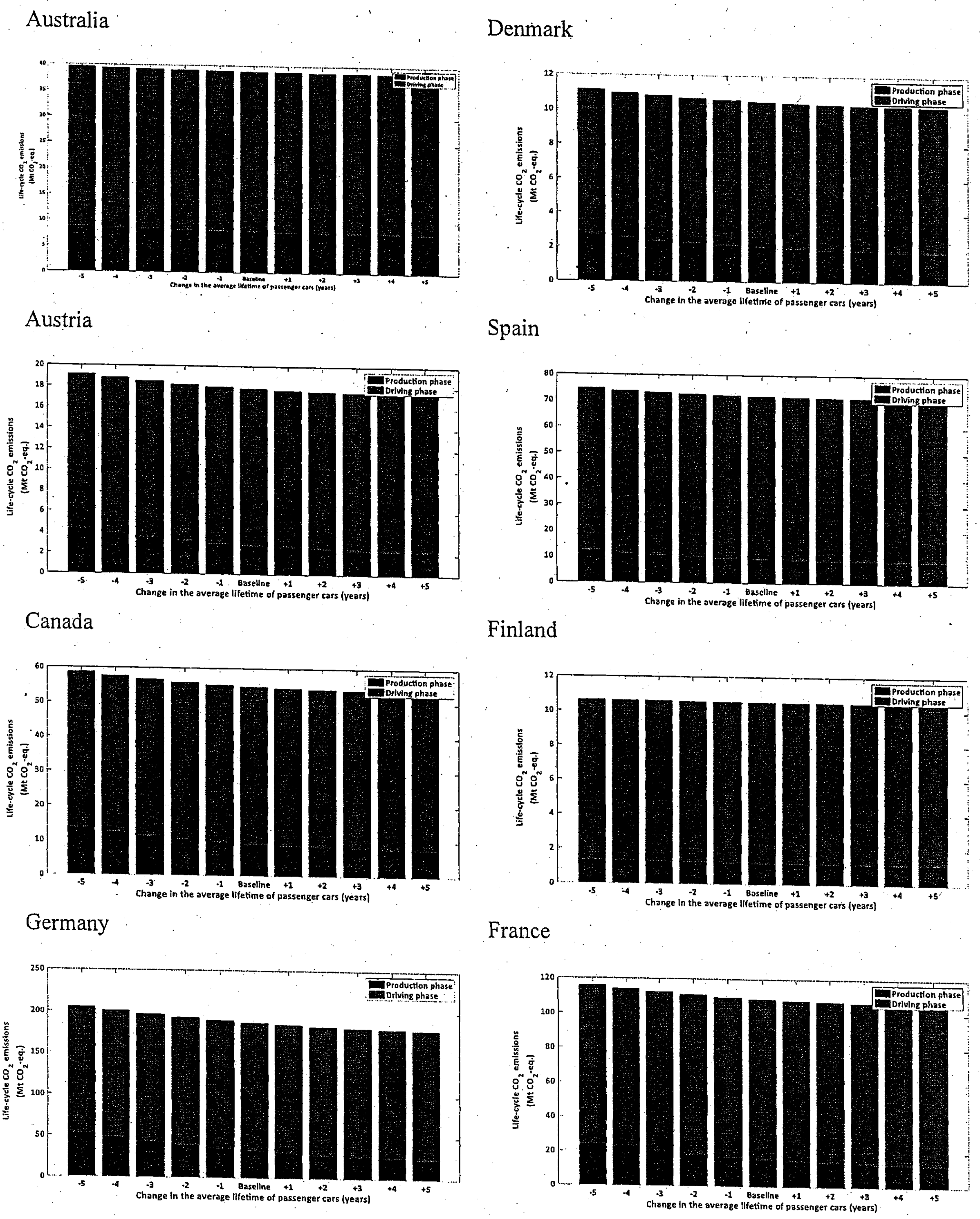

Figure S3.2: Life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under lifetime scenarios

