REVISITING DECOMPOSITION ANALYSIS FOR CARBON DIOXIDE EMISSIONS FROM CAR TRAVEL: INTRODUCTION OF MODIFIED LASPEYRES INDEX METHOD

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Revisiting Decomposition Analysis for Carbon Dioxide Emissions from Car Travel: Introduction of Modified Laspeyres Index Method

By Yoshinori Mishina and Yasunori Muromachi

ABSTRACT

Decomposition analyses are helpful to policymakers and analysts who aim to reduce carbon dioxide (CO₂) emissions from car travel. A large number of decomposition methods have been proposed till date. However, there is still no consensus regarding the best decomposition method because each method has certain advantages and disadvantages. Which method is valid for the decomposition of the changes in CO₂ emissions from car travel? In this paper, we revisit the Refined Laspeyres Index (RLI) method, Logarithmic Mean Divisia Index I (LMDI) method, and Modified Laspeyres Index (MLI) method. After a discussion of theoretical issues, we focus on period-wise, time-series, and cross-region decompositions of the changes in CO₂ emissions from passenger cars in Japan, using the three methods. While the RLI and LMDI methods are the most widely used by researchers and analysts, these methods contain theoretical problems with the attribution and distribution of interaction terms, particularly when some factors change positively and others change negatively. The recently proposed MLI method helps in resolving these issues by attributing and distributing the interaction terms to related factors according to the changes in each factor. Our case studies in Japan also indicate that differences in the attribution of the interaction term to the related factors between the three methods influence the decomposition results significantly. We conclude that the MLI method generates more valid decomposition results than do the RLI and LMDI methods because of the reasonable attribution and distribution of the interaction terms.
INTRODUCTION

Since the oil crisis of 1973, index decomposition analyses have been widely accepted as effective analytical tools for the energy and environmental sectors. Decompositions help in identifying relevant factors that influence changes in an objective variable such as CO₂ emissions and in quantifying the relative contributions of the changes from the relevant factors. Moreover, the chronological and cross-country/region decomposition of the factors that contribute to a decrease in the CO₂ emissions would be helpful to policymakers and analysts who aim to reduce CO₂ emissions from various sources such as cars. The world transport sector accounted for as much as 23% of the global CO₂ emissions in 2008 (1). Transport, particularly car travel, is one of the key sectors targeted for the reduction of CO₂ emissions. Thus, decomposition analysis of the changes in CO₂ emissions from car travel, using a valid method, is important for policymaking with regard to the institution of CO₂ reduction measures. Moreover, in Japan, CO₂ emissions from passenger cars peaked in 2001 and decrease continually thereafter, thus quantitative identification of contributing factors for the rise and decline of CO₂ emissions using decomposition methods and discussion on the policy implications of the changes are very helpful to policymaking to reduce CO₂ emissions.

A large number of decomposition methods have been proposed. By far, the most often used decomposition methods in industrial energy and energy-induced gas emission studies are the so-called Laspeyres and Divisia index approaches, respectively based on the Laspeyres and the Divisia indices in economics and statistics (2). However, conventional Laspeyres and Divisia index methods have some drawbacks. Very often, the conventional Laspeyres index method leaves large residual interaction terms after the decomposition, which might make the decomposition analysis less meaningful (3). To overcome this issue, Sun (4) proposed the RLI method, in which the interaction terms are distributed equally among all factors according to the “jointly created and equally distributed” principle. On the other hand, the conventional Divisia index method always leads to a residual term because of the approximation of theoretical and continuous logarithmic Divisia indices, and to a computational problem when the values of the variables are zero (2). To overcome these issues, Ang et al. (5) proposed the additive LMDI method, and Ang and Liu (6) proposed the multiplicative LMDI by applying a logarithmic mean weight function.

