Spatial Structural Decomposition Analysis with a Focus on Product Lifetime

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Abstract

This study 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. 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. 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 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.

Keywords: *Life-cycle CO_2 emissions*, *Passenger cars*, *Input-output analysis, Lifetime extension, Structural decomposition analysis*

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.

S*tatic* 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.

2. Methodology

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. (1) (e.g., Kagawa *et al.*, 2011; McCool, 2012; Oguchi and Fuse, 2015).

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

$$\mu^c = \eta^c \Gamma\left(1 + \frac{1}{m^c} \right) \tag{2}$$

where m^c represents a shape parameter and η^c represents a scale parameter. In Eq. (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, $S^c\left(t;\bar{\mu}^c\right)$, can be obtained using the following equation as in (Nakamoto *et al*., 2019):

$$S^c\left(t;\bar{\mu}^c\right)=B^c\left(t;\bar{\mu}^c\right)+\sum_{i=1}^{t-1}\varphi^c\left(t-i;\bar{\mu}^c\right)B^c\left(i;\bar{\mu}^c\right) \tag{3}$$

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. (3):

$$\begin{cases} S^c\left(1;\bar{\mu}^c\right)=B^c\left(1;\bar{\mu}^c\right) \\ S^c\left(2;\bar{\mu}^c\right)=B^c\left(2;\bar{\mu}^c\right)+\varphi^c\left(1;\bar{\mu}^c\right)B^c\left(1;\bar{\mu}^c\right) \\ S^c\left(3;\bar{\mu}^c\right)=B^c\left(3;\bar{\mu}^c\right)+\varphi^c\left(1;\bar{\mu}^c\right)B^c\left(2;\bar{\mu}^c\right)+\varphi^c\left(2;\bar{\mu}^c\right)B^c\left(1;\bar{\mu}^c\right) \\ \vdots \end{cases} \tag{4}$$

In this study, the stock of passenger cars in each year $S^c\left(t;\bar{\mu}^c\right)$ is taken to be at steady state, 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 $\varphi^c\left(t;\bar{\mu}^c\right)$ to $\varphi^c\left(t;\mu^c\right)$ 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:

$$
\begin{cases}
B^c\left(1;\mu^c\right)=S^c\left(1;\bar{\mu}^c\right) \\
B^c\left(2;\mu^c\right)=S^c\left(2;\bar{\mu}^c\right)-\varphi^c\left(1;\mu^c\right)B^c\left(1;\mu^c\right) \\
B^c\left(3;\mu^c\right)=S^c\left(3;\bar{\mu}^c\right)-\varphi^c\left(1;\mu^c\right)B^c\left(2;\mu^c\right)-\varphi^c\left(2;\mu^c\right)B^c\left(1;\mu^c\right) \\
\vdots
\end{cases}
\tag{5}
$$

In eq. (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 $B^c\left(t;\mu^c\right)$.

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*, $d^c\left(t\right)\lambda^c\left(i\right)\ \left(i=1,2,\cdots,t\right)$, was calculated by multiplying the annual average travel distance in country *c* in year *t*, defined as $d^c\left(t\right)$ (100km), by the fuel efficiency of *i*-vintage cars in country *c*, denoted as $\lambda^c\left(i\right)$ (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:

$$
\begin{aligned}
q^c\left(t;\mu^c\right) &= d^c\left(t\right)\lambda^c\left(t\right)B^c\left(t;\mu^c\right)+\sum_{i=1}^{t-1}d^c\left(t\right)\lambda^c\left(i\right)\varphi^c\left(t-i;\mu^c\right)B^c\left(i;\mu^c\right) \\
&= q^c_{new}\left(t;\mu^c\right)+q^c_{stock}\left(t;\mu^c\right)
\end{aligned}
\tag{6}
$$

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. (6), $q^c_{new}\left(t;\mu^c\right)$ represents the gasoline consumption generated by cars newly put on the road in country *c* in year *t* and $q^c_{stock}\left(t;\mu^c\right)$ 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, $G^c_{direct}\left(t;\mu^c\right)=e_{petro}q^c\left(t;\mu^c\right)$, 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, $q^c\left(t;\mu^c\right)$.

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 $\mathbf{f}^c\left(t\right)=\left\{f_j^{sc}\left(t\right)\right\}$ $\left(j=1,\ldots,M\right)$, where an element $f_j^{sc}\left(t\right)$ of $\mathbf{f}^c\left(t\right)$ 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*, $f^{sc}_{auto}\left(t\right)$, 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), $\sum_{s=1}^{N}f^{sc}_{auto}\left(t\right)$, for year *t* as follows:

$$\tau_{auto}^{sc}(t) = \frac{f_{auto}^{sc}(t)}{\sum_{s=1}^{N} f_{auto}^{sc}(t)} \quad (c = 1, 2, \cdots, N) \tag{7}$$

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

By multiplying the average sales price (including domestic cars and imported cars) of a vehicle in country c, $p_{auto}^{c}(t)$, 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 $p_{auto}^{c}(t)B^{c}(t;\mu^{c})$. In the same manner, the domestic final demand for auto-related petroleum products can be estimated as $p_{petro}^{c}(t)q^{c}(t;\mu^{c})$. From Eq. (7), the global final demand for passenger cars and auto-related petroleum products in country c in year t can be formulated as follows:

$$
\mathbf{f}^c\left(t;\mu^c\right)=
\begin{array}{r}
\text{Country \#1}\left\{\begin{array}{c} \\ \\ \\ \\ \\ \\ \end{array}\right. \\
\\
\text{Country \#N}\left\{\begin{array}{c} \\ \\ \\ \\ \\ \\ \end{array}\right.
\end{array}
\overbrace{\begin{bmatrix} 0 \\ f_{auto}^{1c}\left(t;\mu^c\right) \\ f_{petro}^{1c}\left(t;\mu^c\right) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ f_{auto}^{Nc}\left(t;\mu^c\right) \\ f_{petro}^{Nc}\left(t;\mu^c\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix}}^{\text{Country } c}
=
\begin{bmatrix} 0 \\ f_{auto}^{1c}\left(t;\mu^c\right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ f_{auto}^{Nc}\left(t;\mu^c\right) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}
+
\begin{bmatrix} 0 \\ 0 \\ f_{petro}^{1c}\left(t;\mu^c\right) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ f_{petro}^{Nc}\left(t;\mu^c\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix}
=
\begin{bmatrix} 0 \\ \tau_{auto}^{1c}(t)\,p_{auto}^{c}(t)\,B^c\left(t;\mu^c\right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ \tau_{auto}^{Nc}(t)\,p_{auto}^{c}(t)\,B^c\left(t;\mu^c\right) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}
+
\begin{bmatrix} 0 \\ 0 \\ \tau_{petro}^{1c}(t)\,p_{petro}^{c}(t)\,q^c\left(t;\mu^c\right) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ \tau_{petro}^{Nc}(t)\,p_{petro}^{c}(t)\,q^c\left(t;\mu^c\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix}
\tag{8}
$$

Note that the global final demand vector of Eq. (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:

$$
Q^c\left(t;\mu^c\right)=\mathbf{e}(t)\left(\mathbf{I}-\mathbf{A}(t)\right)^{-1}\mathbf{f}^c\left(t;\mu^c\right)=\mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c\left(t;\mu^c\right) \tag{9}
$$

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:

$$CF^c(t;\mu^c)=Q^c(t;\mu^c)+G_{direct}^c(t;\mu^c) \tag{10}$$

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).

2.4 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 Logarithmic Mean Divisia Index (LMDI) (Ang, 2015; Ang and Liu, 2007; Wood and Lenzen, 2006), 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. (6) can be expressed as follows:

$$\begin{aligned}\Delta q_{new}^c &= \alpha_{new}^{LM,c}\ln\frac{d^c(t)}{d^c(t-1)}+\alpha_{new}^{LM,c}\ln\frac{\lambda^c(t)}{\lambda^c(t-1)}+\alpha_{new}^{LM,c}\ln\frac{B^c(t;\mu^c)}{B^c(t-1;\mu^c)}\\ &=\Delta d_{new}^c+\Delta\lambda^c+\Delta S^c\end{aligned} \tag{11}$$

Here, $\alpha_{new}^{LM,c} = \dfrac{q_{new}^{c}\left(t;\,\mu^{c}\right) - q_{new}^{c}\left(t-1;\,\mu^{c}\right)}{\ln\left\{q_{new}^{c}\left(t;\,\mu^{c}\right)\right\} - \ln\left\{q_{new}^{c}\left(t-1;\,\mu^{c}\right)\right\}}$ 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 $q_{new}^{c}\left(t;\mu^{c}\right) = q_{new}^{c}\left(t-1;\mu^{c}\right)$, then $\alpha_{new}^{LM,c} = q_{new}^{c}\left(t;\mu^{c}\right) = q_{new}^{c}\left(t-1;\mu^{c}\right)$. 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.