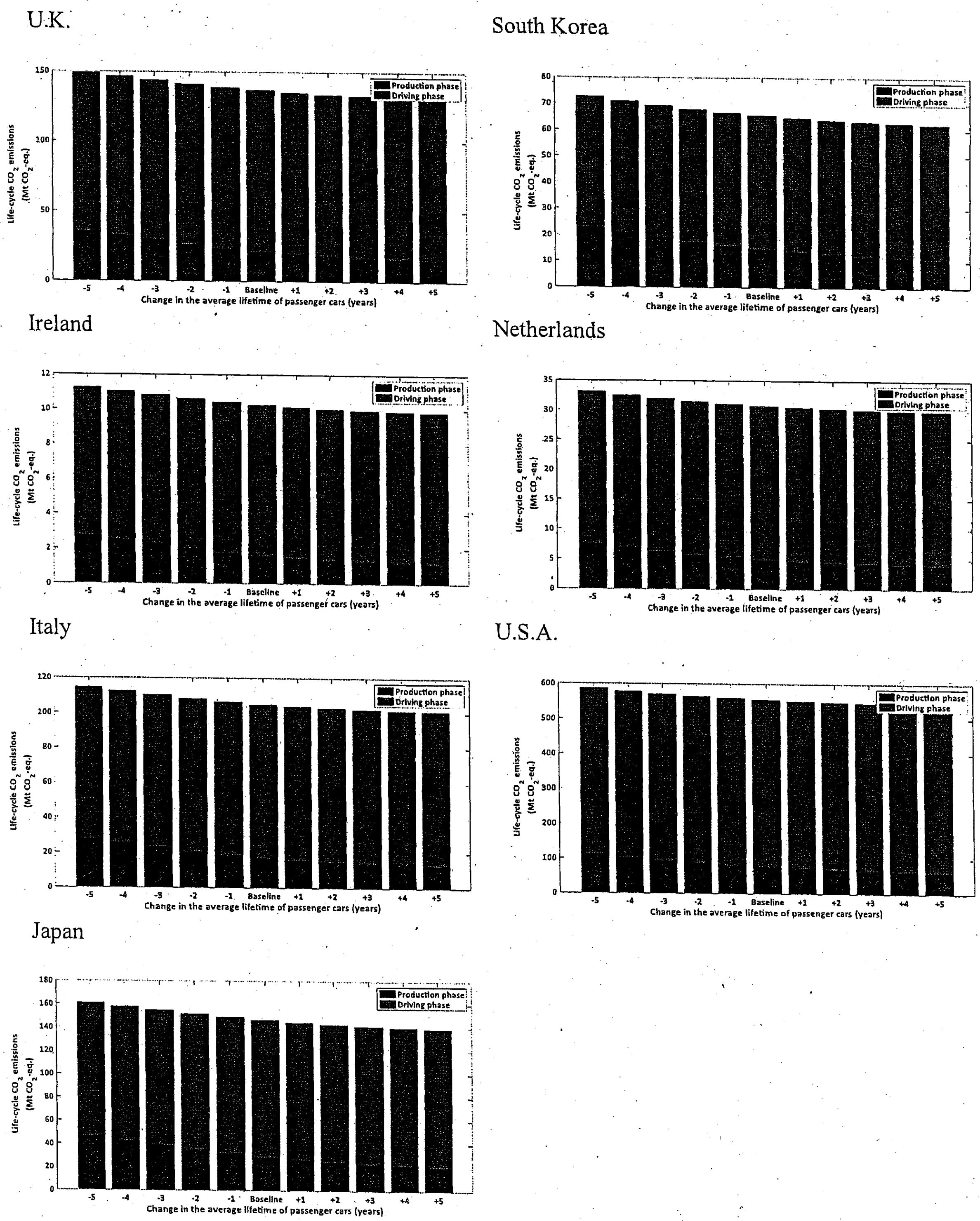

Figure S3.2: Life-cycle CO_2 emissions of passenger cars registered during 1995 to 2008 under lifetime scenarios