A number of previous studies suggest that the RLI and LMDI have several desirable properties and hence would be the preferred decomposition methods. However, they have certain advantages and disadvantages. Thus, there is still no consensus regarding the best decomposition method. Ang (7) recommends the use of additive and multiplicative LMDIs because of their theoretical foundation, adaptability, and ease of use and the ease of result interpretation; in addition, he points out that the RLI formulae are fairly complex when the number of factors exceeds three. He also recommends the use of the RLI when the data set contains negative values, because the logarithms of a negative value cannot yield a real number. Moreover, Ang (7) recommends the RLI to those who favor methods linked to the Laspeyres index approach. International organizations, national agencies, researchers, and analysts mostly use the RLI (8, 9, & 10) or the LMDI (11, 12, & 13) in their empirical studies, including those on car travel. Steenhof (14) prefers the Laspeyres approach over the Divisia approach because the former is easier to interpret and use, and arguably more assessable and usable by practitioners, policy makers, and other stakeholders. On the other hand,
Papagiannaki and Diakoulaki (11) point out that the LMDI has the most robust theoretical foundation, provides complete and more stable decomposition results without the residual term, and is very easy to implement for the decomposition of CO₂ emissions from passenger cars.

While decomposition analysis would be helpful to researchers and analysts who aim to reduce CO₂ emissions from car travel (15 & 16), previous studies mostly focused on regions or countries where CO₂ emissions were increasing. Moreover, most studies do not address the issues of attribution and distribution of the interaction terms in the decomposition methods, particularly when they are applied to a case where some factors change positively and others change negatively.

Recently, Mishina et al. (17) pointed out a concern over the reliability and accuracy of decomposition using the RLI, particularly in a case where some factors change positively and others change negatively. They then proposed the MLI method. The MLI attributes the interaction terms to the related factors according to the changes in each factor and distributes them in a manner proportional to a symmetrical rate of the changes. However, sufficient experiments have not been carried out to confirm the validity of the MLI.

In this study, we investigate which among the RLI, LMDI, and MLI is valid for the decomposition of CO₂ emissions from car travel. First, we highlight the characteristics of the three methods and some issues. We next identify the differences among the three methods by decomposing a simple hypothetical dataset. Then, using the three methods, we conduct period-wise and time-series decompositions of the changes in CO₂ emissions from passenger cars in Japan over the period 1990–2008 and a cross-region decomposition between metropolitan regions and the remaining regions in Japan in 2008 and then compare the decomposition results.

THE REFINED LASPEYRES INDEX (RLI) METHOD

Methodology

The Laspeyres index measures the percentage change in some aspect of a group of items over time, using weights derived from values in some base year (7). This method isolates a factor’s impact by letting variables related to the other factor at their base-year values (18). The most serious issue in the conventional Laspeyres index method is the existence of a large residual interactive term, which leads to difficulties in the interpretation of the results obtained. Sun (4) proposes the RLI to overcome this issue.

In a two-change-factor model \( (F, D) \), CO₂ emissions \( (CO_2) \) from car travel can be determined by the factors \( F \) and \( D \).

\[
CO_2 = CFD
\]  

(1)

where \( F \) and \( D \) represent the actual road fuel efficiency (\( \ell / \text{km} \)) and the travel distance (km), respectively. For simplification, \( C \) representing the CO₂ emission factor (metric ton-CO₂/\( \ell \)) is assumed to be constant and equal to 1.0.
Over a period \([0, t]\), the change in the CO\(_2\) emissions (\(\Delta CO_2\)) is given by

\[
\Delta CO_2 = CO_2^t - CO_2^0 = F' D' - F^0 D^0 = (F' - F^0) D^0 + F^0 (D'-D^0) + (F' - F^0)(D' - D^0)
\]

\[
= \Delta F D^0 + F^0 \Delta D + \Delta F \Delta D
\]  

(2)

where \(\Delta F D^0\) and \(F^0 \Delta D\) represent the changes in the factors \(F\) and \(D\) as components of \(\Delta CO_2\) over the given period. \(\Delta F \Delta D\) is the residual interaction term resulting from simultaneous changes in the factors.

