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Abstract

This paper examines the efficiency and distributional effects of the fuel tax and feebate policies. I employ a model with households' two-stage decisions on car ownership and utilization and estimate model parameters by combining micro-level data from a household survey and macro-level aggregate data for the Japanese new car markets from 2006 through 2013, with a car price endogeneity being dealt with. Counterfactual analyses show that the Japanese feebate results in a significant increase in social welfare while augmenting environmental externalities. In particular, the rebound effect induced by the feebate cancels out about 7% of the reduction in CO_2 emissions that would originally have been attained by the fuel economy improvement. In addition, I find that the fuel tax at the current tax rate in Japan is 1.7 times less costly than the product tax, an alternative feebate scheme considered in the counterfactuals, in all income classes to reduce environmental externalities by the same amount, with no difference between the regressivity of the two policies.

Keywords: Discrete-Continuous choice, Fuel tax, Feebate policy, Rebound effect, Decomposition, Distributional impact
JEL Codes: D12, H23, H30, L62, Q53

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1 Introduction

Reducing fuel consumption from car driving is an urgent challenge common to most countries. At the same time, resolving the challenge is hopefully compatible with the economy. Among the requirements, the feebate has gained in popularity. In particular, faced with the financial crisis in 2008, a growing number of countries have adopted feebate schemes as a green economic stimulus program to tackle both issues of economic recession and climate change. On the other hand, policymakers tend to avoid raising a fuel tax or introducing a carbon tax. The main reason for this is that policymakers have concerns about the distributional impacts of fuel taxes. This study then tries to empirically answer the following questions: Can we achieve the economic and environmental goals simultaneously with feebate policies? And, is the fuel tax more regressive than the feebate?

In this paper, I evaluate the welfare effects of the fuel tax and feebate policies, focusing on efficiency and distributional equity. To do so, I resort to a structural model that accounts for behavioral responses of the demand- and supply-side agents. Understanding the policy impacts on the demand and supply sides in the market requires detailed knowledge about behavioral changes of economic agents in response to the introduction of policies. The automobile market in most countries is an oligopoly, where differentiated, multiproduct firms behave strategically. In such a market, each firm must know the own- and cross-price elasticities of demand for all vehicles and the substitution patterns between heavily taxed and tax-reduced vehicles to maximize their profits (Holland et al., 2009; Anderson et al., 2011). On the demand side, the fuel tax is expected to affect not only driving distances but also car choices by changing expected future fuel costs. Similarly, the feebate directly affects car choices by incentivizing consumers to purchase fuel-efficient vehicles, meanwhile, it should presumably affect mileage choices by altering the attributes of cars purchased. Therefore, one needs to incorporate decisions on the purchase and use of cars into a demand model for a comprehensive policy evaluation.

Moreover, the social outcomes of the two policies largely depend on a rebound effect. The rebound effect here refers to the upward pressure on driving demand that results from the improvement of fuel economy followed by a downward shift of the per-kilometer marginal cost of driving. Because of the rebound effect, policies that encourage improvements in fuel economy do not always result in the intended reduction of fuel consumption. Many researchers have identified the existence of the rebound effect empirically (e.g., Gillingham et al., 2016). Since the fuel tax directly suppresses driving demand by imposing a tax on marginal environmental externalities from car use, the fuel tax can control upward pressure on driving demand spurred by the rebound effect. In addition, the fuel tax can be an efficient policy instrument because it equates marginal abatement costs incurred by individuals even where actual individual car usage varies. Meanwhile, the feebate promotes the dissemination of fuel-efficient cars by providing tax incentives for their purchase; however, it fails to control the driving demand after purchase. Thus, the feebate is expected to stimulate households to drive more through the rebound effect (Anderson and Sallee, 2016).

To take the rebound effect into account in evaluating policy impacts, I need to model two household decisions, one concerning which car they purchase and, following that, another as to how long they drive the car. Few studies focus on two-stage decision-making due to issues of data availability. For instance, Goldberg (1998) and Bento et al. (2009) model the two decisions to analyze the effects of fuel economy standards and a fuel tax using data from a large sample of households in the United States. To perform such an analysis requires large-scale household-level data, including detailed information on the choice and usage of cars. However, in many cases, such micro-level data are not available, and this data limitation has hindered the analysis.

In this study, I attempt to overcome this problem by combining two data sets. The first data set comes from a household survey conducted in 2013 for households in Japan who had purchased a passenger vehicle in the preceding five years. This survey provides detailed information on car ownership and utilization for each household, such as the car model, the year purchased, and the travel distance. The survey also reports household demographics, such as household income, family size, and residential address. On the other hand, the second set of data comes from an aggregate data set of the Japanese new car market between 2006 and 2013. This aggregate data set contains information on sales volume, price, and other car attributes for each base model and covers almost all models in the Japanese new car market. Especially, the combination of the data sets at the different levels helps construct choice sets faced by surveyed households in each market. I match the household survey micro-level information and the macro-level information from the aggregate data set by using a model name common across the two data sets.

I begin by constructing a model that describes the behaviors of households and firms in the automobile market. On the demand side, I describe the joint demand for vehicle and use with the Discrete-Continuous Choice (DCC) model following Dubin and McFadden (1984). On the supply side, I model the pricing strategies of car manufacturers in the oligopoly market. Following Berry et al. (henceforth BLP, 1995) and subsequent studies, I assume that differentiated, multiproduct firms determine their prices based on those of rival firms. The model in this study has two advantages. First, it allows me to rule out the restrictive assumption made in most previous studies that driving demand is completely inelastic with respect to operating costs; I thus evaluate the policy effects without making any assumptions concerning the elasticity of driving demand. Second, incorporating the DCC model into the BLP framework allows me to deal with a car price endogeneity issue associated with demand estimation based on market aggregate data. In particular, I identify parameters of the DCC model using micro-level and macro-level moment conditions and estimate the parameters with the maximum likelihood estimation (MLE) by following the estimation strategy of Goolsbee and Petrin (2004) and Train and Winston (2007).

Moreover, I account for the heterogeneity of the rebound effect across individuals in the model. Existing empirical studies on the rebound effect find that since actual car usage patterns differ considerably between urban and rural areas, the magnitude of the rebound effect varies across regions even within the same country (e.g., Gillingham, 2014). I present evidence of the heterogeneity of the rebound effect by performing a preliminary analysis before the structural estimation. The simple regression analysis suggests the possibility of a large inter-regional disparity in the rebound effect over the sample period in Japan. I attempt to capture this heterogeneity by introducing a random coefficient to the model.

I make the following two findings associated with the rebound effect. First, the empirical result indicates the existence of the rebound effect and its heterogeneity across individuals. I estimate a rebound effect of 0.10%, which means that a 1% decrease in the cost of driving leads to an increase in driving demand of 0.10%. In addition, I find the rebound effect to exist heterogeneously across individuals, with spreading over the interquartile range of 0.07–0.12%. Second, the result by the structural estimation points to the importance of considering household decisions regarding the choice and use of cars. As a result of a simple regression that focuses only on the relationship between driving demand and the cost of driving, I find that, compared to the result by the structural estimation, the OLS result significantly overestimates the rebound effect. This suggests that it is crucial to model the two endogenous household decisions.

I perform several counterfactuals to examine the welfare impacts of policies. There are two primary findings from the simulation. First, I find that the Japanese feebate policies boost the sales of automobiles and result in a significant increase in social welfare, while it augments the environmental externalities. In particular, a decomposition analysis reveals that the rebound effect induced by the feebate cancels out about 7% of the reduction in CO_2 emissions that would originally have been attained by the fuel economy improvement. The results suggest that the green economic stimulus policies such as the feebate fail to achieve both economic and environmental goals simultaneously, and Pigouvian policies such as the fuel tax are required to supplement the feebate.

Second, I find that the fuel tax is cost-effective compared to the product tax, which is an alternative feebate scheme considered in the counterfactual analysis. Specifically, the simulation shows that the fuel tax at the current tax rate in Japan is 1.7 times less costly than the product tax in all income classes to reduce environmental externalities by the same amount. In addition, I find that there is not much difference in terms of regressivity between the fuel tax and the product tax, rather with the latter being slightly more regressive than the former. Indeed, it makes clear that both policies are regressive until the fourth quintile income group and in turn progressive in the fifth quintile income group.

This study contributes to two strands of the literature. First, this study is related to the literature that evaluates the welfare effects of green economic stimulus policies, particularly focusing on environmental consequences. Several papers have studied the welfare impacts of feebate policies in the car markets (e.g., D'Haultfœuille et al., 2014 and Durrmeyer, 2021 for the study about the French feebate scheme). Li et al. (2021) examine the impacts of the cash-for-clunkers program in the United States and focus on the trade-off between the economic stimulus and environmental objectives. Here, Tinbergen (1952) points out that more policies than the number of the policy targets are needed to achieve the multiple policy targets. The results of Li et al. (2021) suggest that the green stimulus program such as the cash-for-clunkers program fails to achieve their multiple targets simultaneously and one should supplement it with Pigouvian policies that directly suppress environmental externalities from energy use. The spirit of my work is in line with that of Li et al. (2021). In particular, I contribute to the literature by demonstrating Tinbergen's rule by modeling the behavioral response about both households' vehicle choice and use to feebate policies. This study supports the result of Li et al. (2021), suggesting that the feebate alone augments environmental damage while it stimulates demand, and further, the policy mix of the fuel tax and feebate scheme can improve social welfare.

Second, this paper also has a contribution to studies on regressivity. Seminal papers that analyze the distributional impacts of regulations in the car market are Bento et al. (2009) and Jacobsen (2013), who have focused on the impacts of the fuel tax and the corporate average fuel economy standards in the United States. Recent emerging studies also have an ongoing discussion on the regressivity of these regulations (e.g., Davis and Knittel, 2019; Levinson, 2019). To the best of my knowledge, however, no empirical studies have compared the distributional impacts of a fuel tax and a feebate by employing a model with households' two-stage decisions and considering the equilibrium in the car market. This paper attempts to add some empirical findings of the regressivity of the fuel tax and feebate policies in the Japanese new car market to the literature above.

The remainder of this paper is organized as follows. Section 2 describes the data sets and presents evidence suggesting a rebound effect during the sample period. Sections 3 and 4 outline the model and the estimation strategy, and Section 5 discusses the estimation results. Section 6 presents the results of counterfactual analysis, and Section 7 concludes.

2 Data

In this section, I explain the data sets and provide evidence suggesting the possible existence of a rebound effect in Japan during the sample period.

Data used for the analysis stem mainly from two data sets. The first data set is a household survey commissioned by the Nippon Research Center (NRC). This survey was conducted online in November 2013 and was targeted at households nationwide who purchased passenger cars in the preceding five years. The survey provides 548 observations for this study. The household survey contains information about the model purchased, purchase year, total travel distance for each vehicle, and household demographics such as the income, the age of the household head, and the residential area address.

The second data set is a market-level aggregate data set from 2006 to 2013. Using this market-level data enables me to construct the choice set faced by households in selecting a car. I obtain information on sales volumes of automobiles made by Japanese manufacturers from the Annual Report on New Motor Vehicle Registrations (*shinsha-touroku-daisuu-nennpou* in Japanese) published by the Japan Automobile Dealers Association and from statistics on mini-vehicles released by the Japan Mini Vehicles Association. Information on sales volumes of imported vehicles comes from statistics released by the Japan Automobile Importers Association (JAIA). The statistics include sales data of the top-20 best-selling imported vehicles sold in Japan for each year.[1] In addition to the sales data, I obtain information on the car attributes, including price, curb weight, size, and fuel economy, on the Carview! website. Consequently, the market aggregate data set has 1,302 observations over eight years for each base model, with nine Japanese and seven overseas car manufacturers. I combine the household survey and aggregate data based on the model name common to both data sets.

In addition, I supplement the main data sets with the following data sources. First, to construct the population density for household demographics, I make use of the Comprehensive Survey of Living Conditions (CSLC) in 2013 administrated by the Ministry of Health, Labour and Welfare. Second, to calculate the annual averages of gasoline and diesel prices nationwide, I collect statistics on retail fuel prices released by the Oil Information Center in the Institute of Energy Economics, Japan. Finally, I exploit the 2015-base consumer price index released by the Statistics Bureau of Japan to deflate the household income, car prices, and fuel prices.

Table 1 presents the summary statistics for variables used in the analysis. The first row in Panel A reports the annual vehicle kilometers traveled (VKT) for each vehicle owned by households.[2] The annual vehicle kilometers traveled takes approximately 5,480km on average. This value is roughly close to the average travel distance obtained from the nationwide survey of the Japan Automobile Manufacturers Association (JAMA).[3] In addition, I find that the household incomes are slightly higher than the national average because the NRC's survey only targets households who have purchased cars. Indeed, the household income in my sample indicates 7.56 million JPY on average, while the population average reported in the CSLC for 2013 is 5.28 million JPY. On the other hand, other demographics such as family size, the age of the household head, and the urban dummy take values close to the population averages, where the urban dummy indicates whether a household resides in the ordinance-designated cities.