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. (6) can be obtained as follows:

$$\begin{aligned}\Delta q_{stock}^{c} &= q_{stock}^{c}\left(t;\mu^{c}\right) - q_{stock}^{c}\left(t-1;\mu^{c}\right)\\ &= \sum_{i=1}^{t-1} d^{c}\left(t\right)\lambda^{c}\left(i\right)\varphi^{c}\left(t-i;\mu^{c}\right)B^{c}\left(i;\mu^{c}\right) - \sum_{i=1}^{(t-1)-1} d^{c}\left(t-1\right)\lambda^{c}\left(i\right)\varphi^{c}\left(t-1-i;\mu^{c}\right)B^{c}\left(i;\mu^{c}\right)\end{aligned} \tag{12}$$

Then, referring to (Kagawa et al., 2012), Eq. (12) can be transformed algebraically as follows:

$$
\begin{aligned}
\Delta q_{stock}^{c} &= d^{c}(t)\underbrace{\begin{bmatrix}\lambda^{c}(1) & \lambda^{c}(2) & \cdots & \lambda^{c}(t-2) & \lambda^{c}(t-1)\end{bmatrix}}_{\boldsymbol{\lambda}^{c}(t)}\underbrace{\begin{bmatrix}\varphi^{c}(t-1;\mu^{c})B^{c}(1;\mu^{c})\\ \varphi^{c}(t-2;\mu^{c})B^{c}(2;\mu^{c})\\ \vdots \\ \varphi^{c}(2;\mu^{c})B^{c}(t-2;\mu^{c})\\ \varphi^{c}(1;\mu^{c})B^{c}(t-1;\mu^{c})\end{bmatrix}}_{\mathbf{k}^{c}(t;\mu^{c})} \\
&\quad - d^{c}(t-1)\underbrace{\begin{bmatrix}\lambda^{c}(1) & \lambda^{c}(2) & \cdots & \lambda^{c}(t-2) & \lambda^{c}(t-1)\end{bmatrix}}_{\boldsymbol{\lambda}^{c}(t-1)}\underbrace{\begin{bmatrix}\varphi^{c}(t-2;\mu^{c})B^{c}(1;\mu^{c})\\ \varphi^{c}(t-3;\mu^{c})B^{c}(2;\mu^{c})\\ \vdots \\ \varphi^{c}(1;\mu^{c})B^{c}(t-2;\mu^{c})\\ 0\end{bmatrix}}_{\mathbf{k}^{c}(t-1;\mu^{c})}
\end{aligned}
\tag{13}
$$

where $\boldsymbol{\lambda}^{c}(t)$ denotes the fuel efficiency vector for older vintage vehicles in year *t*. $\mathbf{k}^{c}(t;\mu^{c})=\left\{k_{h}^{c}(t;\mu^{c})\right\}$ is the number of in-use 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. (13) can be rewritten as follows:

$$
\begin{aligned}
\Delta q_{stock}^{c} &= \sum_{h}\alpha_{stock,h}^{LM,c}\ln\frac{d^{c}(t)}{d^{c}(t-1)}+\sum_{h}\alpha_{stock,h}^{LM,c}\ln\frac{k_{h}^{c}(t;\mu^{c})}{k_{h}^{c}(t-1;\mu^{c})} \\
&= \Delta d_{stock}^{c}+\Delta K^{c}
\end{aligned}
\tag{14}
$$

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 cars in use. In particular, $\alpha_{stock,h}^{LM,c} = \frac{q_{stock,h}^{c}\left(t;\mu^{c}\right) - q_{stock,h}^{c}\left(t-1;\mu^{c}\right)}{\ln\left\{q_{stock,h}^{c}\left(t;\mu^{c}\right)\right\} - \ln\left\{q_{stock,h}^{c}\left(t-1;\mu^{c}\right)\right\}}$ represents the logarithmic mean weight of the annual gasoline consumption generated by h-vintage vehicles in years t-1 and t. If $q_{stock,h}^{c}\left(t;\mu^{c}\right) = q_{stock,h}^{c}\left(t-1;\mu^{c}\right)$, then we have $\alpha_{stock,h}^{LM,c} = q_{stock,h}^{c}\left(t;\mu^{c}\right) = q_{stock,h}^{c}\left(t-1;\mu^{c}\right)$.

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:

$$\begin{aligned}\Delta q^{c} &= \Delta q_{new}^{c} + \Delta q_{stock}^{c} \\ &= \Delta d_{new}^{c} + \Delta\lambda^{c} + \Delta S^{c} + \Delta d_{stock}^{c} + \Delta K^{c}\end{aligned} \tag{15}$$

From Eqs. (11)-(15), we can decompose the change in the direct emission associated with petroleum consumption ΔG_{direct}^{c} into factors as follows:

$$\begin{aligned}\Delta G_{direct}^{c} &= G_{direct}^{c}\left(t;\mu^{c}\right) - G_{direct}^{c}\left(t-1;\mu^{c}\right) \\ &= \Delta d_{direct,new}^{c} + \Delta\lambda_{direct}^{c} + \Delta S_{direct}^{c} + \Delta d_{direct,stock}^{c} + \Delta K_{direct}^{c}\end{aligned} \tag{16}$$

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 cars in use, respectively. Recalling the definition of direct CO_2 emissions in the driving phase, $G_{direct}^{c}\left(t;\mu^{c}\right) = e_{petro}q^{c}\left(t;\mu^{c}\right)$, these effects were easily calculated by multiplying the effects of change in the gasoline consumption of all vintages of vehicles from Eq. (15) by the direct CO_2 emission intensity from gasoline combustion.

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

In additive decomposition, 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. (9) can be expressed as follows:

$$\begin{aligned} \Delta Q^c &= Q^c\left(t;\mu^c\right) - Q^c\left(t-1;\mu^c\right) \\ &= \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c\left(t;\mu^c\right) - \mathbf{e}(t-1)\mathbf{L}(t-1)\mathbf{f}^c\left(t-1;\mu^c\right) \end{aligned} \tag{17}$$

Accordingly, by using the LMDI, Eq. (17) can be transformed as follows:

$$\Delta Q^c = \Delta E^c + \Delta L^c + \Delta F^c \tag{18}$$

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 1.

To extend the decomposition analysis with a focus on product lifetime, I consider 6 elements that constitute global final demand vector of Eq. (8). The Hadamard product (or element-wise product) can be considered for detecting the elements in a global final demand vector as follows:

$$
\begin{aligned}
\mathbf{f}^{c}\left(t;\mu^{c}\right)=\mathbf{f}^{c}_{auto}\left(t;\mu^{c}\right)+\mathbf{f}^{c}_{petro}\left(t;\mu^{c}\right)&=\begin{bmatrix} 0 \\ \tau^{1c}_{auto}(t)\,p^{c}_{auto}(t)\,B^{c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ \tau^{Nc}_{auto}(t)\,p^{c}_{auto}(t)\,B^{c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}+\begin{bmatrix} 0 \\ 0 \\ \tau^{1c}_{petro}(t)\,p^{c}_{petro}(t)\,q^{c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ \tau^{Nc}_{petro}(t)\,p^{c}_{petro}(t)\,q^{c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
&=\begin{bmatrix} 0 \\ \tau^{1c}_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ \tau^{Nc}_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}\odot\begin{bmatrix} 0 \\ p^{c}_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ p^{c}_{auto}(t) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}\odot\begin{bmatrix} 0 \\ B^{c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ B^{c}\left(t;\mu^{c}\right) \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}+\begin{bmatrix} 0 \\ 0 \\ \tau^{1c}_{petro}(t) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ \tau^{Nc}_{petro}(t) \\ 0 \\ \vdots \\ 0 \end{bmatrix}\odot\begin{bmatrix} 0 \\ 0 \\ p^{c}_{petro}(t) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ p^{c}_{petro}(t) \\ 0 \\ \vdots \\ 0 \end{bmatrix}\odot\begin{bmatrix} 0 \\ 0 \\ q^{c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ 0 \\ q^{c}\left(t;\mu^{c}\right) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
&=\boldsymbol{\tau}^{c}_{auto}(t)\,p^{c}_{auto}(t)\,B^{c}\left(t;\mu^{c}\right)+\boldsymbol{\tau}^{c}_{petro}(t)\,p^{c}_{petro}(t)\,q^{c}\left(t;\mu^{c}\right)
\end{aligned}
\tag{19}
$$

