Proposing Effective Strategies for Meeting an Environmental Regulation with Attainable Technology Improvement Targets

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Proposing Effective Strategies for Meeting an Environmental Regulation with Attainable Technology Improvement Targets

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Abstract

The Japanese government will adopt the CAFE standard after 2020. By using a "modified" slack-based measure (SBM) model, this study analyzed the technical efficiency of 113 gasoline vehicle models (GVs) and 54 hybrid vehicle models (HVs) sold by Japanese manufacturers in 2016. We also estimated attainable fuel efficiency of specific vehicle models that can be further improved referring to the nearest point on the best practice frontier. The improved CAFE values and standards of the nine automobile manufacturers were calculated. The technology gap from the vehicle technology frontier was more noticeable among gasoline vehicles than among hybrids. Moreover, most automobile manufacturers can achieve the CAFE standard through an effective achievement strategy based on best practice technologies, whereas the others will not achieve the CAFE standard even given a rapid technology innovation beyond the best practice frontiers for GVs and HVs.

Keywords: data envelopment analysis; slack based measure; nearest reference point; CAFE standard; automobile manufacturer

I. Introduction

Green House Gas (GHG) emissions are expected to increase by over 30 percent in 2040, compared to 2010 emission levels. This is due to the economic growth and population increase in developing countries such as China, India, and numerous African and Southeast Asian countries (International Energy Agency, 2015). To achieve the GHG reduction target established by the Paris Agreement of 2015, it is crucial to improve energy efficiency in the industrial, construction, and transport sectors (International Energy Agency, 2016). Specifically, the global CO_2 emissions attributed to the transport sector is the second largest—after the electricity sector—accounting for 23 percent of the total global emissions in 2015 (International Energy Agency, 2016). The CO_2 emissions from the transport sector mainly results from automobiles (International Energy Agency, 2016).

The European Union (EU) has the strictest regulations globally for the transport sector and all automobile companies located within EU member countries were required to achieve the CO_2 emission standard of 130 g-CO_2/km in 2015 and are required to reach 95 g-CO_2/km by 2021 (European Commission, 2017). This EU CO_2 emission standard is called the CAFE (Corporate Average Fuel Efficiency) standard (European Commission, 2017). Automobile manufacturers in EU countries are obligated to improve automobile fuel efficiency and stay compliant with CAFE standards. These standards are based on sales-weighted average targets for vehicles manufactured (European Commission, 2017).

Meanwhile, the Japanese government has been investigating efficient emission reduction targets for gasoline and diesel vehicles based on the Revision of the Act on the Rational Use of Energy (Ministry of Economy, Trade, and Industry, 2014). Based on these investigations, the Japanese government has decided to adopt the CAFE standard by 2020 to encourage automobile manufacturers to improve fuel efficiency through the flexible competition of vehicle sales (Kaneko, 2019; Ministry of Economy, Trade, and Industry, 2014).

However, vehicle performance should be evaluated not only according to fuel efficiency, but also by economic efficiency, driving performance, and safety, since consumers choose vehicles by comprehensively considering all these characteristics (Greene *et al*., 2018; Hess *et al*., 2012).

Data Envelopment Analysis (DEA) is a well-known method for evaluating comprehensive performance. DEA can estimate the efficiency of numerous decision-making units (DMUs) simultaneously by considering multiple input and output factors and provide useful information for efficiency improvement (Charnes *et al*., 1978; Cooper *et al*., 2007). Sueyoshi *et al*. (2017) reviewed a variety of previous studies in the environmental and energy fields and concluded that DEA has contributed to solving many environmental and energy issues by demonstrating the relationship between technological improvement in enterprise and industry and environmental issues (Emrouznejad and Yang, 2017; Sueyoshi and Goto, 2017). DEA is a frontier analysis and the performance of a DMU is evaluated according to its relative distance to the frontier line enveloped by a reference set (i.e., best practice frontier). DEA models can be roughly divided into two: radial and non-radial. Radial models evaluate the performance of DMUs by proportionally reducing input or increasing output levels

(Charnes *et al*., 1978; Cooper *et al*., 2007). Although radial models can manage multiple inputs and outputs, they neglect slacks and substitutional changes among inputs or outputs (Cooper *et al*., 2007; Tone, 2017). To address this problem, Tone (2001) first developed a non-radial and slack-based measure (SBM) model and succeeded in dealing with inputs and outputs unproportionally and incorporating slacks in evaluating performance of DMUs. However, as pointed out in Tone (2010) and Tone (2016), the SBM models tend to evaluate the performance of DMUs referring to the furthest frontier point. This means that the performance index computed using these SBM models might be underestimated, making it difficult for decision makers and engineers to use the estimated results as a reference for improving the performance of the products and companies.

Considering this problem, Tone (2010) made an attempt to search the nearest projection point on the frontier. Although this paper developed a method to find the nearest point on the "efficient" frontier line by providing four variants of the SBM model, it ignored the inefficient part of the production possibility frontier. Hadi-Vencheh *et al*. (2015) developed an SBM model—including supporting hyperplanes—to find the nearest point of the frontier line. However, as their computational framework requires large scale programming and software that uses fractional coefficients instead of decimals to avoid data loss, the computational time increases (see also Aparicio and Pastor, 2014; Aparicio *et al*., 2007; Baek and Lee, 2009; Fukuyama *et al*., 2014; Pastor and Aparicio, 2010; Portela *et al*., 2003). On the other hand, Tone (2016) developed a new framework called the SBM-Max model, with which a "nearly" closest projection point on the frontier can be found with allowable computation loads (see also Tone, 2017). Therefore, by using the SBM-Max model developed by Tone (2016), we can efficiently provide decision makers and engineers with practical information and measures for the performance improvement of products and companies. Figure 1 shows a comparison of the projections by an "ordinary" SBM-Min—provided by Tone (2001)—and the SBM-Max model developed by Tone in 2016. In Figure 1, for an inefficient DMU Z, the projection points A and B represent the SBM-Min and SBM-Max models respectively. Compared with projection point A, efficiency can be achieved with less reduction in inputs at projection point B. Therefore, the projection points computed by the SBM-Max model is easier to achieve and more practical for performance improvement.

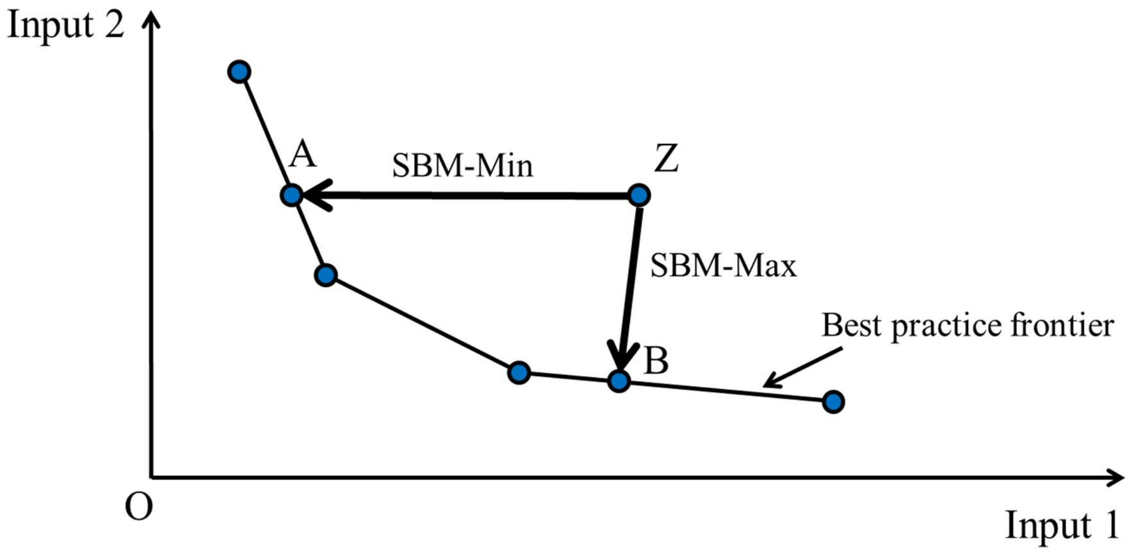

Figure 1. Illustration of the projections by the SBM-Min and SBM-Max models

Concerning DEA studies focusing on the automobile industry, Voltes-Dorta *et al*. (2013) analyzed the automobile market in Spain and examined the possibility of automobile manufacturers achieving the regulatory emission standard in the future. Moreover, Ylvinger (2003) evaluated the external impacts of a market expansion of light-duty vehicles in Sweden and Odeck (2000) conducted an efficiency analysis targeting the Norwegian automobile market. However, even though DEA analyses focusing on the automobile market have been conducted in European countries, there are few studies focusing on the automobile markets in Asian countries such as China, India, and Japan. Furthermore, none of the above-mentioned previous studies found the nearest projection point on the frontier, meaning that their estimated results might not be practical for decision makers and engineers.

