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Can Green Car Taxes Restore Efficiency? Evidence from the Japanese New Car Market

Yoshifumi Konishi
Meng Zhao

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TOKYO CENTER FOR ECONOMIC RESEARCH
1-7-10-703 Iidabashi, Chiyoda-ku, Tokyo 102-0072, Japan

Abstract

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Yoshifumi Konishi
TCER
and
Sophia University
Faculty of Liberal Arts
7-1 Kioi-cho, Chiyoda-ku, Tokyo 102-8554, Japan
y-konishi@sophia.ac.jp

Meng Zhao
University of Tokyo
Faculty of Economics
7-3-1, Hongo, Bunkyo-ku, Tokyo 113-0033, Japan
mzkonishi@gmail.com

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Can Green Car Taxes Restore Efficiency?
Evidence from the Japanese New Car Market*

Yoshifumi Konishi†
Faculty of Liberal Arts
Sophia University

and

Meng Zhao
Department of Economics
The University of Tokyo

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†Corresponding author: y-konishi@sophia.ac.jp.

Abstract: We investigate the efficiency of vehicle taxation in second-best settings. A random-coefficients logit model is estimated for quarterly automobile sales data between 2004 and 2012 from the Japanese new car market. The quasi-experimental nature of the data is exploited in two ways. First, we construct the location of product-specific tax rates in the characteristics space as a set of instruments to control for endogeneity of observed car prices. Second, the large and persistent variation in effective vehicle prices, caused due to Japan's green car tax policy since 2009, are used to obtain consistent estimates of the own- and cross-price elasticities. Our results indicate evidence for substantial scale and composition effects: Though the policy successfully reduced sales-weighted average emissions, it also increased total sales substantially. Consequently, the policy-induced reduction in annual vehicle CO_2 emissions was small. In contrast, a modified version of the emissions-based vehicle tax à la Fullterton and West (2002), based on the fuel efficiencies of car models, could have reduced annual vehicle CO_2 emissions substantially more while increasing total economic surplus relative to the no policy counterfactual.

Key Words: Random-coefficients logit, discrete choice models, product differentiation, automobiles, carbon emissions, environmental policies

1. Introduction

Emissions from motor vehicles continue to present a daunting challenge to policy practitioners. An efficient emissions tax would be infeasible, either economically because measurement of such emissions would be inaccurate and expensive (Fullerton and West, 2002; Fullerton and Gan, 2005), or politically because monitoring of such emissions would likely intrude drivers' privacy. The existing literature (Fullerton and West, 2002; Innes, 1996) suggests that at least in theory, some optimal combinations of car and gasoline taxes can induce the first-best outcome by correctly accounting for the negative externality cost of vehicle emissions, which inherently depend on vehicle miles traveled (VMT), fuel types as well as car characteristics (e.g., engine size, combustion system, and pollution control equipment).[1] Taken in this view, several developed countries have recently gone through green reforms on vehicle taxation. Examples include France's subsidy program, Germany's car tax reform, Japan's ecocar subsidy program, Sweden's green car rebate program, and U.S. accelerated vehicle retirement program.

Optimal coordination of the fiscal instruments is, however, complicated for a number of reasons. First, emissions from motor vehicles include not only carbon dioxides (CO_2), which depend only on fuel consumption, but also carbon monoxide (CO), nitrogen oxides (NO_x), and reactive hydrocarbons (HC), whose emissions per unit of fuel consumption may vary substantially due to vehicle characteristics. In theory, optimal vehicle taxation must reflect the negative external costs associated with vehicle choice that are *not* internalized by optimal fuel taxation. Because consumers choose car characteristics by partly internalizing the negative external cost of fuel consumption, the optimal amount of vehicle tax may be lower than the negative externality costs of their vehicle choice in the absence of fuel taxation (Fullerton and West, 2002).[2]

Second, automobile industries are oligopolistic industries with a small number of automakers competing in multiproduct pricing. The markup pricing tends to under-provide the goods relative to the perfectly competitive equilibrium. On the other hand, the negative externality associated with vehicle emissions implies that the market equilibrium tends to over-provide the goods relative to the social optimum. Which of the effects tends to dominate is largely an empirical question. In this context, vehicle tax reforms must take into account its effect on extensive margins. Indeed, green car tax reforms often effectively subsidize purchase of new or more fuel efficient cars, either relative to the pre-existing tax system or the efficient benchmark, which may result in a perverse *entry-inducing* effect (Baumol, 1988). Such an entry-inducing effect might be potentially very large in countries where there are a large pool of potential car owners.[3] Whether such an entry-inducing effect improves efficiency depends largely on the pre-existing market conditions.

The primary objective of the present paper is, therefore, to empirically investigate the effects of vehicle taxation on vehicle emissions and social welfare, taking into account these second-best settings and the policy-induced substitution patterns. To that end, we focus on the Japanese new car market and CO_2 emissions from the lifespans of the new cars. The Japanese new car market is characterized by an oligopolistic industry with nine domestic automakers. The pre-existing taxation system consists of both a gasoline tax and a suit of vehicle taxes based on car characteristics. Most importantly, the Japanese government implemented a series of economic incentive policies

[1] The result assumes homogeneity of consumer preferences. With heterogeneous consumers, the separate car and gasoline taxes can only achieve the second-best (or ex ante) optimum (see Fullterton and West, 2002).

[2] Gasoline taxes in many countries are set either substantially higher or lower than the estimated negative externality cost (Ley and Boccardo, 2010).

[3] For example, in Japan, a large number of driver's license holders in urban areas are 'paper drivers' with no car ownership because reliable public transportation systems and high parking costs induce them to be so, yet they still hold the licenses as their primary ID cards.

on car taxes, called Ecocar Subsidy (ES) and Ecocar Tax Credits (ETC) since 2009. Their unique features created large exogenous variations in the effective prices of cars across brands and over time. Exploiting this quasi-experimental setup, we first estimate the structural parameters of the consumer demand for new passenger cars, and then use the estimated demand to simulate the policy impacts on expected annual vehicle CO_2 emissions and total economic surplus (i.e., the sum of tax revenues, industry profits, and compensating variation), relative to the no-policy counterfactual and relative to the emissions-based vehicle tax in the spirit of Fullerton and West (2002).