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. (15) and (19), 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 cars in use $\Delta K^c_{indirect}$:

$$
\begin{aligned}
\Delta F^c = & \underbrace{\Delta\tau^c_{auto} + \Delta p^c_{auto} + \Delta B^c}_{\mathbf{e}(t)\mathbf{L}(t)\Delta\mathbf{f}^c_{auto}(t;\mu^c)} \\
& + \underbrace{\Delta\tau^c_{petro} + \Delta p^c_{petro} + \Delta d^c_{indirect,\,new} + \Delta\lambda^c_{indirect} + \Delta S^c_{indirect} + \Delta d^c_{indirect,\,stock} + \Delta K^c_{indirect}}_{\mathbf{e}(t)\mathbf{L}(t)\Delta\mathbf{f}^c_{petro}(t;\mu^c)}
\end{aligned}
\tag{20}
$$

The mathematical formula for calculating each effect is presented in Appendix 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 cars in use on direct and indirect gasoline emission (Car_stock: $\Delta K_{direct}^{c} + \Delta K_{indirect}^{c}$), changes in the travel distance on direct and indirect gasoline emission of new and vintage cars (Travel_dist.: $\Delta d_{direct,new}^{c} + \Delta d_{direct,stock}^{c} + \Delta d_{indirect,new}^{c} + \Delta d_{indirect,stock}^{c}$), changes in the international trade of cars (Car_trade: $\Delta \tau_{auto}^{c}$), and changes in the international trade in petroleum products (Petro_trade: $\Delta \tau_{petro}^{c}$) (Figure 1).

[INSERT FIGURE 1 ABOUT HERE]

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 S1 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 S1 and S2). 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. Results and discussion

4.1 Carbon footprint of automobiles

The solid lines in Figure 2 represent change in CF of automobiles between 1995 and 2009 estimated using Eq. (11). 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 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 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 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 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 2).

The dashed lines in Figure 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. (1) and (2)) and changing the scale parameter η^c (see Eqs. (1) and (2)) to shift average lifetime μ^c of passenger vehicles newly registered between 1987 and 2009 by −1 year or +1 year. The dashed line above the solid line in Figure 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 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.

[INSERT FIGURE 2 ABOUT HERE]

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 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). 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 Eq. (12), 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 3, 4, and 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 environmentally conscious automotive manufacturing are advancing worldwide through technological innovation (Figures 3, 4, and 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 3, 4, and 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 3, 4, and 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.

[INSERT FIGURE 3 ABOUT HERE]

[INSERT FIGURE 4 ABOUT HERE]

[INSERT FIGURE 5 ABOUT HERE]

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. (13)-(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 1, 3, 4, and 5).

Figures 3, 4, and 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 and 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 cars in use (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 3, 4, and 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 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 3, 4, and 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 cars in use (Car_stock) and the effects of changes in new car demand (Car_demand) (Figures 3, 4, and 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 E-SDA under the automobile lifetime scenarios

The influence of changes in lifetime of passenger cars (dashed lines in Figure 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, 6, 7, and 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, 6, 7, and 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 cars in use (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, 6, 7, and 8). This reduction effect was particularly large in Germany and Japan.

The E-SDA results for Japan between 2000 and 2005 in Figure 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 6, 7, and 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 3-5). 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).

[INSERT FIGURE 6 ABOUT HERE]

[INSERT FIGURE 7 ABOUT HERE]

[INSERT FIGURE 8 ABOUT HERE]

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. 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.

Appendix 1

The LMDI formulae for calculating each effect are as follows:

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

$$\Delta L^c = \sum_{i,j,s,r} \beta_{ij}^{LM,rsc} \ln \frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)} \tag{A.2}$$

$$\Delta F^c = \sum_{i,j,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_{ij}^{sc}(t;\mu^c)}{f_{ij}^{sc}(t-1;\mu^c)} \tag{A.3}$$

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 . $\beta_{ij}^{LM,rsc} = \dfrac{Q_{ij}^{rsc}(t) - Q_{ij}^{rsc}(t-1)}{\ln\left\{Q_{ij}^{rsc}(t)\right\} - \ln\left\{Q_{ij}^{rsc}(t-1)\right\}}$ 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 2

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

$$\begin{aligned}\Delta F^c = &\sum_{i,j=auto,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_j^{sc}(t;\mu^c)}{f_j^{sc}(t-1;\mu^c)} \\ &+ \sum_{i,j=petro,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_j^{sc}(t;\mu^c)}{f_j^{sc}(t-1;\mu^c)} \\ &+ \sum_{i,j\neq auto,j\neq petro,s,r} \beta_{ij}^{LM,rsc} \ln \frac{f_j^{sc}(t;\mu^c)}{f_j^{sc}(t-1;\mu^c)}\end{aligned} \tag{A.4}$$

In Eq. (A.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. (9) and (19), 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:

$$\begin{aligned}\mathbf{e}(t)\mathbf{L}(t)\mathbf{f}^c(t;\mu^c) &= \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}_{auto}^c(t;\mu^c) + \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}_{petro}^c(t;\mu^c) \\ &= \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}_{auto}^c(t)\, p_{auto}^c(t) B^c(t;\mu^c) + \mathbf{e}(t)\mathbf{L}(t)\boldsymbol{\tau}_{petro}^c(t)\, p_{petro}^c(t) q^c(t;\mu^c)\end{aligned} \tag{A.5}$$

Inserting $q^c(t;\mu^c) = q_{new}^c(t;\mu^c) + q_{stock}^c(t;\mu^c)$ in Eq. (6) into the second term of Eq. (19) yields the following the global final demand vectors for petroleum products related to new vehicles and older vehicles in country c in year t:

$$\mathbf{f}^c_{petro}\left(t;\mu^c\right)=\mathbf{f}^c_{petro,new}\left(t;\mu^c\right)+\mathbf{f}^c_{petro,stock}\left(t;\mu^c\right)$$

$$=\begin{bmatrix}0\\0\\\tau^{1c}_{petro}\left(t\right)p^c_{petro}\left(t\right)q^c_{new}\left(t;\mu^c\right)\\0\\\vdots\\0\\\vdots\\0\\0\\\tau^{Nc}_{petro}\left(t\right)p^c_{petro}\left(t\right)q^c_{new}\left(t;\mu^c\right)\\0\\\vdots\\0\end{bmatrix}+\begin{bmatrix}0\\0\\\tau^{1c}_{petro}\left(t\right)p^c_{petro}\left(t\right)q^c_{stock}\left(t;\mu^c\right)\\0\\\vdots\\0\\\vdots\\0\\0\\\tau^{Nc}_{petro}\left(t\right)p^c_{petro}\left(t\right)q^c_{stock}\left(t;\mu^c\right)\\0\\\vdots\\0\end{bmatrix} \tag{A.6}$$

By integrating Eqs. (6), (13), and (A.6) into the second term of Eq. (A.5), the indirect emission associated with petroleum consumption can be formulated as follows:

$$\begin{aligned}\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\mathbf{f}^c_{petro}\left(t;\mu^c\right)&=\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\mathbf{f}^c_{petro,new}\left(t;\mu^c\right)+\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\mathbf{f}^c_{petro,stock}\left(t;\mu^c\right)\\&=\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\boldsymbol{\tau}^c_{petro}\left(t\right)p^c_{petro}\left(t\right)q^c_{new}\left(t;\mu^c\right)+\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\boldsymbol{\tau}^c_{petro}\left(t\right)p^c_{petro}\left(t\right)q^c_{stock}\left(t;\mu^c\right)\\&=\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\boldsymbol{\tau}^c_{petro}\left(t\right)p^c_{petro}\left(t\right)d^c\left(t\right)\lambda^c\left(t\right)B^c\left(t;\mu^c\right)\\&\quad+\sum_h\mathbf{e}\left(t\right)\mathbf{L}\left(t\right)\boldsymbol{\tau}^c_{petro}\left(t\right)p^c_{petro}\left(t\right)d^c\left(t\right)\lambda^c\left(h\right)k^c_h\left(t;\mu^c\right)\end{aligned} \tag{A.7}$$

