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Factors affecting CO_2 emissions from private automobiles in Japan: The impact of vehicle occupancy

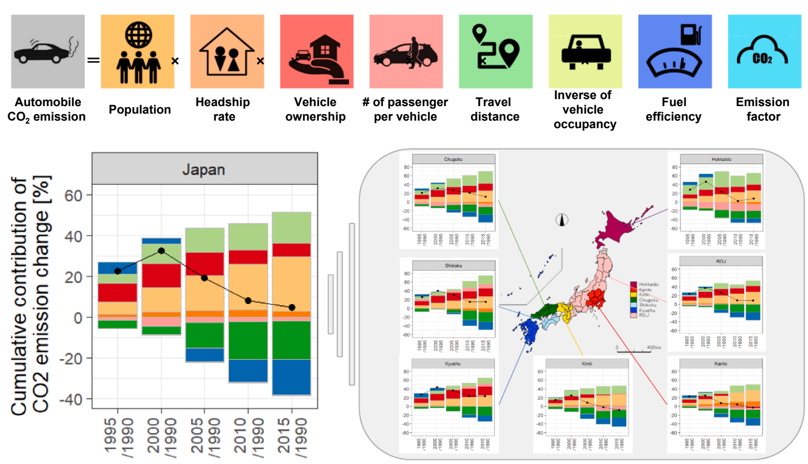
Hiroto Shiraki[a,*], Ken'ichi Matsumoto[b], Yosuke Shigetomi[b], Tomoki Ehara[c], Yuki Ochi[c], Yuki Ogawa[c]

[a] School of Environmental Science, The University of Shiga Prefecture, 2500 Hassaka, Hikone, Shiga 522-8533, Japan
[b] Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1-14 Bunkyo-machi, Nagasaki 852-8521, Japan
[c] E-konzal, 3-8-15-1207 Nishinakajima, Yodogawa-ku, Osaka 532-0011, Japan

HIGHLIGHTS

- We decomposed sub-national automobile emissions in Japan into eight factors.
- Vehicle occupancy was identified as one of the driving forces of emission change.
- Vehicle occupancy change increased emissions by 15.2% from 1990 to 2015.
- Ordinances for air pollution may have resulted adoption of fuel-efficient vehicles.
- Vehicle occupancy improvement would mitigate future automobile emissions.

GRAPHICAL ABSTRACT



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ABSTRACT

The road transport sector accounted for 18.8% of global CO_2 emissions in 2016. Regional efforts are indispensable for reducing automobile emissions, especially considering the diversity in regional transportation systems. Existing studies of automobile emissions have focused on nationwide transportation systems or differences in city size without considering regionality and long-term changes in vehicle occupancy. In this study, we decomposed national and regional automobile emissions in Japan between 1990 and 2015 by the Logarithmic Mean Divisia Index method. Statistical data that took vehicle occupancy into account were used. Results showed that nationwide vehicle occupancy increased (due to increased vehicle size and vehicle ownership), which increased emissions by 15.2% compared to 1990 levels. In highly populated regions, fuel efficiency decreased earlier than other regions thanks to the strengthening of ordinances regarding air pollution. In Western Japan, which includes less-populated prefectures, the rising popularity of mini-vehicles resulted in increased vehicle ownership and a decrease in occupancy but also led to improvements in fuel economy. To reduce automobile CO_2 emissions, it will be essential to improve fuel efficiency and to increase vehicle occupancy through mechanisms, such as ridesharing and vehicle right sizing.

* Corresponding author.
E-mail address: shiraki.h@ses.usp.ac.jp (H. Shiraki).

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1. Introduction

In 2016, CO_2 emissions from the transportation sector reached approximately 8 Gt-CO_2, an increase of 71% when compared to 1990 levels and equal to one-quarter of total global emissions [1]. In particular, the increase in emissions from Asian countries has been remarkable, reaching almost the same level as in the Americas, which is the highest emission-producing region [1]. While the direct CO_2 emissions of each transportation mode vary by region, condition, and fuel type, light-duty vehicles emit much more CO_2 on average than other land transportation modes (e.g., rail and bus) [2]. The importance of shifting to lower emission modes of transportation is generally acknowledged, however, the share of road transportation emissions has still increased by two percentage points from 1990 (72%) to 2016 (74%) [1]. It is necessary to identify the factors affecting changes in CO_2 emissions in the automobile sector.

Decomposition analysis is an effective way to identify key drivers and provide insights for CO_2 emission reduction [3] not only on a national scale (e.g., OECD [4], Latvia [5], and China [6,7]) but also in a specific sector (e.g., industrial sector in China [8], Korea [9], and UK [10], and residential sector in China [11,12]). There are several studies on decomposition of CO_2 emissions from transport sector. Timilsina and Shrestha [13] analyzed the factors that influencing the growth of CO_2 emission from transport sector in the selected Asian countries during the 1980–2005 period. Wang et al. [14] decomposed transport sector CO_2 emissions in China over the period 1985–2009 considering changes in transport activity, modal shift, GDP per capita, and population. Wang et al. [15] analyzed CO_2 emission from China's passenger and freight transportation sectors between 1990 and 2015 focusing on the similarities and differences among these sectors. Lipscy and Schipper [16] examined energy efficiency in the Japanese transportation sector from 1970s to 2008 by decomposing CO_2 emission into three indexes: total activity (passenger-kilometers), transportation mode structure, and CO_2 intensity. Jian [17] introduced an indicator analysis to evaluate and select most important affecting factors to decompose transportation energy consumption and adopted four factors for decomposition; energy intensity, mode share, number of trips, and average distance for each passenger. Luo et al. [18] conducted a decomposition analysis with comparative studies on two Asian mega cities, Tokyo and Shanghai by decomposing the transportation sector's CO_2 emissions into six factors.

Decomposition analysis has also been used to assess policy options based on subsector variables. Lu et al. [19] identified vehicle ownership as one of the factors affecting CO_2 emissions from highway transportation in four countries. Papagiannaki and Dialoulaki [20] decomposed CO_2 emissions from passenger vehicles in Greece and Denmark for 1990–2005 using annual mileage, engine capacity, and technology as decomposition factors. Mishina et al. [21] decomposed Japanese CO_2 emissions into six factors: travel distance per passenger vehicle, vehicle ownership, population, average weight of passenger vehicle, reciprocal of annual road fuel efficiency per average vehicle weight, and emission intensity. They conducted cross-regional decomposition and showed that the average number of vehicles was the dominant factor for regional differences. Matsuhashi et al. [22] decomposed per capita CO_2 emissions into four indexes: vehicle ownership, trip per vehicle, average trip distance, and CO_2 emission per distance. They focused on municipal populations and found that decreasing average trip distance in cities with more than 200,000 residents resulted in lower per capita emissions from 2005 to 2010. Zang et al. [23] identified the relationships between transportation energy consumption and its impacted factors, such as transportation activity effect and energy intensity effect.