There are, however, a number of empirical challenges in doing so. First, to investigate the question at hand, one would ideally like to fit the behavioral model with aggregate market-level sales data and estimate own- and cross-price elasticities for *all* brands. In the earlier literature (e.g., Bento *et al.*, 2009; Feng *et al.*, 2013; Goldberg, 1998; West, 2004), survey-based micro data are often used to make inferences about the policy impacts. Such an approach has an obvious advantage that individual-level heterogeneity in tastes for car and driving choice can be properly accounted for. However, these survey-based studies often artificially aggregate choices into a smaller number of categories (e.g., small compact, large compact, small SUVs, large SUVs etc), as the number of observed purchases in the survey data is typically very small compared to the number of brands available in the market. This is problematic in our context, as we observe substantial variation in fuel efficiency even within car categories of similar sizes. Hence, such artificial aggregation may result in misleading inferences about the policy impacts. Second, car prices are a well-known endogenous variable for at least two reasons. There are car characteristics (e.g., brand images, style, and prestige) that consumers and firms observe but are unobservable or unquantifiable to the researchers that are likely correlated with the market prices of cars. Moreover, because individual consumers often negotiate with retailers on prices, observed sales prices such as suggested retail prices or average market prices may have measurement errors. Lastly, fitting the market-level data with conventional logit models is known to result in unrealistic or counterintuitive substitution elasticities (Nevo, 2000; 2001).

To overcome these challenges, we employ a widely accepted random-coefficients (RC) logit model, known as the Berry-Levinsohn-Pakes (BLP) estimator. The BLP estimator was developed in Berry (1994) and Bery, Levingsohn, and Pakes (1995), and has been successfully applied in a number of empirical studies since then (e.g., BLP, 1999; Nevo, 2001; Petrin, 2002; Villas-Boas, 2007). The method makes use of market-level data only (so does not require consumer-level data), deals with endogeneity of prices, yet allows for estimation of rich and realistic substitution patterns, which has been the problem with earlier logit models. Its main drawback, however, has been the computational burden and numerical accuracy, as it requires running a nested fixed point (NFP) algorithm as an inner-loop subroutine for the generalized method-of-moments (GMM) estimation. To circumvent some of the computational problems, we take advantage of recent advances in the study of the BLP estimator (Dube *et al.*, 2012; Knittel and Metaxoglou, 2012).

For estimation of the model, we make use of detailed market-level data on sales by car model and quantifiable car characteristics including prices and taxes collected between 2004 and 2012. This study period includes the policy period (April, 2009 – December, 2012), during which the Japanese government implemented a series of subsidy and tax incentive programs for low-emission, fuel-efficient cars. We make use of this quasi-experimental setup in two innovative ways. First, we take advantage of the policy-driven large variation in the effective car prices across car models and over time to obtain the consistent estimates of own- and cross-price elasticities not only among the large number of car models but also with respect to the outside option. This allows us to distinguish between the effect of inducing more consumption (called the *scale effect* hereafter) and the effect of inducing substitution into more ecofriendly cars (called the *composition effect* hereafter). Consequently, we are able to make more accurate inferences about the impacts of the policy against the counterfactuals.

Second, we exploit the exogenous changes in the tax rates as instruments to take care of the price endogeneity. Implementation of the BLP estimator requires a set of instruments for identification of parameter estimates. Earlier studies often used the 'location' of observed product characteristics in the product space as instruments, arguing that such product-location variables are at least predetermined prior to the determination of consumer demand. Though this may be a valid assumption in some contexts, there are growing concerns with the validity of the assumption. In our context, the location of observed product attributes may be highly correlated with brand images (e.g., Toyota Prius' brand image may come from its high fuel efficiency). Moreover, sales subsidiaries of the automakers tend to offer a variety of sales promotions based on product-specific sales channels. Hence, the location of product attributes may be causally correlated with the measurement errors in observed prices. Indeed, our earlier estimation runs have revealed a number of concerns with the validity of the traditional IVs. We circumvent these concerns by constructing variables that represent the location of vehicle tax rates in the characteristics space in a manner analogous to the product location variables. The vehicle taxes in Japan are indeed a function of observed product characteristics (i.e., prices, vehicle weight, and displacement size). Hence, they are correlated with prices. Yet, the frequent *changes* in the location of the effective tax rates over the study period are unlikely to be causally related to the unobserved product characteristics such as style and brand images, which presumably stay more or less constant over time. We document the problems we encountered with the traditional IVs in Section 4.2 and report the results that indicate the success of our IVs in Section 6.

Our results indicate evidence for both substantial scale and composition effects of the ES/ETC policy. Though the policy successfully reduced sales-weighted average emissions, it also increased total sales substantially. Consequently, the policy-induced reduction in annual CO_2 emissions was only 0.5% relative to no policy scenario. Albeit its negligible impacts on vehicle CO_2 emissions, the ES/ETC policy was indeed welfare-enhancing because it substantially increased total economic surplus (i.e., the sum of compensating variation, industry profits, and tax revenues) relative to no such policy.[4] To further investigate the efficiency properties of vehicle taxation, we also examine the effects of an emissions-based vehicle tax (EVT) in the spirit of Fullerton and West (2002). In first-best settings, the EVT policy should charge a tax only on the part of externality costs of vehicle characteristics that are not internalized by a complementary gasoline tax. Because motor vehicles are already heavily taxed based on vehicle weights and displacement levels, we first consider, as a benchmark, the 'EVT-rebate' policy that would offer a rebate based on fuel efficiencies car models to account for part of the external costs that are already internalized by the gasoline tax. As expected, we find that such a policy would have increased both annual vehicle CO_2 emissions and total economic surplus substantially. The estimated gradient of the EVT policy between the vehicle emissions and the total economic surplus is approximately 8,700 yen per ton of vehicle CO_2 emissions. Hence, the EVT-rebate policy would have been welfare-improving only relative to no policy if the negative external cost per ton of vehicle emissions was less (more) than 8,700 yen. Interestingly, our results also indicate that the EVT-rebate policy would have been strictly welfare-decreasing relative to the ES/ETC policy — it would result in more vehicle CO_2 emissions and less total economic surplus than the ES/ETC policy. Given this finding, we simulate the impacts of a modified version of the EVT policy based upon the ES/ETC policy (instead of the pre-existing

[4]In the literature, it is customary to calculate total economic surplus as the sum of consumer surplus, producer surplus, and tax revenues, less environmental damages. In this paper, however, we only report changes in vehicle CO_2 emissions and total economic surplus excluding environmental damages. We do not attempt to quantify the monetary value of environmental damages associated with CO_2 emissions because estimates of the monetary value are known to vary substantially across studies (see, for example, Tol, 2005).

tax system). We find that a version of the EVT-tax policy, which would *add a tax* (instead of a rebate) based on fuel efficiencies of car models *on top of the ES/ETC policy*, could have reduced vehicle CO_2 emissions substantially more, yet still increase the total surplus relative to the no policy counterfactual.