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:

$$\Delta\tau^c_{auto}=\sum_{i,j=auto,s,r}\beta^{LM,rsc}_{ij}\ln\frac{\tau^{sc}_{auto}\left(t\right)}{\tau^{sc}_{auto}\left(t-1\right)} \tag{A.8}$$

$$\Delta p^c_{auto}=\sum_{i,j=auto,s,r}\beta^{LM,rsc}_{ij}\ln\frac{p^c_{auto}\left(t\right)}{p^c_{auto}\left(t-1\right)} \tag{A.9}$$

$$\Delta B^c=\sum_{i,j=auto,s,r}\beta^{LM,rsc}_{ij}\ln\frac{B^c\left(t\right)}{B^c\left(t-1\right)} \tag{A.10}$$

$$\Delta\tau^c_{petro}=\sum_{i,j=petro,s,r}\beta^{LM,rsc}_{ij,new}\ln\frac{\tau^{sc}_{petro}\left(t\right)}{\tau^{sc}_{petro}\left(t-1\right)}+\sum_h\sum_{i,j=petro,s,r}\beta^{LM,rsc}_{ij,stock,h}\ln\frac{\tau^{sc}_{petro}\left(t\right)}{\tau^{sc}_{petro}\left(t-1\right)} \tag{A.11}$$

$$\Delta p_{petro}^{c}=\sum_{i,j=petro,s,r}\beta_{ij,new}^{LM,rsc}\ln\frac{p_{petro}^{c}\left(t\right)}{p_{petro}^{c}\left(t-1\right)}+\sum_{h}\sum_{i,j=petro,s,r}\beta_{ij,stock,h}^{LM,rsc}\ln\frac{p_{petro}^{c}\left(t\right)}{p_{petro}^{c}\left(t-1\right)} \tag{A.12}$$

$$\Delta d_{indirect,\ new}^{c}=\sum_{i,j=petro,s,r}\beta_{ij,new}^{LM,rsc}\ln\frac{d^{c}\left(t\right)}{d^{c}\left(t-1\right)} \tag{A.13}$$

$$\Delta\lambda_{indirect}^{c}=\sum_{i,j=petro,s,r}\beta_{ij,new}^{LM,rsc}\ln\frac{\lambda^{c}\left(t\right)}{\lambda^{c}\left(t-1\right)} \tag{A.14}$$

$$\Delta S_{indirect}^{c}=\sum_{i,j=petro,s,r}\beta_{ij,new}^{LM,rsc}\ln\frac{B^{c}\left(t;\mu^{c}\right)}{B^{c}\left(t-1;\mu^{c}\right)} \tag{A.15}$$

$$\Delta d_{indirect,\ stock}^{c}=\sum_{h}\sum_{i,j=petro,s,r}\beta_{ij,stock,h}^{LM,rsc}\ln\frac{d^{c}\left(t\right)}{d^{c}\left(t-1\right)} \tag{A.16}$$

$$\Delta K_{indirect}^{c}=\sum_{h}\sum_{i,j=petro,s,r}\beta_{ij,stock,h}^{LM,rsc}\ln\frac{k_{h}^{c}\left(t;\mu^{c}\right)}{k_{h}^{c}\left(t-1;\mu^{c}\right)} \tag{A.17}$$

where $Q_{i,j=petro,new}^{rsc}\left(t\right)=e_{i}^{r}\left(t\right)L_{i,j=petro}^{rs}\left(t\right)\tau_{petro}^{sc}\left(t\right)p_{petro}^{c}\left(t\right)d^{c}\left(t\right)\lambda^{c}\left(t\right)B^{c}\left(t;\mu^{c}\right)$ denotes the CO_2 emissions associated with the global final demand for petroleum products related to new vehicles in country c in year t . $\gamma_{ij,new}^{LM,rsc}=\frac{Q_{ij,new}^{rsc}\left(t\right)-Q_{ij,new}^{rsc}\left(t-1\right)}{\ln\left\{Q_{ij,new}^{rsc}\left(t\right)\right\}-\ln\left\{Q_{ij,new}^{rsc}\left(t-1\right)\right\}}$ represents the logarithmic mean weight. Noted that when we have $Q_{ij,new}^{rsc}\left(t\right)=Q_{ij,new}^{rsc}\left(t-1\right)$, $\gamma_{ij,new}^{LM,rsc}=Q_{ij,new}^{rsc}\left(t\right)=Q_{ij,new}^{rsc}\left(t-1\right)$. Similarly, $Q_{i,j=petro,stock,h}^{rsc}\left(t\right)=e_{i}^{r}\left(t\right)L_{i,j=petro}^{rs}\left(t\right)\tau_{petro}^{sc}\left(t\right)p_{petro}^{c}\left(t\right)d^{c}\left(t\right)\lambda^{c}\left(h\right)k_{h}^{c}\left(t;\mu^{c}\right)$ 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 . $\gamma_{ij,stock,h}^{LM,rsc}=\frac{Q_{ij,stock,h}^{rsc}\left(t\right)-Q_{ij,stock,h}^{rsc}\left(t-1\right)}{\ln\left\{Q_{ij,stock,h}^{rsc}\left(t\right)\right\}-\ln\left\{Q_{ij,stock,h}^{rsc}\left(t-1\right)\right\}}$

is a weighting factor. If $Q_{ij,stock,h}^{rsc}(t)=Q_{ij,stock,h}^{rsc}(t-1)$, then we have $\gamma_{ij,stock,h}^{LM,rsc}=Q_{ij,stock,h}^{rsc}(t)=Q_{ij,stock,h}^{rsc}(t-1)$.

Defining the relevant weighting factors of $\beta_{ij}^{LM,rsc}$, $\gamma_{ij,new}^{LM,rsc}$, and $\gamma_{ij,stock,h}^{LM,rsc}$ from Eqs. (A.8)-(A.17), the effect of technological changes in the industrial emission intensities can be further decomposed as follows:

$$\Delta E^{c}=\sum_{i,j=auto,s,r}\beta_{ij}^{LM,rsc}\ln\frac{e_i^r(t)}{e_i^r(t-1)}+\sum_{i,j=petro,s,r}\gamma_{ij,new}^{LM,rsc}\ln\frac{e_i^r(t)}{e_i^r(t-1)}+\sum_{h}\sum_{i,j=petro,s,r}\gamma_{ij,stock,h}^{LM,rsc}\ln\frac{e_i^r(t)}{e_i^r(t-1)} \tag{A. 18}$$

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

$$\Delta L^{c}=\sum_{i,j=auto,s,r}\beta_{ij}^{LM,rsc}\ln\frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)}+\sum_{i,j=petro,s,r}\gamma_{ij,new}^{LM,rsc}\ln\frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)}+\sum_{h}\sum_{i,j=petro,s,r}\gamma_{ij,stock,h}^{LM,rsc}\ln\frac{L_{ij}^{rs}(t)}{L_{ij}^{rs}(t-1)} \tag{A. 19}$$

Acknowledgment:

I am grateful to Shigemi Kagawa and Koji Negishi for their constructive comments about this work. All errors remain mine. This research was financially supported by JSPS KAKENHI Grant Number JP18J13430.

Reference

1. Aguilar-Hernandez, G. A., Sigüenza-Sanchez, C. P., Donati, F., Rodrigues, J. F. D. and Tukker, A. (2018) ‘Assessing circularity interventions: a review of EEIOA-based studies’, *Journal of Economic Structures,* 7(1).