Although these studies tried to capture the impact of automobile-specific factors, such as vehicle ownership and trip distance per vehicle, the impact of vehicle occupancy was not considered. Some studies recommended the development of policies for high-occupancy vehicles to mitigate the expected increase in demand from ride-hailing services and automated vehicles [24,25]. Moreover, carpooling options are increasing due to casual carpooling, digital ride-sharing applications, and volume control in mega cities (e.g., odd-even rationing and road space rationing). Some studies projected future scenarios that assumed increases in the occupancy rate of vehicles [26,27]. It is becoming increasingly important for studies to focus on vehicle occupancy.

Another shortcoming of existing studies in the automobile sector is the lack of regional analysis within countries. Most studies focused on differences among countries (e.g., Asian countries [13], Japan and the United States [16], Taiwan, Germany, Japan and South Korea [19], and Greece and Denmark [20]) or among cities (e.g., Shanghai and Tokyo [18]). Although some studies examined regional differences within a single country, they focused on the urban-rural difference [21] or population size [22]. Some studies revealed that regional characteristics, such as climate and policy, can affect manufacturing and household emissions [28,29]. Therefore, it would be beneficial to understand the key factors driving CO_2 emissions by utilizing detailed spatial resolution.

This study applied decomposition analysis to identify factors affecting changes in regional CO_2 emissions from private automobiles through the use of statistics that allowed vehicle occupancy to be taken into account. Japan was selected for the study because of the availability of detailed regional statistics, including maximum vehicle seating capacity. The goals of this study were: (1) to quantify the driving forces of regional changes in CO2 emissions in the automobile sector; (2) to estimate the influence of region-specific transportation systems and policies on regional emissions; and (3) to identify policy implications for reducing future CO_2 emissions from the automobile sector.

Contributions of our findings are twofold. First, to the best of our knowledge, this study is the first to quantify the impact of vehicle occupancy on historical CO_2 emissions. Recently, global consumer preferences shifted to larger-sized-vehicle segments, such as sports-utility vehicles and pick-up trucks [30]. The number of global vehicles in use has increased at an annual rate of 3.7% from 2005 to 2015 [31]. Both of these trends may result in lower occupancies per vehicle. Although some existing studies estimated the potential impact of vehicle occupancy improvement on future CO_2 emissions [32,33], there are no empirical studies which quantify the historical contribution of changes in vehicle occupancy. By comparing the impact of vehicle occupancy and other factors on historical CO_2 emissions, this study quantitatively shows the relative importance of transport efficiency improvement measures.

Second, our sub-national scale analysis provides a link between regional differences of CO_2 emission change and municipal policies. Automobile CO_2 emissions are affected not only by national policies and technology trends but also by regional characteristics and policies. For example, local authorities aim to reduce congestion and emissions through various freight transport policies [32]. Another study points out that urban air pollution policies and measures have led to a reduction in greenhouse gas emissions [33]. By linking the sub-national scale quantitative analysis with regional transport policies, this study emphasizes the role of local municipalities in reducing automobile CO_2 emissions together with the effects of national policies.

2. Materials and methods

2.1. Decomposition analysis

CO_2 emissions from private automobiles were decomposed into eight factors:

$$\begin{aligned} C_i &= P_i \cdot \frac{H_i}{P_i} \cdot \frac{NV_i}{H_i} \cdot \frac{TP_i}{NV_i} \cdot \frac{Pkm_i}{TP_i} \cdot \frac{ASkm_i}{Pkm_i} \cdot \frac{E_i}{ASkm_i} \cdot \frac{C_i}{E_i} \\ &= P_i \cdot HR_i \cdot VO_i \cdot PV_i \cdot TD_i \cdot OC_i \cdot FE_i \cdot EF_i \end{aligned} \quad (1)$$

where C_i is CO_2 emissions from private automobiles in region i; P_i is population in region i; H_i is the number of households in region i; NV_i is the number of vehicles in region i; TP_i is the number of passengers carried in region i; Pkm_i is passenger-kilometers in region i; $ASkm_i$ is available seat-kilometers in region i; and E_i is energy consumption by private automobiles in region i. Available seat-kilometers equals maximum seating capacity multiplied by the distance of passenger ride. In the second line of Eq. (1), $HR_i(=H_i/P_i)$ denotes headship rate in region i, $VO_i(=NV_i/H_i)$ denotes vehicle ownership per household in region i; $PV_i(=TP_i/NV_i)$ denotes number of passengers carried per vehicle in region i; $TD_i(=Pkm_i/TP_i)$ denotes average travel distance per passenger carried in region i; $OC_i(=ASkm_i/Pkm_i)$ denotes overcapacity index in region i, which represents the inverse of vehicle occupancy; $FE_i(=E_i/ASkm_i)$ denotes fuel efficiency calculated using available seat-kilometers in region i; and $EF_i(=C_i/E_i)$ denotes the emission factor in region i. Out of eight factors, overcapacity index OC_i and fuel efficiency calculated using available seat-kilometers FE_i are features of our studies. Overcapacity index OC_i represents number of seats used by one passenger. Fuel efficiency calculated using available seat-kilometers FE_i corresponds fuel consumption for moving one available seat one kilometer. Thus, "general" fuel efficiency scaled by liter per km can be obtained by multiplying the maximum seating capacity of the vehicle.

This study used index decomposition analysis to capture the impact of selected individual factors, which are detailed in Eq. (1), on CO_2 emissions from private automobiles. Decomposition analysis has been applied to a wide variety of issues including the assessment of energy consumption structures [34]. After reviewing the application and methodology, Ang [34] recommended the Logarithmic Mean Divisia Index method 1 (LMDI-I) for decomposition analysis in the energy fields based on its adaptability and ease of use, understanding, and presentation. Indeed, numerous studies have been conducted in various countries and sectors using the original LMDI (e.g. industrial sector in Korea [9], China [35], and Japan [29], residential sector in China [12], and Japan [28,36], Chinese transport sector [14], Chinese coal consumptions [37], energy sector in the European countries [38] and China [39,40], and toxicological footprints in the United States [41]). Accordingly, LMDI-I was used for decomposition analysis in this study. There are two types of decomposition methods in LMDI-I: multiplicative and additive [42]. While the former analyzes the relative change in CO_2 emissions between the base year and the targeted year, the latter expresses the absolute difference. In this study, multiplicative LMDI-I was adopted to analyze cumulative emission change during the entire analytical period (1990–2015) and at five-year intervals (1990–1995, 1995–2000, etc.).