Our study complements a large body of literature that has empirically investigated the impacts of a variety of fiscal policy instruments on the demand for automobiles and vehicle miles traveled. Goldberg (1998) used the U.S. Consumer Expenditure Survey for 1984-1990 to examine the effects of the Corporate Average Fuel Economy (CAFE) Standards on automobile sales, prices, and fuel consumption. She finds empirical evidence that the CAFE standards indeed worked as an implicit tax/subsidy on size of cars, effectively inducing consumers to purchase smaller cars. West (2004) used the same survey data for 1997 but investigated the distributional effects of a variety of fiscal instruments such as gasoline tax, taxes on engine size, and subsidies on new vehicles. Both studies estimated household's joint decision on vehicles and vehicle miles traveled, sequentially applying the nested logit in the first stage and the selection correction model in the second stage. Bento *et al.* (2009) augmented these studies' approach substantially by applying the mixed logit, imposing the cross-equation restrictions implied by Roy's identity between the two stages, and considering not only the new car market but also the used car and scrap markets. These studies rely on household-level micro data, and hence, were able to directly control for household-level idiosyncratic tastes. However, these studies do not control for the potential endogeneity of price due to unobserved product characteristics or measurement errors. Furthermore, these studies often suffer from small variation in the observed prices of the *same* car models over time. In contrast, ours exploits the panel structure from 36 quarters of automobile sales data and the large and persistent policy-induced variation in car taxes to control for the endogeneity of price. Furthermore, ours is probably the first attempt to empirically investigate the efficiency of the vehicle-gasoline tax system developed in Fullerton and West (2002) and Innes (1996) in second-best settings.

The rest of the paper is organized as follows. The next section introduces the institutional background of the ES/ETC policies and presents the first cut of the analysis. Section 3 describes the empirical model. Section 4 discusses the estimation and identification strategy. Data and instrumental variables are described in Section 5. Our estimation results are presented in Section 6. Section 7 reports the estimated impacts of the ES/ETC and other counterfactual policies. The last section concludes.

2. Institutional Background

The Japanese new car market offers a unique quasi-experimental setup for our analysis. Under the Japanese taxation system, consumers face a variety of car taxes at the time of purchase as well as throughout the ownership of cars. Prior to 2009, these car taxes were only tied to the vehicle weights, displacement levels, and sales values of cars, but were not explicitly tied to the fuel efficiency or emissions performance. Consumers pay three types of taxes at the time of new car registration. First, automobile acquisition tax is a prefectural ad valorem tax, and 5% of the sales value is collected at the time of car purchase.[5] Second, vehicle weight tax is a national tax collected at the time of car inspections every 1-3 years, and was set at 12,600 yen (or 10,000 yen) per ton of vehicle weight before (or after) April of 2010. Third, annual automobile tax is a prefectural tax imposed on ownership of cars, and ranges from 29,500 to 111,000 yen for passenger cars again

[5]On top of these car taxes, the consumers also need to pay the 5% ad valorem sales tax, which did not change throughout the study period.

depending on displacement level. The last two taxes are taxes on ownership, but consumers also pay them at the time of car registration.

In 2009, the Japanese government implemented a series of policy experiments on the taxation of automobiles. The policy roughly consists of the Ecocar Tax Credits (ETC) program and the Ecocar Subsidy (ES) program. The ETC offered a variety of tax incentives based on fuel efficiency and emissions performance. For example, models exceeding the 2010 fuel efficiency standard by 15% (but less than 25%) and receiving a four-star rating on the 2005 emissions standard would receive a 50% tax cut on vehicle weight tax, a 50% tax cut on acquisition tax, and a 25% tax cut on annual automobile tax.[6] The ETC program was originally scheduled to continue until March 31, 2012 (April 30, 2012 for vehicle weight tax), but was extended (in March, 2012) to April, 2015.

The ES program, on the other hand, offered a cash rebate of 100,000 (50,000) yen for purchase of a passenger car (mini-car) if it achieves 15% above the 2010 fuel efficiency standard and the four-star rating on the 2005 emissions standard.[7] Initially, the ES program was scheduled to last until March 31, 2010. However, it was extended to September 30, 2010, as part of the 2010 economic stimulus package. Furthermore, the second phase of the ES program was re-implemented in December 20, 2011 and continued until January 31, 2013. The eligibility requirements in the second phase were made stricter than those in the first phase. Table 1 summarizes the eligibility requirements for different ES and ETC programs.

[Table 1. Model Eligibility Requirements for ES and ETC]

Our empirical analysis covers the period from January, 2004 to December, 2012. We use the pre-policy period (April, 2004 – March, 2009) as our control period. The policy period (from April, 2009 to December, 2012), thus, can be divided into three distinct subperiods: (A) April, 2009 – September, 2010 in which ETC and the first phase of ES were in place; (B) October, 2010 – December, 2011 in which only ETC was in effect; and (C) January, 2012 – December, 2012 in which ETC and the second phase of ES were in effect.

[Figure 1. Data Coverage and Policy Periods]

The frequent policy changes and the resulting variation in eligibility and tax rates provide important exogenous variations in the effective car tax rates over time and across car models. More importantly, these ES/ETC programs allowed the car taxes to be closely linked to the carbon emissions rates of the vehicles. Figure 2-(a) shows the scatter plots of the car taxes against the corresponding carbon emissions rates for all car models sold during the pre-policy period (January, 2004 – March, 2009) and during the policy period (April, 2009 – December, 2012). The figure illustrates that the linkage between the car taxes and the emissions performance of the cars became much tighter during the policy period than during the pre-policy period. This is also confirmed with Figure 2-(b), which plots the kernel density of car taxes. Prior to the policies, variation in car taxes is relatively small, with the mode of the distribution around 180,000 yen. During the policy period, substantially more variation is observed, and some of the car models received negative tax rates due to the ES program.

[6] To be more precise, the tax incentive on the automobile tax started in April, 2004 before the ETC program, and its eligibility requirements have been changing over time. The text refers to the requirements for cars sold in FY2009.

[7] The cash rebate is increased to 250,000 (125,000) yen for purchase of a passenger car (mini-car) if it replaces old cars aged 13 years or more and meets the 2010 fuel efficiency standard.

[Figure 2. Regulatory Changes in Car Taxes in Japan]

The policy changes seemed to have affected both the sales and prices of new cars significantly. The average tax rate sharply dropped during the first policy subperiod.[8] It then increased slightly during the second policy subperiod due to the temporary suspension of the ecocar subsidy, and then decreased again during the third subperiod when the second phase of the ES was implemented (see Figure 3, panel b). A casual look at the sales patterns over time suggests that these changes in tax rates appear to have induced substantial behavioral changes in terms of both aggregate consumption and substitution patterns across models. First, the share of hybrid cars in the total car sales increased dramatically during the first policy subperiod, and the trend continued throughout the policy period.[9] Second, total sales quantity (detrended by regressing it on quarter dummies) also jumped dramatically during the first policy subperiod, and then dropped sharply after the ES was ceased. The impact on the total sales is somewhat complicated, because the Japanese economy went through two substantial macroeconomic shocks during the study period (the financial crisis, known as the *Lehman Shock*, and the 2011 *Tohoku* Earthquake). The effects of these two macroeconomic shocks appear particularly evident during 2008/Q3 – 2009/Q1 and during 2011/Q1 – 2011/Q2.