Based on the above, this study aims to evaluate the performance of automobile manufacturers in Japan based on a product level analysis and to provide practical measures for technology improvement by introducing an SBM-Max framework. This study not only considers fuel efficiency but also other vehicle characteristics. Thereby, we provide a technology improvement target aimed at catching up to the best practice frontier with minimum effort. Furthermore, although none of the previously mentioned DEA studies on the automobile industry considered eco-friendly vehicles in their analysis, we included hybrid vehicles in our research framework. Finally, we investigate how a technology improvement in automobile manufacturers in Japan would contribute to achieving the CAFE standard by the target year of 2020.

The remainder of this study is organized as follows: The methodology is described in the next section, the dataset is presented and explained in Section III, the results and discussion are presented in Section IV, and the concluding remarks are provided in Section V.

II. Methodology

The SBM model can be classified into three variations; input-, output-, and non-oriented models. This study uses the output-oriented SBM-Max model to evaluate the performance of the vehicles. Following Tone (2016), we performed five steps to attain the SBM-Max scores.

2.1 Step 1: Solve SBM-Min

First, we solve the SBM-Min model—described by Tone (2001)—to identify the DMUs which are on the efficient frontier line. The output-oriented SBM model under variable returns to scale (VRS) assumption is defined as follows (Cooper *et al.*, 2007; Tone, 2017):

$$
\begin{aligned}
&\frac{1}{\rho_z^{\min *}} = \max_{\boldsymbol{\lambda}, \mathbf{s}^+} \ 1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_{rz}^+}{y_{rz}} \\
&s.t. \\
&x_{iz} = \sum_{j=1}^{n^{G,H}} x_{ij}\lambda_j \quad (i = 1,\dots,m) \\
&y_{rz} = \sum_{j=1}^{n^{G,H}} y_{rj}\lambda_j - s_{rz}^+ \quad (r = 1,\dots,s) \\
&\sum_{j=1}^{n^{G,H}} \lambda_j = 1 \\
&\lambda_j, s_r^+ \geq 0
\end{aligned}
\tag{1}
$$

In this equation, G and H represent the gasoline vehicle (GV) and hybrid vehicle (HV) respectively. We distinguished between GVs and HVs, as HVs clearly show higher performance in terms of fuel efficiency. Additionally, x_{iz} is the input vector for input i of DMU$_z$ and y_{rz} is the output vector for input r of DMU$_z$. x_{ij} and y_{rj} are the input and output matrices. λ_j is a weight vector for DMU j and s_r^+ is an output slack vector for output r, endogenously determined by solving equation (1). This study did not consider input slacks to estimate the performance of vehicles under the given input level. $\sum_{j=1}^{n^{G,H}} \lambda_j = 1$ is a constraint to allow for VRS assumption (Banker *et al.*, 1984). In this study, $m = 2$ and $s = 3$, as we assume two inputs (vehicle weight and retail price) and three outputs (engine power, space volume, and fuel efficiency). Additionally, $n^G = 113$ and $n^H = 54$. The optimal solution of equation (1) is expressed as $(\boldsymbol{\lambda}^*, \mathbf{s}^{+*})$. A DMU$_z$ = ($\mathbf{x}_z$, $\mathbf{y}_z$) is called SBM-efficient if $\rho_z^{\min *} = 1$ holds, which means that all the output slacks are zero. Therefore, the production possibility frontier is constructed by the SBM-Min-efficient DMUs.

2.2 Step 2: Define efficient DMUs

The set R^{eff} of all the efficient DMUs is defined as follows:

$$R^{eff} = \{ j \mid \rho_j^{\min} = 1,\ j = 1, \dots, n^{G,H} \} \tag{2}$$

These efficient DMUs are denoted as $\left(\mathbf{x}_1^{eff}, \mathbf{y}_1^{eff}\right), \left(\mathbf{x}_2^{eff}, \mathbf{y}_2^{eff}\right), \dots, \left(\mathbf{x}_{Neff}^{eff}, \mathbf{y}_{Neff}^{eff}\right)$, where *Neff* is the number of efficient DMUs.

2.3 Step 3: Local reference set

The local reference set, R_z^{local}, is defined for an inefficient DMU ($\mathbf{x}_z$, $\mathbf{y}_z$), that is, efficient DMUs set for DMU ($\mathbf{x}_z$, $\mathbf{y}_z$) is defined as follows:

$$R_z^{local} = \{ j \mid \lambda_j^* > 0,\ j = 1, \dots, n^{G,H} \} \tag{3}$$

2.4 Step 4: Pseudo-Max score

We solve the following equation for each inefficient DMU:

$$\begin{aligned} [\text{Psuedo}-1] \quad & \min \ 1 + \frac{1}{s}\sum_{r=1}^{s} \frac{s_{rz}^+}{y_{rz}} \\ & s.t. \\ & x_{iz} = \sum_{j \in R_z^{local}} x_{ij}\lambda_j \quad (i = 1, \dots, m) \\ & y_{rz} = \sum_{j \in R_z^{local}} y_{rj}\lambda_j - s_{rz}^+ \quad (r = 1, \dots, s) \\ & \sum_{j \in R_z^{local}} \lambda_j = 1 \\ & \lambda_j, s_r^+ \geq 0 \end{aligned} \tag{4}$$

The optimal output slack is defined as $\mathbf{s}^{+*}$. We further solve the following equation with the variables $\left(\boldsymbol{\lambda}, \mathbf{s}^+\right)$.

$$
\begin{aligned}
[\text{Psuedo}-2] \quad & \max \ 1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_{rz}^{+}}{y_{rz}+s_{rz}^{+*}} \\
& s.t. \\
& x_{iz} = \sum_{j\in R^{eff}} x_{ij}^{eff}\lambda_j \quad (i=1,\dots,m) \\
& y_{rz}+s_{rz}^{+*} = \sum_{j\in R^{eff}} y_{rj}^{eff}\lambda_j - s_{rz}^{+} \quad (r=1,\dots,s) \\
& \sum_{j\in R^{eff}} \lambda_j = 1 \\
& \lambda_j, s_r^{+} \geq 0
\end{aligned}
\tag{5}
$$

The optimal output slack is defined as $\mathbf{s}^{+**}$. Pseudo-Max score $\rho_z^{pseudo\max}$ is defined by the following equation:

$$
[\text{Psuedo}-\max] \quad \rho_z^{pseudo\max} = 1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_{rz}^{+*}+s_{rz}^{+**}}{y_{rz}} \tag{6}
$$

2.5 Step 5: Distance and SBM-Max score

For each inefficient DMU ($\mathbf{x}_z$, $\mathbf{y}_z$), the distance between ($\mathbf{x}_z$, $\mathbf{y}_z$) and $\left(\mathbf{x}_h^{eff}, \mathbf{y}_h^{eff}\right)$ (h = 1,..., *Neff*) is calculated as follows:

$$
[Distance] \quad d_h = \sum_{i=1}^{m}\frac{\left|x_{ih}^{eff}-x_{iz}\right|}{x_{iz}} + \sum_{r=1}^{s}\frac{\left|y_{rh}^{eff}-y_{rz}\right|}{y_{rz}} \tag{7}
$$

Step 5.1. Reorder the distance

We renumbered the efficient DMUs in the ascending order of d_h as follows:

$$
d_1 \leq d_2 \leq \dots \leq d_{Neff} \tag{8}
$$

Then, we defined the set R_h by

$$
R_h = \{1,\dots,h\}\left(h=1,\dots,Neff\right) \tag{9}
$$

Step 5.2. Find slacks and max-score for the set R_h

Referring to the set R_h, the performance index for an inefficient DMU ($\mathbf{x}_z$, $\mathbf{y}_z$) is estimated by solving the following equation:

$$
\begin{aligned}
[\mathrm{Max}-1] \quad & \min_{\boldsymbol{\lambda}, \mathbf{s}^+} \; 1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_{rz}^+}{y_{rz}} \\
& s.t. \\
& x_{iz} = \sum_{j\in R_h} x_{ij}^{eff}\lambda_j \quad (i=1,\ldots,m) \\
& y_{rz} = \sum_{j\in R_h} y_{rj}^{eff}\lambda_j - s_{rz}^+ \quad (r=1,\ldots,s) \\
& \sum_{j\in R_h}\lambda_j = 1 \\
& \lambda_j, s_r^+ \geq 0
\end{aligned} \tag{10}
$$

(a) If this equation is infeasible, we define that $\rho_{zh}^* = 0$. Otherwise, the optimal slack is $\mathbf{s}^{+*}$.