For the multiplicative LMDI-I [42], we decomposed the ratio of CO_2 emission change for private automobiles from the base year to the target year. Eqs. (2)–(10) can be obtained using the eight factors from Eq. (1). The equations are:

$$\begin{aligned} D_i &= C_i^t/C_i^0 \\ &= D_{i,P}\cdot D_{i,HR}\cdot D_{i,VO}\cdot D_{i,PV}\cdot D_{i,TD}\cdot D_{i,OC}\cdot D_{i,FE}\cdot D_{i,EF} \end{aligned} \tag{2}$$

$$D_{i,P} = P_i^t/P_i^0 \tag{3}$$

$$D_{i,HR} = HR_i^t/HR_i^0 \tag{4}$$

$$D_{i,VO} = VO_i^t/VO_i^0 \tag{5}$$

$$D_{i,PV} = PV_i^t/PV_i^0 \tag{6}$$

$$D_{i,TD} = TD_i^t/TD_i^0 \tag{7}$$

$$D_{i,OC} = OC_i^t/OC_i^0 \tag{8}$$

$$D_{i,FE} = FE_i^t/FE_i^0 \tag{9}$$

$$D_{i,EF} = EF_i^t/EF_i^0 \tag{10}$$

where $D_{i,X}$ indicates the ratio of each factor for the target year t over the base year 0.

2.2. Data

To focus on the change in CO_2 emissions between the reference year of the Kyoto Protocol and the commitment for Annex I countries in the United Nations Framework Convention on Climate Change, the analytical period was set from 1990 to 2015. Population P_i and the number of households H_i for each year were obtained from the national population statistics database [43]. The number of passengersTP_i, passenger-kilometers Pkm_i, available seat-kilometers $ASkm_i$, and energy consumption by private automobiles E_i were taken from the Survey on Motor Vehicle Transport [44] and the Survey on Motor Vehicle Fuel Consumption [45]. These indices were calculated from maximum seating capacity, the number of passengers, and travel distances collected by the questionnaire survey. The number of vehicles NV_i was taken from Statistics of Motor Vehicles Owned [46]. Due to the availability of regional data, the number of vehicles in each region includes commercial vehicles along with privately-owned ones. Data for Japan confirms that commercial vehicles account for only about 1.8% of passenger and freight vehicles (excluding buses and special vehicles) in 2016 [46]. CO_2 emissions from private automobiles C_i was calculated by multiplying E_i by fuel type, and CO_2 emission factor EF_f by fuel type [47]:

$$C_i = \sum_f (E_{i,f}\cdot EF_f) \tag{11}$$

where $E_{i,f}$ is the energy consumption of fuel f by private automobiles in region i, and EF_f is the emission factor of fuel f.

Due to changes in the statistical surveys, available seat-kilometers $ASkm_i$ values were not obtainable after 2010. Thus, after 2010, available seat-kilometers values were estimated with the following equation:

$$ASkm_i^t = a_i\cdot \sum_j NV_{ij}^t\cdot SC_j^t\cdot T_i^t \quad (t = 2010 - 2015) \tag{12}$$

which uses the number of vehicles by model j (NV_{ij}) [48,49], maximum seating capacity by vehicle model j (SC_j), transport distance (T_i) [44], and the regional adjustment parameter (a_i). Maximum seating capacity by vehicle model SC_j (see Table 1) and the regional adjustment parameter a_i (see Table S1) were assumed using available data of NV_{ij}, [46] $ASkm_i$, and T_i from 1995 to 2009 [44–46]. Classification of the vehicle model was adopted from statistics [48,49]. Note that in the classifications, the models starting with "mini" are the category for the smallest cars in Japan (length < 3.4 m, width < 1.48 m, height < 2.0 m, and engine displacement < 660 cc).

Note that the statistical surveys for energy consumption changed from the Survey on Motor Vehicle Transport to the Survey on Motor Vehicle Fuel Consumption in 2010 (see Table 2). In addition, the Survey

Table 1
Assumed maximum seating capacity by vehicle model.

Purpose	Vehicle model	Maximum seating capacity (Average by vehicle model)
Passenger	Large to medium-sized[a]	5.0
	Small-sized[b]	5.0
	Popular car[c]	5.0
	Bonnet wagon (Sports Utility Vehicles)	6.5
	Onebox	7.0
	Mini passenger cars	4.0
Freight	Mini "bonnet" vans	4.0
	Cab-over-engine minivans	2.0
	Mini-trucks	2.0
	Other	5.1

[a] E.g., Toyota Celsior, Nissan President, Toyota Crown, Nissan Fuga.
[b] E.g., Toyota Mark X ,Nissan Bluebird.
[c] E.g., Toyota Corolla, Nissan March (Micra).

on Motor Vehicle Transport's regional definition changed in 2010 due to the reorganization of the District Transport Bureau [50]. To ensure consistency in regional classification, we recalculated each variable following the regional classification in Table S2, Column 1. Thus, prefectures in the three district transport bureaus were merged as the Rest of Japan (ROJ) region due to the data availability.

Fig. 1 shows a time series of regional population and CO_2 emissions from private automobiles. CO_2 emissions from private automobiles increased from 1990 and peaked in 2000. Emissions then fell drastically until 2005 and gradually decreased thereafter. While the regions of Kanto and Kinki account for 50% of the population, they are responsible for only 40–45% of total emissions.

There were limitations due to the regional resolution of the available data. Calculations for vehicle occupancy required seating capacity and the number of passengers carried, but these statistics were only available from the District Transport Bureau data. Although the surveys were revamped in 2010 and have started to gather travel distance and fuel consumption at the prefecture level, the seating capacity and the number of passengers carried were unfortunately removed from the surveys [44,45]. Several statistics are collected at the prefecture scale and/or higher regional resolution (e.g., the Person-Trip Survey [51]), however, it is difficult to ensure consistency between statistics due to differences in the survey target, period, item, and area. In the future, it will be necessary to implement comprehensive statistics in order to take vehicle occupancy into account.