The variables in Panel B are defined as follows. The rental price represents the annual cost of vehicle ownership and is calculated based on the purchase price. Specifically, I construct the rental price as the sum of depreciation, repayment amount of a car loan interest, and annualized

[1] In Japan, imported vehicles sales make up a small portion of total new vehicle sales. Indeed, JAIA (2016) reports that the share of imported vehicles to total new vehicle sales in 2013 is about 6.5%.

[2] I define the annual vehicle kilometers traveled as the total travel distance divided by years of use.

[3] The JAMA conducts a market-trend survey of passenger vehicles for households nationwide every two years and reports an average monthly vehicle kilometer traveled of 380km for 2013 (JAMA, 2013). Therefore, a rough estimate of the annual vehicle kilometers traveled comes to 4,560km.

Table 1: Summary Statistics

	Unit	Mean	St. Dev.	1st Q.	3rd Q.
Panel A. Household survey ($N = 548$)					
Annual vehicle kilometers traveled (VKT)	10,000km	0.55	0.33	0.30	0.75
Household income	million JPY	7.56	4.23	4.35	9.64
Family size	person	2.92	1.13	2.00	4.00
Age of household head	age	54.62	12.59	45.00	64.00
Urban dummy	binary	0.47	0.50	0.00	1.00
Panel B. Aggregate data, 2006-2013 ($N = 1,302$)					
Sales	1,000	24.70	40.05	3.11	28.31
Price	million JPY	2.68	1.90	1.50	3.08
Rental price	million JPY	0.58	0.37	0.36	0.65
Cost of driving per kilometer	100 JPY/km	0.11	0.04	0.08	0.13
Horsepower per weight	ps/kg	0.10	0.03	0.08	0.11
Size	10 meters	0.75	0.07	0.69	0.81
Kei-car dummy	binary	0.20	0.40	0.00	0.00
Transmission dummy (AT/CVT)	binary	0.98	0.13	1.00	1.00

Note: The 1st Q. and 3rd Q. in the table stand for the first and third quantiles.

automobile taxes in each year.[4] In addition, the cost of driving per kilometer is defined as the fuel price (JPY/ℓ) divided by the fuel economy (km/ℓ), and the vehicle size is measured as the sum of the length, width, and height of the vehicle. Finally, AT/CVT is a dummy for Automatic Transmissions (AT) or Continuously Variable Transmissions (CVT).

2.1 Suggestive Evidence

Before constructing a structural model, I show the suggestive evidence about the presence of the rebound effect by simple regression analysis. The results suggest that there might be inter-regional heterogeneity in the rebound effect during the sample period in Japan.

Using data in the household survey and aggregate data set, I estimate the following equation

[4] The depreciation is calculated based on the legal durable years by vehicle types. The National Tax Agency in Japan stipulates that the legal durable years are six years for ordinary passenger vehicles and four years for mini-vehicles (Kei-cars). Repayment amounts of a car loan interest are calculated by the purchase price times the annual interest rate of 3%, which is roughly the average interest rate of car loans in Japan. Note that the purchase price here includes the excise tax-inclusive price, an acquisition tax, and a subsidy amount in the presence of feebate policies explained in Section 6.1.2. Finally, annualized automobile taxes consist of the total amounts of a motor vehicle tonnage tax and an automobile tax which car owners are obligated to pay every year.

by OLS:

$$\log(M_{ijt}) = x'_{jt}\beta + h'_i\gamma - \rho \log\left(p^M_{jt}\right) + \varepsilon_{ijt} \tag{2.1}$$

In the equation, the dependent variable M_{ijt} is the annual distance traveled of car j purchased by household i in year t. On the right-hand side, x_{jt} and h_i are vectors of the vehicle and household characteristics, respectively, and per-kilometer cost of driving p^M_{jt} is defined as the fuel price p^{gas}_t divided by the fuel economy of car j. The above equation has an idiosyncratic error term ε_{ijt}. The parameter of interest here is ρ, a coefficient of p^M_{jt}. Defining the rebound effect by the elasticity of driving demand M_{ijt} with respect to the cost of driving p^M_{jt}, the parameter ρ corresponds to the rebound effect. To verify its existence and the inter-regional disparity in the effect, I add the interaction between $\log(p^M_{jt})$ and population density in the area of household residence to (2.1).[5]

Table 2 shows the estimation results. The estimates of parameter ρ do not vary with specifications, and all are statistically significant. Using the result of Model 3, I find a national average of the rebound effect to be 0.26. This suggests that the driving distance increases by 0.26% when the operating cost declines by 1%. Moreover, the summary statistics for population density indicate that the interquartile range of the rebound effect takes a value of 0.16–0.40, suggesting that the rebound effect is larger in rural areas than in urban areas.[6] This result provides evidence that there may be inter-regional heterogeneity in the rebound effect in Japan.

However, the above estimation does not deal with the endogeneity issue associated with driving costs, so that ρ cannot be interpreted as a causal relationship between driving demand and driving cost. For example, if households who frequently use cars tend to purchase fuel-efficient cars to save on the costs of driving, driving demand M_{ijt} should affect driving cost p^M_{jt}. Therefore, the estimates of parameter ρ in Table 2 include two effects with opposing directions: the first corresponds to the tendency of households with high driving demand to choose fuel-efficient cars and the second corresponds to the tendency of an improvement in fuel economy to increase driving demand through the rebound effect. This suggests that I need to carefully consider the choice of car and the driving demand to identify the latter effect.

On the other hand, the following two findings, at least, emerge from the above simple regression analysis. To assess the impacts of the fuel tax and the feebate policy taking the rebound effect into account, it is necessary (1) to incorporate into a structural model two household decisions, car purchase and car utilization, and (2) to consider the heterogeneity of the rebound effect in designing the model. I explain the methodology in the next section.

[5] Abe et al. (2017) run regressions (2.1) by region to analyze the inter-regional heterogeneity of the rebound effect in Japan.

[6] Data for the population density come from Statistical Observations of Municipalities 2013 published by Statistics Bureau, Ministry of Internal Affairs and Communications, Japan. In the data set, the population density with the unit of 10,000 persons/km^2 indicates the mean of 0.55 and the interquartile range of 0.17–0.82.

Table 2: Results for Regression of Driving Demand on Driving Cost

		Dependent variable: $\log(M_{ijt})$		
	Coefficients	(1)	(2)	(3)
$\log(p^M_{jt})$	ρ	0.456	0.568	0.468
		(0.122)	(0.146)	(0.151)
$\log(p^M_{jt})\times$ poplation density	-	-0.574	-0.627	-0.366
		(0.158)	(0.156)	(0.164)
Car characteristics		No	Yes	Yes
Household characteristics		No	No	Yes
R^2		0.034	0.065	0.102
Observations		536	536	536

Note: The heteroskedasticity robust standard errors are in parentheses.

3 Model

In this section, I construct a structural model in the new car market. I assume for the demand model that each household makes two decisions—one for a car purchase and one for the use of that car. For the supply model, I assume differentiated, multiproduct firms that compete in the oligopoly market in the Bertrand-Nash manner.

3.1 Demand

I first exposit a demand model and describe its specification. Following Goldberg (1998) and Bento et al. (2009), I construct a model with two household decisions—car choice and car usage—by using the DCC model developed by Hanemann (1984) and Dubin and McFadden (1984). Specifically, each household makes a car choice decision based on their indirect utility, and after that, decides how long to drive their purchased car; the latter decision is described by a demand function for driving derived from Roy's identity.

Suppose that there exist N_t potential households in the automobile market which is divided by year t $(= 1, \ldots, T)$. I assume that household i $(= 1, \ldots, N_t)$ buys at most one car j $(= 1, \ldots, J_t)$ or an outside option $(j = 0)$ each year. I define indirect utility U_{ijt} of household i conditional on purchasing car j or outside option in year t as

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{3.1}$$

where V_{ijt} is part of the indirect utility that depends on both observed and unobserved car attributes and observed household attributes. The indirect utility U_{ijt} includes an idiosyncratic shock ε_{ijt} in the last term. In the real world, even though all households with the same characteristics face the same product-choice set, they do not necessarily all make the same choice. The inclusion of the idiosyncratic shock ε_{ijt} allows me to explain this choice variation across households. I assume ε_{ijt} to be an independently and identically distributed stochastic variable and follow the type I extreme value distribution.

Given purchasing car j in year t, household i determines vehicle kilometers traveled M_{ijt} subject to the budget constraint,

$$p_{jt}^{M} M_{ijt} + X_{it} = y_i - r_{jt}.$$

In the budget constraint, p_{jt}^{M} denotes the per-kilometer cost of driving, which is defined as gasoline price p_t^{gas} at the time of purchase divided by car j's fuel economy. The second term X_{it} expresses the Hicksian composite good consumption for household i, where the price of the composite good is normalized to one.[7] On the right-hand side, y_i dentoes household i's income, and r_{jt} the rental price that is calculated based on the purchase price p_{jt}, so that $y_i - r_{jt}$ expresses the residual income after purchasing car j.

I specify the part of the indirect utility V_{ijt} in (3.1) from purchasing car j by household i in year t as follows:

$$V_{ijt} = \alpha_i \left(y_i - r_{jt}\right) + \lambda \exp\left(x_{jt}'\beta + h_i'\gamma - \rho_i p_{jt}^{M}\right) + w_{jt}'\psi + \xi_{jt} \tag{3.2}$$

In this specification, each of x_{jt} and w_{jt} represent vectors of observed car attributes. As shown below, x_{jt} appears in both the car choice and usage equations, while w_{jt} appears only in the car choice equation. The vector of household characteristics h_i includes family size, age of household head, and an urban dummy. Note that the second term of (3.2) expresses the interaction term between the car and household attributes. Additionally, ξ_{jt} captures car attributes observed by households and firms but unobserved by researchers. As assumed in BLP (1995), I assume rental price r_{jt} to be endogenous because r_{jt} may correlate with unobserved car attributes ξ_{jt}. Indeed, several factors in ξ_{jt}, such as advertisement and brand image of automobile firms, are expected to affect the rental price. Finally, I normalize the indirect utility from the outside option ($j = 0$) to $V_{i0t} = \alpha y_i$. Regarding a direct utility function assumed under the indirect utility specification above, see Appendix A.1.

The specification of V_{ijt} in (3.2) involves random coefficients. I specify coefficients α_i and ρ_i as

$$\alpha_i = \alpha_0 + \alpha_1 y_i + \sigma_\alpha v_{i\alpha}, \quad \rho_i = \exp\left(\rho + \sigma_\rho v_{i\rho}\right), \tag{3.3}$$

where $v_{i\alpha}$ and $v_{i\rho}$ are independently distributed the standard normal. In the specification of α_i, α_0 represents a mean parameter when household income is zero, and σ_α represents a standard deviation parameter. Specifically, as assumed in BLP (2004), I include household income y_i as a

[7] To make the normalization, I divide both sides of the budget constraint with the composite good price.

preference shifter in α_i to capture the heterogeneity of price elasticities of demand across households with different incomes. I expect that households with higher income are unlikely to respond to the vehicle price change so that the coefficient α_1 becomes negative. On the other hand, the coefficient ρ_i captures the heterogeneous impacts of the driving cost on households' preferences. In the specification of ρ_i in (3.3), ρ and σ_ρ correspond to the mean and standard deviation parameters for the distribution of ρ_i, respectively. I assume the remaining parameters λ, β, γ, and ψ in (3.2) to be constant.

Given the model parameters, the conditional probability of household i in year t choosing car j or the outside option is written as

$$\frac{\exp\left(V_{ijt}\right)}{\sum_{k=0}^{J_t}\exp\left(V_{ikt}\right)}.$$

Finally, I derive the demand for distance traveled predicted by the model when household i purchases car j in year t. Applying Roy's identity to the indirect utility (3.2) yields the driving demand M_{ijt} as follows:[8]

$$\begin{aligned}\log(M_{ijt}) &= \log\left(-\frac{\partial V_{ijt}/\partial p_{jt}^M}{\partial V_{ijt}/\partial y_i}\right)\\ &= \log\left(\frac{\lambda\rho_i}{\alpha_i}\right) + x_{jt}'\beta + h_i'\gamma - \rho_i p_{jt}^M. \end{aligned} \tag{3.4}$$

3.2 Supply

Next, I consider the pricing strategies of car manufacturers. I assume that differentiated, multiproduct firms strategically determine the prices of their products in an oligopoly market to maximize their profit, given the prices of rival firms' products. From the conditions for profit maximization, I derive pricing equations for each firm that arrive at a Bertrand-Nash equilibrium.