Chapter 4

Appendix 4.1

The LMDI formulae for calculating each effect are as follows:

$$\Delta E^{c} = \sum_{i,j,s,r} \beta_{ij}^{LM,rsc} \ln \frac{e_{i}^{r}(t)}{e_{i}^{r}(t-1)} \tag{A.4.1}$$

$$\Delta L^{c} = \sum_{i,j,s,r} \beta_{ij}^{LM,rsc} \ln \frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)} \tag{A.4.2}$$

$$\Delta F^{c} = \sum_{i,j,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_{ij}^{sc}(t;\mu^{c})}{f_{ij}^{sc}(t-1;\mu^{c})} \tag{A.4.3}$$

where $Q_{ij}^{rsc}(t) = e_{i}^{r}(t) L_{ij}^{rs}(t) f_{j}^{sc}(t;\mu^{c})$ denotes the CO_2 emissions induced by the products produced by industry i of country r that are directly and indirectly required for the products produced by industry j of country s associated with the global final demand in country c in year t. $\beta_{ij}^{LM,rsc} = \dfrac{Q_{ij}^{rsc}(t) - Q_{ij}^{rsc}(t-1)}{\ln\{Q_{ij}^{rsc}(t)\} - \ln\{Q_{ij}^{rsc}(t-1)\}}$ represents the logarithmic mean.

It should be noted that when we have $Q_{ij}^{rsc}(t) = Q_{ij}^{rsc}(t-1)$, $\beta_{ij}^{LM,rsc} = Q_{ij}^{rsc}(t) = Q_{ij}^{rsc}(t-1)$.

Appendix 4.2

The LMDI formula for the effect of changes in the final demand can also be expressed as:

$$\begin{aligned}\Delta F^c = &\sum_{i,j=auto,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_j^{sc}(t;\mu^c)}{f_j^{sc}(t-1;\mu^c)} \\ &+ \sum_{i,j=petro,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_j^{sc}(t;\mu^c)}{f_j^{sc}(t-1;\mu^c)} \\ &+ \sum_{i,j\neq auto,j\neq petro,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_j^{sc}(t;\mu^c)}{f_j^{sc}(t-1;\mu^c)}\end{aligned} \tag{A.4.4}$$

In Eq. (A.4.4), the first term on the right-hand side constitutes the decomposition for the changes in the final demand for passenger cars (f_{auto}), while the second term expresses the decomposition for the changes in the final demand for petroleum products (f_{petro}). It should be noted that the final demand for other products except for passenger cars and petroleum products is zero in this study.

From Eqs. (4.9) and (4.20), the indirect CO_2 emissions associate with the global final demand of passenger cars and auto-related petroleum products in country c in year t can also be written as follows:

$$\begin{aligned}\mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c(t;\mu^c) &= \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}_{auto}^c(t;\mu^c) + \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}_{petro}^c(t;\mu^c) \\ &= \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}_{auto}^c(t)\,p_{auto}^c(t)\,B^c(t;\mu^c) + \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}_{petro}^c(t)\,p_{petro}^c(t)\,q^c(t;\mu^c)\end{aligned} \tag{A.4.5}$$

Inserting $q^c(t;\mu^c) = q^c_{new}(t;\mu^c) + q^c_{stock}(t;\mu^c)$ in Eq. (4.6) into the second term of Eq. (4.20) yields the following the global final demand vectors for petroleum products related to new vehicles and older vehicles in country c in year t:

$$
\mathbf{f}^c_{petro}(t;\mu^c) = \mathbf{f}^c_{petro,new}(t;\mu^c) + \mathbf{f}^c_{petro,stock}(t;\mu^c)
$$
$$
= \begin{bmatrix} 0 \\ 0 \\ \tau^{1c}_{petro}(t)\, p^c_{petro}(t)\, q^c_{new}(t;\mu^c) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ \tau^{Nc}_{petro}(t)\, p^c_{petro}(t)\, q^c_{new}(t;\mu^c) \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \tau^{1c}_{petro}(t)\, p^c_{petro}(t)\, q^c_{stock}(t;\mu^c) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ \tau^{Nc}_{petro}(t)\, p^c_{petro}(t)\, q^c_{stock}(t;\mu^c) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{A.4.6}
$$