3. Results and discussion

3.1. Trends in the eight factors used for LMDI-I

The trends in the factors used for the LMDI-I, equations (2–10), are shown in Fig. 2. The emission factor was not depicted since that value was almost unchanged. The headship rate increased over time even though the absolute values varied by region. The vehicle per household in Japan gradually decreased after an initial increase until 2000. There were different regional trends in the number of vehicles per household; this number gradually decreased in urban areas while it increased or flattened in the others. Similarly, while the average number of passengers per vehicle was flat at the national level, differences were observed in that it decreased in the Kanto and Kinki regions while it increased in the others. These differences may be caused by the high share of public transportation in the Kanto and Kinki regions which include highly populated prefectures (e.g., Tokyo and Osaka). While the national travel distance decreased from 16.5 km per passenger in 1990 to 13.4 km per passenger in 2015, it was shorter in the Shikoku region and longer in the Hokkaido region during most of the study period. The overcapacity index increased in most regions except for Hokkaido and ROJ, where it plateaued after 2005. Fuel efficiency continued a declining trend after 1995. The emission factor decreased slightly thanks to the substitution of diesel with gasoline (from 2.336 t-CO_2/kl-gasoline equivalent in 1990 to 2.328 t-CO_2/kl-gasoline equivalent in 2015).

Trends for seating capacity and vehicle occupancy that affect transportation efficiency are shown in Fig. 3. Before 2003, national seating capacity had increased, but it has since remained flat at around five seats per vehicle. Seating capacities in the Chugoku, Shikoku, and Kyushu regions were small, while those in the Hokkaido and Kanto regions were larger. Because the western regions have a mild climate compared with the northeastern regions, the penetration rate of the mini-vehicles, which has a maximum seating capacity of four seats per vehicle, was relatively high as they are often used as a second car [49]. On the other hand, the Kanto region has a lower share of the mini-vehicles due to its high public transportation share. In addition, high-powered vehicles are preferred for winter driving in Hokkaido. These conditions may explain the regional variation in seating capacities.

Vehicle occupancy in Japan has gradually decreased since 1990. The Chugoku, Shikoku, and Kyushu regions had the lowest vehicle occupancy rates, while Hokkaido had the highest. This is probably caused by the regional differences in seating capacity explained above. Vehicle occupancy in the Kanto region is lower than the national average, while seating capacity is 1.05 times higher than the national average. Similarly, vehicle occupancy in the Kinki region is less than the national average while the seating capacity hovers around the national average. These trends confirm the relatively high overcapacity index values in the Kanto and Kinki regions (see Fig. 2). In the Hokkaido region, vehicle occupancy decreased by 24% from 1990 to 2005. This might be caused by a combination of factors: an increase in vehicle ownership (Fig. 2b), a decrease in household size (Fig. 2a), and the emergence and improved speed of express trains connecting cities within Hokkaido [52].

3.2. LMDI-I: Relative change between 1990 and 2015

Factors of cumulative CO_2 emission change by region are shown in Fig. 4a. Total CO_2 emissions have decreased by 2.7% and 8.1% in the Kanto and Kinki regions, respectively, whereas emissions have increased by 7.6–23.2% in the other regions. In 2015, CO_2 emissions from private automobiles increased by 4.7% compared with 1990 levels. While the headship rate and overcapacity index both increased, this was reduced by emissions, travel distance, and fuel efficiency. The largest contribution of headship rate was observed in ROJ (28.3%), while the smallest was in the Chugoku region (25.5%). The contribution of overcapacity index varied by region from 11.7% in ROJ to 28.0% in Chugoku. The largest contribution for emission reduction came from travel distance changes in the Hokkaido, Kanto, Shikoku, and Kyushu regions. Specifically, the shortening of travel distance in the Shikoku and Kyushu regions resulted in more than a 20% emission reduction compared to the 1990 levels. In the Kinki, Chugoku, and ROJ regions, the largest factor for emission reduction was improvement in fuel efficiency (−22.3%, −17.9%, and −18.1%, respectively). Improvements in fuel efficiency in the Hokkaido region had a relatively smaller effect (−10.5%) compared to other regions (from −13.3% in Kyushu to −20.3% in Kinki). This may be due to the low share of mini-vehicles in the Hokkaido region that have small, light bodies and are therefore more fuel efficient than normal-sized cars.

Although the direction of effects by population and vehicle per household differed by region, vehicle per household contributed to

Table 2
Data availability for private automobiles in the transportation statistics.

Sources	Variables	Spatial resolution	1990–2009	2010–2012	2013–2015
Survey on Motor Vehicle Transport	Number of passengers	District Transport Bureau	✓	✓	✓
	Passenger-kilometers		✓	✓	✓
	Available seat-kilometers		✓	–	–
	Energy consumption		✓	–	–
	Transport distances		✓	–	–
Survey on Motor Vehicle Fuel Consumption	Energy consumption	Prefectures	–	✓	✓
	Transport distances		–	–	✓
		District Transport Bureau	–	✓	✓