(b) If the optimal objective value is 1, i.e. $\mathbf{s}^{+*} = 0$, we define it as $\rho_{zh}^* = 0$. This indicates that DMU ($\mathbf{x}_z$, $\mathbf{y}_z$) can be expressed as a non-negative combination of DMUs in R_h and therefore—keeping in mind that $\rho_z^{\min} < 1$—it is inside the production possibility set.

(c) If the optimal objective value is less than 1, we again solve the following equation with the variables $(\boldsymbol{\lambda}, \mathbf{s}^+)$.

$$
\begin{aligned}
[\mathrm{Max}-2] \quad & \max_{\boldsymbol{\lambda}, \mathbf{s}^+} \; 1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_{rz}^+}{y_{rz}+s_{rz}^{+*}} \\
& s.t. \\
& x_{iz} = \sum_{j\in R^{eff}} x_{ij}^{eff}\lambda_j \quad (i=1,\ldots,m) \\
& y_{rz}+s_{rz}^{+*} = \sum_{j\in R^{eff}} y_{rj}^{eff}\lambda_j - s_{rz}^+ \quad (r=1,\ldots,s) \\
& \sum_{j\in R^{eff}}\lambda_j = 1 \\
& \lambda_j, s_r^+ \geq 0
\end{aligned} \tag{11}
$$

The optimal output slack is defined as $\mathbf{s}^{+**}$. Then, ρ_{zh}^* is defined as follows:

$$[\rho_{zh}^{*}] \quad \rho_{zh}^{*} = 1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_{rz}^{+*} + s_{rz}^{+**}}{y_{rz}} \tag{12}$$

ρ_{zh}^{*} is assigned as the max-score, referring to the set R_h.

Step 5.3. SBM-Max and projection

Finally, the max-score $\rho_z^{\max}$ of inefficient DMU ($\mathbf{x}_z$, $\mathbf{y}_z$) is defined as follows:

$$[\mathrm{SBM-Max}] \quad \rho_z^{\max} = \max\{\rho_z^{pseudo\ \max}, \rho_{z1}^{*}, \ldots, \rho_{zNeff}^{*}\} \tag{13}$$

The optimal output slack $\mathbf{s}^{+**}$ is kept at a value corresponding to the maximum $\rho_z^{\max}$. The projection of DMU ($\mathbf{x}_z$, $\mathbf{y}_z$) onto the efficient frontier is provided by the following:

$$[Projection] \quad \mathbf{y}_z^{*} = \mathbf{y}_z + \mathbf{s}_z^{+*} + \mathbf{s}_z^{+**} \tag{14}$$

The projection point $\left(\mathbf{x}_z^{*}, \mathbf{y}_z^{*}\right)$ is efficient considering the efficient DMU set R^{eff}.

III. Data

This study evaluates the performance of vehicle models and considers three outputs and two inputs that represent vehicle technology. The representative vehicle outputs are engine power (Horse power: HP), space in volume—defined by multiplying the height, width, and depth of the inside of a vehicle (m^3)—to accommodate people and luggage, and fuel efficiency (km/L). The vehicle inputs are vehicle weight (tons) and retail price (JPY). Although using the labor cost associated with vehicle production as an input variable would have been ideal, we cannot make use of it due to data availability. Therefore, the retail price per vehicle was used as a proxy variable of the labor cost for the specific vehicles in this study (Papahristodoulou, 1997). The data pertaining to vehicle weight and fuel efficiency were obtained from the vehicle fuel efficiency list (Ministry of Land, Infrastructure, Transport and Tourism, 2017). Lastly, we collected data concerning vehicles' engine power, volume, and retail price from Autoc one K.K.'s website (Autoc one, 2019). This study utilizes input and output data from 2016.

We focused on nine Japanese domestic automobile manufacturers selling vehicles in Japan: LEXUS, TOYOTA, NISSAN, HONDA, MAZDA, SUBARU, MITSUBISHI, SUZUKI, and DAIHATSU. Foreign automobile manufacturers are excluded from the research due to data availability. Moreover, despite diesel vehicles having a higher market share in European countries (European Automobile Manufacturers Association, 2018), the number of diesel vehicles sold in Japan is negligible (Ministry of Land, Infrastructure, Transport, and Tourism, 2017). We therefore excluded diesel vehicles from the data. As mentioned in Section I, we distinguished between GVs and HVs. The sample sizes are 113 for GVs and 54 for HVs. The detailed list of all the vehicle models—GV and HV—is shown in Appendix 1.

Table 1 provides the descriptive statistics of the dataset. Considering the average values, the vehicle weight of the HVs is heavier than that of GVs by 9 percent, which is partially due to extra equipment such as an electric motor and battery loaded in HVs. The average retail price of HVs is higher than that of the GV by 32 percent, while GVs has an advantage regarding engine power. It should also be noted that the HVs show better performance than GVs in terms of fuel efficiency.

Table 1. Descriptive statistics of the data used in this study

Year	Gasoline Vehicle (GV)	Input		Output		
		Vehicle weight (tonnes)	Retail price (Ten thousand JPY)	Fuel efficiency (km/L)	Engine power (HP)	Space volume (m^3)
2016	Ave.	1408.0	273.3	16.1	161.5	4.0
	Max.	2720.0	1105.5	27.8	560.0	7.1
	Min.	890.0	112.5	6.5	68.0	1.4
	SD	329.3	183.2	4.7	85.6	1.1
Year	Hybrid Vehicle (HV)	Vehicle weight (tonnes)	Retail price (Ten thousand JPY)	Fuel efficiency (km/L)	Engine power (HP)	Space volume (m^3)
2016	Ave.	1536.0	362.0	24.8	151.6	4.1
	Max.	2230.0	1081.1	40.8	394	7.1
	Min.	850.0	138.2	11.6	74.0	2.5
	SD	314.0	188.3	6.2	74.2	1.1

IV. Results and Discussion

4.1 Results of Performance Indices and Slacks

Figure 2 presents the beeswarm plots concerning the performance indices for GVs. We discuss the results by focusing on the median rather than mean, as some manufacturers—such as MITSUBISHI and DAIHATSU—have few vehicle models compared to others. Figure 2 also indicates that of the 113 GV models, there are 25 vehicle models with a value of unity as their performance index, indicating that these 25 models achieve best practice. The figure further shows that the grand median of the performance index of all the manufacturers for the GVs is 0.86. Considering the different manufacturers, HONDA has the highest performance index median (0.943) and the medians of TOYOTA, MITSUBISHI, SUZUKI, and DAIHATSU are higher than the grand median (Figure 2). These results indicate that the vehicle models of these five manufacturers show a higher performance than their counterparts from other manufacturers. Conversely, the medians of LEXUS, NISSAN, MAZDA, and SUBARU are lower than the grand median.