I denote a set of cars that firm f produces in year t as $\mathcal{J}_{ft}$. Firm f determines their prices to maximize variable profit defined as follows:

$$\sum_{j\in\mathcal{J}_{ft}}\left(p_{jt}^e - mc_{jt}\right)N_t s_{jt}(r_t),$$

where p_{jt}^e is the tax-exclusive price of car j in year t, and $s_{jt}(r_t)$ is the market share obtained under a $J_t \times 1$ vector of tax-inclusive rental prices r_t. Additionally, mc_{jt} denotes marginal cost, which is assumed to be constant in quantity.

For the profit maximization, the first-order condition to be satisfied by p_{jt}^e is written as

$$s_{jt}(r_t) + \left(1+\tau_{jt}^{ad}\right)\frac{dr_{jt}}{dp_{jt}}\sum_{k\in\mathcal{J}_{ft}}\left(p_{kt}^e - mc_{kt}\right)\frac{\partial s_{kt}(r_t)}{\partial r_{jt}} = 0,$$

[8] Note that the income y_i that appears in (3.3) is not structurally embedded into the indirect utility but in a reduced form way.

where τ_{jt}^{ad} represents an ad valorem tax. Note that, in the derivation of the first-order conditions, rental price r_{jt} is a function of purchase price p_{jt}. I can rewrite these J_t first-order conditions for the profit maximization in matrix form and obtain pricing equations for each firm. I define a $J_t \times J_t$ matrix S_t, comprising partial derivatives of market share $s_{jt}(r_t)$ with respect to r_{jt} times (-1), and denote the (j,k) element as $S_{jk,t} = -\partial s_{kt}/\partial r_{jt}$. I also define the ownership matrix Ω_t^* with (j,k) element $\Omega_{jk,t}^*$,

$$\Omega_{jk,t}^* = \begin{cases} 1 & \text{if } \exists f \text{ s.t. } \{j,k\} \subset \mathcal{J}_{ft} \\ 0 & \text{otherwise.} \end{cases}$$

With these matrices, defining $J_t \times J_t$ matrix $\Omega_t = \Omega_t^* \odot S_t$, where operator $\odot$ denotes the element-wise Hadamard product, I obtain the $J_t \times 1$ vector of tax-exclusive prices p_t^e from the following expression:

$$p_t^e = mc_t + \Omega_t^{-1} s_t^e(r_t) \tag{3.5}$$

In the expression, mc_t is a column vector of marginal costs, and $s_t^e(r_t)$ is a column vector with $s_{jt}(r_t)/\{(1+\tau_{jt}^{ad})dr_{jt}/dp_{jt}\}$ as its jth element.

4 Estimation and Identification

I explain the estimation and identification strategies for the model parameters. The basic idea for the estimation is that I embed the estimation procedure of the DCC model with the MLE in the framework of BLP (1995), following Gloosbee and Petrin (2004) and Train and Winston (2007). I attempt to identify the parameters with micro-level and macro-level moments and deal with price endogeneity when estimating the demand function. Based on the demand parameters and conditions for profit maximization, I recover the marginal costs faced by each firm in the production process.

4.1 Estimation Strategy

I first present the overview of the estimation strategy before describing the details. First of all, I divide parameters in V_{ijt} into two parts and denote them by vectors θ_1 and θ_2:

$$V_{ijt} = \delta_{jt}(\theta_1) + \mu_{ijt}(\theta_2), \tag{4.1}$$

where $\delta_{jt}(\theta_1)$ and $\mu_{ijt}(\theta_2)$ represents a mean utility that is common to all households and part of utility depending on household characteristics, respectively. Specifically, for $j = 1, \ldots, J_t$, vectors θ_1 and θ_2 are composed of

$$\theta_1 = (\alpha_0, \psi), \quad \theta_2 = (\alpha_1, \lambda, \beta, \gamma, \rho, \sigma_\alpha, \sigma_\rho),$$

and for the outside option ($j = 0$), both $\delta_{0t}(\theta_1)$ and $\mu_{i0t}(\theta_2)$ are zero by definition. Both of the parameter vectors are supposed to be estimated with the MLE when household-level data are available. However, a likelihood function defined under this specification includes over 1,300 fixed effects $\{\delta_{jt}\}_{j,t}$, and it is unrealistic to conduct a nonlinear search over all these parameters using the MLE. Then, the market aggregate data help reduce the number of parameters to be estimated in a nonlinear search. Specifically, Berry's inversion (Berry, 1994; BLP, 1995) based on market shares in the aggregate data set enables me to express the fixed effects $\{\delta_{jt}\}_{j,t}$ in the function of parameters θ_2 only. Finally, using parameters θ_1 and θ_2 estimated from a regression of the fixed effects and MLE, I estimate the marginal costs in the supply model.

As the first step, I express fixed effects $\{\delta_{jt}\}_{j,t}$ in a function of parameter vector θ_2. Under the assumption that ε_{ijt} in (3.1) follows the type I extreme value distribution, I calculate predicted market share s_{jt} of car j in year t as follows:

$$s_{jt}(\{\delta_{jt}\}_j, \theta_2) = \int\int \frac{\exp\{\delta_{jt} + \mu_{ijt}(\theta_2)\}}{\sum_{k=0}^{J_t} \exp\{\delta_{kt} + \mu_{ikt}(\theta_2)\}} \, dF(D_i)\, dG(v_i),$$

where $D_i = (y_i, h_i')'$ and $v_i = (v_{i\alpha}, v_{i\rho})'$, and $F(\cdot)$ and $G(\cdot)$ are cumulative distributions of D_i and v_i, respectively.[9] Using the predicted market share s_{jt} and observed market share S_{jt}, I define a contraction mapping $T(\delta)$ as proposed by Berry (1994) and BLP (1995):

$$T(\delta) = \delta + \log(S_{jt}) - \log(s_{jt}(\{\delta_{jt}\}_j, \theta_2))$$

I find that the predicted market share s_{jt} matches the observed market share S_{jt} at a fixed point of the mapping $T(\delta)$. Given the parameter θ_2, I solve the fixed point for mapping $T(\delta)$ by iterating the following calculation:

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \log(S_{jt}) - \log(s_{jt}(\{\delta_{jt}^{h}\}_j, \theta_2))$$

I obtain the fixed point for $T(\delta)$ as the convergent point when iterating the calculation until $\|\delta_{jt}^{h+1} - \delta_{jt}^{h}\|_\infty < \epsilon^{tol}$ is satisfied and back out the fixed point $\delta_{jt} = s_{jt}^{-1}(S_{jt}, \theta_2)$.[10] The crucial point here is that all the fixed effects $\{\delta_{jt}\}_{j,t}$ are expressed in the function of parameter θ_2. This implies that the number of parameters to be estimated by nonlinear search in MLE decreases dramatically.

As the second step, I estimate θ_1 using the fixed point δ_{jt} obtained in the previous step. Recall that δ_{jt} in (4.1) can be written out as

$$\delta_{jt} = -\alpha_0 r_{jt} + w_{jt}'\psi + \xi_{jt}. \tag{4.2}$$

[9] I compute the multiple integrals in the market share s_{jt} by simulation. I first take R random draws from demographic and stochastic variable distributions and denote them as v_{iD}^r and v_i^r ($r = 1, \ldots, R$). In this study, I construct the distribution $F(\cdot)$ using the CSLC data. With these random draws, I approximate market share s_{jt} as follows:

$$s_{jt}(\{\delta_{jt}\}_j, \theta_2) \approx \frac{1}{R} \sum_{r=1}^{R} \frac{\exp\{\delta_{jt} + \mu_{ijt}(v_{iD}^r, v_i^r, \theta_2)\}}{\sum_{k=0}^{J_t} \exp\{\delta_{kt} + \mu_{ikt}(v_{iD}^r, v_i^r, \theta_2)\}}.$$

[10] I set the tolerance criterion ϵ^{tol} at 10^{-12}.

Since assuming that rental price r_{jt} correlates with unobservable attribute ξ_{jt}, I estimate parameters α_0 and ψ by generalized method of moments (GMM). For the GMM estimation, I prepare $L \times 1$ vector z_{jt} as instruments for r_{jt} that satisfies moment conditions $E[z_{jt}\xi_{jt}] = 0$. Given parameters θ_2, GMM estimates $\hat{\theta}_1$ are defined as

$$\hat{\theta}_1 = \underset{\theta_1}{\operatorname{argmin}}\, \xi' Z W Z' \xi,$$

where Z is a $JT \times L$ ($J = \sum_{t=1}^{T} J_t$) matrix for instruments z_{jt}, and ξ is a $JT \times 1$ vector for ξ_{jt}. Additionally, W is an efficient weight matrix and a consistent estimate of $E[\xi_{jt}^2 z_{jt} z_{jt}']^{-1}$. In estimation, I implement the two-step GMM by setting $W = (Z'Z)^{-1}$ in the first stage estimation.

Finally, I define a likelihood function for the estimation of θ_2. When household i purchases car j in year t, let $\tilde{M}_{ijt}$ donote the observed annual mileage and η_{ijt} an error between the log of observed mileage $\tilde{M}_{ijt}$ and the log of mileage predicted by the model M_{ijt},[11]

$$\eta_{ijt} \equiv \log \tilde{M}_{ijt} - \log M_{ijt}.$$

Moreover, assuming that η_{ijt} follows the normal distribution with mean zero and variance σ_η^2, the conditional density of observing $\tilde{M}_{ijt}$ has the form,

$$\ell\left(\tilde{M}_{ijt}\middle| i \text{ chooses } j \text{ at } t,\ X_{ijt}\right) = \frac{1}{\sqrt{2\pi\sigma_\eta^2}} \exp\left\{-\frac{1}{2}\left(\frac{\log \tilde{M}_{ijt} - \log M_{ijt}}{\sigma_\eta}\right)^2\right\},$$

where $X_{ijt} = (x_{jt}', p_{jt}^M, w_{jt}', D_i', v_i)'$. In the expression, $\log(M_{ijt})$ is the log of the driving demand obtained in (3.4). Denoting $\tilde{\theta}_2 = (\theta_2, \sigma_\eta)$, I define the likelihood function for each household $L_{ijt}(\tilde{\theta}_2)$ as[12]

$$L_{ijt}(\tilde{\theta}_2) = \int \left[\frac{1}{\sqrt{2\pi\sigma_\eta^2}} \exp\left\{-\frac{1}{2}\left(\frac{\log \tilde{M}_{ijt} - \log M_{ijt}}{\sigma_\eta}\right)^2\right\} \cdot \frac{\exp\left(V_{ijt}\right)}{\sum_{k=0}^{J_t} \exp\left(V_{ikt}\right)}\right] dG(v_i).$$

I approximate the likelihood function L_{ijt} by simulation and denote the simulated likelihood function for household i as $\check{L}_{ijt}$. Then, the simulated log-likelihood function to be maximized is written as

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{J_t} d_{ijt} \cdot \log \check{L}_{ijt}(\tilde{\theta}_2),$$

[11] Following Bento et al. (2009) and D'Haultfœuille et al. (2014), I assume that error η_{ijt} is independent of the car choice decision of households. Under this assumption, even though I construct joint demand for car choice and use, accounting for unobservables that enter both demands by random coefficients, the possibility of overestimating the rebound effect remains (Dubin and McFadden, 1984; Newey, 2007). However, because the model in this study allows for estimating parameters in the driving demand equation controlling for fixed effects δ_{jt} as well as car attributes x_{jt} and demographics h_i, I expect that the biases of the estimates become small compared with the results of Bento et al. (2009) and D'Haultfœuille et al. (2014).

[12] Note that the likelihood function does not include a probability of choosing the outside option because the household survey used in this study is targeted at households who purchased cars in the preceding years and does not include any information about households who have not purchased cars.

where $d_{ijt} = 1[i \text{ chooses } j \text{ at } t]$. I maximize the above objective function, with the parameters θ_1 being replaced with the estimates $\hat{\theta}_1$.[13]

In the supply model, marginal cost mc_{jt} is a parameter to be estimated. Based on the estimates of demand parameters, I obtain the following expression for marginal costs by rearranging the pricing equations (3.5):

$$\widehat{mc}_t = p_t^e - \Omega_t^{-1} s_t^e(r_t).$$

On the left-hand side of the expression, $\widehat{mc}_t$ is a $J_t \times 1$ vector of estimated marginal costs in year t.

4.2 Identification

I face a price endogeneity issue in estimating the demand parameters. In the automobile market, there are many cases where vehicle models with a high market share are sold at higher prices. As regards this phenomenon, I can interpret it as automobile manufacturers assigning high prices to high-quality vehicles. This fact produces the correlation between the car price and unobserved attributes such as the product quality and the brand image. Following BLP (1995), I then assume a possibility that rental price r_{jt} is correlated with unobserved attribute ξ_{jt}. Since I expect a positive correlation between them, the coefficient of the rental price will be overestimated in a positive direction if the endogeneity issue is ignored.