2. Alcántara, V. and Duarte, R. (2004) ‘Comparison of energy intensities in European Union countries. Results of a structural decomposition analysis’, *Energy Policy*, 32(2), pp. 177–189.
3. Ang, B. W. (1994) ‘Decomposition of industrial energy consumption’, *Energy Economics*, 16(3), pp. 163–174.
4. Ang, B. W., Zhang, F. Q. and Choi, K. H. (1998) ‘Factorizing changes in energy and environmental indicators through decomposition’, *Energy*, 23, 489–495.
5. Ang, B. W. (2015) ‘LMDI decomposition approach:A guide for implementation’, *Energy Policy*, 86, pp. 233–238.
6. Ang, B. W. and Liu, N. (2007) ‘Handling zero values in the logarithmic mean Divisia index decomposition approach’, *Energy Policy*, 35(1), pp. 238–246.
7. Baiocchi, G. and Minx, J. C. (2010) ‘Understanding changes in the UK’s CO2 emissions:A global perspective’, *Environmental Science and Technology*, 44(4), pp. 1177–1184.
8. Cao, S., Xie, G. and Zhen, L. (2010) ‘Total embodied energy requirements and its decomposition in China’s agricultural sector’, *Ecological Economics*, 69(7), pp. 1396–1404.
9. Das Umweltbundesamt. (2017) ‘Fuel efficiency of passenger cars’, https://www.umweltbundesamt.de/daten/verkehr/kraftstoffe. Accessed July 6, 2018. (**In Germany**).
10. Defourny, J. and Thorbecke, E. (1984) ‘Structural Path Analysis and Multiplier Decomposition within a Social Accounting Matrix Framework’, *The Economic Journal*, 94(373), pp. 111–136.
11. Dietzenbacher, E. and Los, B. (1998) ‘Structural Decomposition Techniques: Sense and Sensitivity’, *Economic Systems Research*, 10(4), pp. 307–324.

12. Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M., de Vries, G. (2013) 'The Construction of World Input-Output Tables in the Wiod Project'. *Economic Systems Research*, 25(1), pp.71–98.
13. European Commission (2015) 'An EU action plan for the circular economy', Com, 614, p. 21.
14. Enerdata (2018) 'Annual distance traveled by cars' Odyssee database
15. FOURIN (2010), World Motor Vehicle Statistics Yearbook from 1995 to 2009 (**In Japanese**).
16. Haan, M. D. E. (2001) 'A Structural Decomposition Analysis of Pollution in the Netherlands', *Economic Systems Research*, 13(2), pp. 181–196.
17. Hertwich, E. G. and Peters, G. P. (2009) 'Carbon footprint of nations:A global, trade-linked analysis', *Environmental Science and Technology*, 43(16), pp. 6414–6420.
18. Hoekstra, R. and van der Bergh, J. J. C. J. M. (2003) 'Comparing structural and index decomposition analysis', *Energy Economics*, 25(1), pp. 39–64.
19. Horvath, A. and Hendrickson, C. (1998) 'Comparison of environmental implications of asphalt and steel-reinforced concrete pavements', *Transportation Research Record*, 1626, pp. 105–113.
20. International Energy Agency (2014) '*Energy Prices and Taxes*', Quarterly Statistics., (Second Quarter 2014).
21. International Energy Agency (2017) 'International comparison of light-duty vehicle fuel economy 2005-2015' GFEI Working Paper 15, OECD/IEA, Available at:http://www.globalfueleconomy.org/Documents/Publications/wp5_iea_fuel_Economy_report.pdf.

22. International Organization of Motor Vehicle Manufacturers (2018) ‘Vehicle in use’, http://www.oica.net/category/vehicles-in-use/. Accessed September 11, 2018.
23. Japan Automobile Manufacturers Association. (2016) Environmental programs. http://www.jama.or.jp/eco/earth/index.html. Accessed May 21, 2018. (**In Japanese**).
24. Kagawa, S., Goto, Y., Suh, S., Nansai, K. and Kudoh, Y. (2012) ‘Accounting for Changes in Automobile Gasoline Consumption in Japan:2000–2007’, *Journal of Economic Structures*, 1(1).
25. Kagawa, S., Kudoh, Y., Nansai, K. and Tasaki, T. (2008) ‘The economic and environmental consequences of automobile lifetime extension and fuel economy improvement: Japan’s case’, *Economic Systems Research*, 20(1), pp. 3–28.
26. Kagawa, S., Nansai, K., Kondo, Y., Hubacek, K., Suh, S., Minx, J., Kudoh, Y., Tasaki, T. and Nakamura, S. (2011) ‘Role of Motor Vehicle Lifetime Extension in Climate Change Policy’, *Environmental Science & Technology*, 45(4), pp. 1184–1191.
27. Kagawa, S., Suh, S., Hubacek, K., Wiedmann, T., Nansai, K. and Minx, J. (2015) ‘CO2emission clusters within global supply chain networks: Implications for climate change mitigation’, *Global Environmental Change*, 35, pp. 486–496.
28. Kraftfahrt-Bundesamt (2010) ‘*KBA - Wir punkten mit Verkehrssicherheit – Statistik*’, **(In Germany)**.
29. Lenzen, M. (2003) ‘Environmentally important paths, linkages and key sectors in the Australian economy’, *Structural Change and Economic Dynamics*, 14(1), pp. 1–34.
30. Lenzen, M. (2016) ‘Structural analyses of energy use and carbon emissions – an overview’, *Economic Systems Research*, 28(2), pp. 119–132.
31. Lim, H. J., Yoo, S. H. and Kwak, S. J. (2009) ‘Industrial CO2emissions from energy use in Korea:A structural decomposition analysis’, *Energy Policy*, 37(2), pp. 686–698.

32. Leontief, W. and Ford, D. (1971) '*Air pollution and the economic structure: empirical results of input–output computations*', Fifth International Conference on Input–Output Techniques, Geneva, Switzerland. North-Holland Publishing Company.

33. McCool, J. I. (2012) "*Using the Weibull Distribution: Reliability, Modeling and Inference*," John Wiley & Sons, Inc., New Jersey, U.S.A.

34. Ministry of Land, Infrastructure, Transport and Tourism, Japan (2010) http://www.mlit.go.jp/jidosha/jidosha_mn10_000002.html. Accessed 27 May 2018 (**In Japanese**).

35. Munksgaard, J., Pedersen, K. A. and Wien, M. (2000) 'Impact of household consumption on CO2 emissions', Energy Economics, 22(4), pp. 423–440.

36. Nakamoto, Y. (2017) 'CO2 reduction potentials through the market expansion and lifetime extension of used cars', *Journal of Economic Structures*, 6(1).

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

38. Nakamoto, Y., Nishijima, D. and Kagawa, S. (2019) 'The Role of Vehicle Lifetime Extensions of Countries on Global CO2 Emissions', *Journal of Cleaner Production*, 207:1040-1046.

39. Nakamura, S., Kondo, Y., Kagawa, S., Matsubae, K., Nakajima, K. and Nagasaka, T. (2014) 'MaTrace: Tracing the Fate of Materials over Time and Across Products in Open-Loop Recycling', *Environmental Science and Technology*, 48(13), pp. 7207–7214.

40. National Institute for Environmental Studies, Japan (2010) Embodied energy and emission intensity data for japan using input–output tables. http://www.cger.nies.go.jp/publications/report/d031/jpn/datafile/embodied/2005/403.htm. Accessed March 4, 2018. (**In Japanese**).

41. Nishijima, D. (2017) ‘The role of technology, product lifetime, and energy efficiency in climate mitigation: A case study of air conditioners in Japan’, *Energy Policy*, 104, pp. 340–347.

42. de Nooij, M., van der Kruk, R. and van Soest, D. P. (2003) ‘International comparisons of domestic energy consumption’, *Energy Economics*, 25(4), pp. 359–373.

43. Oguchi, M. and Fuse, M. (2015) ‘Regional and longitudinal estimation of product lifespan distribution: A case study for automobiles and a simplified estimation method’, *Environmental Science and Technology*, 49(3), pp. 1738–1743.

44. Ohno, H., Matsubae, K., Nakajima, K., Kondo, Y., Nakamura, S., Fukushima, Y. and Nagasaka, T. (2017) ‘Optimal Recycling of Steel Scrap and Alloying Elements: Input-Output based Linear Programming Method with Its Application to End-of-Life Vehicles in Japan’, *Environmental Science and Technology*, 51(22), pp. 13086–13094.