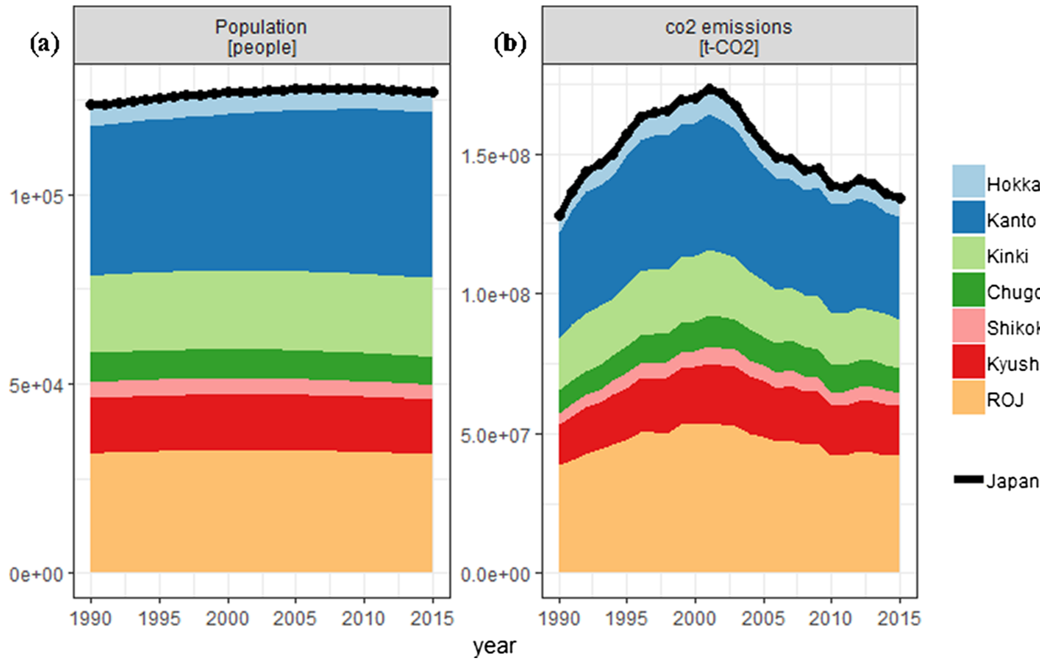

Fig. 1. Trends in (a) population P_i and (b) CO_2 emissions of private automobiles C_i from 1990 to 2015.

decreased emissions in areas where the population was increasing. This may be because regions with an increasing population have well-established public transportation systems; thus, there is less motivation to own vehicles. The number of passengers carried per vehicle contributed to decreased emissions for most regions, except for Shikoku and Kyushu.

To facilitate the interpretation of results, the eight original factors were aggregated into three composite factors (Fig. 4b). Population and headship rate were considered as a *demographic effect*. Vehicle ownership, passengers carried per vehicle, travel distance, and overcapacity index factors were attributed to a *behavioral effect*. Fuel efficiency and emission factors were classified as a *technological effect* (for specific equations, see supporting information). In all regions, the demographic effect increased CO_2 emissions, while the technological effect offset this increase. In contrast, the behavioral effect differed by region. In the Kanto and Kinki regions, the behavior effect reduced emissions, while it led to increased emissions elsewhere. These trends were in perfect agreement with changes in total CO_2 emissions. This suggests that the behavioral effect can determine whether CO_2 emissions from private automobile increased or decreased over the study period.

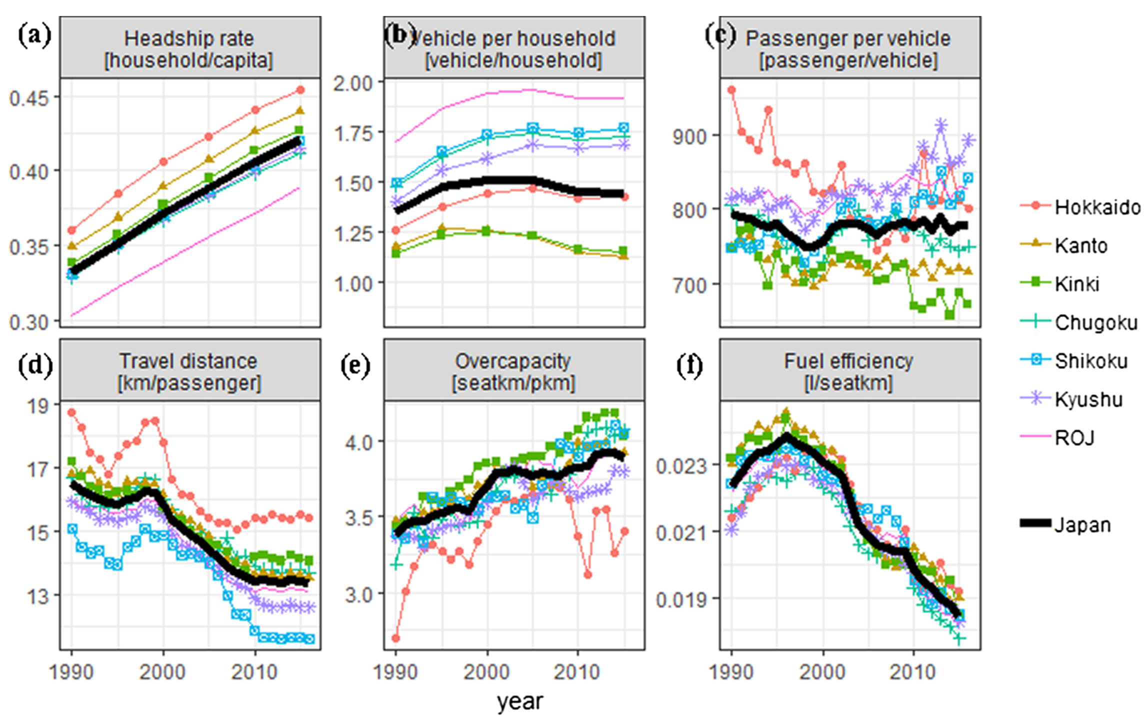

Fig. 2. Trends in factors used for the LMDI-I from 1990 to 2015; (a) headship rate HR_i, (b) vehicle ownership VO_i, (c) passenger per vehicle PV_i, (d) travel distance TD_i, (e) overcapacity index OC_i, and (f) fuel efficiency scaled by available seat-km FE_i