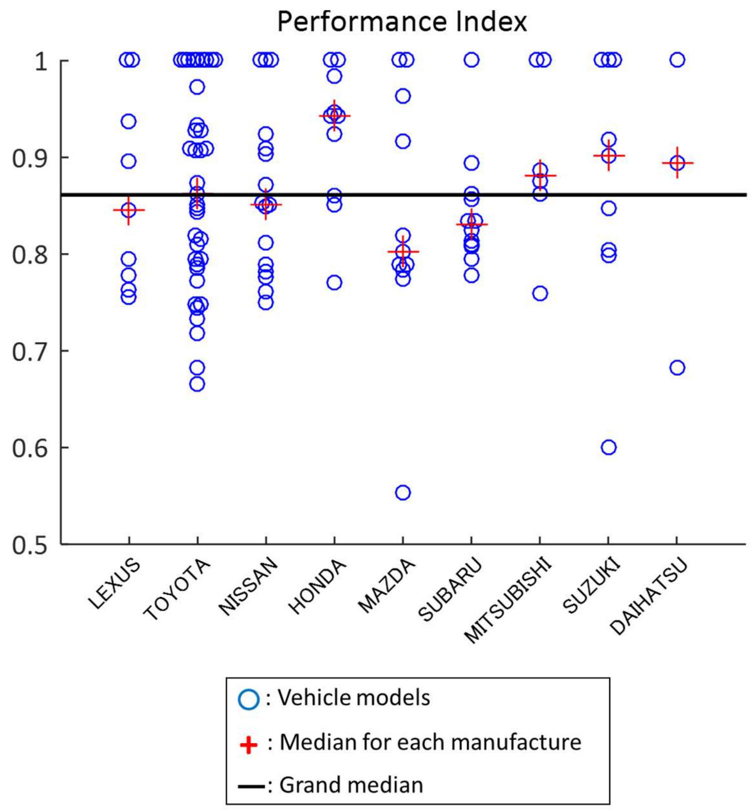

Figure 2. Beeswarm plots of the performance indices for GVs

Figure 3 shows the beeswarm plots of the performance indices for HVs. In Figure 3, it can be seen that of the 54 HV models, 17 models are on the best practice frontier. The performance index grand median for HVs is 0.91, which is higher than that that of GVs. Considering each manufacturer, although HONDA has the highest median of the performance index for GVs, NISSAN's median is the highest for the HVs. Other than NISSAN, the performance index medians of HONDA, MITSUBISHI, and SUZUKI are also higher than the grand median (Figure 3). Conversely, the performance index medians of LEXUS, TOYOTA, MAZDA, SUBARU, and DAIHATSU are lower than the grand median (Figure 3). Of their 20 models, TOYOTA has no less than seven HV models that achieve best practice. However, the median of TOYOTA is still lower than the grand median. These results indicate that there is a large and noticeable technology gap among the HV models within TOYOTA. Moreover, MAZDA shows the lowest performance index median for both GVs and HVs. In recent years, MAZDA has been focusing on technology development concerning diesel vehicles. These results may indicate that due to their focus on diesel, MAZDA may have fallen behind other manufacturers concerning the technology of the GVs and HVs (Marklines, 2018).

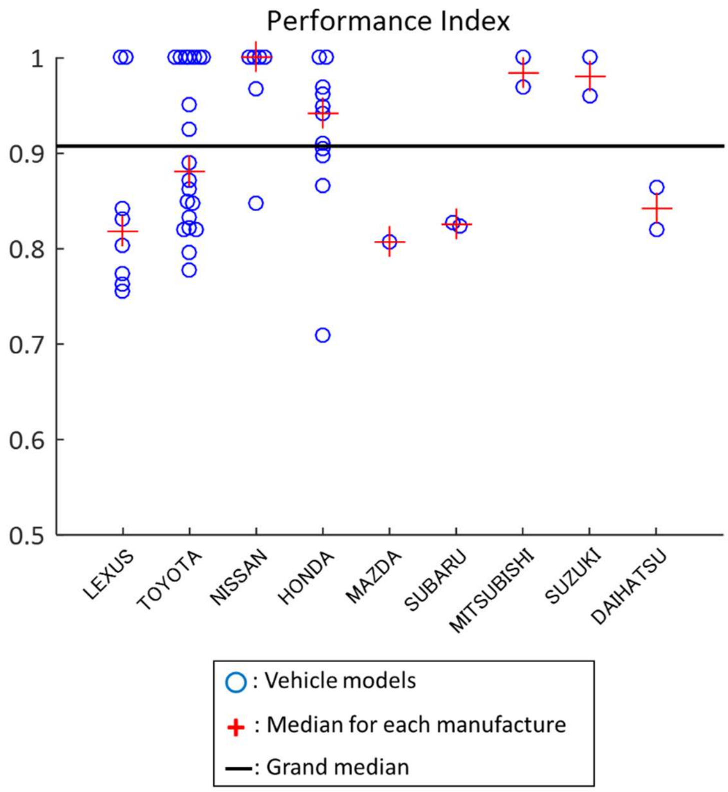

Figure 3. Beeswarm plots for the performance index for the HVs

As a vehicle's performance index is a unified value of the three output slacks of fuel efficiency, engine power, and space volume, it is necessary to focus on each slack to determine how to improve the performance of inefficient vehicle models. Furthermore, slack values can be interpreted as the improvement target for projecting the inefficient vehicle models onto the best practice frontier with minimum effort. Within the DEA framework, vehicle models with larger input and output values tend to have larger slack values. Therefore, we calculate the "slack proportion" as follows:

$$Slack\ proportion = \frac{s_{rz}^{+*} + s_{rz}^{+**}}{y_{rz}} \tag{15}$$

Slack proportion can be regarded as the technology improvement potential of the current technology level of each output value: fuel efficiency, engine power, and space volume. A larger slack proportion value indicates greater inefficiency. Figure 4 shows the beeswarm plots representing the slack proportion for the three outputs for GVs. To focus on the inefficient vehicle models that require technology improvement (i.e., $\rho_z^{\max} < 1$), we exclude the vehicle models that achieved the best practice (i.e., $\rho_z^{\max} = 1$). First, if we focus on TOYOTA, for which the medians of the slack proportion of fuel efficiency, engine power, and space volume are 0.175 (17.5 percent), 0.096 (9.6 percent), and 0.284 (28.4 percent) respectively (Figure 4). TOYOTA could reach the best practice frontier with minimum effort by achieving technology improvement based on these slack proportion results. These results also indicate that, to improve the "unified" performance of the TOYOTA GV vehicles, the necessity of technology improvement on the space volume is relatively high. Furthermore, by comparing the slack proportion for fuel efficiency of the nine manufacturers, we can see that the median of the slack proportion of DAIHATSU is the highest (Figure 4). This indicates that—among all the manufacturers—DAIHATSU may have the highest necessity of technology improvement for fuel efficiency to improve the overall performance of the inefficient GV vehicle models. Conversely, the slack proportion medians of HONDA for all the three outputs are lower than the grand medians, meaning that HONDA can achieve best practice for the GV vehicle models with less effort than other manufacturers.