By integrating Eqs. (4.6), (4.16), and (A.4.6) into the second term of Eq. (A.4.5), the indirect emission associated with petroleum consumption can be formulated as follows:

$$
\begin{aligned}
\mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c_{petro}(t;\mu^c) &= \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c_{petro,new}(t;\mu^c) + \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c_{petro,stock}(t;\mu^c) \\
&= \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}^c_{petro}(t)\, p^c_{petro}(t)\, q^c_{new}(t;\mu^c) + \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}^c_{petro}(t)\, p^c_{petro}(t)\, q^c_{stock}(t;\mu^c) \\
&= \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}^c_{petro}(t)\, p^c_{petro}(t)\, d^c(t)\, \lambda^c(t)\, B^c(t;\mu^c) \\
&\quad + \sum_h \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}^c_{petro}(t)\, p^c_{petro}(t)\, d^c(t)\, \lambda^c(h)\, k^c_h(t;\mu^c)
\end{aligned} \tag{A.4.7}
$$

Thus, the final demand effect ΔF_c underlying the change in CF from year t-1 to year t in country c can be additionally decomposed as follows:

$$\Delta \tau^{c}_{auto} = \sum_{i,j=auto,s,r} \beta_{ij}^{LM,rsc} \ln \frac{\tau^{sc}_{auto}(t)}{\tau^{sc}_{auto}(t-1)} \tag{A.4.8}$$

$$\Delta p^{c}_{auto} = \sum_{i,j=auto,s,r} \beta_{ij}^{LM,rsc} \ln \frac{p^{c}_{auto}(t)}{p^{c}_{auto}(t-1)} \tag{A.4.9}$$

$$\Delta B^{c} = \sum_{i,j=auto,s,r} \beta_{ij}^{LM,rsc} \ln \frac{B^{c}(t)}{B^{c}(t-1)} \tag{A.4.10}$$

$$\Delta \tau^{c}_{petro} = \sum_{i,j=petro,s,r} \beta_{ij,new}^{LM,rsc} \ln \frac{\tau^{sc}_{petro}(t)}{\tau^{sc}_{petro}(t-1)} + \sum_{h} \sum_{i,j=petro,s,r} \beta_{ij,stock,h}^{LM,rsc} \ln \frac{\tau^{sc}_{petro}(t)}{\tau^{sc}_{petro}(t-1)} \tag{A.4.11}$$

$$\Delta p^{c}_{petro} = \sum_{i,j=petro,s,r} \beta_{ij,new}^{LM,rsc} \ln \frac{p^{c}_{petro}(t)}{p^{c}_{petro}(t-1)} + \sum_{h} \sum_{i,j=petro,s,r} \beta_{ij,stock,h}^{LM,rsc} \ln \frac{p^{c}_{petro}(t)}{p^{c}_{petro}(t-1)} \tag{A.4.12}$$

$$\Delta d^{c}_{indirect,\,new} = \sum_{i,j=petro,s,r} \beta_{ij,new}^{LM,rsc} \ln \frac{d^{c}(t)}{d^{c}(t-1)} \tag{A.4.13}$$

$$\Delta \lambda^{c}_{indirect} = \sum_{i,j=petro,s,r} \beta_{ij,new}^{LM,rsc} \ln \frac{\lambda^{c}(t)}{\lambda^{c}(t-1)} \tag{A.4.14}$$