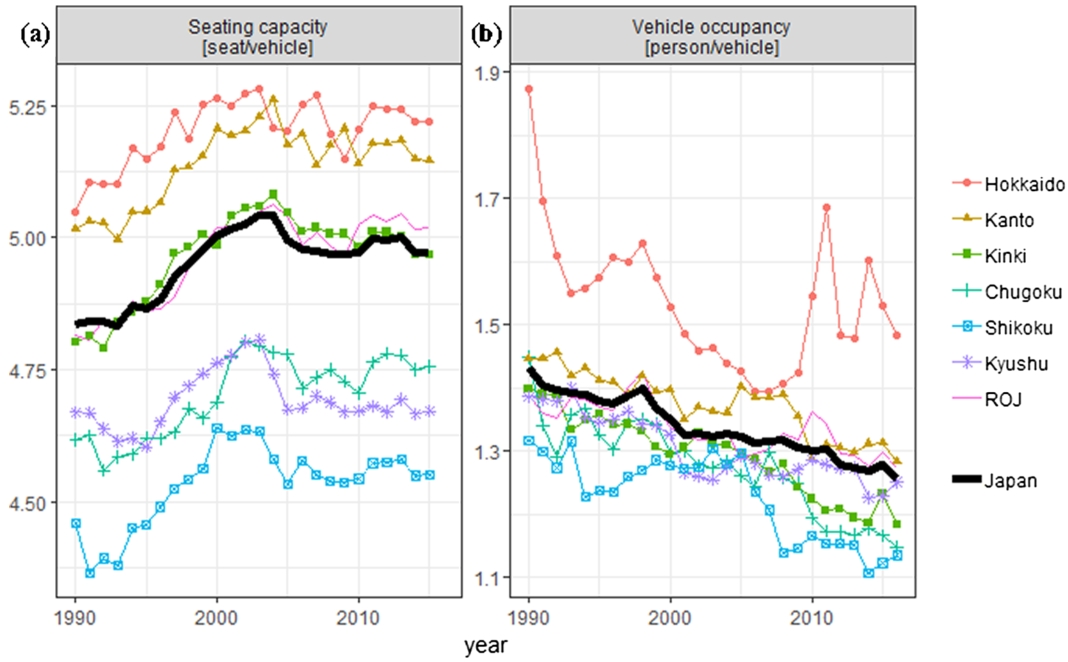

Fig. 3. Trends in (a) seating capacity and (b) vehicle occupancy from 1990 to 2015.

3.3. LMDI-I: Relative change in five-year intervals

The factors of CO_2 emission change in five-year intervals by region are shown in Fig. 5. In Japan, the headship rate and overcapacity index increased automobile emissions in all the intervals while travel distance reduced it. Fuel consumption per available seat-kilometers pushed up emissions from 1990 to 1995, but it accounts for most of the decrease in emissions after 2000. This may be caused by the introduction of the Top Runner Program in 1999. Under this program, manufacturers must achieve targets based on the value of the most energy-efficient items on the market at the time [53]. As a result, the fuel efficiency of passenger cars and freight cars (scaled by km/l) improved by 48.8% and 13.2%, respectively, from 1995 to 2010 [53]. The effect of emission factor and population on CO_2 emissions was limited.

In the Kanto, Kinki, and ROJ regions, fuel efficiency was a major decreasing factor, especially from 2000 to 2005, while it contributed the same level of decline in other regions for the intervals 2000–2005 and 2005–2010. This may be caused by regional differences in the adoption of fuel-efficient vehicles that were likely due to the enforcement of laws and ordinances. In 2001, the Government of Japan revised and enforced the Automobile NO_x and PM Law (The Law Concerning Special Measures for Total Emission Reduction of Nitrogen Oxides from Automobiles in Specified Areas) [54]. This law restricted the use of polluting diesel vehicles in metropolitan areas, including Tokyo, Osaka, and Aichi. Questionnaires have confirmed that this law accelerated the replacement of old diesel vehicles with newer vehicles [55]. In addition, several municipalities in the Kanto region started to prohibit the operation of diesel vehicles in these prefectures between 2000 and 2003 [54]. Two prefectures in the Kinki region began implementing similar ordinances for trucks and busses, Hyogo in 2002 and Osaka in 2009. Because of strengthened regulations for air pollution, old diesel vehicles, especially in urban areas, were replaced by fuel-efficient vehicles earlier than the other regions.

The overcapacity index accounted for most of the increase in emissions between 1990 and 1995 in the Hokkaido region, between 2005 and 2010 in Kanto, and between 1995 and 2000 in Kinki. This suggests that the overcapacity index was one of the main factors for changes in CO_2 emissions along with the other major indexes used mostly in similar decomposition analyses, such as trip per households and travel distance.

4. Conclusions and policy implications

4.1. Conclusions

In this study, we analyzed factors of sub-national CO_2 emission changes from private automobiles in Japan between 1990 and 2015, utilizing statistics that took vehicle occupancy into consideration. Historical CO_2 emissions were decomposed into eight factors: population, headship rate, vehicle ownership, annual passenger per vehicle, averaged travel distance, overcapacity index (inverse of vehicle occupancy), fuel efficiency scaled by seat-km, and emission factor. From 1990 to 2015, these factors had changed by multiples of 1.03, 1.27, 1.07, 0.98, 0.81, 1.15, 0.83, and 1.00 compared to 1990 levels, respectively. As a result, Japanese automobile emissions reached 134 Mt-CO_2, 4.8% higher than 1990 levels.

We quantified the factors of regional changes in CO_2 emissions in the automobile sector by using the Logarithmic Mean Divisia Index method 1 (LMDI-I). The analysis of relative change between 1990 and 2015 revealed that while technological factors such as fuel efficiency have contributed to decreased emissions, demographic factors such as headship rate worked to increase CO_2 emissions. Regional differences existed in the form of behavioral factors; they reduced emissions in urban areas, such as the Kanto region, and increased emissions in the rural areas. The behavioral factor of vehicle occupancy (which is one of the featured indexes in this study) tended to increase nationwide. Of the behavioral factors, vehicle per household can be a determinant of regional differences.

One of the featured factors in this study was overcapacity index which was not treated in the existing studies. Our detailed analysis showed that the change of vehicle occupancy contributed more than 10% of emission increase from 1990 to 2015 and that varied by region from 11.7% to 28.0%. These results quantitatively showed that the importance of the vehicle occupancy on analyzing automobile emissions.

As a result of analyzing the factors of change in CO_2 emissions every five years in each region, there were several regions and/or times when vehicle occupancy was the main impact on CO_2 emission increase. By region, periods when fuel efficiency improved were different between urban and rural areas. This may be caused by the NO_x and PM Law (The