[Figure 3. Trends in New Car Sales, Hybrid Shares, Prices, and Car Tax Rates
from 2008 to 2012]

There may be a concern that some consumers might have shifted their consumption in anticipation of future policies. Such an intertemporal substitution of car purchase may complicate the identification of the policy effects. In our case, however, the effect seems negligible. The ES/ETC policy was announced in April, 2009 and administered in June, 2009, yet covered cars purchased in April and May, 2009. Moreover, the ES program was initially scheduled to end in March, 2010, but was unexpectedly extended to September, 2010. The second ES period was also similar. It was adopted on December 20, 2011 and started its administration in April, 2012, but covered cars purchased since December 20, 2011. Figure 4 shows the (detrended) trends in monthly new car sales during 2006 and 2010. The sales amount and seasonal pattern were quite stable before and after the first ES policy. Although the sales were relatively lower at the beginning of 2009 compared to the same period in the previous years, the trend actually continued until the end of the second quarter of 2009.

[Figure 4. Trends in Monthly New Car Sales from 2006 to 2010]

3. Empirical Framework

3.1. Consumer

[8] The average tax rate was calculated as a simple unweighted average over all car models sold during each time period.

[9] In Japan, diesel-based cars represent a tiny fraction of the total sales. Instead, hybrid cars such as Toyota Prius and Honda Civic Hybrid are more closely equated with "eco-friendly" cars in the minds of Japanese consumers.

Our empirical framework builds upon the extensive literature on the estimation of automobile demand. In particular, we make use of the random-coefficients (RC) logit model developed in Berry (1994) and Berry, Levinsohn, and Pakes (BLP, 1995).

Assume in each market $t = 1, ..., T$, there are I_t consumers, each with $i = 1, ..., I_t$. In this paper, a market t is defined as the market for new passenger cars in each quarter. We consider quarterly markets because all policy treatments coincide with quarter periods. Each consumer is assumed to derive utility from buying and utilizing a car. The level of utility she derives from it depends on a vector of individual characteristics $\boldsymbol{\eta}$, the effective (or tax-inclusive) price of the car $(1 + \tau)p$, and a vector of car characteristics $\boldsymbol{\psi}$.

As in BLP, there are observable and unobservables for both the individual characteristics and the product characteristics. Let y_i be the income of individual i, $\boldsymbol{\nu}_i$ be the unobservable characteristics of the individual that are important in the decision of which brand to buy, and ϵ_i be a mean-zero stochastic term so $\boldsymbol{\eta}_i = (y_i, \boldsymbol{\nu}_i, \epsilon_i)$. The variable $\boldsymbol{\nu}_i$ might include things like proximity to public transportation, environmental awareness, and commuting distance that is hard to obtain even in detailed survey studies.

Let $\mathbf{x}$ and ξ be observable and unobservable parts of the product characteristics, so $\boldsymbol{\psi} = (\mathbf{x}, \xi)$. We shall discuss ξ in more detail below. As discussed above, a variety of taxes and other incentives are imposed, at the consumer level, on car sales (in Japan and many other parts of the world). These tax incentives are functions of observable car characteristics, so that $\tau = \tau(\mathbf{x})$. τ is allowed to take negative values, in which case the consumer receives a subsidy.

In each period, the consumer is assumed to buy at most one car. She can choose to buy one of the J_t brands or not to buy any car ($j = 0$). In the latter case, she chooses to use public transportation or continues to use a car she already owns (i.e., the outside option). Allowing for the outside option is important not only for estimation of the RC logit model, but also for estimating the environmental effect of the regulatory change. This is so particularly because we do not consider scrappage decisions explicitly as in Goldberg (1998) and BLP (1995).

In each market t, we assume that (indirect) utility of consumer i from choosing alternative j is given by

$$u((1 + \tau_j)p_j, \boldsymbol{\psi}_j, \boldsymbol{\eta}_i; \boldsymbol{\theta}) = \mathbf{x}_j \boldsymbol{\beta}_i + \alpha_i [y_i - (1 + \tau_j)p_j] + \xi_j + \epsilon_{ij}, \tag{1}$$

where $(\alpha_i, \boldsymbol{\beta}_i)$ is a vector of "random coefficients" to be estimated and assumed to vary over individuals.[10] Following BLP (1995; 1999) and Nevo (2000; 2001), we assume that:

$$\begin{pmatrix} \alpha_i \\ \boldsymbol{\beta}_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \boldsymbol{\beta} \end{pmatrix} + \boldsymbol{\Sigma} \circ \boldsymbol{\nu}_i, \tag{2}$$

where $\boldsymbol{\Sigma} = (\sigma^p, \sigma^1, ..., \sigma^K)'$ is a $(K+1)$-dimensional (row) vector of parameters and $\boldsymbol{\nu}_i$ is a $(K+1)$-dimensional (row) vector of unobservable characteristics of individual i. The number of dimension K is equal to the number of variables in $\mathbf{x}_j$.

Given this specification, the utility can be decomposed into the mean utility δ_j, which only depends on product-specific attributes and is common to all individuals, and the idiosyncratic random utility μ_{ij}, which depend on both product-specific attributes and individual (unobservable) attributes:

$$\begin{aligned} &u((1 + \tau_j)p_j, \boldsymbol{\psi}_j, \boldsymbol{\eta}_i; \boldsymbol{\theta}) = \alpha_i y_i + \delta_j + \mu_{ij} + \epsilon_{ij}, \\ &\delta_j = \mathbf{x}_j \boldsymbol{\beta} - \alpha(1 + \tau_j)p_j + \xi_j; \quad \mu_{ij} = [-(1 + \tau_j)p_j, \ \mathbf{x}_j] \boldsymbol{\Sigma} \circ \boldsymbol{\nu}_i, \end{aligned} \tag{3}$$

[10] For notational simplicity, we suppress index t because the model is identical for all quarterly markets.

where $\boldsymbol{\theta}_1 = (\alpha, \boldsymbol{\beta})$ are "linear parameters" and $\boldsymbol{\theta}_2 = \boldsymbol{\Sigma}$ are "nonlinear parameters" of the model, because $\boldsymbol{\theta}_1$ can be estimated by linear regression of δ_j on product attributes whereas $\boldsymbol{\theta}_2$ need to be estimated in a nonlinear way (Nevo, 2000). It is this nonlinear part that enables us to model richer and realistic substitution patterns, as will be discussed below.