$$\Delta S^{c}_{indirect} = \sum_{i,j=petro,s,r} \beta_{ij,new}^{LM,rsc} \ln \frac{B^{c}(t;\mu^{c})}{B^{c}(t-1;\mu^{c})} \tag{A.4.15}$$

$$\Delta d^{c}_{indirect,\,stock} = \sum_{h} \sum_{i,j=petro,s,r} \beta_{ij,stock,h}^{LM,rsc} \ln \frac{d^{c}(t)}{d^{c}(t-1)} \tag{A.4.16}$$

$$\Delta K^{c}_{indirect} = \sum_{h} \sum_{i,j=petro,s,r} \beta_{ij,stock,h}^{LM,rsc} \ln \frac{k^{c}_{h}(t;\mu^{c})}{k^{c}_{h}(t-1;\mu^{c})} \tag{A.4.17}$$

where $Q^{rsc}_{i,j=petro,new}(t)=e^r_i(t)L^{rs}_{i,j=petro}(t)\tau^{sc}_{petro}(t)p^c_{petro}(t)d^c(t)\lambda^c(t)B^c(t;\mu^c)$ denotes the CO_2 emissions associated with the global final demand for petroleum products related to new vehicles in country c in year t. $\gamma^{LM,rsc}_{ij,new}=\frac{Q^{rsc}_{ij,new}(t)-Q^{rsc}_{ij,new}(t-1)}{\ln\{Q^{rsc}_{ij,new}(t)\}-\ln\{Q^{rsc}_{ij,new}(t-1)\}}$ represents the logarithmic mean weight. Noted that when we have $Q^{rsc}_{ij,new}(t)=Q^{rsc}_{ij,new}(t-1)$, $\gamma^{LM,rsc}_{ij,new}=Q^{rsc}_{ij,new}(t)=Q^{rsc}_{ij,new}(t-1)$. Similarly,

$Q^{rsc}_{i,j=petro,stock,h}(t)=e^r_i(t)L^{rs}_{i,j=petro}(t)\tau^{sc}_{petro}(t)p^c_{petro}(t)d^c(t)\lambda^c(h)k^c_h(t;\mu^c)$ represents the CO_2 emissions associated with the global final demand for petroleum products related to h-vintage vehicles in country c in year t. $\gamma^{LM,rsc}_{ij,stock,h}=\frac{Q^{rsc}_{ij,stock,h}(t)-Q^{rsc}_{ij,stock,h}(t-1)}{\ln\{Q^{rsc}_{ij,stock,h}(t)\}-\ln\{Q^{rsc}_{ij,stock,h}(t-1)\}}$ is a weighting factor. If $Q^{rsc}_{ij,stock,h}(t)=Q^{rsc}_{ij,stock,h}(t-1)$, then we have $\gamma^{LM,rsc}_{ij,stock,h}=Q^{rsc}_{ij,stock,h}(t)=Q^{rsc}_{ij,stock,h}(t-1)$.

Defining the relevant weighting factors of $\beta^{LM,rsc}_{ij}$, $\gamma^{LM,rsc}_{ij,new}$, and $\gamma^{LM,rsc}_{ij,stock,h}$ from Eqs. (A.4.8)-(A.4.17), the effect of technological changes in the industrial emission intensities can be further decomposed as follows:

$$\Delta E^c=\sum_{i,j=auto,s,r}\beta^{LM,rsc}_{ij}\ln\frac{e^r_i(t)}{e^r_i(t-1)}+\sum_{i,j=petro,s,r}\gamma^{LM,rsc}_{ij,new}\ln\frac{e^r_i(t)}{e^r_i(t-1)}+\sum_h\sum_{i,j=petro,s,r}\gamma^{LM,rsc}_{ij,stock,h}\ln\frac{e^r_i(t)}{e^r_i(t-1)} \tag{A.4.18}$$