45. Oshita, Y. (2012) ‘Identifying critical supply chain paths that drive changes in CO 2 emissions’, *Energy Economics*, 34(4), pp. 1041–1050.

46. Owen, A., Wood, R., Barrett, J. and Evans, A. (2016) ‘Explaining value chain differences in MRIO databases through structural path decomposition’, *Economic Systems Research*, 28(2), pp. 243–272.

47. Pauliuk, S., Kondo, Y., Nakamura, S. and Nakajima, K. (2017) ‘Resources, Conservation and Recycling Regional distribution and losses of end-of-life steel throughout multiple product life cycles — Insights from the global multiregional MaTrace model’, *Resources, Conservation & Recycling*, 116, pp. 84–93.

48. Pavlínek, P. and Ženka, J. (2011) ‘Upgrading in the automotive industry: Firm-level evidence from Central Europe’, Journal of Economic Geography, 11(3), pp. 559–586.

49. Peters, G. P., Weber, C. L., Guan, D. and Hubacek, K. (2007) ‘China’s growing CO2 emissions - A race between increasing consumption and efficiency gains’, *Environmental Science and Technology*, 41(17), pp. 5939–5944.
50. Roca, J. and Serrano, M. (2007) ‘Income growth and atmospheric pollution in Spain:An input – output approach’, *Ecological Economics*, 63(1), pp. 230–242.
51. Serrenho, A. C. and Allwood, J. M. (2016) ‘Material Stock Demographics: Cars in Great Britain’, *Environmental Science and Technology*, 50(6), pp. 3002–3009.
52. Shironitta, K. (2016) ‘Global structural changes and their implication for territorial CO2emissions’, *Journal of Economic Structures*, 5(1).
53. Spielmann, M. and Althaus, H. J. (2007) ‘Can a prolonged use of a passenger car reduce environmental burdens? Life Cycle analysis of Swiss passenger cars’, *Journal of Cleaner Production*, 15, pp. 1122–1134.
54. Strømman, A. H., Peters, G. P. and Hertwich, E. G. (2009) ‘Approaches to correct for double counting in tiered hybrid life cycle inventories’, *Journal of Cleaner Production*, 17(2), pp. 248–254.
55. Su, B. and Ang, B. W. (2012) ‘Structural decomposition analysis applied to energy and emissions:Some methodological developments’, *Energy Economics*, 34(1), pp. 177–188.
56. Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J. (2015) ‘An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production’, *Review of International Economics*, 23(3), pp. 575–605.
57. Tokito, S. (2018) ‘Environmentally-Targeted Sectors and Linkages in the Global Supply-Chain Complexity of Transport Equipment’, *Ecological Economics*, 150, pp. 177–183.

58. Unander, F., Karbuz, S., Schipper, L., Khrushch, M. and Ting, M. (1999) 'Manufacturing energy use in OECD countries:Decomposition of long-term trends', *Energy Policy*, 27(13), pp. 769–778.

59. Wiedmann, T. and Minx, J. (2008) '*A Definition of 'Carbon Footprint''*, Ecological economics research trends.

60. Wood, R. and Lenzen, M. (2006) 'Zero-value problems of the logarithmic mean divisia index decomposition method', *Energy Policy*, 34(12), pp. 1326–1331.

61. Wood, R. and Lenzen, M. (2009) 'Structural path decomposition', *Energy Economics*, 31(3), pp. 335–341.

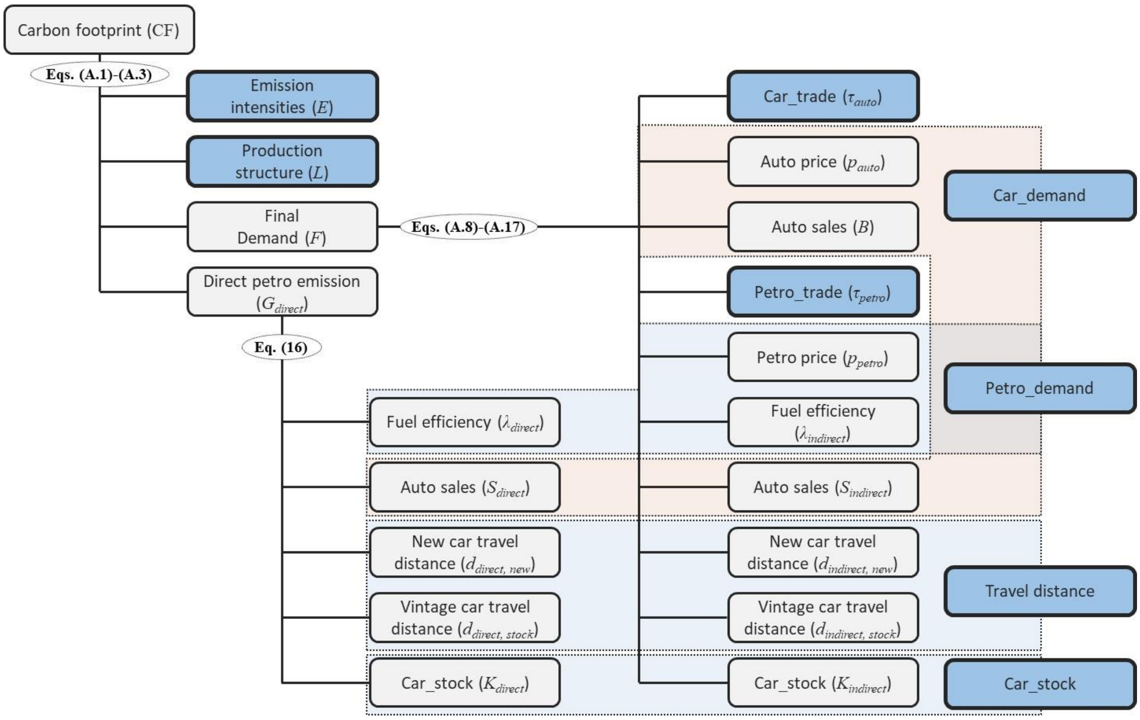

Figure 1: Structure of Extended-Structural Decomposition Analysis (E-SDA)

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.

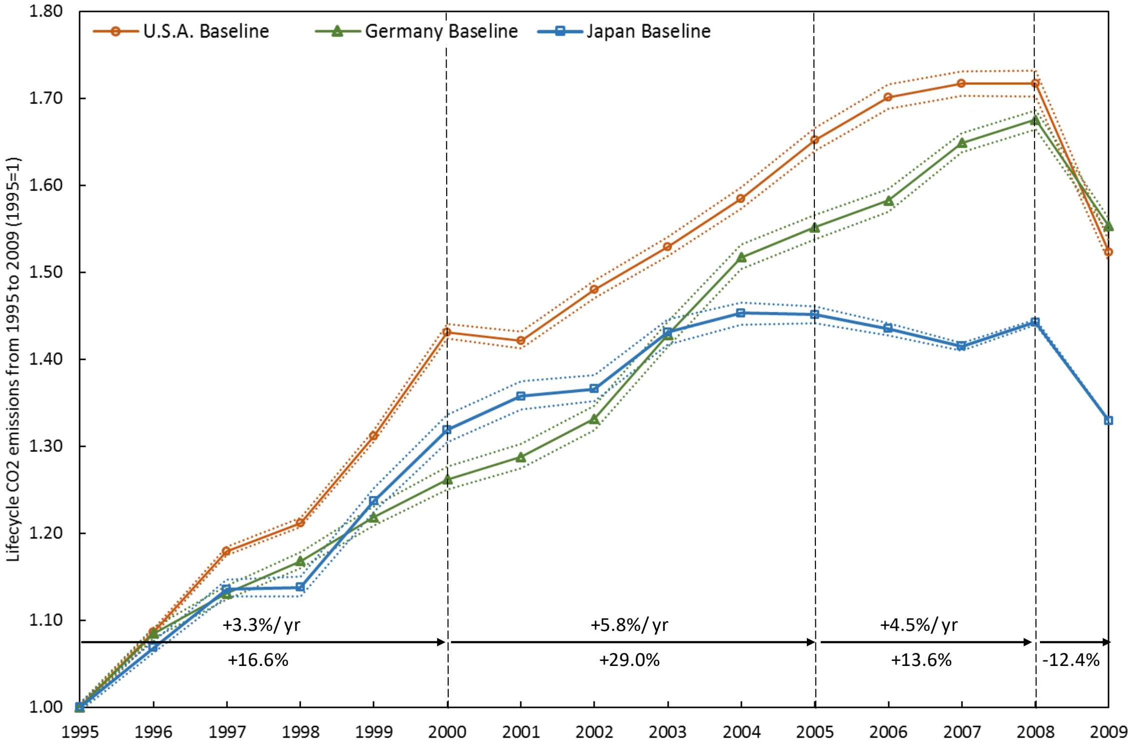

Figure 2: Life-cycle CO_2 emissions of automobiles during 1995 to 2009 (1995=1).