Two caveats on this specification are in order. First, we slightly diverge from BLP (1995; 1999) and exclude the nonlinear income effect as in Nevo (2000; 2001). If we are to include the nonlinear income effect, we would either take $\log(y_i - (1+\tau_j)p_j)$ or make α_i inversely proportional to income $\alpha_i = \alpha/y_i$ in (1). We chose this specification because our earlier attempts to estimate such a model resulted in either insignificant or positive price coefficients. Second, we also diverge from Nevo in that we do not interact the random-utility terms with observable demographic variables. We chose to do so for two reasons. First, identification of interaction parameters would require variation in the distribution of demographic variables over different markets, yet we found there was very little variation during the study period. In contrast, Nevo was able to use variation across cities as additional source of variation. Second, we had to estimate the model with a much larger number of brands (an average of 120 per market) than Nevo's study (25 brands). Thus, we concluded that little variation in the distribution of demographic variables compared with a larger number of brands would result in inefficient estimates of the parameters. Indeed, our trial runs with different sets of demographic variables resulted in non-convergence of the estimation algorithm (after days of running it for each run).

We also assume that (indirect) utility from the outside option is given by

$$u_{i0} = \sigma_0 v_{i0} + \epsilon_{i0}.$$

Note that the term v_{i0} still needs to be included, despite that there are no observable attributes for the outside option, to account for the possibility that the idiosyncratic variance for this option may be larger than that for the "inside" goods. In other words, the term accounts for the individual-specific differences on the outside option (such as access to public transportation, used car holdings etc).

Consumer i chooses alternative j if and only if

$$u((1+\tau_j)p_j, \boldsymbol{\psi}_j, \boldsymbol{\eta}_i; \boldsymbol{\theta}) \geq u((1+\tau_r)p_r, \boldsymbol{\psi}_r, \boldsymbol{\eta}_i; \boldsymbol{\theta}) \quad \text{for} \quad r = 0, 1, ...J_t.$$

Assuming that ϵ_{ij} are i.i.d. with a Type-I extreme value distribution, the market share of brand j is given by

$$s_j = \int \frac{\exp(\mathbf{x}_j \boldsymbol{\beta}_i - \alpha_i(1+\tau_j)p_j + \xi_j)}{1 + \sum_{r=1}^{J_t} \exp(\mathbf{x}_r \boldsymbol{\beta}_i - \alpha_i(1+\tau_r)p_r + \xi_r)} dP(\boldsymbol{\nu}). \tag{4}$$

where $P(\cdot)$ is the population distribution of the individual attributes $\boldsymbol{\nu}$, which we assume to follow an i.i.d. standard normal per BLP (1995; 1999).[11]

One important aspect of the expression is that the unobserved product attribute ξ_j is not integrated out. Allowance of this term allows for a difference between the predictions of the model (based on observed attributes and estimated parameters) and the observed market shares. One way to interpret the term ξ_j is that it measures the unobserved product attributes such as brand images, style, and prestige. Another way to interpret it is that it represents the measurement errors in observed market prices such as product-specific sales promotions and marketing strategies. The empirical challenge is that ξ are likely to be correlated with p — e.g., consumer demand is higher for products with better brand images, and measurement errors with respect to prices are likely

[11] The integral is only with respect to $\boldsymbol{\nu}$ because y_i vanishes in the linear income specification.

to be related to sales promotions and sales channels. We take the estimation strategy proposed by BLP (1995; 1999) to take care of this endogeneity, which we shall turn to in Section 4.

3.2. Producer

There are F firms in all markets and each firm produces a subset of the products $\mathcal{J}_f$. In each quarterly market t, the profits of firm f are given by:

$$\sum_{j \in \mathcal{J}_f} \left(p_j - mc_j\right) M s_j(\mathbf{p}^e) - FC_f,$$

where s_j is the market share of brand j as defined in (4), $\mathbf{p}^e$ is the vector of effective, tax-inclusive prices defined as $p^e = (1+\tau)p$, mc_j is the marginal cost of each brand j, M is the market size of the new car market, and FC_f is the fixed cost of production.

Assuming that firms compete in the Bertrand manner and the unique pure-strategy Bertrand-Nash equilibrium exists (as in BLP, 1995, 1999 and Nevo, 2000, 2001), the price of each brand j satisfies the following first-order condition:

$$s_j(\mathbf{p}^e) + (1+\tau_j) \sum_{k \in \mathcal{J}_f} (p_k - mc_k) \frac{\partial s_k}{\partial p_j} = 0.$$

For each market, this set of J equations determines the optimal markup for each brand. These markups can be solved explicitly a la Nevo (2001). Let us define the matrix Ω such that each element of Ω is defined as $\Omega_{jk} = O_{jk} * D_{jk}$, where O_{jk} is the matrix describing the ownership structure:

$$O_{jk} = \begin{cases} 1 & \text{if } \exists f : \{j,k\} \in \mathcal{J}_f \\ 0 & \text{o.w.} \end{cases},$$

and D_{jk} is the matrix of share derivatives with respect to prices, multiplied by -1: $D_{jk} = -\partial s_k / \partial p_j$. Then the first-order condition implies:

$$\mathbf{p} - \mathbf{mc} = \Omega^{-1} \mathbf{s}^e(\mathbf{p}^e), \tag{5}$$

where $\mathbf{s}^e$ is a vector of market shares adjusted for tax rates: i.e., the j-th element of $\mathbf{s}^e$ is $s_j^e = s_j/(1+\tau_j)$.

Once we obtain the consistent estimates of demand parameters, we can estimate the price-cost margins or the marginal costs using (5), which can then be used to simulate the policy-induced effects on industry profits. This strategy was taken in Nevo (2001). One could impose further structures on the supply relationship, and the cost parameters could then be jointly estimated with the demand parameters. For example, BLP (1995; 1999) specify the marginal costs as functions of cost shifters such as observed product attributes, wages, and unobservable product attributes. Such a strategy would improve the efficiency of the estimates, but at the cost of imposing more structures and increasing computational burden. As we do not directly make use of the cost side parameters in our simulation analysis, we shall take Nevo's approach to avoid undue complexity.

4. Empirical Strategy

4.1. Estimation

For estimation of the model, we closely follow the methods proposed in BLP (1995) and its detailed explanation offered in Nevo (2000). Suppose we have data on a set of exogenous instruments $\mathbf{z}$ such that the unobserved product attributes are mean independent of $\mathbf{z}$:

$$E[\boldsymbol{\xi}_t(\boldsymbol{\theta})|\mathbf{z}_t] = 0 \quad \text{for all } t. \tag{6}$$

This gives us a set of population moment restrictions. Then the generalized method of moments (GMM) estimates of the parameters is:

$$\hat{\boldsymbol{\theta}} = \arg\min_{\theta} \ \boldsymbol{\xi}\left(\boldsymbol{\theta}\right)' \mathbf{z}\Omega^{-1}\mathbf{z}'\boldsymbol{\xi}\left(\boldsymbol{\theta}\right), \tag{7}$$

where Ω is a consistent estimate of $E[\mathbf{z}'\boldsymbol{\xi}\boldsymbol{\xi}'\mathbf{z}]$, which is used to weight moments in accordance to their variance.