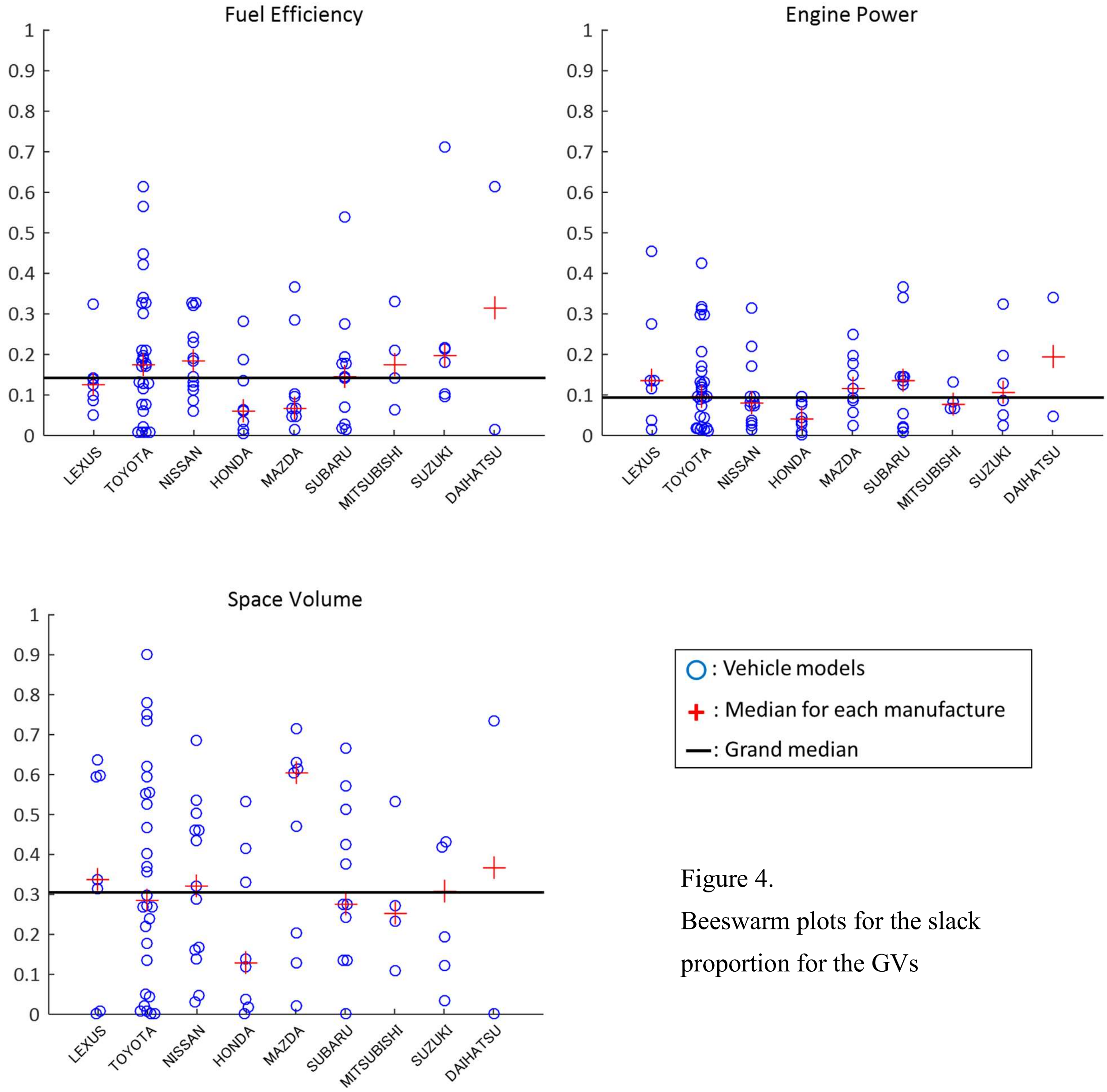

Figure 4.
Beeswarm plots for the slack proportion for the GVs

Figure 5 is the beeswarm plots representing the slack proportion for the three outputs for the HVs. The grand medians of the slack proportion of fuel efficiency, engine power, and space volume are 0.100 (10.0 percent), 0.066 (6.6 percent), and 0.232 (23.2 percent) respectively (Figure 5). We can see that all the grand medians of the slack proportion of the three outputs are lower than those of the GVs. These results indicate that, compared to the GVs, the technology gap among the vehicle models and manufacturers is small for the HVs, inferring that the technology improvement potential to the best practice frontier is also small for the HVs.

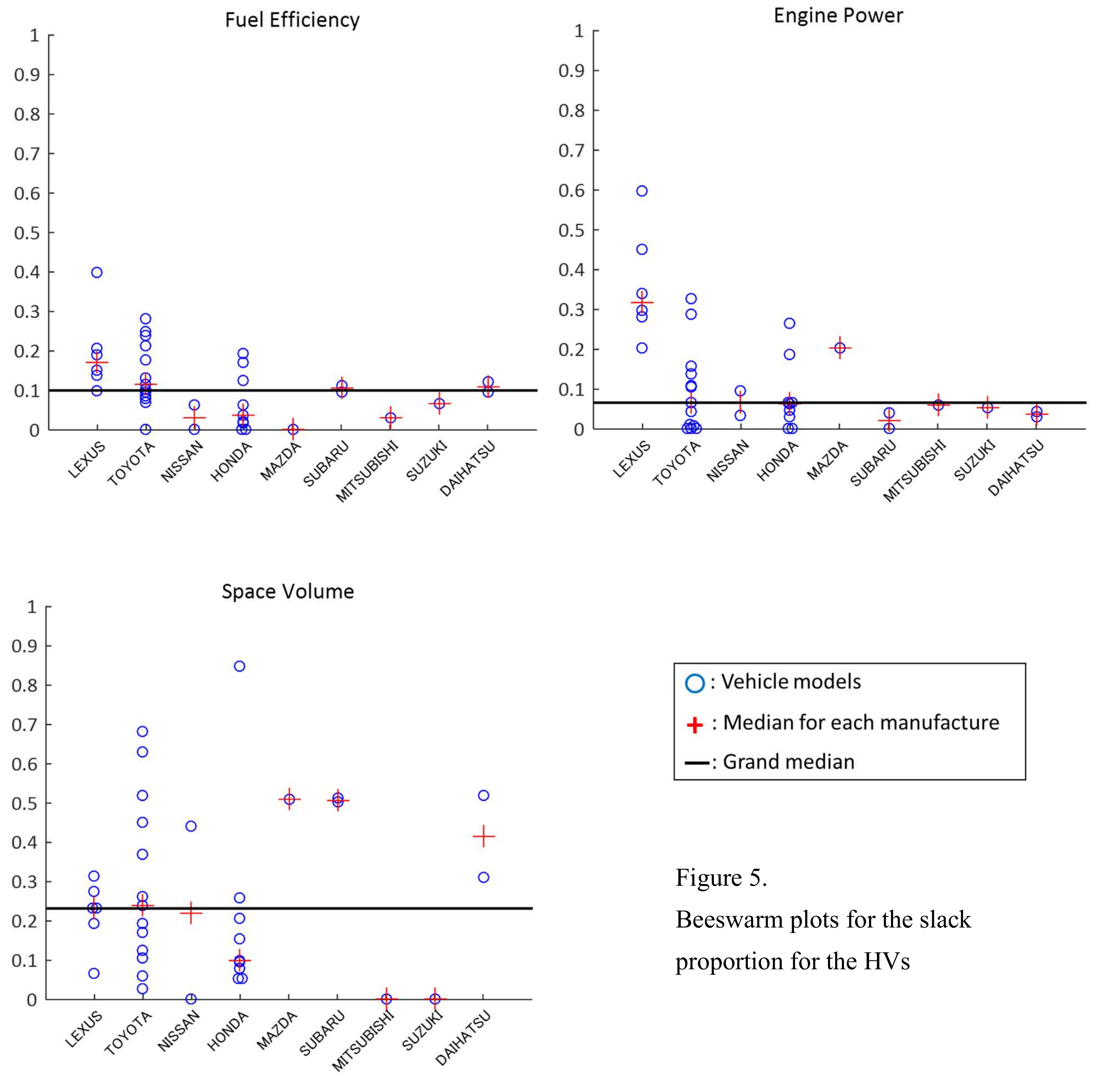

Figure 5.
Beeswarm plots for the slack proportion for the HVs

This section focused on the estimated results for the slack proportions of the three outputs to determine which technology each manufacturer gives the highest priority to for improving the overall performance. However, we can also compute an improved fuel efficiency for each manufacturer after technology improvement by using the estimated slack value for fuel efficiency. Furthermore, based on the improved fuel efficiency, we can then estimate the improved CAFE value after technology improvement in inefficient vehicle models of each manufacturer.

5.2 How would vehicle performance improvement contribute to achieving CAFE standard?

As stated in Section 1, the Japanese government decided to adopt the CAFE standard by 2020 to achieve the CO_2 reduction target in the transport sector. Figure 6 shows the CAFE values and CAFE standard values for each manufacturer. Note that we exclude MAZDA from the analysis in this section due to data availability. Here, the CAFE value (C_k) and CAFE standard value ($\tilde{C}_k$) for manufacturer l can be defined as equations (16) and (17) respectively (National Highway Traffic Safety Administration 2016). In these equations, $q_{l,m}$ represents the vehicle unit sales for vehicle model m of manufacturer l, $f_{l,m}$ represents the fuel efficiency of vehicle model m of manufacturer l, $q_{l,n}$ represents the vehicle unit sales for weight category n of manufacturer l, and $\tilde{f}_n$ represents the fuel efficiency target of weight category n. Q_l, M_l, and N represent the total vehicle unit sales by manufacturer l, the number of the vehicle models sold by manufacturer l, and the weight category respectively. In this study, N = 15 because vehicle weights in Japan are classified into 15 categories (See Table 2 for the definition of weight category and fuel efficiency target in Japan). If manufacturer l satisfies the condition of $C_l \geq \tilde{C}_l$, manufacturer l can be regarded achieving the CAFE standard.

$$C_l = \frac{Q_l}{\sum_{m=1}^{M_l} \frac{q_{l,m}}{f_{l,m}}} \tag{16}$$

$$\tilde{C}_l = \frac{Q_l}{\sum_{n=1}^{N} \frac{q_{l,n}}{\tilde{f}_n}} \tag{17}$$

Figure 6 shows that of the eight manufacturers, three manufacturers—namely NISSAN, SUBARU, and MITSUBISHI—would fail to achieve the CAFE standard based on their current technology levels for fuel efficiency. Therefore, these three manufacturers are required to reconsider their strategy for achieving the CAFE standard by the improvement of fuel efficiency and the reconstruction of the composition of vehicle unit sales. Next, we discuss a strategy for achieving the CAFE standard by considering the technology improvement potential for fuel efficiency focusing on NISSAN, SUBARU, and MITSUBISHI.