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.

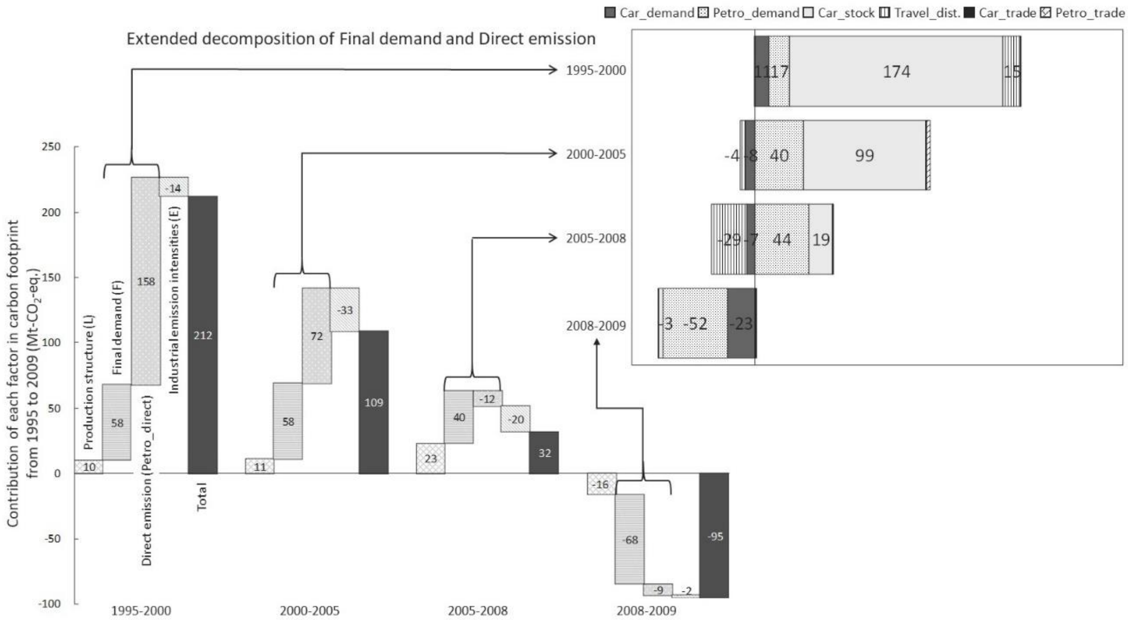

Figure 3: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 (U.S.A.).

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).

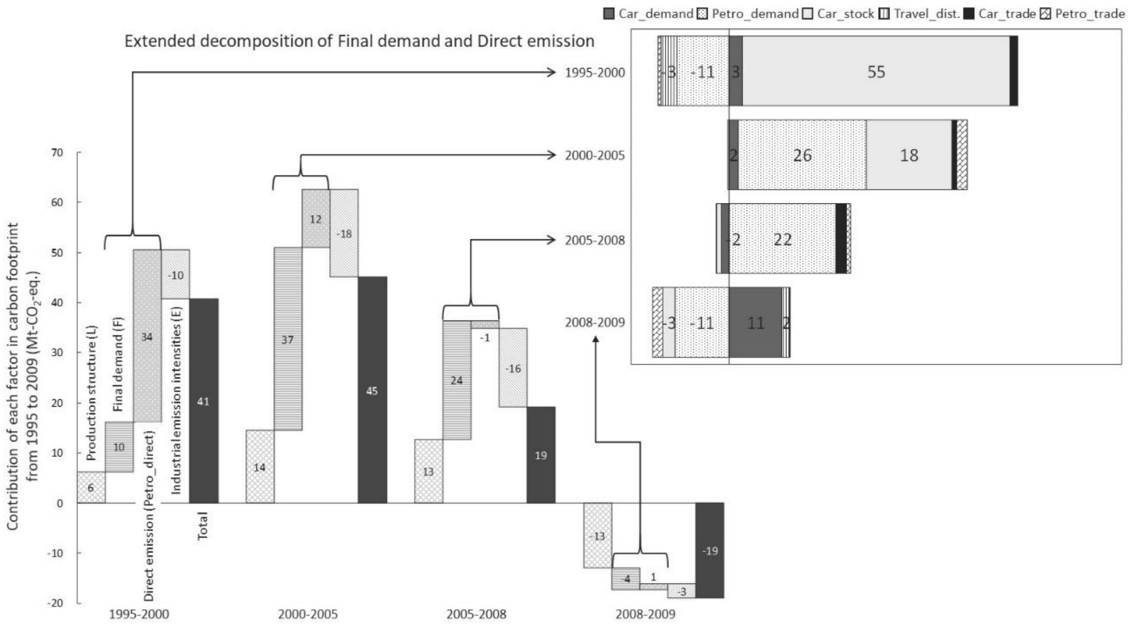

Figure 4: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 (Germany).

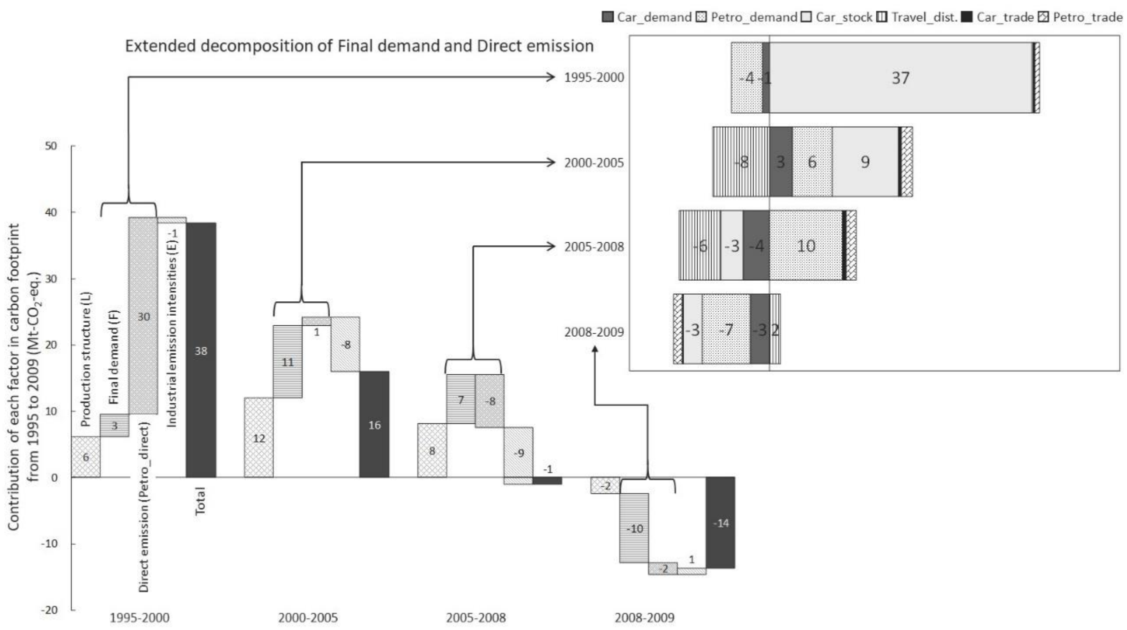

Figure 5: SDA and E-SDA of the carbon footprint of automobiles during 1995 to 2009 (Japan).