I deal with this endogeneity problem by the instrumental variable approach. I construct a vector of instrument variables z_{jt} that satisfies the following condition:

$$E[\xi_{jt}|z_{jt}] = 0$$

For the instruments, I consider tax-location instruments following Konishi and Zhao (2017) and Kitano (2022). The tax-location instruments are constructed based on tax reduction amounts applied under the feebate scheme which I will explain in section 6.1.2. There are two advantages to using the tax reduction amounts as instruments. First, under the feebate scheme in Japan, tax reduction amounts are determined by observed vehicle attributes, such as fuel economy, weight, and engine displacement. Thus, I expect the tax reduction amounts to be uncorrelated with the unobserved attribute ξ_{jt} after controlling for the vehicle attributes in the demand estimation and to satisfy the exclusion restriction. Second, the Japanese feebate experiences several scheme changes during the study period, so the tax reduction amounts applied for each vehicle model change across time. As a consequence, the tax reduction amounts have two-dimensional variations across vehicles and time. I construct tax-location instruments based on the tax reduction amounts in a manner of

[13] Note that although α_i appears in the constant term of the driving demand expression defined in (3.4), it captures primitively the relationship between the quantity demanded for vehicles and the prices and thus should not be estimated from the driving demand expression but from the expression for δ_{jt} in (4.2). Therefore, I first retrieve α_0 by running the regression in (4.2) with the parameter θ_2 holding fixed, and after that, maximize the simulated log-likelihood function with the estimate $\hat{\alpha}_0$ being embedded in the constant term for the driving demand M_{ijt}.

BLP (1995). Specifically, I use as the instruments a sum of the tax reduction amounts applied to vehicles produced by the same producer, and a sum of those applied to vehicles produced by the other producers.[14] Moreover, I also use the per-kilometer operating cost p_{jt}^{M} and car attribute w_{jt} as instruments since they are assumed to be uncorrelated with ξ_{jt}.

Other parameters in the demand model are identified by exploiting several variations in the sample. Since parameters β, γ, and ρ are coefficients for interaction terms between car and household attributes in the indirect utility, I expect that they are identified from the joint distribution of car ownership and household demographics. For the identification of the heterogeneity of households' preferences, I need another micro-level variation than the car choice variation among households. Indeed, parameters in the random coefficients are identified from the variation in the travel distances as well as that in the car choices among households. In addition, parameter λ appears in the second term of the indirect utility function and captures the degree to which factors determining driving demand affect car choice. Therefore, λ is also identified by the variations in car choice and travel distance across households. Finally, since parameter vector ψ appears only in the car choice expression, I expect ψ is estimated from the variation in car purchase decisions across households.

On the supply side, the parameter to be estimated is marginal cost mc_{jt}. The identification of this parameter relies on the demand parameters. In particular, the variation in car prices and market share across models and years allow me to identify the marginal cost mc_{jt}.

5 Empirical Results

In this section, I present the estimation results for the demand and supply models. Table 3 displays the results for the demand estimation. For the robustness check, Table 3 lists the results obtained by the BLP instruments and the tax-location instruments. In the estimation, I use horsepower per weight, vehicle size, Kei-car dummy, and other dummies as car attributes, and family size, age of household head, and urban dummy as household demographics.

The panel A in Table 3 reports the regression results by GMM. The estimates of rental price coefficient α_0 obtained by both instruments are quitely similar and statistically significant. In addition, the results indicates that the demand for mini-vehicles (Kei-cars) is high relative to regular vehicles, while the demand for regular vehicles tends to be higher for vehicles with greater size.

[14] I exclude the tax reduction amounts themselves from the instruments because of the performance in the first stage estimation. In addition, as I explain in section 6.1.2, three taxes are applied for the tax break under the feebate scheme during the study period; the acquisition tax, the tonnage tax, and the automobile tax. As Kitano (2022) notes, because the acquisition tax is an ad valorem tax, it is correlated with the unobservable ξ_{jt} and fails to satisfy the exclusion restriction. Thus, I construct the tax-location instruments based solely on the tax reduction amounts of the tonnage tax and automobile tax.

Table 3: Estimation Results

		(1)		(2)	
	Coefficients	Est.	S.E.	Est.	S.E.
Panel A. Results of regression of δ_{jt} by GMM					
Rental price	α_0	11.799	0.754	11.513	0.753
Horsepower/Weight	ψ_1	31.651	5.037	30.417	5.031
Size	ψ_2	12.352	1.934	11.885	1.958
Kei-car dummy	ψ_3	36.091	3.139	35.306	3.163
AT/CVT	ψ_4	1.154	0.420	1.169	0.422
Hybrid dummy	ψ_5	1.419	0.294	1.429	0.295
Maker dummies		Yes		Yes	
Year dummies		Yes		Yes	
Instrumental variables		BLP IV		Tax-location IV	
GMM objective (degrees of freedom)		16.389 (8)		11.209 (4)	
Panel B. Result of the DCC model by MLE					
Mean parameters:					
Rental price × income	α_1	-0.232	0.025	-0.227	0.012
Constant	λ	1.932	0.311	1.953	0.329
Horsepower/Weight	β_1	0.670	0.412	0.648	0.396
Size	β_2	1.705	0.172	1.708	0.169
Kei-car dummy	β_3	-0.140	0.250	-0.144	0.242
Family size	γ_1	1.882	0.427	1.797	0.456
Age of household head	γ_2	-1.716	0.264	-1.697	0.379
Urban dummy	γ_3	0.946	0.106	0.934	0.107
Cost of driving per kilometer	ρ	-0.357	0.155	-0.395	0.139
Standard deviation parameters:					
Rental price	σ_α	1.202	0.136	1.172	0.062
Cost of driving per kilometer	σ_ρ	0.793	0.006	0.791	0.006
Error term	σ_η	0.020	0.004	0.019	0.004
Log-likelihood		-7.560		-7.560	
Observations in the aggregate data set		1,302		1,302	
Observations in the household survey		548		548	

Note: This table reports estimation results with 2,000 random draws. The estimations are run with the family size measured in 100 persons, and the age of household head in 1,000 ages, and the Kei-car dummy and urban dummy multiplied by 0.1. As for the other variables, I follow the units listed in Table 1.

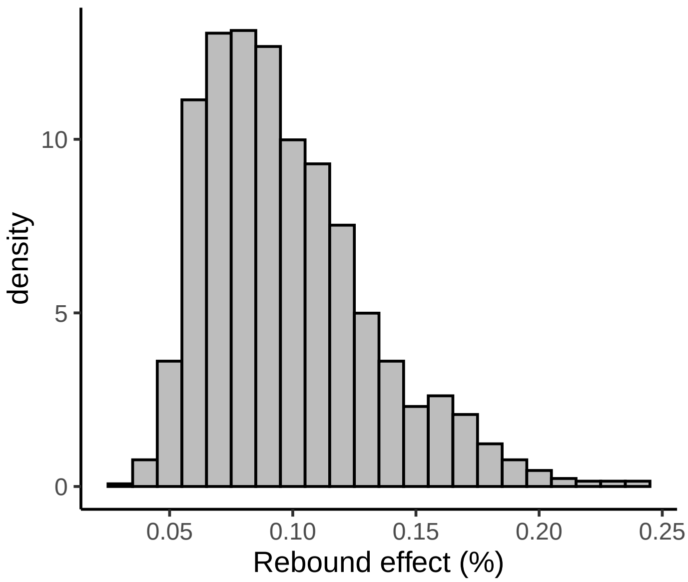

Figure 1: Heterogeneity of the Rebound Effect

The panel B reports the estimation results for the DCC model by MLE. The results shows all the estimates of coefficients have the expected signs. Since the coefficients of the horsepower per weight and vehicle size have positive signs, it suggests that as the engine power and vehicle size are larger, the demand for driving is higher. By contrast, the estimate of the coefficient of the Kei-car dummy has a negative sign, which reflects the fact that households tend not to drive long distances in mini-vehicles.

The estimate of the rebound effect is calculated based on the results in Table 3. The panel B in the table shows that both the estimates of mean parameter ρ and variance parameter σ_ρ of random coefficient ρ_i are statistically significant. With these estimates, I obtain the estimate of the rebound effect by calculating the elasticity of the driving demand M_{ijt} with respect to the driving cost p_{jt}^M as follows:

$$\frac{\partial M_{ijt}}{\partial p_{jt}^M}\frac{p_{jt}^M}{M_{ijt}} = -\rho_i p_{jt}^M$$

Figure 1 displays the histogram of the rebound effects calculated using the estimates of model 2 in Table 3. The figure shows that the mean value of the estimated rebound effect is 0.10, meaning that a 1% decrease in the per-kilometer cost of driving will increase the driving demand by 0.10%. Note that this estimate obtained by structural estimation is smaller than the OLS estimate of 0.26 obtained in the previous section as an absolute value. I find that the OLS estimate of the rebound effect involves some biases and significantly overestimates the true value. Existing studies show that estimates of the rebound effect differ greatly with types of data set and estimation models (e.g., Graham and Glaister, 2002; Gillingham et al., 2016). However, the estimate of the rebound

Table 4: Elasticities, Marginal Costs, and Markups

	Mean	St. Dev.	1st Q.	3rd Q.
Own-rental price elasticities of demand	-4.79	2.05	-5.61	-3.38
Marginal costs (in millions of JPY)	1.86	1.61	0.87	2.17
Markups	0.27	0.09	0.20	0.33

Note: This table shows estimates of marginal costs and markups for all firms during the sample period, 2006-2013. The markups are defined as $(p - mc)/p$. The 1st Q. and 3rd Q. in the table stand for the first and third quantiles.

effect in this study falls in the range of estimates obtained in the most recent studies.[15] Indeed, my estimate, obtained by combining the household-level cross-sectional data and the market-level panel data, is comparable to the estimate by Gillingham et al. (2015), who estimate a short-run rebound effect of 0.10 using an individual-level massive panel data set in a state of the United States.[16]

Table 4 presents the summary statistics of estimated own-rental price elasticities, marginal costs, and markups. Here, I calculate the own- and cross-rental price elasticities of market share as follows:

$$\frac{\partial s_{jt}}{\partial r_{kt}} \frac{r_{kt}}{s_{jt}} = \begin{cases} -\frac{r_{jt}}{s_{jt}} \int \int \alpha_i s_{ijt}(1 - s_{ijt})\, dF(D)\, dG(v) & \text{if } j = k, \\ \frac{r_{kt}}{s_{jt}} \int \int \alpha_i s_{ijt} s_{ikt}\, dF(D)\, dG(v) & \text{otherwise,} \end{cases}$$

where $s_{ijt} = \exp(V_{ijt}) \big/ \sum_{k=0}^{J_t} \exp(V_{ikt})$. Table 4 reports that the estimated own-rental price elasticity is -4.79 on average.[17] In addition, the estimated markups are, on average, around 27%. Those estimates are comparable to estimates found in BLP (1995) and Grigolon et al. (2018) using data for the United States and European countries, respectively.

6 Counterfactual Analysis

I perform counterfactual analyses based on estimated parameters to examine efficiency and distributional effects of the fuel tax and the feebate policy. I also conduct a decomposition analysis of

[15] Gillingham et al. (2016) review recent empirical studies on the rebound effect and conclude that the short- and medium-run elasticities of gasoline/driving demand with respect to gasoline price in developed countries fall in the range from 0.05 to 0.25.

[16] Gillingham et al. (2015) estimate a gasoline price elasticity of driving demand.

[17] For the comparison, I report that the sales-weighted average of the own-rental price elasticities in 2012 is -3.64. Konishi and Zhao (2017) who use quarterly data in Japan for almost the exact period of this study report the sales-weighted average of elasticities in 2012 of -2.66. Although the estimate in my study indicates a larger value in absolute magnitude than that of Konishi and Zhao (2017), note here that the estimate of Konishi and Zhao (2017) is not for the rental price elasticities but for the price elasticities.

CO_2 emissions to demonstrate the contribution of the rebound effect to environmental externalities under various policy scenarios. I first describe the policy scenarios assumed in the analyses and then assess the policy impacts on various outcome variables and welfare.

6.1 Scenarios

I consider six policy scenarios in the counterfactuals. Based on the estimated parameters, I simulate the baseline scenario in which neither fuel tax nor feebate policies are enforced. The remaining scenarios are generated and introduced to the baseline to assume situations in which fuel taxes at different tax rates and feebate policies take effect during the sample period in Japan.

6.1.1 Fuel Taxes

In the second and third scenarios, I consider situations in which fuel taxes at the same rate as the SCC level and the current tax rate in Japan of 56.6 JPY/ℓ are added to the pre-tax prices.