Table 2. Vehicle weight category and fuel efficiency targets in Japan

Weight category	Weight range (kg)			Fuel efficiency target (km/L)
C1		-	740	24.6
C2	741	-	855	24.5
C3	856	-	970	23.7
C4	971	-	1080	23.4
C5	1081	-	1195	21.8
C6	1196	-	1310	20.3
C7	1311	-	1420	19.0
C8	1421	-	1530	17.6
C9	1531	-	1650	16.5
C10	1651	-	1760	15.4
C11	1761	-	1870	14.4
C12	1871	-	1990	13.5
C13	1991	-	2100	12.7
C14	2101	-	2270	11.9
C15	2271	-		10.6

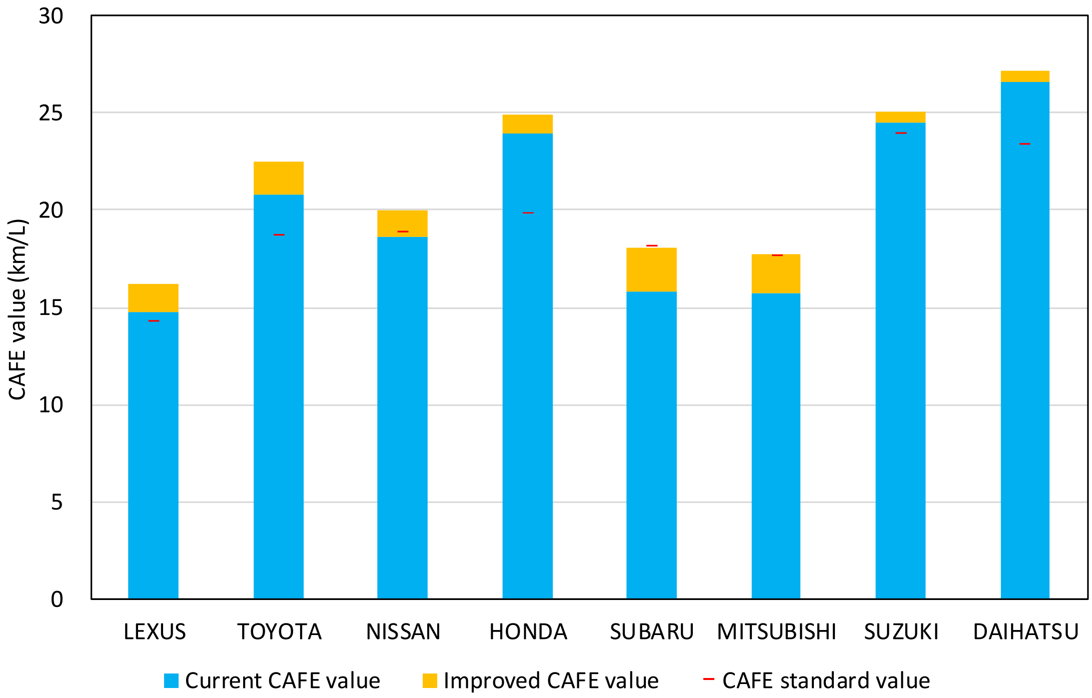

Figure 6. CAFE standard value, current value, and improved CAFE value per manufacturer

In Section III-A, we provided the results of the estimated "practical" performance improvement potential of inefficient vehicle models compared with the vehicle models that achieved the best practice, done by using the SBM-Max model. With the current fuel efficiency value ($f_{z,\text{Fuel}}$) and estimated slack value for fuel efficiency ($s^{+*}_{z,\text{Fuel}}$ and $s^{+**}_{z,\text{Fuel}}$), we can also calculate the improved fuel efficiency (f^{*}_{z}) for each inefficient vehicle model z using equation (18). Furthermore, by using the improved fuel efficiency, we can then calculate the improved CAFE value (C_l^*) for manufacturer l after the performance improvement of inefficient vehicle models of manufacturer l with equation (19).

$$f_z^* = f_{z,\text{Fuel}} + s_{z,\text{Fuel}}^{+*} + s_{z,\text{Fuel}}^{+**} \tag{18}$$

$$C_l^* = \frac{Q_l}{\sum_{z=1}^{M_l} \frac{q_{z,l}}{f_{z,l}^*}} \tag{19}$$

Figure 6 also presents the improved CAFE value for each manufacturer. The figure shows that the CAFE standard and improved CAFE values for NISSAN are 18.83 and 20.01 respectively, meaning that this manufacturer would be able to achieve the CAFE standard sufficiently through performance improvement. The CAFE standard and improved CAFE values for MITSUBISHI are 17.69 and 17.77 respectively. These results indicate that this manufacturer will barely achieve the CAFE standard through performance improvement. Moreover, although the CAFE standard value for SUBARU is 18.14, the improved CAFE value for this manufacturer is 18.06, implying that it will be difficult for SUBARU to achieve the CAFE standard, even if they fully improve the performance referring to the best practice frontier.

Considering the results provided in Figure 6, for many manufacturers, a better strategy may be focusing on improving the performance of inefficient vehicle models with the best practice frontier of 2016 in mind. For example, SUBARU should either apply innovative technology to develop a new vehicle model with better performance than the existing vehicle models on the best practice frontier in 2016 or reconstruct the composition of vehicle unit sales. This can be achieved by reducing the unit sales of vehicle models with poor fuel efficiency and increasing the unit sales of vehicle models that achieve the fuel efficiency target by weight category. Similarly, for manufacturers that cannot achieve the CAFE standard based on their current technology level for fuel efficiency, it will be difficult to improve the performance of all the inefficient vehicle models referring to the best practice frontier. Since the CAFE standard is an inclusive regulation that considers weight category, fuel efficiency, and vehicle unit sales, it would be more helpful and practical for decision makers to consider weight category and vehicle unit sales as well as fuel efficiency when developing strategies for achieving the CAFE standard. In the next section, we discuss effective strategies for the achievement of CAFE standard for each manufacturer.

5.3. Effective strategies for achieving CAFE standard

Concerning effective strategies to achieve the CAFE standard, manufacturers should consider vehicle unit sales, current technology for fuel efficiency, and the improvement potential of fuel efficiency comprehensively. We focus on three manufacturers: NISSAN, SUBARU, and MITSUBISHI and discuss their strategies. Figure

7 presents the total vehicle unit sales (horizontal axis), target fuel efficiency value (vertical axis: red bold line), "current" weighted-average fuel efficiency of vehicle sales (vertical axis: solid line), and the "improved" weighted-average fuel efficiency of vehicle sales (vertical axis: dotted line) by weight category. Here, the "current" and "improved" weighted-average fuel efficiency of vehicle sales in weight category *n* of manufacturer *l* are estimated as the following equations (20) and (21) respectively.

$$[\textit{Current weighted-average fuel efficiency}] \quad \overline{y}_{l,n} = \frac{\sum_{m=1}^{M_l}\left(q_{l,m,n}\cdot f_{l,m,n}\right)}{\sum_{m=1}^{M_l} q_{l,m,n}} \tag{20}$$

$$[\textit{Improved weighted-average fuel efficiency}] \quad \overline{y}^*_{l,n} = \frac{\sum_{m=1}^{M_l}\left(q_{l,m,n}\cdot f^*_{l,m,n}\right)}{\sum_{m=1}^{M_l} q_{l,m,n}} \tag{21}$$

Figure 7 shows that in a manufacturer's specific weight category when the "current" weighted-average fuel efficiency exceeds the fuel efficiency target, the manufacturer can obtain "credit" in that category, which is shown as the area filled in green. Conversely, when the "current" weighted-average fuel efficiency falls below the fuel efficiency target, the manufacturer is given a "discredit" in that weight category, which is indicated by the area filled in red. Furthermore, when the "improved" weighted-average fuel efficiency exceeds the fuel efficiency target, the manufacturer can obtain credit by improving the performance of inefficient vehicle models referring to the best practice frontier. When the "improved" weighted-average fuel efficiency falls below the fuel efficiency target, it is not possible for the manufacturer to obtain credit merely by improving the performance of inefficient vehicle models in that weight category.