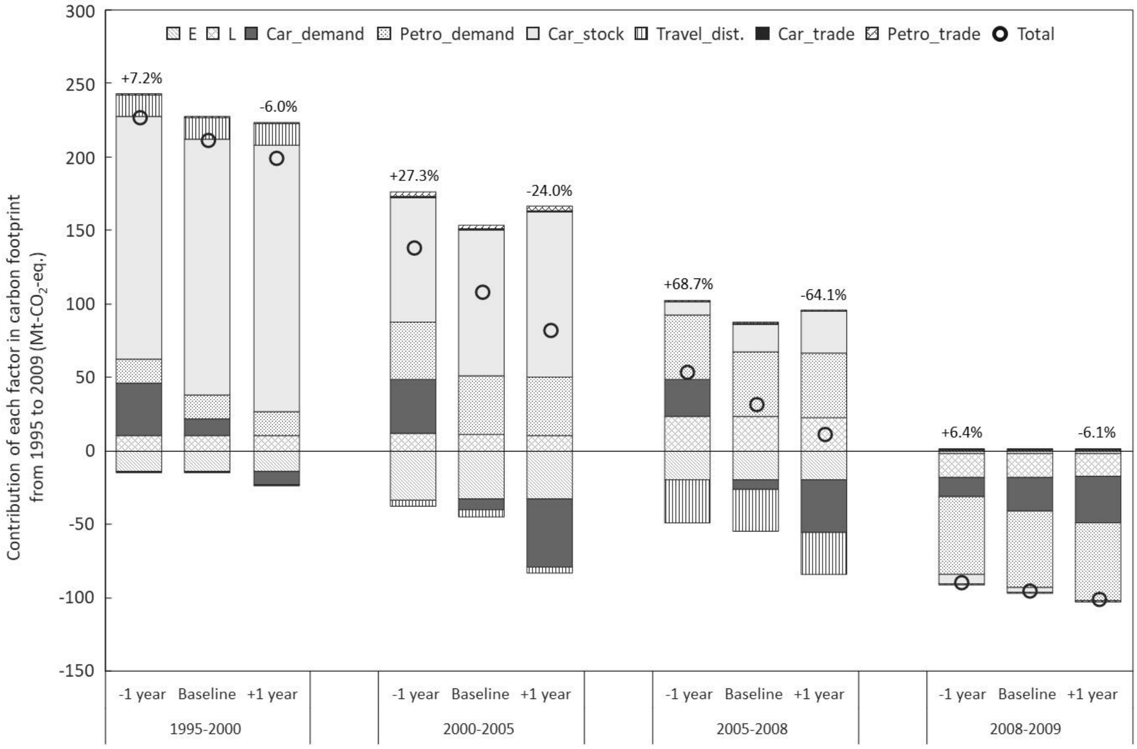

Figure 6: E-SDA of the carbon footprint of automobiles during 1995 to 2009 under the automobile lifetime scenario (U.S.A.).

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

Right bars: +1 year lifetime scenario.

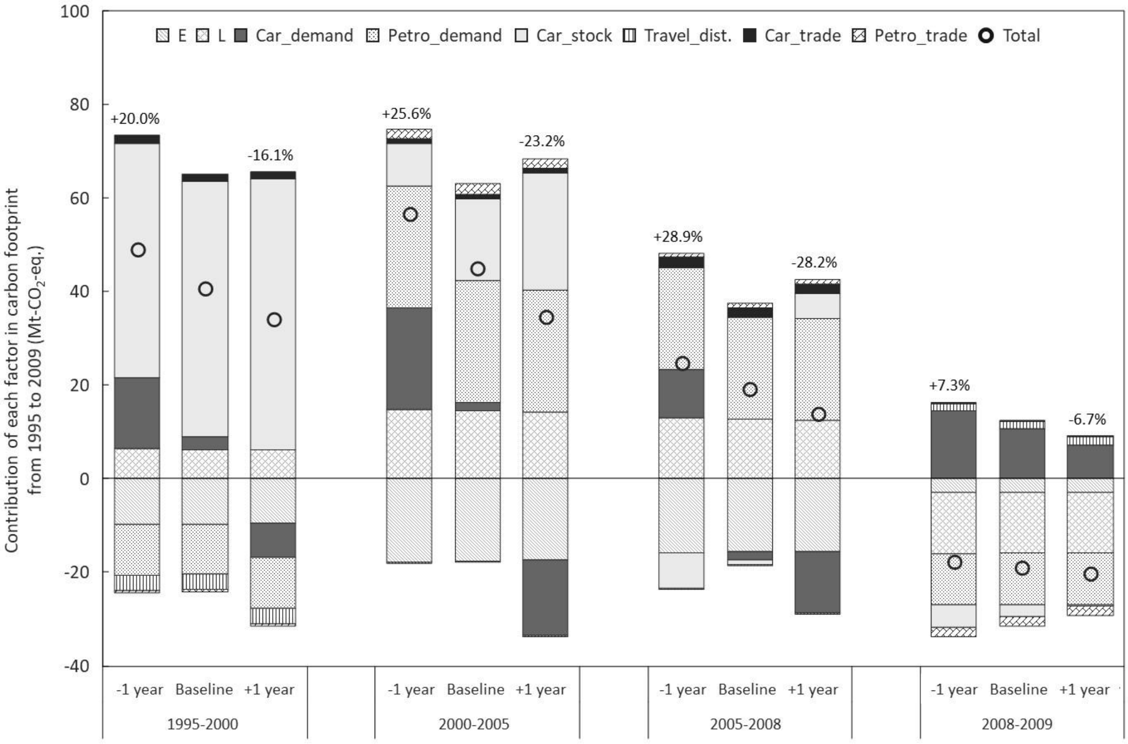

Figure 7: E-SDA of the carbon footprint of automobiles during 1995 to 2009 under the automobile lifetime scenario (Germany).

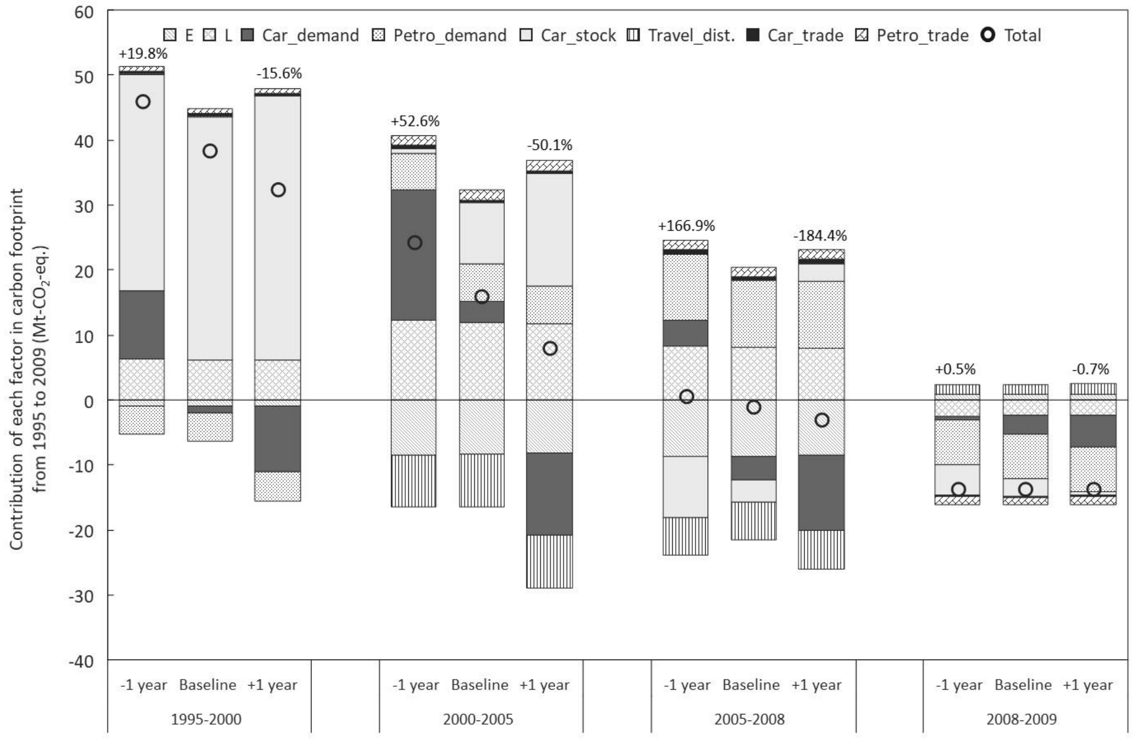

Figure 8: E-SDA of the carbon footprint of automobiles during 1995 to 2009 under the automobile lifetime scenario (Japan).