I first briefly outline the fuel tax situation in Japan. There has long been a fuel tax of 55.84 JPY/ℓ for gasoline.[18] On top of the pre-existing fuel tax, the Japanese government phased in a carbon tax, beginning in October 2012. The rate of the newly introduced carbon tax has been set at 0.76 JPY/ℓ (289 JPY/ton of CO_2) since 2016.[19] Thus, the price of gasoline that households face in year t is written as[20]

$$p_t^{gas} = p_t^{\textit{pre-tax}} + \tau^{gas} + \tau^{carbon},$$

where

- $p_t^{\textit{pre-tax}}$ is the pre-tax price of gasoline in year t,
- τ^{gas} is the pre-existing gasoline tax rate of 55.84 JPY/ℓ,[21] and

[18] For the diesel, there has been a diesel handling tax of 32.1 JPY/ℓ.

[19] The carbon tax rate has reached the current level in two phases. For example, the carbon tax rate for petroleum was set to 95 JPY/ton of CO_2 (0.25 JPY/ℓ) from October 2012 to March 2014, 190 JPY/ton of CO_2 (0.5 JPY/ℓ) from April 2014 to March 2016, and 289 JPY/ton of CO_2 (0.76 JPY/ℓ) from April 2016.

[20] For expositional simplicity, I omit the excise tax τ^{ex} on the fuel prices in the body of the paper. In practice, however, since the excise tax τ^{ex} is imposed on the gasoline and diesel prices, p_t^{gas} and p_t^{diesel} are calculated as follows:

$$p_t^{gas} = \left(p_t^{\textit{pre-tax}} + \tau^{gas} + \tau^{carbon}\right) \times (1 + \tau^{ex}),$$

and

$$p_t^{diesel} = \left(p_t^{\textit{pre-tax}} + \tau^{petroleum} + \tau^{carbon}\right) \times (1 + \tau^{ex}) + \tau^{diesel},$$

where $\tau^{petroleum}$ represents the petroleum and coal tax of 2.04 JPY/ℓ and τ^{diesel} represents the diesel handling tax rate of 32.1 JPY/ℓ.

[21] The existing tax on gasoline is divided into a petroleum and coal tax levied upstream and a gasoline tax and a local gasoline tax levied downstream. The rate for the petroleum and coal tax is 779 JPY/ton of CO_2 (2.04 JPY/ℓ) and the sum of rates of the gasoline tax and the local gasoline tax amounts to 23,173 JPY/ton of CO_2 (53.8 JPY/ℓ).

- τ^{carbon} is the additional carbon tax rate, which is 0.76 JPY/ℓ at current levels.

Since the price of gasoline averages around 150 JPY/ℓ during the sample period, the current gasoline tax rate of 56.6 JPY/ℓ accounts for about one-third of the gasoline price.

The second scenario in the simulation is for analyzing the welfare impact of the Pigouvian tax for fuels on the automobile market. I then impose the SCC of 4,000 JPY/ton of CO_2 (10.48 JPY/ℓ), which is approximately 40 USD/ton of CO_2, on the pre-tax price of fuels $p_t^{pre\text{-}tax}$ and set other fuel taxes to zero.[22] In the third scenario, I explore the effect of the fuel tax using the current tax rate in Japan and add to the pre-tax price of fuels $p_t^{pre\text{-}tax}$ the current tax rate of 56.6 JPY/ℓ (21,603 JPY/ton of CO_2).[23]

6.1.2 Feebate Schemes

In the remaining scenarios, I examine the effects of the feebate policies implemented in Japan and alternative feebate schemes. In what follows, I briefly explain automobile-related taxes relating to the feebate schemes explained below. During the study period between 2006 and 2013, new car purchasers were obliged at the time of purchase to pay three types of automobile-related taxes: the acquisition tax, the motor vehicle tonnage tax, and the automobile tax.[24] Denoting a vector of the three automobile-related taxes as T_{jt}, the tax-inclusive price p_{jt} faced by a purchaser of car j in year t is represented by the function p as follows:

$$\begin{aligned} p_{jt} &= p_{jt}^e + p\left(p_{jt}^e, T_{jt}\right) \\ &= \left(1+\tau^{ex}\right) p_{jt}^e + T_{jt}^{acquisition} + T_{jt}^{tonnage} + T_{jt}^{auto}, \end{aligned}$$

where τ^{ex} represents the excise tax rate of 5%. The amount of the acquisition tax $T_{jt}^{acquisition}$ is proportional to the acquisition price of the purchased car so that the sum of the rates of excise tax and acquisition tax comes to the ad valorem tax.[25] The acquisition tax rates are 5% for ordinary passenger cars and 3% for mini-vehicles.[26] On the other hand, the amounts of tonnage tax $T_{jt}^{tonnage}$ and automobile tax T_{jt}^{auto} are proportional to the curb weight and engine displacement, respectively. For example, until March 2010, the tonnage tax amount was determined by a tax rate

[22] The SCC comes from IWG (2016) and corresponds to the estimate for 2020, which is calculated with a discount rate of 3%.

[23] For the diesel, I set different tax rates from gasoline and add to the pre-tax price of diesel the tax rate of 34.9 JPY/ℓ, which is the sum of the pre-existing fuel tax rate and the additional carbon tax rate.

[24] While the acquisition tax involves a duty to pay only at the time of purchase, the tonnage tax and the automobile tax (or mini-vehicle tax for mini-vehicles) are payable by the owners every year after purchase. When you buy a new car, the first inspection is due three years after purchase. After that, the vehicle must be inspected every two years. As for the tonnage tax, the amount of tax due each year is paid together at the time of the vehicle inspection. Therefore, the purchaser of a new vehicle is obligated at the time of purchase to pay the tonnage tax for the three years until the next vehicle inspection.

[25] In practice, the acquisition price is about 90% of the tax-exclusive price p_{jt}^e.

[26] The acquisition tax is not imposed if the acquisition price of a vehicle is less than 500,000 JPY.

of 6,300 (4,400) JPY per 0.5 tonnes for ordinary passenger cars (for mini-vehicles).[27] The amount of automobile tax is shown in Appendix Table A.1.

Actual Feebate Scheme The fourth scenario assumes a situation where the feebate scheme implemented in Japan during the sample period is introduced to the baseline scenario. The Japanese feebate scheme is essentially a rebate program, consisting of a tax incentive measure for the automobile-related taxes and a subsidy program for fuel-efficient vehicles. Under the feebate, the tax-inclusive vehicle price p_{jt} is written as

$$p_{jt} = p^e_{jt} + p\left(p^e_{jt}, dr_{jt} \cdot T_{jt}\right) - ES_{jt},$$

where dr_{jt} denotes a vector of discount rates for the automobile-related taxes T_{jt}, and ES_{jt} the amount of subsidy for fuel-efficient cars. As explained below, the discount rates and the subsidy amount are determined according to fuel economy standards and emission standards.

Table 5 shows the eligibility requirements for the tax incentive measures and the discount rates (or the deductible amounts) for target taxes during the sample period. As shown in Table 5, the reduction rates for the three automobile-related taxes are determined according to the achievement rates for the fuel economy standards and the emission standards (for the target values for the fuel economy standards, see Appendix Table A.2).[28] For example, for purchasers of a new car meeting the 2010 fuel economy standard by 20% or more during the period between 2007 and 2008, the acquisition tax was deducted 300,000 JPY (in the case of hybrid vehicles, the tax was cut by 2.0% in 2007 and 1.8% in 2008), and the automobile tax was cut by 50%. In 2009, the tax incentives measures experienced a scheme change and were largely expanded as one of the Green New Deal programs.[29] The tax incentives from 2009 to 2013 had two implementation periods: the first term corresponding to a period from April 2009 to April 2012 and the second from May 2012 to 2013. Table 5 shows that hybrid vehicles were exempt from their acquisition tax and tonnage tax regardless of their fuel economy achievement level in the first term after 2009.

In addition to the tax incentives, a subsidy program for fuel-efficient cars has been implemented since 2009.[30] The subsidy program also had two periods. The first and second terms ran from April

[27] The tonnage tax rate was revised twice during the study period: 5,000 JPY (3,800 JPY) from April 2010 to April 2012 and 4,100 JPY (3,300 JPY) from May 2012 was added for every 0.5 tonnes for ordinary passenger cars (mini-vehicles).

[28] Fuel economy standards have been revised many times since first established in 1979. For ordinary passenger cars, the 2010 and 2015 target values were established in March 1999 and in March 2006, respectively. Each of the target values is used during the sample period. In particular, the 2010 target values are used in the first term and the 2015 target values in the second term to select vehicles for tax reduction.

[29] The tax incentives implemented until 2008 aimed to reduce the acquisition tax and the automobile tax (or the mini-vehicle tax) for low-emission vehicles, comprising the following three schemes: the green tax scheme, the special scheme for fuel-efficient vehicles, and the acquisition tax incentive for clean-energy vehicles.

[30] In addition to the subsidy program, there was a cash-for-clunkers program for replacing gasoline vehicles registered for more than 13 years with fuel-efficient vehicles between 2009 and 2010. For details of the cash-for-clunkers program, see Kitano (2022).

Table 5: Eligibility Requirements for the Tax Incentive Measures (2006-2013)

Requirements	Acquisition Tax	Tonnage Tax	Automobile Tax
Panel A. Year 2006			
2010 FE target values +10% and ES 4 stars	150,000 JPY (2.2%)	-	25%
2010 FE target values +20% and ES 4 stars	300,000 JPY (2.2%)	-	50%
Panel B. Years 2007-2008			
2010 FE target values +10% and ES 4 stars	150,000 JPY	-	25%
2010 FE target values +20% and ES 4 stars	300,000 JPY (2.0%, 1.8%)	-	50%
Panel C. Years 2009-2011 (1st term)			
2010 FE target values +15% and ES 4 stars	50% (100%)	50% (100%)	25%
2010 FE target values +25% and ES 4 stars	75% (100%)	75% (100%)	50%
Panel D. Years 2012-2013 (2nd term)			
2015 FE target values and ES 4 stars	50%	50%	25%
2015 FE target values +10% and ES 4 stars	75%	75%	50%
2015 FE target values +20% and ES 4 stars	100%	100%	50%

Source: JAMA (2006, 2007, 2008, 2009, 2012).

Note: The table presents the eligibility requirements for the tax incentive measures from 2006 to 2013. In the requirements shown in the table, the 2010 (2015) FE target values refer to the 2010 (2015) fuel economy target values, and the ES 4 stars represent the emission-standard four stars, awarded to vehicles whose emission values represent a reduction of at least 75% from the 2005 regulatory levels (JAMA, 2006). The money amounts are what is deductible from the purchase price, and figures in percentage terms represent the reduction rates for each automobile-related tax. The reduction rates for hybrid vehicles are reported in parentheses. The light vehicle tax is not included in the tax incentive measures between 2009 and 2013.

2009 to September 2010 and then from January 2012 to September 2012.[31] In the first term, purchasers of a car achieving the 2010 fuel economy standard by 15% or more received a subsidy ES_{jt} of 100,000 JPY (50,000 JPY for mini-vehicles), and in the second term, purchasers of a car achieving the 2010 fuel economy standard by 25% or more or achieving the 2015 fuel economy standard received a subsidy of 100,000 JPY (70,000 JPY for mini-vehicles).

Since the data available in this study are annual, I define the first period for the tax incentives

[31] Initially, the second term was scheduled to last until December 2012, however, due to budget constraints, it was completed by September 2012.

and subsidy programs as the period from 2009 to 2011 and the second period as running from 2012 to 2013. As is discussed in later sections, even with such definitions, the results obtained in this study are consistent with external data. This indicates that summarizing the monthly regulatory effects into annual effects does not have a significant impact on the analysis.

Alternative Feebate Schemes I consider alternative feebate schemes in the fifth and sixth scenarios. Specifically, I design a product subsidy and a product tax, such that each of them determines the subsidy amounts and the tax burden based solely on the vehicle's CO_2 emissions per kilometer. Under the product subsidy and product tax schemes, the tax-inclusive prices p_{jt} are determined as follows:

$$p_{jt} = p_{jt}^e + p\left(p_{jt}^e, T_{jt}\right) - \tau^E \cdot \frac{1}{e_{jt}},$$

and

$$p_{jt} = p_{jt}^e + p\left(p_{jt}^e, T_{jt}\right) + \tau^E e_{jt}.$$

In the expressions, τ^E represents the subsidy/tax rates in each scenario, and e_{jt} denotes CO_2 emissions per kilometer (kg-CO_2/km) from driving car j in year t.[32] For the comparison with the policy effects of the actual feebate scheme and the fuel tax, I set τ^E such that the product subsidy and the product tax achieve the same environmental externalities as those occurring under the actual feebate and the current fuel tax.

6.2 Welfare Effects

I describe the computation of equilibrium prices after policy changes and then consider the results of simulation analysis.