Figure 7a (NISSAN) shows that the volume of the vehicle unit sales in weight category C4 is relatively large and the improved weighted-average fuel efficiency exceeds the fuel efficiency target. It can therefore be said that this manufacturer should focus on improving the performance of inefficient vehicle models belonging to this category, as substantial credit may be rewarded by performance improvement referring to the best practice frontier. The same can be said for weight category C9. On the other hand, considering weight category C5 in Figure 7a, as the current weighted-average fuel efficiency greatly exceeds the fuel efficiency target in this category, an effective strategy for NISSAN could be focusing on the sales promotion of vehicle models belonging to this weight category, rather than technology improvement. Considering weight category C6 of NISSAN, although this manufacturer has the largest potential for improving fuel efficiency in this weight category compared with the other weight categories, the volume of the vehicle unit sales for this weight category is not remarkable. Therefore, this manufacturer should first focus on improving the performance of the vehicle models belonging to this weight category and then facilitate their sales. This strategy may be more difficult to implement than those for weight categories C4, C5, and C9. For weight categories C10, C11, and

C12, as the vehicle unit sales volume is quite small, the impact on obtaining credit and achieving the CAFE standard of technology improvement and sales promotion is marginal in those weight categories. This indicates that NISSAN would not have to place a high priority on these weight categories when considering an effective strategy to achieve the CAFE standard.

Next, we discuss effective strategies for MITSUBISHI. Considering weight category C10 in Figure 7b, reducing discredit in this weight category through technology improvement referring to the best practice frontier could have a significant influence, because the volume of the vehicle unit sales is the largest and the current weighted-average fuel efficiency falls far below the fuel efficiency target in this weight category. The vehicle models in weight category C3 have the potential to earn substantial additional credit on the current technology level. Therefore, MITSUBISHI should focus on the sales promotion of these vehicle models. As we mentioned in Section III-B, MITSUBISHI may barely—and with great difficulty—achieve the CAFE standard if they succeed in improving the performance of all the inefficient vehicle models referring to the best practice frontier. Based on this result, MITSUBISHI might have to focus on a vehicle model belonging to weight category C12. In the DEA model, the vehicle model belonging to weight category C12 of MITSUBISHI that has the advantage of space volume, achieves best practice (i.e., $\rho_z^{\max} = 1$). Therefore, this vehicle model has no potential to improve its fuel efficiency referring to the best practice frontier technology. However, the current weighted-average fuel efficiency of weight category C12 falls significantly below the fuel efficiency target (Figure 7b). Therefore, it might be necessary for MITSUBISHI to improve the technology of this vehicle model while focusing on fuel efficiency or advancing technology innovation beyond the best practice frontier to reduce the discredit in weight category C12.

Finally, we propose effective strategies for SUBARU. According to Figure 7c, SUBARU should focus on improving fuel efficiency in vehicle models belonging to weight category C8, as this category shows large potential for improving fuel efficiency and its volume of vehicle unit sales is the largest in all the weight categories (Figure 7c). On the other hand, although category C4's current weighted-average fuel efficiency exceeds its fuel efficiency target, the volume of the vehicle unit sales of this weight category is quite small. Vehicle models in this weight category are relatively small ones and popular in Japan because of their handling advantage in narrow streets (Marklines, 2018). With this in mind, SUBARU has enough potential to facilitate the sales of the vehicle models in weight category C4 and this strategy could contribute to effectively obtaining additional credit. However, in weight categories C6, C7, and C9—categories with substantial discredit—the SBM-Max projection is not sufficient for achieving the weight category fuel efficiency targets and obtaining credit. Therefore, for these weight categories, SUBARU needs to focus on technology development concerning fuel efficiency or technology innovation beyond the best practice frontier.

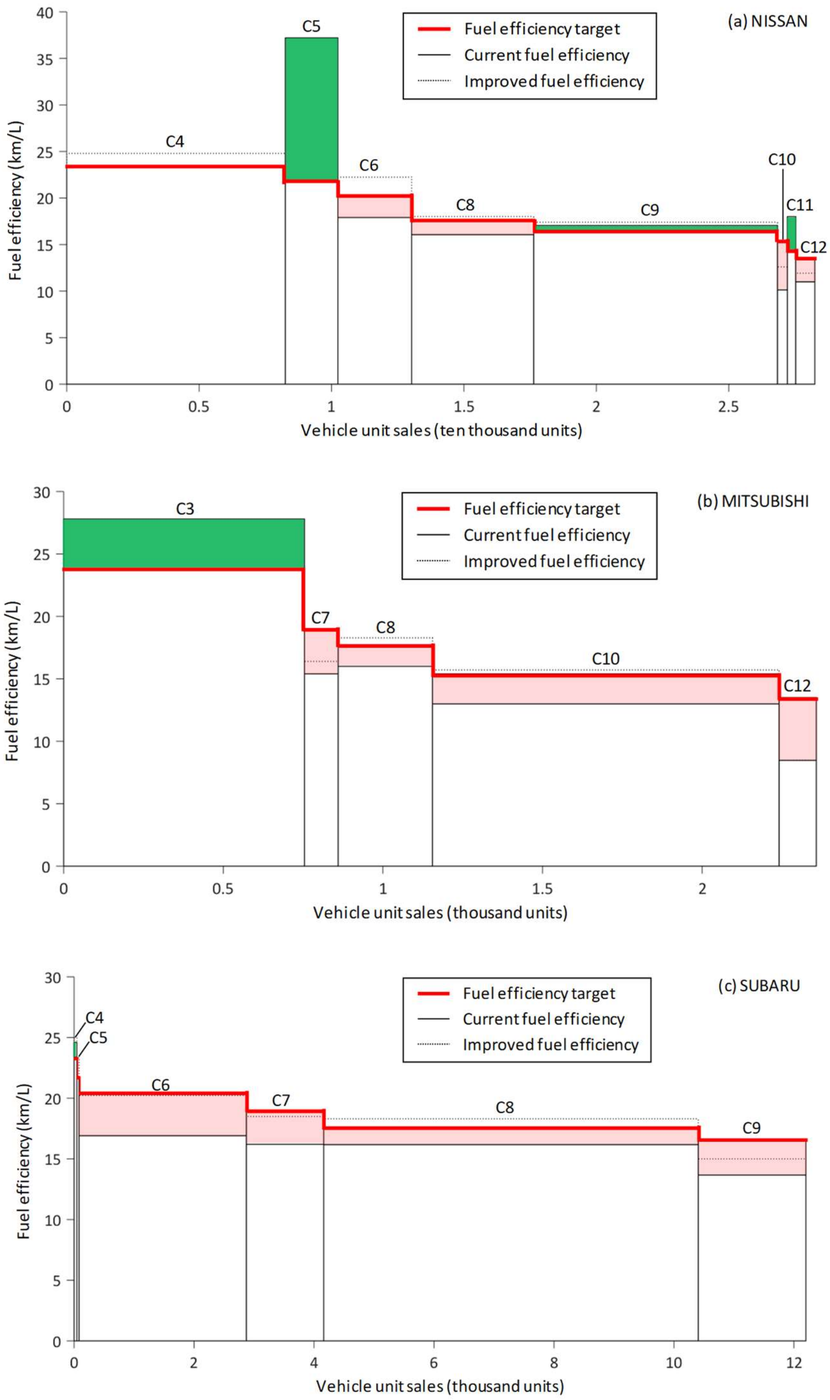

Figure 7. Vehicle unit sales, fuel efficiency targets, and current and improved weighted-average fuel efficiency by weight category for the three manufacturers

Table 3 describes and summarizes effective strategies for the three manufacturers. We classify five types of strategies: Strategy 1 involves technology development referring to the best practice frontier and Strategy 2 refers to the promotion of vehicle unit sales. Strategy 3 concerns the promotion of vehicle unit sales after technology development referring to the best practice frontier. We propose this strategy for the weight categories in which great potential of earning the credit is expected, even though these categories show small volumes of vehicle unit sales. Strategy 4 concerns technology development with a focus on fuel efficiency or technology innovation beyond the best practice frontier. We propose this strategy for weight categories in which the SBM-Max projection is not sufficient for achieving the weight category fuel efficiency targets. Finally, Strategy 5 corresponds to the weight categories in which the volume of the vehicle unit sales is quite small (specifically, the share of total vehicle unit sales is less than 5 percent of the total vehicle unit sales of the manufacturer). Therefore, the manufacturer does not have to assign a high priority to these categories because the impact of technology improvement and sales promotion is expected to be marginal. However, although the share of total categorical vehicle unit sales in weight category C4 of SUBARU is less than 5 percent, we propose Strategy 2 for this weight category, because of the reason mentioned in the discussion on the effective strategies for SUBARU.