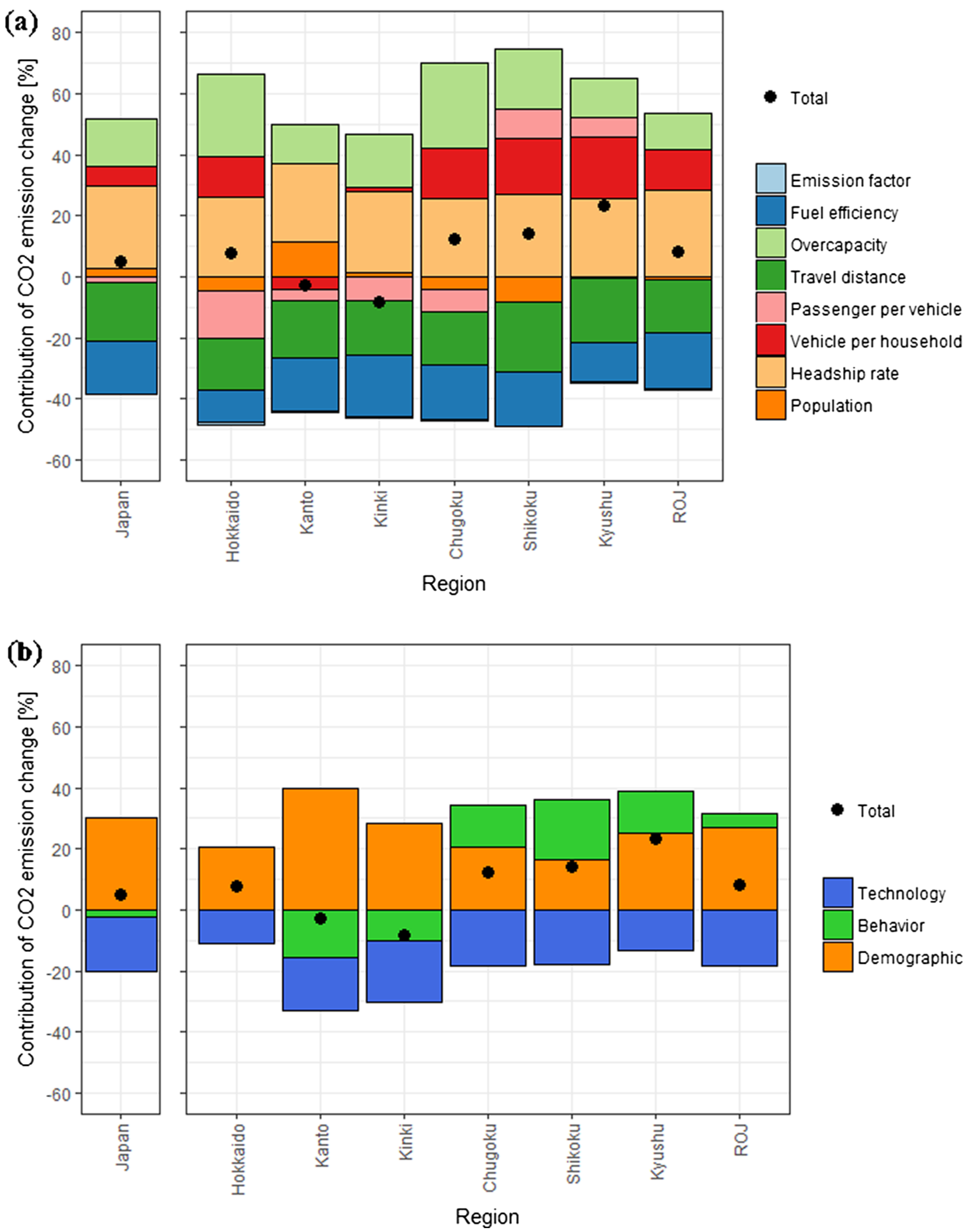

Fig. 4. Changes in the automobile CO_2 emissions from 1990 to 2015 by region and contribution of cumulative CO_2 emission change by (a) the eight factors and (b) aggregated three effects.

Law Concerning Special Measures for Total Emission Reduction of Nitrogen Oxides from Automobiles in Specified Areas) that was implemented as a measure against air pollution, but further analysis would be needed to confirm this. There were regional differences for trends of vehicle occupancy change. In rural areas with fewer public transportation systems, people prefer to use mini-vehicles for their personal mobility, and vehicle ownership was higher than urban regions; thus, vehicle occupancy was low in these regions. Our findings revealed that regional policy and transport system differences affected regional automobile emissions.

4.2. Policy implication for future automobile emissions reduction

The global population has been concentrated in urban areas, and this trend of urbanization is expected to continue at least until 2050 [56]. The world's regions can be distinguished as urban areas where the population will be concentrated and rural areas where the population will be drained. Furthermore, the latter can be divided into rural areas where the population will be distributed throughout the area and ones where the population is concentrated in core cities. The target regions of this study can also be classified into three area types using regional population projections of Japan [57]:

- Urban areas where the population is concentrated (Kanto and Kinki);
- Rural areas where the population is distributed throughout the whole region (Chugoku, Shikoku, and Kyushu); and
- Rural areas where the population is concentrated in a core city (Hokkaido).

Therefore, the results of this study can provide policy implications corresponding to each of the above area types, not only for Japan but also for similar situations throughout the world. In addition, the analysis in this study demonstrates the need for the development of

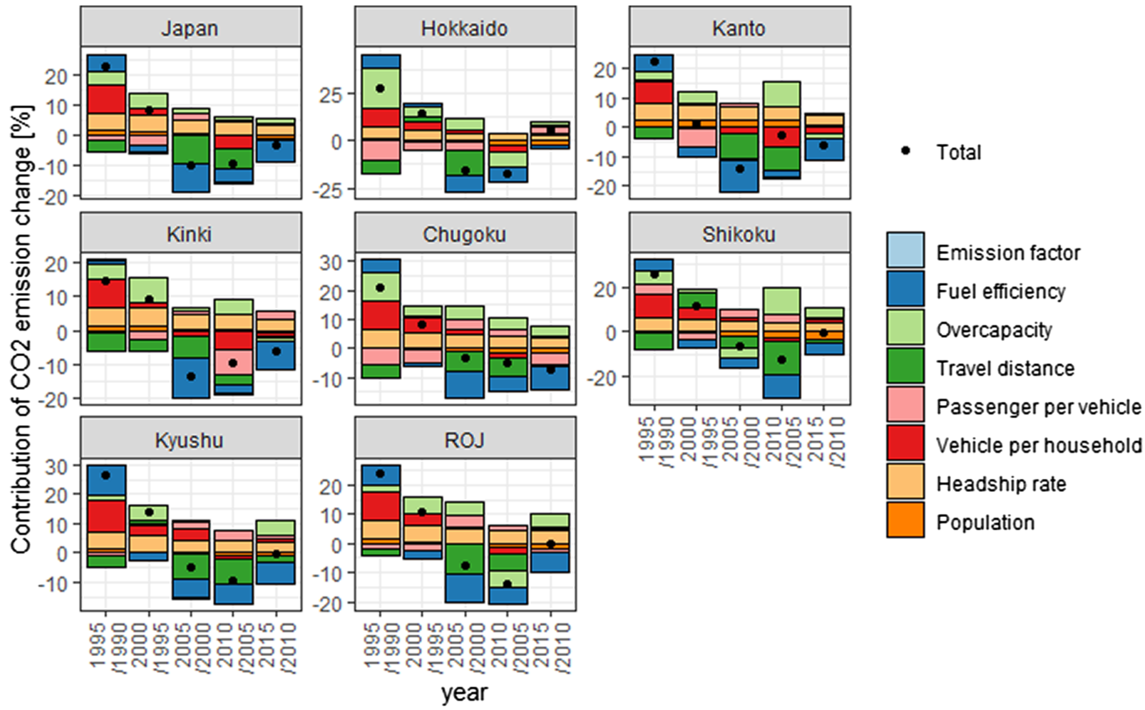

Fig. 5. Changes in the automobile CO_2 emissions and contribution of CO_2 emission change by eight factors in five-year intervals by region.

detailed statistics, particularly with the ongoing rapid changes in transportation systems in the context of recent digitization.