A question remains as to how we might obtain $\boldsymbol{\xi}$, which by assumption is unobservable to researchers. A key here is to recognize that ξ_j can be considered as an unobservable error in the mean utility δ_j in (3). In the simple logit model, ξ_j could be estimated by simply regressing $\ln(S_j) - \ln(S_0)$ on $(\mathbf{x}_j, p_j)$ because then $\delta_j = \ln(S_j) - \ln(S_0) = \mathbf{x}_j\boldsymbol{\beta} - \alpha(1+\tau_j)p_j + \xi_j$. In our case, however, s_j is given by (4) and is a nonlinear function of the $(\mathbf{x}_j, p_j)$. BLP (1995) proposed a nested fixed point (NFP) algorithm to numerically solve for $\boldsymbol{\xi}$. Let S_j be the observed market share of brand j and s_j be the market share function defined by Eq. (4). Then the value of the mean utility term δ can be solved numerically by the contraction mapping:[12]

$$\delta^{h+1} = \delta^h + \ln(S) - \ln(s(\delta^h|\boldsymbol{\theta})) \quad \text{for } h = 1, ...H.$$

Once the convergence is achieved and the estimate of $\hat{\delta}$ so obtained, the estimate of the unobservable product attribute can be easily computed by:

$$\hat{\xi}_j = \hat{\delta}_j - \left(\mathbf{x}_j\hat{\boldsymbol{\beta}} - \hat{\alpha}(1+\tau_j)p_j\right).$$

Thus in essence, the estimation is done by repetition of the two-step procedure. First, given the initial guess of the parameters $\hat{\boldsymbol{\theta}}_0$, run the NFP algorithm to get the estimate of $\hat{\delta}_0$ and obtain the estimate of the error $\hat{\xi}_0$ (this is the "inner loop" of the estimation). Second, solve the optimization program (7) to get the estimate of $\hat{\boldsymbol{\theta}}$. We repeat the process until the optimization routine achieves desired tolerance. Our estimation is done by carefully modifying the Matlab code supplied at Nevo's website.[13]

Recently, however, studies have found important problems with implementation of the NFP algorithm and the resulting estimates (see Dube *et al.* (2012) and Knittel and Metaxoglou (2012) for a more detailed review of such issues). In particular, Dube *et al.* showed that use of loose tolerance criteria for the inner-loop algorithm to ease the computational burden may result in (i) failure of the optimization program to converge or (ii) the optimization finding parameter estimates that are not even local optima. Indeed, our earlier attempt to directly use Nevo's code revealed both of these problems. To overcome these problems, we adjusted Nevo's original code and used inner-loop tolerance of 1E-14 as suggested by Dube *et al*. We also replaced Matlab's optimization routine "fminu" with Zeina's KNITRO program, which is substantially more robust and efficient than

[12] BLP (1995) also offers a proof of the convergence of this NFP algorithm.

[13] The modifications include, but are not limited to: allowing the set of products in each market to vary, modifying the inner loop tolerance, replacing the minimization routine, replacing the mean-distance procedure, supplying the code for calculation of own- and cross-price elasticities for both 'inside' and 'outside' goods, and supplying the code for calculation of price-cost margins.

"fminu". Dube *et al.* also suggested an alternative algorithm known as a mathematical program with equilibrium constraints (MPEC). We also tested this method and found the estimates were similar.

4.2. Identification and Instrumental Variables

The key to the estimation of the model is a set of instrumental variables required for the moment condition in (6). The common identifying assumption, used in BLP (1995; 1999) and subsequent studies, is that the 'location' of observed product attributes for each brand in the characteristics space is exogenous, or at least predetermined prior to the determination of consumer's valuation of unobserved brand-specific attributes. More specifically, BLP used the observed product characteristics, the values of the characteristics summed over all brands produced by each firm, and the values of the characteristics summed over all brands produced by other firms. Because firms' marginal costs are likely to correlate with their own product characteristics, and because their price markups depend on their product characteristics relative to their competitors, these product-location variables are also likely to correlate with prices. On the other hand, because the product-location variables are at least predetermined at the time of consumers' decisions, they may not be causally related to the unobservable product attributes such as style, prestige, and reputation. This approach has been successfully applied in BLP (1995; 1999) and other subsequent studies.

In our case, however, this common identifying assumption may not be truly valid. For example, Toyota's well-know compact-car/hybrid-car strategies suggest that the location of observed attributes such as size and fuel efficiency for their most-selling brands such as Vitz (known as Yaris in U.S. and Europe) and Prius may be highly correlated with unobserved brand images consumers have about these products. In addition, in Japan, some brands are sold exclusively through certain sales channels. For example, Toyota Camry and Vitz, two flagship models, are sold only through stores under the franchises of the Corolla and the Netz, respectively. Because we only observe regular market prices, $\boldsymbol{\xi}$ can also include brand-specific or franchise-specific sales promotions or marketing champaigns, information on which is not readily available to us. Some of the location variables, such as those for size and fuel efficiency, may then be causally related to these unobservable sales promotions. Indeed, our earlier attempt to estimate the RC logit with the traditional IVs resulted in both very large GMM objective values and the estimates of price coefficients that are highly sensitive to the random draws $\boldsymbol{\nu}$.

Given the above concerns, we consider an alternative set of instruments, exploiting the unique quasi-experimental setup in the Japanese new car market. As discussed in Section 2, the series of green tax policies generated exogenous variations in tax rates across brands and over time. Because these tax rates are functions of the observable product characteristics (price, weight, and displacement level), they would surely be correlated with prices. On the other hand, the ES/ETC policy caused the effective tax rates to change three times over the study period, which shifted the location of the tax rates in the characteristics space, while the unobserved product characteristics such as style and brand images presumably stayed largely constant. Hence, our tax-location variables are unlikely to be causally related to the unobserved characteristics. Some may argue that though these tax rates are not explicitly chosen by automakers or by consumers, automakers may have influenced the design of the policy in favor of some particular brands (e.g., hybrid cars). Even so, the frequent changes should minimize that causal link between the unobservable attributes and the tax rates. Therefore, our tax-location IVs would be a better instrument, if not perfect, than the traditional IVs. To operationalize this idea, we construct the tax-location variables in a manner analogous to BLP: i.e., the sums of own-firm tax rates/amounts and the sums of rival-firm tax rates/amounts.