Table 3. Summary of effective strategies for the three manufacturers

Weight category	NISSAN	MITSUBISHI	SUBARU
C3	-	2	-
C4	1	-	2
C5	2	-	5
C6	3	-	4
C7	-	5	4
C8	1	3	1
C9	1	-	4
C10	5	1	-
C11	5	-	-
C12	5	4	-

Code	Strategy
1	Technology development reffering to the best practice frontier
2	Sales promotion
3	Technology development and then sales promotion
4	Technology development with a focus on fuel efficiency/ Technology innovation beyond the best practice frontier
5	Low priority

V. Conclusion

This study proposed an analysis framework to identify whether specific automobile manufacturers have efficient vehicle technology to reach CAFE standards by 2020. This means that, for a specific vehicle model produced by the manufacturer, three outputs;—engine power (Horse power: HP), space in volume (m^3), and fuel efficiency (km/L)—can be maximized under the current input level of vehicle weight (tons) and retail price (JPY). This was accomplished by employing the novel approach of the SBM-Max model to discover the "closest" projection point in the vehicle technology frontier. This study focused on 113 gasoline vehicle models (GVs) and 54 hybrid vehicle models (HVs) produced by nine Japanese domestic auto manufacturers (LEXUS, TOYOTA, NISSAN, HONDA, MAZDA, SUBARU, MITSUBISHI, SUZUKI, and DAIHATSU) and two vehicle technology frontiers for the GVs and HVs were identified by applying the SBM-Max approach to detailed Japanese vehicle technology data of 2016.

We found that 25 vehicle models with a value of unity for the performance index measured by the SBM-Max model, indicating that they had achieved best practice in 2016. HONDA, particularly, showed the highest performance index median for GVs. On the other hand, the result shows that the performance index medians for the GVs produced by LEXUS, TOYOTA, MAZDA, SUBARU, and DAIHATSU are lower than the grand median. In other words, the gasoline vehicle technologies of these five manufacturers should be improved by referring to the best practice technology frontier. Concerning the 54 hybrid vehicle models, 17 vehicle models have a value of unity for the performance index. It was revealed that NISSAN has the highest median for the performance index of HVs.

Subsequently, for the inefficient vehicle models produced by a specific auto manufacturer, we estimated attainable fuel efficiency based on the vehicle technology frontier and calculated the CAFE value that will be improved by increasing the efficiency of inefficient vehicle models. A major finding is that the CAFE standard value for SUBARU was 18.14, whereas the "improved" CAFE value for this manufacturer was 18.06, implying that it might be difficult for SUBARU to achieve the CAFE standard, even if this manufacturer fully improves their vehicles' performance referring to the best practice technology frontier.

Finally, we formulated four effective strategies for achieving the CAFE standard, provided in Table 3. The first of these strategies is to further improve vehicle technology referring to the best practice frontiers for GVs and HVs identified in this study. The second is to simply promote unit sales of those vehicles with higher fuel efficiency. The third concerns promoting vehicle unit sales after technology development referring to the best practice frontier. The fourth strategy is to focus on improving vehicle technologies for GVs and HVs with a focus on fuel efficiency through the technological innovation *beyond* those best practice frontiers. A variety of combined corporate strategies considering the above-mentioned core strategies is crucial in achieving the CAFE standard.

For SUBARU—that was identified as a relatively inefficient auto producer—we suggest the following combined strategy: SUBARU should implement the first core strategy, focusing on vehicle models belonging to vehicle weight category C8 (ranging from 1,421 kg to 1,530 kg) as there is great potential for improving fuel efficiency in this particular weight category and the volume of the vehicle unit sales is the largest of all the weight categories. Furthermore, the second strategy should be implemented for vehicle models belonging to vehicle weight category C4 (ranging from 971 kg to 1,080 kg), as vehicle models in this category are relatively small and popular in Japan due to their handling advantage in narrow streets. In weight categories C6, C7, and C9, which shows substantial discredit, the SBM-Max projection is not sufficient for achieving the weight category fuel efficiency targets and obtaining credit. Therefore, for these categories, SUBARU would need to focus on technology development concerning fuel efficiency through the innovation beyond the best practice frontier. Based on the best practice frontier analysis, we presented effective strategies for Japanese domestic auto manufacturers that may face difficulties in achieving the CAFE standard.

Based on our findings above, we further suggest that automobile manufacturers should regularly publish a corporate social responsibility (CSR) report clearly describing the CAFE value. A corporate strategy for achieving the CAFE standard should be described/included in this CSR report. The analysis framework developed in this study can help policymakers and practitioners of CSR reporting understand vehicle technology potentials more clearly and facilitate the publication of crucial reports.

We are aware that there are certain limitations to the study. We recognize the importance of considering other performance indicators, such as safety or durability. We could not, however, make use of these indicators due to data limitations. These performance indicators need to be considered in future research should the data become available.

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Appendix 1. Lists of all the vehicle models analyzed in this study

Manufacturer	Vehicle name (GV)
LEXUS	LX, RX, GS, GS F, IS, LS, NX, RC, RC F
TOYOTA	C-HR, Alphard, Wish, Vitz, Vellfire, Voxy, Esquire, Auris, Carolla Axio, Carolla Fielder, Sienta, Tank, Noah, Harrier, Land Cruiser 200, Land Cruiser Prado, Roomy, bB, iQ, ist, RAV 4, Carolla Rumion, Ractis, Rush, FJ Cruiser, 86, Isis, Avensis Wagon, Allion, Estima, Crown Athelete, Crown Royal, Spade, Passo, Premio, Porte, Mark X
NISSAN	X-trail, Juke, Sylphy, Fuga, Skyline Crossover, GT-R, Wingroad, Elgrand, Cube, Skyline, Serena, Tiana, Note, Fairlady Z, Lafesta
HONDA	Grace, Jade, Fit, CR-V, Vezel, Odyssey, Shuttle, Stepwagon, Freed, Freed+
MAZDA	Biante, Premacy, Roadster, Roadster RF, MPV, CX-5, Axela, Axela Sports, Atenza, Atenza Wagon, Demio
SUBARU	Exiga, Impreza XV, Trezia, Justy, BRZ, WRX, Impreza G4, Impreza Sports, Forester, Levog, Legacy B4, Legacy Outback
MITSUBISHI	RVR, Outlander, Delica: D5, Mirage, Proudia, Pajero
SUZUKI	SX4-Cross, Escudo, Escudo 2.4, Baleno, Kizashi, Jimny Wagon, Solio, Swift, Landy
DAIHATSU	Thor, Be-Go, Boon

Manufacturer	Vehicle name (HV)
LEXUS	CT, RX, GS, HS, IS, LS, NX, RC
TOYOTA	C-HR, Aqua, Alphard, Vellfire, Voxy, Esquire, Auris, Carolla Axio, Carolla Fielder, Sienta, Noah, Harrier, Prius, Prius α, SAI, Camry, Estima, Crown Athlete, Crown Majesta, Crown Royal
NISSAN	X-trail, Cima, Fuga, Skyline, Serena, Note
HONDA	Grace, Jade, Fit, Legend, Vezel, Odyssey, Shuttle, Freed, CR-Z, Accord, Freed+
MAZDA	Axela
SUBARU	Impreza XV, Impreza Sports
MITSUBISHI	Delica: D2, Dignity
SUZUKI	Ignis, Swift
DAIHATSU	Mebius, Altis