Sun (4) proposes equal distribution of the interaction term to the all factors, according to the “jointly created and equally distributed” principle (Figure 1). The contributions of \(F\) and \(D\) are then given by

\[
\Delta CO_{2F} = \Delta F D^0 + 1/2 \Delta F \Delta D
\]

\[
\Delta CO_{2D} = F^0 \Delta D + 1/2 \Delta F \Delta D
\]  

(3)

(4)

**FIGURE 1 Concept of distribution of the interaction term in the Refined Laspeyres Index method.**

### Issues with the Refined Laspeyres Index (RLI) Method

Previous studies reported that the issue with the RLI is that the RLI formulae are fairly complex when the number of factors exceeds three (7 & 19). However, the “jointly created and equally distributed” principle has not been discussed fully. Recently, Mishina et al. (17) pointed out two problems with this principle.

One of the issues is the method of attributing the interaction term to related factors. In the two-change-factor model \((F, D)\), the interaction term can be attributed to both the related factors \((F, D)\) when the changes in these factors from year 0 to year \(t\) increase from \(F^0\) to \(F^t\) and from \(D^0\) to \(D^t\) (Figure 2, left), or when they decrease from \(F^0\) to \(F^t\) and from \(D^0\) to \(D^t\) (Figure 2, center). However, when the change in one factor \((F)\) increases while that in another factor \((D)\) decreases, the interaction term relates only to the increasing factor \((F)\), and not to the decreasing factor \((D)\) (Figure 2, right). Thus, the interaction term should only be attributed to the increasing factor \((F)\). In the case of more than three factors, the interaction terms should be
attributed to the increasing factors, only when increasing and decreasing factors exist in the same residual term, as in the two-change-factor model.

\[
\Delta CO_{2F} = \Delta FD_0 + \Delta F \Delta D \\
\Delta CO_{2D} = F^0 \Delta D
\]

**FIGURE 2 Attribution of the interaction term.**

Another issue is the method of distributing the interaction term between the related factors. As discussed earlier, we can attribute the interaction term to the related factors when changes in both factors increase or decrease simultaneously. However, equal distribution of the interaction term—regardless of the magnitude of the changes and according to the “jointly created and equally distributed” principle—is likely to afford excessive distribution to the smaller factor changes and, conversely, afford too little distribution to the larger. The interaction term should be distributed between the related factors according to the magnitude of the changes.

Because of these two issues, the RLI may not yield valid decomposition results in the case of car travel when some factors change positively and others change negatively, as in Japan, where the number of passenger cars in use has increased but the travel distance per passenger car has decreased.

**THE LOGARITHMIC MEAN DIVISIA INDEX I (LMDI) METHOD**

**Methodology**

The Divisia index is a weighted sum of logarithmic growth rates, where the weights are the components’ shares in total value, given in the form of a line integral (7). While the Divisia index is a continuous line integral developed by economists, most observation data are available for discrete time points, including those for car travel. Thus, a discrete approximation is required for empirical studies. Both the additive and multiplicative LMDI are proposed using a logarithmic mean weight function (5 & 6); they provide complete decomposition results without the residual term (2 & 5). In this investigation, we focus on the additive LMDI.
In the two-change-factor model \((F, D)\), the \(CO_2\) emissions \((CO_2)\) from car travel are determined by factors \(F\) and \(D\).

\[
CO_2 = FD \tag{5}
\]

The LMDI gives the change in the \(CO_2\) emissions \((\Delta CO_2)\) over the period \([0, t]\) by

\[
\Delta CO_2 = CO_2^t - CO_2^0 = L(CO_2^t, CO_2^0)(\ln \frac{F^t}{F^0} + \ln \frac{D^t}{D^0}) \tag{6}
\]

\[
L(CO_2^t, CO_2^0) = \frac{CO_2^t - CO_2^0}{\ln(CO_2^t / CO_2^0)} \text{ for } CO_2^t \neq CO_2^0, \tag{7}
\]

\[
L(CO_2^t, CO_2^0) = CO_2^t \text{ for } CO_2^t = CO_2^0, \tag{8}
\]

where \(L(CO_2^t, CO_2^0)\) is the logarithmic average of two positive values.