I compute equilibrium prices by following the method proposed by Morrow and Skerlos (2011).[33] First, I divide the Jacobian matrix $\partial s_t(r_t)/\partial r_t$ into the following two matrices:

$$\frac{\partial s_t(r_t)}{\partial r_t} = \Lambda_t - \Gamma_t$$

where Λ_t is a $J_t \times J_t$ diagonal matrix and Γ_t is a $J_t \times J_t$ matrix with the following elements:

$$\Lambda_{jj,t} = \int\int (-\alpha_i) s_{ijt}\, dF(D)\, dG(v), \quad \Gamma_{jk,t} = \int\int (-\alpha_i) s_{ijt} s_{ikt}\, dF(D)\, dG(v)$$

Substituting these matrices into the pricing equations defined in (3.5), I have the following:[34]

$$p_t^e = \widehat{mc}_t + \zeta_t, \quad \text{where} \;\; \zeta_t = \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)(p_t^e - \widehat{mc}_t) - \Lambda_t^{-1} s_t^e(r_t). \tag{6.1}$$

[32] Per-kilometer CO_2 emissions e_{jt} is defined as fuel economy divided by CO_2 emission intensity per liter of fuel consumption. The CO_2 emission intensity per liter of gasoline (diesel) is 2.322 kg-CO_2/ℓ (2.621 kg-CO_2/ℓ), which is obtained by multiplying the calorific value per liter of gasoline, 34.6 MJ/ℓ (38.2 MJ/ℓ), by CO_2 emission intensity per calorific value of gasoline, 0.0671 kg-CO_2/MJ (0.0686 kg-CO_2/MJ).

[33] See Conlon and Gortmaker (2020) for the advantages of this method.

[34] See Appendix A.2 for derivation details.

Then, I iterate function $\widehat{mc}_t + \zeta_t \mapsto p_t^e$ until $\|\Lambda_t(p_t^e - \widehat{mc}_t - \zeta_t)\|_\infty < \epsilon^{tol}$ is satisfied and define the convergence points as the new equilibrium prices.

Given the equilibrium prices, I evaluate welfare effects of policies by using four measures for surplus as components of social welfare: consumer surplus (CS), producer surplus (PS), tax revenues (TR), and environmental externalities (EXT). Following Small and Rosen (1981), the change in consumer surplus due to a policy change is calculated as follows:

$$\Delta E(CS) = N_t \int\int \frac{1}{\alpha_i} \left[\log \left\{ \sum_{j=0}^{J_t} \exp\left(V_{ijt}^1\right) \right\} - \log \left\{ \sum_{j=0}^{J_t} \exp\left(V_{ijt}^0\right) \right\} \right] dF(D_i)\, dG(v_i),$$

where V_{ijt}^0 and V_{ijt}^1 represent the indirect utility under the baseline scenario and after a policy change, respectively. In addition, the other measures for surplus are calculated as follows:

$$\begin{aligned}
PS &= \sum_{f\in\mathcal{F}} \sum_{j\in\mathcal{J}_{ft}} \left(p_{jt}^e - \widehat{mc}_{jt}\right) N_t s_{jt}(r_t), \\
TR &= N_t \int\int \sum_{f\in\mathcal{F}} \sum_{j\in\mathcal{J}_{ft}} \left(p\left(p_{jt}^e, dr_{jt}\cdot T_{jt}\right) - ES_{jt} + T_{ijt}^{fuel}\right) s_{ijt}(r_t)\, dF(D_i)\, dG(v_i), \\
EXT &= N_t \times \mathrm{SCC} \times \int\int \sum_{f\in\mathcal{F}} \sum_{j\in\mathcal{J}_{ft}} e_{jt} M_{ijt} s_{ijt}(r_t)\, dF(D_i)\, dG(v_i),
\end{aligned}$$

where T_{ijt}^{fuel} in the second expression represents the fuel tax amount from household i's driving of car j in year t, and SCC in the last expression denotes the value of the social cost of carbon.[35] In the second expression, the tax revenues are comprised of the sum of tax revenues from the automobile-related taxes and fuel taxes minus resources used for the feebate policies. Consequently, I define the sum of the above as the total surplus (TS).

I first examine the impacts on outcome variables due to the policy changes. Table 6 reports the results for 2012. Each column in this table presents mean values of equilibrium tax-exclusive and tax-inclusive prices, sales volumes, total travel distances, and fuel usage obtained under each policy scenario. The table confirms that the fuel taxes are less likely to affect the equilibrium prices of automobiles, which is consistent with the results of Grigolon et al. (2018) and Tan et al. (2019). While the fuel tax with the current tax rate of 21,603 JPY/ton of CO_2 moderates the total vehicle kilometers traveled by 23% relative to the baseline scenario, it results, in turn, in an additional reduction of fuel usage. This occurs because the fuel tax improves the average fuel economy of purchased vehicles. Indeed, the sales-weighted average of fuel economy in 2012 under the current fuel tax is 20.81km/ℓ, which is higher by 1.6% than that obtained under the baseline scenario.

In contrast, the actual feebate scheme has significant impacts on the outcomes. As expected, the actual feebate scheme boosts the sales of automobiles, particularly the sales of fuel-efficient vehicles, raising the equilibrium tax-exclusive prices relative to the baseline scenario. Indeed, the feebate increases the sales volume by 28% on average and improves the sales-weighted average of

[35] The amount of fuel tax T_{ijt}^{fuel} is calculated by $(M_{ijt}/fe_{jt})(\tau^{gas} + \tau^{carbon})$, where fe_{jt} is the fuel economy (km/ℓ).

Table 6: Impacts of Policies on Various Outcomes in 2012

Scenarios	Tax-exclusive price p^e (million JPY)	Tax-inclusive price p (million JPY)	Sales	VKT (10,000km)	Fuel usage (kℓ)
Baseline	2.378	2.672	23,418	13,646	7,571
Fuel tax (per ton of CO_2)					
4,000 JPY (SCC)	2.378	2.672	22,814	13,002	7,170
21,603 JPY (Current)	2.379	2.673	20,342	10,573	5,691
Feebate					
Actual feebate scheme	2.382	2.594	30,016	17,438	9,324
Product subsidy	2.376	2.669	30,640	17,495	9,324
Product tax	2.385	2.679	17,749	10,495	5,691

Note: This table reports the mean values for each outcome variable.

fuel economy in 2012 by 3.7% relative to the baseline scenario. Meanwhile, the feebate pushes up fuel usage as well. I investigate the channels through which the feebate augments fuel usage in detail in a later section.

Table 6 also present the impacts of the alternative feebate schemes on outcomes. I perform a grid search to obtain the rate of subsidy/tax τ^E for each alternative scheme. For the product subsidy, that works out to τ^E of 15,000 JPY per kg-CO_2 per kilometer so that the product subsidy achieves the same externality as the actual feebate, and for the product tax, τ^E of 1.21 million JPY per kg-CO_2 per kilometer so that the product tax achieves the same externality as the current fuel tax rate.[36] Table 6 shows that the product subsidy achieves the same fuel usage as the actual feebate without involving a reduction in sales volumes. On the other hand, the product tax decreases the sales volumes considerably relative to the fuel tax. This is because the product tax must ensure the same fuel usage as the fuel tax by reducing the sales volumes to control the total driving demand, while the fuel tax can achieve the same objective by suppressing the driving demand directly.

Table 7 shows the results of welfare analysis using the sample for 2012. The first row reports the welfare obtained for the baseline scenario, and the remaining rows report the changes in welfare compared to that baseline. There are at least three relevant findings. The first finding is about the welfare effects of fuel taxes. Table 7 shows that the fuel taxes reduce environmental externalities with low burdens on consumers and producers. Under the fuel tax scenario with the tax rate of 21,603 JPY/ton of CO_2, externality reduces by 25% while the total revenues, or the tax burden,

[36] Under the estimated subsidy/tax rates, it turns out that the product subsidy scheme provides new car purchasers with a subsidy of 107,348 JPY on average, with a range of 45,445–233,153 JPY, and the product tax scheme imposes tax incidence of 190,718 JPY on average, with a range of 79,080–405,715 JPY.

Table 7: Welfare Effects in 2012 (in billions of JPY)

Scenarios	CS	PS	TR: Automobile-related taxes	TR: Fuel tax	TR: Feebate	EXT	TS
Baseline (in level)	474	1,775	275	0	0	11.6	2,513
Fuel tax (per ton of CO_2)							
4,000 JPY (SCC)	-13	-48	-8	+12	±0	-0.6	-57
21,603 JPY (Current)	-67	-244	-41	+53	±0	-2.9	-296
Feebate							
Actual feebate scheme	+134	+550	+81	±0	-172	+2.7	+590
Product subsidy	+144	+490	+67	±0	-165	+2.7	+533
Product tax	-115	-416	-67	±0	+96	-2.9	-500

Note: The first row lists the welfares obtained under the no-policy baseline scenario, and the remaining rows list changes in welfare associated with policy changes from the no-policy baseline. The sum of the tax revenue amounts from the automobile-related taxes and the feebate schemes refer to the annualized amounts paid by car owners over the ownership duration as a part of the rental price, not the lump sum amounts paid at the time of purchase.

increase by about 4%, suggesting that the fuel tax effectively reduces environmental externality. Meanwhile, the total surplus declines with the fuel tax rate, and particularly, this is also the case with the Pigouvian tax on fuel.

The explanation for the decline of the total surplus under the fuel tax scenarios requires me to consider the changes in welfare in automobile and fuel markets separately. As indicated in Table 7, the decrease in the total surplus due to the fuel tax comes mainly from decreases in the producer surplus arising in the automobile market targeted by households' discrete choices. For instance, in the case of the fuel tax of 4,000 JPY/ton of CO_2, the producer surplus decreases by about 48 billion JPY relative to the baseline scenario. Meanwhile, for the following reasons, I find that the decrease in the consumer surplus mainly comes from that arising in the fuel market targeted by households' continuous choices, and the remaining decrease in the consumer surplus arising in the automobile market is relatively small. Table 7 confirms that fuel tax revenues almost equate to the environmental externalities from driving, offsetting the negative externality in the fuel market. In addition, the fuel tax revenue and the decrease in consumer surplus in the fuel market should be of roughly the same magnitude because the estimated rebound effect implies that the driving demand is inelastic to the cost of driving per kilometer. Therefore, the remaining decrease in consumer surplus corresponds to that arising in the automobile market, which accounts for a small portion of the total decrease in the consumer surplus. This finding implies that the welfare loss borne by producers under the fuel tax scenario is the main driver of the decrease in the total surplus, and even the Pigouvian tax on fuel does not necessarily improve the overall economic welfare in the two markets.

The second finding is that the actual feebate augments the environmental externalities, while it raises the total surplus by 590 billion JPY in 2012 relative to the baseline scenario. A significant majority of this welfare gain comes through increases in consumer surplus and producer surplus. I believe this is attributable to the fact that the pre-existing automobile-related taxes already result in a deadweight loss in the automobile market, and the feebate plays a role in mitigating the market distortions.

Here, as shown below, the validity of the predicted result is ensured for the feebate scheme. Table 7 reports that the annualized feebate resource applied to the rental prices paid by car owners in 2012 is 172 billion JPY. This implies that an estimate of the feebate resource in 2012 amounts to about 631 billion JPY in total. Meanwhile, the actual expenditure for the subsidy program alone, which is a program of the feebate schemes, was 274.7 billion JPY in 2012. Therefore, when the expenditure for the subsidy program is added to the budget for the tax incentives, which is another program composing the feebate scheme, I find that the sum of these expenditures is close to the estimated expenditure above.[37]

The third finding relates to the welfare effects of the product subsidy and the product tax. Table 7 makes clear that the externality equivalent product subsidy is less costly and gains a slightly higher consumer surplus than the actual feebate scheme. The fact that the product subsidy determines the amount of subsidy depending solely on the CO_2 emissions per kilometer helps the product subsidy to improve the sales-weighted fuel economy relatively easily and achieve the same externality as the actual feebate, with the lower resource for the implementation.[38] On the other hand, the fuel tax at the current tax rate attains a higher total surplus than the externality equivalent product tax. In particular, the product tax causes large reductions in the consumer surplus and the producer surplus compared to the fuel tax, which is consistent with the result shown in Table 6. Moreover, the fuel tax requires fewer resources relative to the externality equivalent product tax. I find that the product tax is about 1.7 times more costly than the fuel tax to reduce environmental externalities by the same amount. The results suggest that the fuel tax is more cost-effective than the product tax.

Finally, I examine how much additional increase in the fuel tax rate decreases CO_2 emissions. Figure 2 shows the change in the CO_2 emissions when different carbon tax rates τ^{carbon} are added

[37] Note that since the subsidy program in the second period was completed by September 2012 because of budget constraints, and this study using yearly data does not control the monthly regulatory effects, my estimate of the resource used for the feebate is likely to overestimate the actual value.