Similarly, we can further decompose the effect of changes in the production structure as follows:

$$\Delta L^c = \sum_{i,j=auto,s,r} \beta_{ij}^{LM,rsc} \ln \frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)} + \sum_{i,j=petro,s,r} \gamma_{ij,new}^{LM,rsc} \ln \frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)} + \sum_{h} \sum_{i,j=petro,s,r} \gamma_{ij,stock,h}^{LM,rsc} \ln \frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)}$$

(A.4.19)

Supplementary results

Table S4.1: The passenger car data

Year	Annual average travel distance (km)			Gasoline price (USD)/litter			Vehicle price (USD)		
	U.S.A.	Germany	Japan	U.S.A.	Germany	Japan	U.S.A.	Germany	Japan
1995	18,980	14,444	9,948	0.30	1.05	1.17	19,542	25,822	18,979
1996	18,983	14,247	9,916	0.33	1.04	0.96	20,115	26,196	19,004
1997	19,475	14,102	9,902	0.33	0.93	0.86	20,585	26,688	19,339
1998	19,606	14,096	9,835	0.28	0.88	0.75	20,905	26,938	19,467
1999	19,560	14,355	10,037	0.31	0.90	0.86	21,362	27,091	19,403
2000	19,576	14,104	9,956	0.39	0.91	0.96	22,084	27,490	19,276
2001	19,118	14,455	10,176	0.38	0.90	0.86	22,708	28,035	19,134
2002	19,587	14,475	10,057	0.36	0.97	0.83	23,068	28,434	18,957
2003	19,646	14,240	9,915	0.41	1.21	0.92	23,592	28,728	18,908
2004	19,634	14,562	9,675	0.49	1.39	1.04	24,223	29,206	18,907
2005	19,445	14,142	9,411	0.60	1.49	1.13	25,045	29,658	18,853
2006	19,338	14,213	9,240	0.68	1.59	1.18	25,853	30,126	18,900
2007	19,167	14,270	9,253	0.74	1.82	1.19	26,590	30,818	18,912
2008	18,699	14,147	9,026	0.86	2.05	1.52	27,611	31,628	19,173
2009	18,718	14,255	9,127	0.62	1.80	1.29	27,513	31,727	18,913

Source: US EPA, 2017; UBA, 2017; MLIT, 2010; IEA, 2014; and IEA, 2017.

The data in value terms is normalized to constant 2009 prices.

Table S4.2: The passenger car fuel efficiency (L/100km)

	Fuel efficiency (L/100km)		
Vintage	U.S.A.	Germany	Japan
1987	8.8	9.1	9.9
1988	8.8	9.1	9.7
1989	8.8	9.1	9.9
1990	8.8	9.1	10.1
1991	8.8	9.1	10.0
1992	8.8	9.1	10.2
1993	8.8	9.1	10.0
1994	8.8	9.1	10.1
1995	8.8	9.0	10.0
1996	8.7	9.2	10.1
1997	8.7	8.9	10.1
1998	8.6	8.6	10.1
1999	8.5	8.4	10.2
2000	8.3	8.2	10.3
2001	8.1	7.9	10.2
2002	8.1	7.6	10.2
2003	8	7.6	10.1
2004	7.9	7.4	10.2
2005	7.8	7.4	10.0
2006	7.7	7.1	10.1
2007	7.6	7.1	9.8
2008	7.5	6.8	9.7
2009	7.5	6.1	9.3

Source: US EPA, 2017; UBA, 2017; and MLIT, 2010.

Table S4.3: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 in the U.S.A. (Mt-CO2-eq.).