Then, the changes in \(F\) and \(D\) are given by

\[
\Delta CO_{2F} = L(CO_2^t, CO_2^0)\ln \frac{F^t}{F^0} \tag{9}
\]

\[
\Delta CO_{2D} = L(CO_2^t, CO_2^0)\ln \frac{D^t}{D^0} \tag{10}
\]

**Issues with the Logarithmic Mean Divisia Index I (LMDI) Method**

Ang (7) recommends the use of the additive and multiplicative LMDI from among the many available methods, because of their theoretical foundations, adaptability, and ease of use and result interpretation. However, there has been much debate on the problems associated with the LMDI. First, the use of the LMDI is problematic when data include negative values, because logarithms of a negative value will not be defined in real numbers. Second, computational problems may arise when the dataset contains zero values (5). Ang and Choi (2) recommend a check for zero values in the data set before decomposition and suggest the replacement of these zero values by a number that is at least two orders of magnitude smaller than the lowest nonzero value. However, Wood and Lenzen (20) argue that the LMDI can produce significant errors if applied to the decomposition of a dataset containing a large number of zeros and/or small values, and to overcome this problem, they recommend the use of analytical limits of the LMDI terms when zero values are present. Third, Chug and Rhee (21) point out that the LMDI shows a decrease in the emission for a sector, even though its share of final demand increases over the period. They point out that this counterintuitive result seems to arise because the LMDI formula involves a logarithmic function, which yields negative values when the data contains values close to zero.

In addition, while the RLI explicitly accounts for the interaction terms, the LMDI hides them in the equation of the weighted sum of the logarithmic growth rates. This would not clarify how the interaction terms are attributed and distributed to the related factors in the discrete approximation for the continuous line integral. Moreover, while Lakshmanan and Han (22)
point out that the Divisia index yields accurate estimations for infinitesimal changes and good approximations for short-term discrete changes, the LMDI may not afford accurate estimations in period-wise and cross-country/region decompositions with long-term and/or large discrete change data.

**THE MODIFIED REFINED LASPEYRES INDEX (MLI) METHOD**

**Methodology**

Mishina et al. (17) proposed a new decomposition method (MLI) by modifying the RLI to overcome the issues regarding the attribution and distribution of the interaction terms of the RLI. The features of this method are as follows:

- Attribution of the interaction term to all related factors when changes in all factors increase or decrease with respect to each other in the same interaction term
- Attribution of the interaction term to the increasing factor(s) only, when both increasing and decreasing factors exist in the same interaction term
- Distribution of the interaction term to the related factors in proportion to the symmetric rate of change in each factor

In the two-change-factor model \((F, D)\), the change in each factor, comprising the change in the \(CO_2\) emissions \((\Delta CO_2)\), is given by

\[
\Delta CO_{2F} = \Delta F D^o + \frac{a}{a+b} \Delta F \Delta D \tag{11}
\]

\[
\Delta CO_{2D} = F^o \Delta D + \frac{b}{a+b} \Delta F \Delta D \tag{12}
\]

\[
a = \frac{\Delta F}{(F^o + F^\prime)/2}, b = \frac{\Delta D}{(D^o + D^\prime)/2} \tag{13}
\]

\((a \text{ and } b \text{ represent the symmetric rate of change in each factor, } F \text{ and } D)\)

when \(\Delta F > 0 \text{ and } \Delta D < 0, b = 0,\)

when \(\Delta F < 0 \text{ and } \Delta D > 0, a = 0,\)

when \(\Delta F < 0 \text{ and } \Delta D < 0,\) replace \(\frac{a}{a+b} \text{ and } \frac{b}{a+b} \text{ by } 1 - \frac{a}{a+b} \text{ and } 1 - \frac{b}{a+b}, \) respectively

In a four-change-factor model \((x_1, x_2, x_3, x_4)\), the change in the \(x_1\) factor is given by

\[
\Delta CO_{2x1} = \Delta x_1 x_2^0 x_3^0 x_4^0 + \frac{a_1}{a_1 + a_2} \Delta x_2 x_3^0 x_4^0 + \frac{a_1}{a_1 + a_3} x_2^0 \Delta x_3 x_4^0 + \frac{a_1}{a_1 + a_4} x_2^0 x_3^0 \Delta x_4
\]

\[
+ \frac{a_1}{a_1 + a_2 + a_3} \Delta x_2 \Delta x_3 x_4^0 + \frac{a_1}{a_1 + a_2 + a_4} \Delta x_2 x_3^0 \Delta x_4 + \frac{a_1}{a_1 + a_3 + a_4} x_2^0 \Delta x_3 \Delta x_4 + \frac{a_1}{a_1 + a_2 + a_3 + a_4} \Delta x_2 \Delta x_3 \Delta x_4 \tag{14}
\]
where $a_i = \frac{\Delta x_i}{\left(x_i^0 + x_i^{'0}\right)/2} (i = 1, 2, 3, 4)$