[38] The product subsidy decreases the producer surplus and the tax revenue from the automobile-related taxes relative to the actual feebate scheme. This is attributable to the fact that the product subsidy scheme decreases the sales of fuel-inefficient vehicles with relatively large sizes compared with the actual feebate scheme.

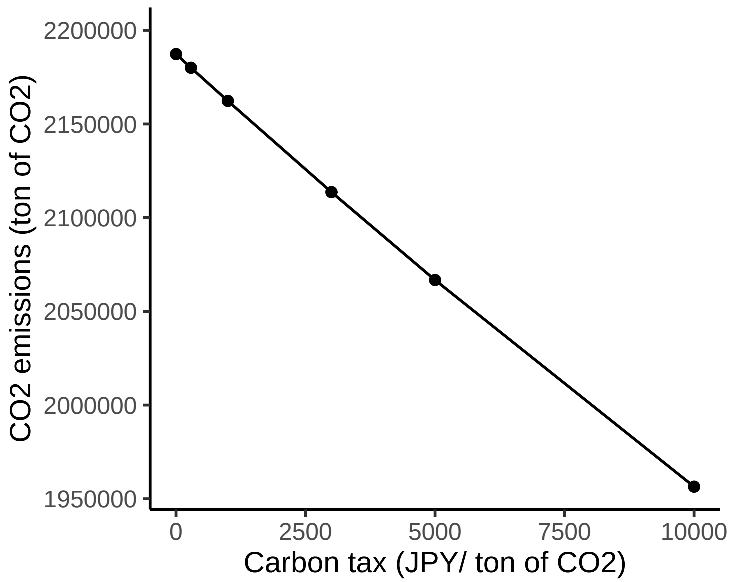

Figure 2: Change in the CO_2 Emissions

Note: The graph shows the change in the total CO_2 emissions from driving cars purchased in 2012 when the carbon taxes of 289, 1000, 3000, 5000, and 10000 JPY/ ton of CO_2 are added to the pre-existing fuel tax.

to the pre-existing fuel tax τ^{gas}. I experiment on the carbon tax rates of 289, 1000, 3000, 5000, and 10000 JPY/ton of CO_2. When the additional carbon tax is zero, and the fuel tax rate equates with the pre-existing fuel tax rate of 55.84 JPY/ℓ, the total CO_2 emissions amount to about 2.19 million tonnes of CO_2. When the carbon tax of 10,000 JPY/ton of CO_2 (26.2 JPY/ℓ) is added, the CO_2 emissions drop by 10.6%, meaning that a 1% increase in the additional carbon tax leads to a 0.22% reduction in CO_2 emissions.

6.3 Distributional Impacts

Next, I analyze the distributional impacts of the policies. To make the comparison fair, I focus on the impacts of the fuel tax at the current tax rate and the externality equivalent product tax. Through the analysis, I argue the regressivity of the two policies.

Table 8 reports the result. It can be seen that the impacts of the fuel tax and the product tax shown in Panels A and B significantly vary by income class. First, the fuel tax works on high-income households to purchase fuel-efficient vehicles. Since the low-income households originally tend to purchase fuel-efficient vehicles, the improvement of the average fuel economy is small in the low-income class. Meanwhile, high-income households who drive long distances greatly react to the fuel tax, purchasing fuel-efficient vehicles to save on driving costs. In contrast, the product tax largely decreases the sales in the low-income class. Particularly, the product tax does not reduce the distance traveled as much as the sales amount partly because the product tax induces the rebound

Table 8: Policy Impacts by Income Quintile in 2012

Income quintile	Sales (1,000)	VKT (1,000km)	Fuel economy (km/ℓ)	ΔCS (billion JPY)	$\lvert\Delta CS\rvert$/ ton CO_2 (JPY)	$\lvert\Delta CS\rvert$/ income
Panel A. Fuel tax						
1	2.5 (-13.1%)	1.1 (-22.5%)	21.4 (+1.2%)	-6.20	94,869	2.43
2	2.9 (-13.3%)	1.3 (-23.0%)	21.3 (+1.3%)	-7.87	92,430	1.41
3	3.3 (-13.4%)	1.6 (-23.0%)	21.2 (+1.4%)	-9.49	91,700	1.08
4	4.1 (-13.3%)	2.1 (-22.7%)	21.0 (+1.5%)	-12.64	92,691	0.95
5	7.1 (-13.0%)	4.4 (-22.4%)	20.2 (+2.0%)	-29.19	91,530	1.26
Panel B. Externality equivalent product tax						
1	2.0 (-28.2%)	1.0 (-27.8%)	21.6 (+2.2%)	-13.19	165,259	5.17
2	2.5 (-27.3%)	1.2 (-26.9%)	21.5 (+2.2%)	-15.85	160,994	2.85
3	2.8 (-26.3%)	1.5 (-25.8%)	21.4 (+2.2%)	-18.31	159,587	2.08
4	3.6 (-25.0%)	2.0 (-24.5%)	21.2 (+2.3%)	-23.17	159,169	1.75
5	6.7 (-20.5%)	4.5 (-19.4%)	20.2 (+2.2%)	-42.61	158,095	1.84

Note: The rate of the fuel tax is set at the current tax rate of 21,603 JPY/ton of CO_2. The figures for the fuel economy indicate the sales-weighted averages. ΔCS represents the change in the consumer surplus from the no-policy baseline, and $\lvert\Delta CS\rvert$ the absolute value.

effect.

Second, both policies impose heavy costs on low-income classes to abate a ton of CO_2. The change in consumer surplus as a percentage of CO_2 reduction allows me to be interpreted as a shadow cost of a policy. Table 8 shows that, in the lowest-income group, the shadow costs of the fuel tax and the product tax to reduce a ton of CO_2 are about 94,000 JPY and 165,000 JPY, respectively. I find that because the low-income households already own fuel-efficient vehicles and drive not so long distances before the imposition of taxes, the additional costs for CO_2 abatement come to be high for the low-income households. In contrast, since high-income households fully have an abatement potential compared to low-income households, the shadow costs are relatively low for high-income households. In addition, compared the shadow costs of both policies, I find the fuel tax is 1.7 times less costly than the product tax in all income classes.

Finally, the changes in consumer surplus as a percentage of income become larger as lower-income classes. Specifically, both policies are regressive until the fourth quintile and in turn progressive in the highest income group. Additionally, the results show that the product tax is slightly more regressive than the fuel tax, although the difference is quite small (see also Figure A.1 in the appendix).

6.4 Decomposition of CO_2 Emissions

I conduct a decomposition analysis to disentangle the sources of environmental externalities arising under policy scenarios. Through the decomposition analysis of CO_2 emissions, it is evident which factor contributes to the change in CO_2 emissions, and particularly the extent to which the rebound effect estimated in the previous section affects the externality.

Following D'Haultfœuille et al. (2014), I define some potential variables for the decomposition analysis. Let $d \in \{0, 1\}$ denote a policy indicator that takes zero before a policy introduction (a policy status that corresponds to the baseline scenario in the simulation analysis) and one after a policy introduction. Denoting $\mathrm{CO}_{2,t}(d)$ potential total CO_2 emissions arising from driving cars purchased in year t with policy status d, the variation in CO_2 emissions in year t due to a policy introduction Δ_t is written as

$$\Delta_t = \mathrm{CO}_{2,t}(1) - \mathrm{CO}_{2,t}(0),$$

where

$$\mathrm{CO}_{2,t}(d) = N_t \int \int \sum_{j=1}^{J_t} e_{jt} M_{ijt}(d) s_{ijt}(d) \, dF(D_i) \, dG(v_i).$$

In the expression, $M_{ijt}(d)$ is the annual travel distance of car j purchased by household i in year t with policy status d, and $s_{ijt}(d) = s_{ijt}(r_t(d))$ is a choice probability evaluated at equilibrium rental prices r_t. In what follows, to control for the impacts of other vehicle attributes than e_{jt} on CO_2 emissions, I separate vehicles into K groups of $\{\mathcal{J}_1, \ldots, \mathcal{J}_K\}$ based on vehicle attributes in x_{jt} and calculate Δ_t by adding up the changes in CO_2 emissions by groups.[39]

[39] In practice, I form 100 groups $\{\mathcal{J}_1, \ldots, \mathcal{J}_{100}\}$ based on vehicle attributes x_{jt}.

I decompose the change in CO_2 emissions Δ_t into the following four components:[40]

$$\Delta_t = \sum_{k=1}^{K} \int\int \Bigg[\underbrace{Q_{k,t}(0) \sum_{j \in \mathcal{J}_k} (e_{jt} - \bar{e}_{k,t}) M_{ijt}(1) \Delta s_{ijt}^{inside}}_{\text{Composition effect}} + \underbrace{Q_{k,t}(0) \bar{e}_{k,t} \sum_{j \in \mathcal{J}_k} (M_{ijt}(1) - \bar{M}_{k,it}(1)) \Delta s_{ijt}^{inside}}_{\text{Rebound effect}}$$

$$+ \underbrace{N_t \sum_{j \in \mathcal{J}_k} e_{jt} (\Delta M_{ijt}) s_{ijt}(0)}_{\text{Fuel cost effect}} + \underbrace{N_t \left(\sum_{j \in \mathcal{J}_k} e_{jt} M_{ijt}(1) s_{ijt}^{inside}(1) \right) \sum_{j \in \mathcal{J}_k} \Delta s_{ijt}}_{\text{Fleet size effect}} \Bigg] \, dF(D_i) \, dG(v_i),$$

where

$$Q_{k,t}(0) = N_t \sum_{j \in \mathcal{J}_k} s_{ijt}(0), \quad s_{ijt}^{inside}(d) = \frac{s_{ijt}(d)}{\sum_{j \in \mathcal{J}_k} s_{ijt}(d)},$$

$$\Delta M_{ijt} = M_{ijt}(1) - M_{ijt}(0), \ \Delta s_{ijt} = s_{ijt}(1) - s_{ijt}(0), \ \text{and} \ \ \Delta s_{ijt}^{inside} = s_{ijt}^{inside}(1) - s_{ijt}^{inside}(0).$$

Additionally, $\bar{e}_{k,t}$ and $\bar{M}_{k,it}(d)$ represent the average CO_2 emissions per kilometer e_{jt} and the average travel distance $M_{ijt}(d)$ in group k, respectively. The first term in the above expression refers to a composition effect, which captures an expected decrease of CO_2 emissions caused by the change in sales mix when one assumes driving distance stays unchanged against the policy introduction. If the elasticity of driving distance with respect to a policy change is assumed to be zero, CO_2 emissions should decrease in response to the introduction of the fuel tax or the feebate; they are expected to encourage households to buy fuel-efficient cars. Therefore, the composition effect will be negative when the expected policy effect is sufficiently large.

In practice, however, the driving distance will change with policy statuses. There are two channels through which a policy change affects driving distance. The first channel is when a household changes their car choice depending on policy status d. The effect through the first channel refers to the rebound effect. In the above expression, the rebound effect captures a correlation between the deviation of $M_{ijt}(1)$ from the mean value and the change in market share within the inside options Δs_{ijt}^{inside}. The second channel arises when a household purchases the same car in either policy status $d = 0, 1$. The effect through the second channel, which I call the fuel cost effect, is the direct effect of the change in the fuel cost on driving distance. Since the feebate does not directly change the fuel cost when a household purchases the same car in either policy status, the fuel cost effect comes to zero. On the other hand, a fuel tax affects driving demand directly. This

[40] The transformation for the CO_2 decomposition used in this study is slightly different from that proposed by D'Haultfœuille et al. (2014). In the decomposition of D'Haultfœuille et al. (2014), the composition effect and the rebound effect contain a part of the fleet size effect because the difference between market shares before and after a policy introduction, $s_{ijt}(1) - s_{ijt}(0)$, that appears in their transformation includes not only the relative changes in market shares within the inside options $s_{ijt}^{inside}(1) - s_{ijt}^{inside}(0)$ but also the change in the aggregate market share $\sum_{j=1}^{J_t} (s_{ijt}(1) - s_{ijt}(0))$. As shown below, I modify their transformation to separate these effects.

Table 9: CO_2 Decomposition in 2012

	Fuel tax		Actual feebate	
	Δ_t	%	Δ_t	%
Total	-711.2	-100.0	670.0	100.0
Composition effect	-12.8	-1.8	-44.2	-6.6
Rebound effect	1.6	0.2	3.0	0.5
Fuel cost effect	-123.9	-17.4	0.0	0.0
Fleet size effect	-576.1	-81.0	711.2	106.2

Note: The rate of the fuel tax in the first column is set at the current tax rate of 21,603 JPY/ton of CO_2. This table reports the change in CO_2 emissions Δ_t from the no-policy baseline and the contribution rate (%) of the four effects. The unit of Δ_t is 1,000 tonnes of CO_2.

direct effect of the fuel tax is captured by the fuel cost effect. Finally, the fourth effect, the fleet size effect, captures the change of CO_2 emissions arising from a change in the number of cars owned by households due to a policy introduction. The fleet size effect here is obtained by the expected CO_2 emissions arising from driving a car multiplied by the change in sales of automobiles.