One may argue (correctly) that if we believe ξ represents unquantifiable brand images or measurement errors in observed prices, simply including brand fixed effects in the set of covariates $\mathbf{x}$ might just take care of the concern. The problem with this approach is that if we include brand dummies in the regression, the matrix of $\mathbf{z}'\mathbf{z}$ will be essentially singular, as they do not vary across brands and over time. Hence it cannot be inverted. An alternative would be to not use the brand dummies in the regression but use them as IVs. We then, however, encounter the same problem — brand dummies could be plausibly correlated with ξ. See Nevo (2001) for more detailed discussions on this and related issues.

5. Data

Our data analysis covers the period from January, 2004 to December, 2012. We obtained the data on product characteristics and listed prices for all the domestic passenger car models marketed during this period from Carsensor.Net, one of the largest used car retailer in Japan.[14] To make our analysis comparable to previous studies, we consider the following major product attributes: the ratio of horsepower to car weight (HP/weight), mileage per yen (MPY), car size (Size), and a dummy indicating whether the model has automatic transmission (AT).[15] Information on fuel efficiency and displacement was also used to determine the ES and ETC eligibility and to calculate MPY, which is the mileage per liter of gasoline divided by the price of gasoline per liter. We treat the same model produced in different time periods as different models: i.e., Honda Accord 2009 versus Honda Accord 2010, as they could be very different due to the rapid technological upgrading. W use the retail sales prices obtained from Carsensor.Net and deflate them by the consumer price index.

The monthly sales data are obtained from Japan Automobile Dealers Association (JADA). Since we have only the total sales for each model and, in many cases, there are many variants (or 'grades') of each model, we obtain the corresponding product attributes and prices by taking the averages over all the variants of the same model marketed in the same time period. We confirmed the validity of this treatment in two ways. First, we were able to obtain detailed used-car sales data by grade for a small fraction of the car models. We used the data to verify that the majority of sales are concentrated around the variant of the model that has close proximity to the mean attributes. Second, we estimated the IV logit model using the maximum, minimum and median as alternatives, and our major results are quite robust to the different choices.

Besides the data mentioned above, we also make use of some macroeconomic data, such as GDP growth rate, CPI, total number of households, and gasoline prices, which were collected from various sources. The GDP and CPI data are taken from the statistics published by the Cabinet Office of the Japanese government. The data on the number of households are based on the estimates from the Institute of Population and Social Security. The monthly prices of gasoline are from the Institute of Energy Economics in Japan.

[14] We hired a doctoral student and two undergraduate students to manually download the catalogue data from the company's website and code the data into excel.

[15] BLP (1995; 1999) used a dummy indicating whether the model has air conditioning as a default or not. For our data, this resulted in virtually no variation across models. We thus replaced this variable with the auto transmission dummy.

Table 2 shows the trends in the sales, prices and major product attribute variables used in our analysis over the study period. The prices and major product attributes are sales-weighted means. The total number of models marketed was around 127-131 before 2006. It started to decline since then and hit the bottom of 111 in the third quarter of 2007. The variety of models gradually recovered in 2008 and reached 125 in the end of 2012. Total quarterly sales series clearly displays a seasonal pattern. Car sales are generally strong in the first and the third quarters, followed by drops in the second and the fourth quarters. Because March is the end of a fiscal year in Japan, sales subsidiaries offer a variety of sales promotions then. The sales increase in the third quarter because working individuals usually receive summer bonus, a lump-sum payment approximately twice of their monthly wages. Taking into account the seasonal cycle, the sales generally trend downward over time: i.e., the first quarter sales decreased from 923,562 in 2004 to 546,509 in 2009 right after the *Lehman Shock* and further hit the bottom of 525,429 in 2011 because of the *Tohoku* Earthquake. It started to recover quickly since then, with the total sales in 2012 reached 2,843,057 in 2012, comparable to the sales levels in 2005 and 2006.

[Table 2. Sales, Price and Product Characteristics of All Brands over Time]

An increasing trend in prices is observed, with the average prices in 2012 more than 10% higher than those in 2004. On the other hand, HP/weight has been fairly constant over time and decreased slightly in recent years. The average MPY first declined from 15.0 in 2004 to 9.3 in the third quarter of 2008, and then bounced back and reached 18.3 in the end of 2012. The downward trend was mainly driven by the increasing price of gasoline, which reached its peak in the third quarter of 2008, while the upward trend reflects the improvement in the fuel efficiency of some car models marketed after 2009. The increasing trend in the MPY is likely to be due to the environment friendly policies introduced in the second quarter of 2009. The car size has been quite constant, while the share of cars equipped with automatic transmission (AT) clearly dropped over time. Note that the drop in the share of the cars with AT from the first quarter to the second quarter in 2009 was 7.2%, much larger than other time periods, which also coincides with the timing of the policies of interest. This may reflect the increase in the non-AT fuel efficient cars, such as hybrid cars.[16]

Table 3 provides the summary descriptive statistics for the hybrid cars only. It is evident that the sales of hybrid cars have been increasing rapidly, especially after the first quarter of 2009. It took five years for the market share of the hybrid cars to triple from 2004 to 2008, while it went six times larger from 0.052 in 2009 to 0.318 in 2012. The prices of hybrid cars are generally higher than the average car prices. During the period 2005-2008, hybrid car prices rose quickly probably because of the increasing demand due to the high prices of gasoline. Compared to non-hybrid cars, hybrid cars tend to have lower ratio of horsepower to weight and larger size, but much higher fuel efficiency. The reason why MPY was relatively higher in 2004 is because only a couple of highly fuel efficient hybrid car models (e.g., Toyota Prius, Honda Civic Hybrid and Honda Insight) were available in the Japanese new car market then. Hybrid cars usually use CVT or manual transmission systems, but automatic transmission was also used in some models (i.e., Nissan Fuga 2011) after 2010.

One take-away message from Tables 2 and 3 is that the trends in the key product characteristics did not change dramatically by the introduction of green car tax policies, yet the increase in the variety and market share of the hybrid cars appear to have increased during the policy period.

[16] Recently, small-sized cars and hybrid cars increasingly use continuously variable transmission (CVT) to improve fuel efficiency.

[Table 3. Sales, Price and Product Characteristics of Hybrid Cars over Time]

6. Results

6.1. Logit Results

We first report the results from the OLS and IV Logit models in Table 4. They give us a sense of the performance of different sets of instrumental variables for the full RC logit model, though these models are known to yield unrealistic substitution patterns (see Nevo, 2001 for a thorough discussion on this point). Note that in the logit models, the stochastic error term includes the unobserved product attribute ξ_j (so does the random utility term μ_{ij}). Therefore, the overidentification tests would likely reject the null hypothesis if the set of instruments are correlated with any of these terms.