The followings explain policy implications from our decomposition analysis includes the policy suggestions for three area types, proposal of detailed statistical gathering, and recommendation from the viewpoint of current rapid change in the transportation sector.

(a) Recommended policy option for urban areas

In the highly populated regions of Kanto and Kinki, the vehicle per household and number of automobile passengers per vehicle were less than the national average because the sharing of automobiles is lower due to the accessibility of public transportation and high parking costs. To reduce future CO_2 emissions from private automobiles in these highly populated regions, it is essential to maintain or reduce the number of vehicles per household and the number of automobile passengers per vehicle. Because populations in these regions are expected to become more concentrated, it is highly likely that public transportation will be maintained or expanded. From this point of view, the number of vehicles per household and automobile passengers per vehicle in these areas are likely to stay below the national average. Enhancing public transportation will reduce CO_2 emissions in urban areas. On the other hand, the overcapacity index in these highly populated regions were higher than in other areas, meaning that vehicle occupancy in these regions was lower than the others. Thus, further CO_2 emission reduction in these areas can be realized by promoting ridesharing and the rightsizing of vehicles. Moreover, the adoption of ridesharing and rightsizing can mitigate not only CO_2 emissions but also air pollution and traffic accidents by reducing congestion.

(b) Recommended policy option for rural areas with distributed population

In the regions with distributed populations, people prefer to use vehicles for personal mobility due to the lack of public transportation and vehicle ownership was higher than in urban regions. In the Chugoku, Shikoku, and Kyushu regions in Japan, while the adoption of mini-vehicles improved fuel economy, this also brought an increase in vehicle occupancy and the overcapacity index. Although enhancing public transportation can improve these factors, the likelihood of large-scale investment is relatively low in areas where population density is expected to decline. Therefore, it would be difficult to reduce CO_2 emissions through improvement of these behavioral factors. Thus, these regions should focus on ways to improve technological factors, e.g., fuel efficiency improvement and the adoption of low-carbon vehicles. Electric vehicles (including fuel cell vehicles) could be a good option in these regions. If these electric vehicles are powered by renewable energy, increasing their use could drastically reduce CO_2 emissions in these regions. Moreover, since the storage battery of the electric vehicle (and electrolysis of water for hydrogen production) can provide flexibility for the power system through demand response, it can assist in the penetration of variable renewables.

(c) Recommended policy option for rural areas with concentrated population

In the regions where less population is concentrated in a core city, promoting public transportation use could reduce automobile CO_2 emission in the core city area. As for intercity transportation, since cities are farther apart than in other area types, a railway transportation system that links cities should be considered, however, large-scale investment is not always economically feasible in rural areas where the population is decreasing. In fact, the railway company in Hokkaido is struggling because of the declining population and the development of other transportation modes [58]. Thus, the following measures would be more effective than in other regions: promoting public transportation with relatively low initial costs (e.g., long-distance express buses); and reducing the need for intercity transport through the use of information and communication technology (e.g., telecommuting).

In additional to differences in population distribution, the regional climate also affects automobile emissions. Improvements in fuel efficiency were lowest in the Hokkaido region due to the influence of winter driving conditions. Developing energy efficient vehicles that can withstand harsh weather conditions could improve fuel efficiency in this region.

(d) Need for development of detailed statistics

In this study, prefectures in the three district transport bureaus were merged as the Rest of Japan region due to the data availability. Therefore, characteristics in the Rest of Japan region were somewhere between the urban and rural types described above. In other words, regional characteristics in the Rest of Japan region were not fully captured in this study. Since transportation statistics by prefecture were gathered after 2013 in Japan, more detailed analysis will be possible when long-term data are available.

Another challenge of data collection was the availability of data related to vehicle occupancy. Calculation for vehicle occupancy requires seating capacity and the number of passengers, but reports in which both variables were available were only obtained from the District Transport Bureau. Unfortunately, although reports, which had been revamped in 2010, have started to gather travel distance and fuel consumption by prefecture, survey items on seating capacity and the number of passengers were removed. There are several sources in the transportation sector collected at the prefectures scale and/or higher regional resolutions, such as the Person-Trip Survey but it is difficult to ensure consistency between sources due to the differences in the survey targets, survey periods, survey items, and survey areas. It is necessary to implement comprehensive statistical gathering that can take vehicle occupancy into account to enable this kind of analysis.

(e) Take the CASE approach into consideration

The CASE (Connected, Autonomous, Shared, and Electric) approach [59] has already resulted in tangible effects on the automobile sector. The electrification of the transportation sector will have a significant influence on travel distance per person, fuel consumption, and emission factors. Autonomous vehicles also have the potential to make dramatic changes in future transportation. Autonomous vehicles could boost demand from people who cannot drive (e.g., children and the elderly), could improve fuel efficiency by optimizing driving, and could induce additional travel demand by marginal cost reduction [60]. These effects would have a significant impact on the factors used in this study, such as number of vehicles per household, the number of passengers per vehicle, travel distance per passenger, and fuel efficiency. In addition, vehicle occupancy, which is one of the featured factors in this study, may be improved when combining ride-hailing and/or ride-sharing services with autonomous vehicles. Furthermore, similar changes can also occur in freight transport along with the expansion of freight demand by increases in e-commerce. More robust policy options could be developed by conducting detailed engineering simulations that consider future innovative technologies in addition to greater understanding from decomposition analysis.

Declaration of Competing Interest

To the best of our knowledge, the named authors have no conflict of interest, financial or otherwise.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.114196.

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