Factors	1995-2000		2000-2005		2005-2008		2008-2009	
	SDA	E-SDA	SDA	E-SDA	SDA	E-SDA	SDA	E-SDA
Emission intensities	-14.41	-14.41	-32.94	-32.94	-19.81	-19.81	-1.78	-1.78
Production structure	10.04	10.04	11.07	11.07	23.01	23.01	-16.32	-16.32
Final demand	57.88		58.02		40.39		-68.36	
Direct petro consumption	158.47		72.48		-11.92		-8.71	
Car_demand		11.44		-7.58		-6.54		-22.53
Petro_demand		16.70		39.54		44.01		-52.45
Car_stock		173.57		99.51		19.28		-3.38
Travel_distance		14.64		-4.53		-29.00		0.74
Car_trade		-0.32		0.92		0.30		0.91
Petro_trade		0.32		2.65		0.41		-0.36
Total	212.00	212.00	108.63	108.63	31.68	31.68	-95.17	-95.17

Table S4.4: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 in Germany (Mt-CO2-eq.).

Factors	1995-2000		2000-2005		2005-2008		2008-2009	
	SDA	E-SDA	SDA	E-SDA	SDA	E-SDA	SDA	E-SDA
Emission intensities	-9.72	-9.72	-17.57	-17.57	-15.67	-15.67	-2.95	-2.95
Production structure	6.28	6.28	14.46	14.46	12.74	12.74	-12.94	-12.94
Final demand	9.85		36.58		23.59		-4.32	
Direct petro consumption	34.36		11.63		-1.46		1.17	
Car_demand		2.70		1.88		-1.55		10.77
Petro_demand		-10.75		26.02		21.74		-11.05
Car_stock		54.51		17.51		-1.05		-2.53
Travel_distance		-3.23		-0.28		-0.02		1.55
Car_trade		1.56		0.96		2.09		0.08
Petro_trade		-0.57		2.13		0.92		-1.96
Total	40.77	40.77	45.10	45.10	19.19	19.19	-19.04	-19.04

Table S4.5: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 in Japan (Mt-CO2-eq.).

Factors	1995-2000		2000-2005		2005-2008		2008-2009	
	SDA	E-SDA	SDA	E-SDA	SDA	E-SDA	SDA	E-SDA
Emission intensities	-0.88	-0.88	-8.30	-8.30	-8.59	-8.59	0.92	0.92
Production structure	6.18	6.18	12.01	12.01	8.08	8.08	-2.40	-2.40
Final demand	3.32		10.90		7.47		-10.42	
Direct petro consumption	29.76		1.34		-7.99		-1.76	
Car_demand		-1.07		3.21		-3.78		-2.80
Petro_demand		-4.40		5.68		10.33		-6.88
Car_stock		37.42		9.44		-3.21		-2.67
Travel_distance		0.15		-8.12		-5.91		1.53
Car_trade		0.27		0.43		0.59		-0.18
Petro_trade		0.71		1.60		1.45		-1.18
Total	38.39	38.39	15.94	15.94	-1.04	-1.04	-13.66	-13.66

Chapter 5

Appendix 5.1

If the expected value function $E_{x,\varepsilon}\left[V\left(x_{t+1},d_{t+1},\varepsilon_{i,t+1},i_{t+1};\theta_1\right)\right]$ discretized in Eq. (5.6) is defined as the expected value function $E_{x',\varepsilon'}\left[V\left(x',d',\varepsilon',i';\theta_1\right)\right]$ containing a continuous variable with relation to time, then expected value function EV can be defined as follows:

$$\begin{aligned}
EV &\equiv E_{x',\varepsilon'}\left[V\left(x',d',\varepsilon',i';\theta_1\right)\right] \\
&= E_{x',\varepsilon'|x,i}\left[\max_{i'\in(0,1)}\left\{u\left(x',d',i';\theta_1\right)+\varepsilon'+\beta EV\left(x',d',i';\theta_1\right)\right\}\right] \\
&= E_{x'|x,i}E_{\varepsilon'|x',x,i}\left[\max_{i'\in(0,1)}\left\{u\left(x',d',i';\theta_1\right)+\varepsilon'+\beta EV\left(x',d',i';\theta_1\right)\right\}\right] \\
&= E_{x'|x,i}\log\left[\sum_{i'=0,1}\exp\left\{u\left(x',d',i';\theta_1\right)+\beta EV\left(x',d',i';\theta_1\right)\right\}\right] \\
&= \int_x \log\left[\sum_{i'=0,1}\exp\left\{u\left(x',d',i';\theta_1\right)+\beta EV\left(x',d',i';\theta_1\right)\right\}\right]p\left(dx'|x,i\right)
\end{aligned} \qquad \text{(A5.1)}$$