The MLI would be more valid than the RLI and LMDI for period-wise, time-series, and cross-region decompositions because it reasonably accounts for the attribution and distribution of the interaction terms to the related factors, and it does not involve logarithmic calculations. Moreover, the MLI provides smaller changes in a factor, in absolute value, than do the RLI and LMDI when both increasing and decreasing factors exist in the same interaction term. This is because as opposed to the RLI and LMDI, the MLI attributes the interaction term only to the increasing factor, and not to the decreasing factor.

### Issues with the Modified Refined Laspeyres Index (MLI) Method

While theoretical robustness is the most important foundation for a decomposition method, ease of use is another consideration from the viewpoint of applicability. The formulae of the MLI are more complex than those of the RLI and LMDI when the number of factors increases. However, higher-order interaction terms in the formulae hardly make a contribution to the aggregated changes in the CO$_2$ emissions. Thus, disregard of the higher-order interaction terms would be practical and have no influence on the decomposition results. Further investigation into this would be necessary.

### COMPARISON OF DECOMPOSITION BETWEEN THE RLI, LMDI, AND MLI: AN ILLUSTRATIVE EXAMPLE

We compared the performance of the RLI, LMDI, and MLI by using a hypothetical dataset for a two-change-factor model. Table 1 and Figure 3 show the hypothetical dataset and the decomposition results, respectively. While the RLI and LMDI provide similar results when changes in all the factors are positive or negative with respect to each other, the results between the MLI and other two methods differ by about 10% because of the change in the distribution method for the interaction term (Cases 1 and 2, Figure 3). In contrast, considerable differences exist between the MLI and the other two methods when one factor changes positively and the others change negatively (Cases 3, 4, and 5). The changes given by the MLI are smaller than those given by the RLI and LMDI, in absolute value, because the MLI attributes the interaction term to the increasing factor, and not to the decreasing factor.

These comparisons prove that the differences in the attribution methods have a notable influence on the decomposition results when some factors change positively and others change negatively.
EMPIRICAL STUDIES: A CASE OF CO₂ EMISSIONS FROM PASSENGER CARS IN JAPAN

Scope of the Study and Data

We conducted period-wise, time-series, and cross-region decompositions of the changes in CO₂ emissions from car travel in Japan by using the RLI, LMDI, and MLI. The period-wise decomposition compares the changes in the CO₂ emissions between the first year and the last year, and the time-series decomposition involves yearly comparison and summation of results over a specific period. The cross-region decomposition compares the difference in CO₂ emissions between specific regions in a specific year. The formulae used for cross-region decomposition are modified by replacing a time period [0, t] by the two specific regions in Eqs. (3), (4), (9), (10), (11), and (12).

The time frame covered by the period-wise and time-series decompositions spans fiscal years 1990 to 2008, and three subintervals are considered: 1990–1995, when the CO₂ emissions from passenger cars continued to increase; 1995–2001, when the CO₂ emissions peaked in 2001; and 2001–2008, when the CO₂ emissions began to decline.
The areas selected for the cross-region decomposition are the Kanto-Kinki region and the remaining regions. The Kanto-Kinki region includes large metropolitan areas such as Tokyo and Osaka, where modes of travel other than passenger cars are available, and the remaining regions include small/medium-sized cities and villages, where transport needs are mostly met by passenger cars. The year 2008 is chosen for the cross-region decomposition.