Table 9 shows the results of the decomposition analysis.[41] The table reports changes in CO_2 emissions Δ_t caused by each decomposed effect and the contribution ratios. As expected, the composition effect contributes to reductions in the CO_2 in all scenarios since each policy introduction changes the fleet composition and occasions the sales shift toward fuel-efficient cars. Meanwhile, the reductions in the CO_2 emissions from the composition effect are partially offset by the rises in the CO_2 emissions resulting from the rebound effect. In particular, the actual feebate scheme results in a large rebound effect compared with the fuel tax scenario. The rebound effect induced by the feebate contributes to the increase in the CO_2 emissions and cancels out about 7% of the decrease in the emissions resulting from the composition effect. In contrast, the fuel tax succeeds in controlling the rebound effect. Although the fuel tax generates a small rebound effect, I find that the increase in CO_2 emissions due to the rebound effect is offset by the decrease in emissions due to the fuel cost effect. Furthermore, the reduction in the CO_2 emissions in the fuel tax scenario is found to be driven primarily by the fuel cost and fleet size effects.

[41] This analysis focuses only on the policy impacts on new vehicles purchased in the corresponding year. I expect the estimates of the fuel cost effect and the fleet size effect to change when considering the impacts on vehicles already owned by households who choose the outside option in the year. Because the fuel tax impacts not only the mileage of vehicles purchased in the year but also the mileage of vehicles already owned, the fuel cost effect becomes larger than that reported in Table 9. In addition, the magnitude of the fleet size effect becomes smaller because policies are expected to reduce CO_2 emissions from old fuel-inefficient vehicles by replacing them with new fuel-efficient vehicles.

7 Conclusion

This study examines the welfare effects of the fuel tax and feebate policies in the Japanese new car market, particularly focusing on the evaluation of the feebate as a green economic stimulus program and the distributional impacts of the two policies. I employ a model with two decisions—on car ownership and utilization—on the demand side and identify model parameters by using both micro-level data from the household survey and macro-level aggregate data. Hence, the intent of this study is in line with a strand of the Micro BLP literature, such as Petrin (2002), Berry et al. (2004), and Gloosbee and Petrin (2004), in which a method is developed allowing for a more robust identification of parameters by adding moment conditions formed by micro-level data to those established using aggregate data.

To answer the two empirical questions proposed in the introduction, I evaluate several policy scenarios in the counterfactuals using four measures for social surplus. The result suggests that the Japanese feebate policies significantly stimulate demand while augmenting the environmental externalities. In particular, by a decomposition analysis, I find that the rebound effect induced by the feebate cancels out about 7% of the reduction in CO_2 emissions that would originally have been attained by the fuel economy improvement. Therefore, I conclude that it is difficult to achieve both economic and environmental goals simultaneously with the feebate policy alone, and Pigouvian policies such as the fuel tax are required to supplement the feebates. In addition, I also analyze the distributional impacts and argue the regressivity of the two policies. It makes clear that there is not much difference in terms of regressivity between the fuel tax and the product tax, rather with the latter being slightly more regressive than the former. Moreover, I find that the fuel tax at the current tax rate in Japan is 1.7 times less costly than the product tax for all income classes to reduce environmental externalities by the same amount.

I acknowledge some limitations to this study. First, I do not consider households' irrationality in facing the vehicle choice. For example, Grigolon et al. (2018) assume the situation in which households, at the time of purchasing, undervalue the future fuel cost savings obtained by purchasing fuel-efficient cars and evaluate the welfare effects of a fuel tax and a product tax, with the belief error being included. Although Grigolon et al. (2018) and other papers studying this issue conclude that there is not much such undervaluation of households, if there is, my study may underestimate the social welfare of the feebate policy. Second, I use static models on the demand and supply sides, and particularly in the supply model, treat only prices as a variable that firms can manipulate endogenously. Therefore, the estimation results should be interpreted as short-term policy impacts. Designing a model to account for the dynamic responses of households and firms is required to analyze the long-term effects of the fuel tax and feebate. Finally, I need to undertake a more careful analysis of optimal policy when considering the two markets targeted by the DCC model. A discussion of the optimal policy is expected to become more complex when a policy designed to reduce a market distortion affects both markets targeted by the discrete and the continuous choices. I would like to make these points the subject of future work.

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A Appendix

A.1 Derivation for the Direct Utility Function

I derive the direct utility function under the indirect utility specified in this paper. By solving the following optimization problem, I can obtain the direct utility function for household i conditional on purchasing car j in year t (Varian, 1992):

$$\begin{aligned}
&\min_{p^M_{jt}, p^X_t} \quad \alpha\left(\frac{y_i - r_{jt}}{p^X_t}\right) + \lambda \exp\left(x'_{jt}\beta + h'_i\gamma - \rho_i \frac{p^M_{jt}}{p^X_t}\right) + w'_{jt}\psi + \xi_{jt} + \varepsilon_{ijt} \\
&\text{subject to} \quad p^M_{jt} M_{ijt} + p^X_t X_{it} = y_i - r_{jt}
\end{aligned}$$

Note that, in this derivation, the price of the Hicksian composite good p^X_t explicitly shows up in the functions, although p^X_t is set to one in the main body of this paper. The Lagrange function with its multiplier μ takes the following form:

$$\mathcal{L} = \alpha\left(\frac{y_i - r_{jt}}{p^X_t}\right) + \lambda \exp\left(x'_{jt}\beta + h'_i\gamma - \rho_i \frac{p^M_{jt}}{p^X_t}\right) + w'_{jt}\psi + \xi_{jt} + \varepsilon_{ijt} - \mu\left(y_i - r_{jt} - p^M_{jt} M_{ijt} - p^X_t X_{it}\right)$$

Then, the optimization problem yields the first-order conditions:

$$\begin{aligned}
&-\frac{\lambda\rho_i}{p^X_t} \exp\left(x'_{jt}\beta + h'_i\gamma - \rho_i \frac{p^M_{jt}}{p^X_t}\right) + \mu M_{ijt} = 0 \\
&-\frac{\alpha(y_i - r_{jt})}{\left(p^X_t\right)^2} + \frac{\lambda\rho_i p^M_{jt}}{\left(p^X_t\right)^2} \exp\left(x'_{jt}\beta + h'_i\gamma - \rho_i \frac{p^M_{jt}}{p^X_t}\right) + \mu X_{it} = 0 \\
&p^M_{jt} M_{ijt} + p^X_t X_{it} = y_i - r_{jt}
\end{aligned}$$

Arranging these conditions, I have the direct utility function as follows:

$$\alpha X_{it} + \left\{1 + \log\left(\frac{\lambda\rho_i}{\alpha}\right) + x'_{jt}\beta + h'_i\gamma - \log M_{ijt}\right\} \frac{\alpha M_{ijt}}{\rho_i} + w'_{jt}\psi + \xi_{jt} + \varepsilon_{ijt}.$$

Note here that the second term in the expression is proven to be concave in driving demand M_{ijt}.

A.2 Derivation for the equation (6.1)

In this subsection, I derive the equation (6.1). First, substituting marginal costs mc_t in (3.5) with the estimates $\widehat{mc}_t$ yields

$$p^e_t = \widehat{mc}_t + \Omega_t^{-1} s^e_t(r_t).$$

Then, I transform the second term by following the matrix algebra and obtain the desired result.

$$
\begin{aligned}
p_t^e &= \widehat{mc}_t + (S_t \odot \Omega_t^*)^{-1} s_t^e(r_t) \\
&= \widehat{mc}_t + (-\Lambda_t + \Gamma_t \odot \Omega_t^*)^{-1} s_t^e(r_t) \\
&= \widehat{mc}_t + \left[-\Lambda_t^{-1} + \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*) \left\{ E - \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*) \right\}^{-1} (-\Lambda_t)^{-1} \right] s_t^e(r_t) \\
&= \widehat{mc}_t - \Lambda_t^{-1} s_t^e(r_t) + \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*) \left[-\Lambda_t \left\{ E - \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*) \right\} \right]^{-1} s_t^e(r_t) \\
&= \widehat{mc}_t - \Lambda_t^{-1} s_t^e(r_t) + \Lambda_t^{-1}(\Gamma_t \odot \Omega_t^*)(p_t^e - \widehat{mc}_t),
\end{aligned}
$$

where E denotes an indentity matrix. In the transformation above, note that $\Lambda_t \odot \Omega_t^* = \Lambda_t$ as Λ_t is a diagonal matrix and the diagnal elements of the ownership matrix Ω_t^* are all ones. Additionally, I apply the Woodbury formula to get the third equation.

A.3 Additional Figures and Tables

Table A.1: Automobile Tax Amounts

displacement (ℓ)	tax amount (JPY)	displacement (ℓ)	tax amount (JPY)
<1.0	29,500	3.5-4.0	66,500
1.0-1.5	34,500	4.0-4.5	76,500
1.5-2.0	39,500	4.5-6.0	88,000
2.0-2.5	45,000	>6.0	111,000
2.5-3.0	51,000	Kei car	7,200
3.0-3.5	58,000		

Table A.2: Fuel Economy Standards

2010 Standard		2015 Standard			
curb weight (kg)	target value (km/ℓ)	curb weight (kg)	target value (km/ℓ)	curb weight (kg)	target value (km/ℓ)
<703	21.2	<601	22.5	1531-1651	13.2
703-828	18.8	601-741	21.8	1651-1761	12.2
828-1016	17.9	741-856	21.0	1761-1871	11.1
1016-1266	16.0	856-971	20.8	1871-1991	10.2
1266-1516	13.0	971-1081	20.5	1991-2101	9.4
1516-1766	10.5	1081-1196	18.7	2101-2271	8.7
1766-2016	8.9	1196-1311	17.2	>2271	7.4
2016-2266	7.8	1311-1421	15.8		
>2266	6.4	1421-1531	14.4		

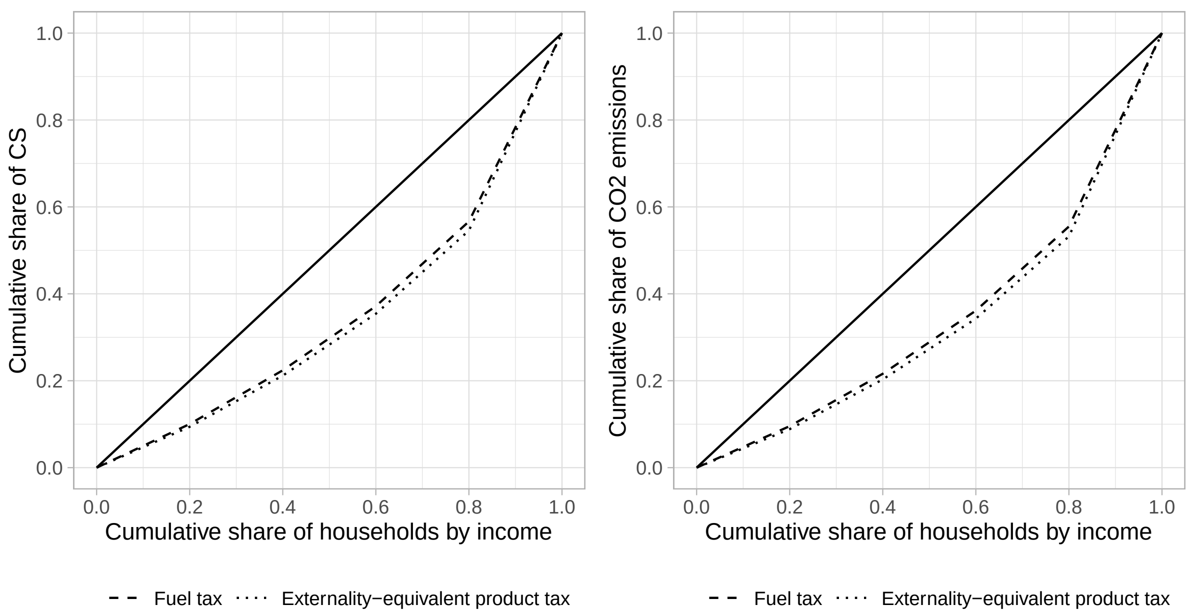

Figure A.1: Regressivity of the fuel tax and product tax

Note: The figures show the Lorenz curves obtained under the scenarios for the fuel tax at the current tax rate in Japan and the externality equivalent product tax. The left and right figures take the cumulative shares of consumer surplus and CO_2 emissions as the vertical axises, respectively. The 45-degree line indicates the situation in which households in each income class incur the tax burden or emit CO_2 evenly.