where $x',d',\varepsilon',i',dx'$ respectively express the cumulative travel distance of a future period, a car inspection dummy of a future period, the error of a future period, the replacement purchase choice of a future period, and the increase in travel distance from the current period to the future period. Since ε' follows an i.i.d. Type I extreme value distribution, Eq. (A5.1) can be formulated as a log-sum operation to express the expected value of the maximum utility in the replacement purchase choice of a car owner (Small and Rosen, 1981).

The term EV in Eq. (A5.1) can be considered a function of the cumulative travel distance in the current period, the car inspection dummy for the current period, and the replacement purchase choice in the current period, $EV(x,d,i)$. Applying the fixed-point theorem for a contraction mapping, the expected value function EV shown in Eq. (A5.1) is known to converge to a unique value (Rust, 2000).

In this case, letting k be an index expressing the number of iterative calculations, $EV^k(x,d,i)$ expresses the expected value function after k computational iterations as

$$\begin{aligned}
EV^{k+1}(x,d,i) &= \int_x \log\left[\sum_{i'=0,1}\exp\{u(x',d',i';\theta_1)+\beta EV(x',d',i';\theta_1)\}\right]p(dx'|x,i) \\
&= \theta_{21}\cdot\int_x^{x+r_1}\log\left[\sum_{i'=0,1}\exp\{u(x',d',i';\theta_1)+\beta EV^k(x',d',i';\theta_1)\}\right]dx' \\
&+\theta_{22}\cdot\int_{x+r_1}^{x+r_2}\log\left[\sum_{i'=0,1}\exp\{u(x',d',i';\theta_1)+\beta EV^k(x',d',i';\theta_1)\}\right]dx' \\
&+\theta_{23}\cdot\int_{x+r_2}^{x+r_3}\log\left[\sum_{i'=0,1}\exp\{u(x',d',i';\theta_1)+\beta EV^k(x',d',i';\theta_1)\}\right]dx' \\
&+(1-\theta_{21}-\theta_{22}-\theta_{23})\cdot\int_{x+r_3}^{\infty}\log\left[\sum_{i'=0,1}\exp\{u(x',d',i';\theta_1)+\beta EV^k(x',d',i';\theta_1)\}\right]dx'
\end{aligned}$$

(A5.2)

where r_1, r_2, r_3 each express a grid of discretized values for the increase in cumulative travel distance (see Eq. (5.8)). To compute EV, an initial value of the expected value function $EV^0(x,d,i)$ (when $k=0$) is set. Generally, $EV^0(x,d,i)$ for all $x \in r$, car inspection dummy d, and replacement purchase choice $i=0,1$. Next, by substituting $EV^0(x,d,i)$ into the right-hand side of Eq. (A5.2), the expected value function $EV^1(x,d,i)$ is calculated for all the discretized cumulative travel distance increase values $x \in r$ and for the replacement purchase choices $i=0,1$. To check whether there is a fixed point due to a contraction mapping, we check that $EV^{k+1}(x,d,i)$ is sufficiently close to $EV^k(x,d,i)$, as follows:

$$\sup_{x,d,i}\left|EV^{k+1}(x,d,i)-EV^k(x,d,i)\right|<\eta \quad (\eta>0) \tag{A5.3}$$

where η is a very small threshold value (for this study, $\eta=0.001$). If Eq. (A5.3) is satisfied and the difference between $EV^{k+1}(x,d,i)$ and $EV^k(x,d,i)$ is sufficiently small compared to η, then the computation of Eq. (A5.2) can be completed to obtain EV.

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