Decomposition analyses are used for quantitatively identifying factors that influence changes in CO₂ emissions and helpful to policymaking to reduce CO₂ emissions. Five change factors are typically considered: travel distance per passenger car (D: km/car); per capita number of passenger cars in use (N: car/population); population (P); average weight of passenger cars in use (W: metric tons/car); and reciprocal of actual road fuel efficiency per average car weight (F: (1/km/l)/(metric tons/car)). The car weight/size, car age in the fleet composition, actual engine efficiency per class of cars, road conditions such as congestion, and driving manners probably influence the actual fuel consumption for calculating the actual road fuel efficiency. However, in the empirical studies, we presumed that the fuel efficiency depended solely on the car weight. Further, constant CO₂ emission factors (C) of 2.32 and 2.59 metric ton-CO₂ per 1,000 liters are used for gasoline and diesel, respectively, on the basis of the data of the Greenhouse Gas Inventory Office of Japan (23). The CO₂ emissions (CO₂: metric tons) are then given by

\[ CO₂ = DNPWFC \]  
(15)

The data used for these decompositions are derived from statistical data drawn from the public domain in Japan (24, 25 & 26) (Table 2). The average weight of standard and small cars is estimated by combining the number of cars in use in each car-weight category and the central weight value for each weight category (25). Because statistical data for the average weight of mini cars (cars with less than 660 cc in engine displacement) are not available, an average weight of 850 kg per mini car is estimated by referring to the catalog data for mini cars manufactured by major automakers. More details can be found in Mishina et al.’s paper (17).

Figure 4 shows the trends in the five change factors as well as the CO₂ emissions over the whole of Japan. The CO₂ emissions peaked in 2001 and continued to decrease afterward. Both the travel distance per car and reciprocal of actual road fuel efficiency per average car weight tended to decrease from 1990 onward. However, the per capita number of cars has been consistently increasing since 1990. The average weight of cars has remained relatively constant from 2001 onward, and the population has continued to increase slightly since 1990. The decrease in the travel distance per car and larger increase in per capita number of cars show that a household, on average, drives more in his different cars but shorter distance per car: the travel distance per household increased by 12% in 2008 from the 1990 level. Moreover, Table 2 shows that the remaining regions including small/medium-size cities and villages have a greater number of mini cars and that the distance traveled by these cars is greater than that in the metropolitan areas.
## TABLE 2 Statistical Data for Empirical Studies

<table>
<thead>
<tr>
<th>Year</th>
<th>Travel Distance ($10^6$ km)</th>
<th>Number of Cars in Use ($10^3$)</th>
<th>Fuel Consumption ($10^3$ k)</th>
<th>Avg. Car Wt. (metric tons/car)</th>
<th>Population ($10^6$)</th>
</tr>
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<tr>
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<td>(Data Source)</td>
<td>(24)</td>
<td>(25)</td>
<td>(26)</td>
<td>(27)</td>
</tr>
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<td>346,249</td>
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<td>446,497</td>
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### Figure 4 Trends in change factors related to CO$_2$ emissions from passenger cars in Japan.
Results of Period-Wise and Chronological Time-Series Decompositions

Table 3 shows the period-wise and time-series decompositions using the RLI, LMDI, and MLI. Figure 5 shows the results of the period-wise decomposition over the period 1990–1995 for the whole of Japan.

In each period, the three methods identify the same dominant factors for the changes in CO₂ emissions in the period-wise and time-series approaches. The dominant factors for emission increases over the period 1990–1995 are the increase in the per capita number of and the large weight of passenger cars in use. For the period 1995–2001, the emission increase is due to the rise in the per capita number of cars. In contrast, the dominant factors for the emission decline over the period 2001–2008 are the decrease in the travel distance per car and the improvement in the actual road fuel efficiency of cars. While a rise in the per capita number of cars has an influence on the increase in CO₂ emissions over the period 2001–2008, the two decreasing factors offset the influence of this factor’s increase. The increases in the per capita number of cars and the large car weight for the period 1990–2001 are probably induced by the decrease in the fuel prices. Conversely, the higher fuel prices and an increase in the number of mini cars over standard and small cars in the period 2001–2008 may have prompted decrease in the travel distance as well as improvements in the actual road fuel efficiency (17).

The period-wise and time-series decompositions using the three methods show almost the same aggregate CO₂ emissions in each period. However, the period-wise decomposition for 1990–1995 shows a maximum difference of about 20% between the MLI and the other two methods in the travel distance per car, population, and reciprocal of actual road fuel efficiency per average car weight, where some factors change positively and others change negatively (Figure 5). The RLI and LMDI provide almost the same calculation results. On the other hand, the differences among the three methods are smaller in the time-series decomposition than in the period-wise decomposition. In the time-series decomposition, the travel distance per car over the period 1995–2001 shows a maximum difference of about 10% between the MLI and the other two methods. The RLI and LMDI provide almost the same calculation results as the period-wise decomposition.
## TABLE 3 Period-Wise and Time-Series Decompositions: CO₂ Emissions in Each Period

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**FIGURE 5** Period-wise decomposition (1990–1995): CO₂ emissions for each change factor, as determined by the three methods (values are given in million metric ton-CO₂).

### Cross-Region Decomposition Results

Figure 6 shows the differences in the CO₂ emissions due to each factor between the Kanto-Kinki region and the remaining regions in 2008, assuming the Kanto-Kinki region as the basis. Among the RLI, LMDI, and MLI, the dominant factor causing higher CO₂ emissions (24.6 million metric ton-CO₂) in the remaining regions is the greater per capita number of cars...
therein. While the travel distance per car and reciprocal of actual road fuel efficiency per average car weight make some contribution to the increased CO₂ emissions from the remaining regions, the average car weight is a factor that causes lowering of the CO₂ emissions. These results suggest that higher car ownership and use in the remaining regions have greater impacts on increases in the CO₂ emissions than do those in the Kanto-Kinki region because transportation alternatives to passenger cars, such as public transportation, are inconvenient in the remaining regions.

This cross-region decomposition gives larger differences for changes in the CO₂ emissions between the MLI and the other two methods than do the period-wise and time-series decompositions. The maximum difference between the MLI and the other two methods, on the basis of the MLI, is about 30% in population and average car weight. The RLI and LMDI provide relatively similar calculation results. As discussed earlier, these comparisons prove that the differences in the attribution methods used for the interaction terms have a marked influence on the decomposition results when some factors change positively and others change negatively.

FIGURE 6 Cross-region decomposition: Differences in CO₂ emissions between the Kanto-Kinki region and the remaining regions in 2008 (values are given in million metric tons-CO₂).

CONCLUSIONS

In this paper, we revisited the RLI, LMDI, and MLI methods. After a discussion of theoretical issues, we focused on period-wise, time-series, and cross-region decompositions of the changes in CO₂ emissions from passenger cars in Japan by the three methods.

The MLI provides more valid results than did the RLI and LMDI because it attributes and distributes the interaction terms to the related factors according to the change in each factor without involving logarithmic calculations. Differences in the method of attribution of the interaction term among the three methods have a marked influence on the decomposition results when both increasing and decreasing factors exist in the same interaction term. In this
case, the MLI—unlike the other two methods—attributes the interaction term to the increasing factor only, and not to the decreasing factor.

In our case studies on CO₂ emissions from car travel in Japan, the period-wise and time-series decompositions showed that the three methods provide the same dominant factor(s) for the increase/decrease in CO₂ emissions: increase in the per capita number of cars and heavy-weight cars for the rise in CO₂ emissions over the period 1990–1995: increase in the per capita number of cars during the period 1995–2001, leading to increased CO₂ emissions: and decrease in the travel distance per car and improvement in the actual road fuel efficiency for the reduction in CO₂ emissions over the period 2001–2008. However, the period-wise decomposition results showed significant differences of about 20% between the MLI and the other two methods in the travel distance per car, population and reciprocal of actual road fuel efficiency per average car weight.

The cross-region decomposition showed that the three methods provide the same dominant factor in the CO₂ emission increase from the remaining regions. However, the maximum difference between the MLI and the other two methods is about 30% in the population and average car weight factors.

To conclude, the MLI generates more a valid decomposition of the changes in CO₂ emissions from car travel than do the RLI and LMDI because it accounts for the attribution and distribution of the interaction terms to the related factors more reasonably.

**REFERENCES**