The results are obtained from regressing $\ln(S_{jt}) - \ln(S_{0t})$ on constants, effective prices, HP/weight, MPY, size, auto transmissions, year dummies, quarter dummies, and maker dummies, with and without the macroeconomic variable (seasonally adjusted GDP growth rates) to account for the effects of the financial crisis and the *Tohoku* earthquake.[17] The first two columns in Table 4 report the results from OLS logit, with and without the macroeconomic variables. Columns (III)-(V) display the results of IV logit with different sets of instruments, without the macroeconomic variable. Columns (VI)-(VIII) report the same, but with the macroeconomic variable.

We include quarter fixed effects, because in Japan at least, the car sales has large seasonal effects, particularly in the first quarter and the third quarter (see our discussion in Section 5). This occurs because these correspond to the two bonus seasons and the Japanese automakers put together sales promotions in response. As discussed above, including brand fixed effects in the regression is problematic. We thus instead included maker fixed effects to control for maker-specific brand values (Nevo, 2001).

[Table 4. Estimation Results: OLS Logit and IV Logit]

For all models, coefficients on MPY and auto transmissions are significant, with signs consistent with our expectation. With the OLS logit, the coefficients on prices are negative and significant. With the traditional 'product-location' IVs, however, coefficients on price and size turn insignificant, whereas with our 'tax-location' IVs, they become significant again. HP/weight is not significant with virtually all models, but this result is indeed consistent with BLP (1995). Importantly, when the 'product-location' IVs are used, the overidentification test rejects the null, suggesting that some of the IVs are endogenous. When the 'tax-location' IVs are used instead, the overidentification test cannot reject the null at the 0.2 significant level with model (VII). We take this as evidence that our 'tax-location' IVs are more reliable than the conventional 'product-location' IVs for our full model. We also examine the weak IV problem. Though not reported, all the tax-location IVs are significant at the 1% level in the first stage regression, and the F-statistic for the explanatory power of these variables is 214.85, much higher than the conventional cutoff of 10, suggesting that our IVs are unlikely to suffer from the weak IV problem.

[17] Inclusion of the macroeconomic variable follows BLP (1999). As BLP points out, it is somewhat arbitrary to include such variables. However, the effects of these macroeconomic shocks appear to be very significant, and removing these variables may bias the estimates. An alternative would be to exclude observations from these periods. However, these periods also overlap with policy periods that are important for our analysis. Thus, excluding observations from these periods appears at least as arbitrary as inclusion of macroeconomic variables.

6.2. Results of the Full RC Logit Model

We now report the results of the full RC logit model, with two alternative sets of IVs. For both IVs, we include the same set of variables as model (VII): constants, effective prices, HP/weight, MPY, size, auto transmissions, GDP growth rate, year-quarter fixed effects, and maker fixed effects. Column (IX) reports the result with the traditional 'product-location' IVs whereas column (X) displays the result with our 'tax-location' IVs. As discussed in Section 5, we used inner-loop tolerance for NFP = 1E-14 and outer-loop tolerance for GMM = 1E-3.

First, the value of the GMM objective is substantially lower with our 'tax-location' IVs than with the traditional IVs. Our GMM objective value is small even compared to the average GMM objective values (178-278, depending on the estimation algorithms used) reported by Knittel and Metaxoglou (2012), who re-estimated the RC model nearly identical to ours using BLP's original auto data. Thus the value of 15.8 appears to substantiate the success of our 'tax-location' IVs.

In interpreting the results in Table 5, note that there are in general two ways to explain the effect of each product characteristic. For example, a large-sized car might be popular, either because an average consumer places a high value for the large-sized car (i.e., the effect of the mean utility) or because there is a large variance in consumers' tastes for the large-sized car (i.e., the effect of the distribution of the random utility).[18] Thus the significance on mean parameters would get at the significance of the former effects whereas that on standard deviation parameters would get at the latter. If we expect any of these variables has significant influence on purchase decision, we should observe at least one of these on each variable is significant.

With the traditional IVs, we observe that all of the mean parameters of the variables (except on AT) are significant at the conventional significance levels, but with signs inconsistent with our expectation. Moreover, virtually all of the standard deviation parameters are insignificant. Another reason why we think the traditional IVs do not perform well in our context is because the estimated parameters appeared to be highly sensitive to both the size and seed of random draws $\mathbf{v}$, the problem we did not encounter with our preferred IVs.

With our preferred IVs, the results are more encouraging. All of the mean parameters are significant at the conventional significance levels with signs in line with our expectation, suggesting that consumers, on average, prefer more HP/weight, MPY, and size and dislike higher prices and AT. Not only that, the standard deviation parameters on price and HP/weight are significant, suggesting that there are large variations in the tastes for these characteristics. In some urban areas in Japan, public roads are notoriously narrow so that some consumers may prefer smaller or less powerful cars. On the other hand, in rural areas, others may prefer larger and more powerful cars for daily operations. The standard deviation parameters on MPY, size, and auto transmissions are insignificant, suggesting that variance in the tastes for these attributes is small.

[Table 5. Estimation Results: Full Random-Coefficients Logit]

One well-documented advantage of the RC logit model over simpler logit models is that it gives richer and more realistic own- and cross-price elasticities of demand (Nevo, 2000; 2001). With the simple logit models, own- and cross-price elasticities depend only on the constant parameter, own and cross prices, and observed market shares, which result in (i) nearly constant own-price elasticities and (ii) counter-intuitive substitution patterns that do not take into account

[18] The logic is well explained in BLP (1995).

similarities between brands. With the RC logit, the own- and cross-price elasticities are instead give by:

$$\varepsilon_{jk} = \frac{\partial s_j p_k}{\partial p_k s_j} = \begin{cases} -\frac{p_j}{s_j} \int \alpha_i s_{ij}(1 - s_{ij}) dP(v_i) & \text{if} \quad j = k \\ \frac{p_k}{s_j} \int \alpha_i s_{ij} s_{ik} dP(v_i) & \text{if} \quad j \neq k \end{cases}, \tag{8}$$

where s_{ij} is the choice probability for brand j by individual i. In this expression, each individual has a different price elasticities, which are averaged out to yield mean elasticities.

Table 6 displays the sales and product characteristics of the 15 top selling brands as well as the estimated elasticities based on our preferred model (X) for 2011. As expected, many of the brands in the table have inelastic demand with respect to own prices because these are top-selling brands with strong brand identities. Though not reported, a vast majority of other brands had much larger own-price elasticities. The weighted average own-price elasticity for all brands in 2011 was -1.7, which is roughly comparable to the reported elasticities in BLP (1995), which range from -3 to -4.5, and in Bento *et al.* (2009), which range from -0.88 to -1.97. Toyota Corolla and Nissan Serena have the largest own-price elasticities among these brands presumably because these brands are much older than others.

The estimated model also allows us to estimate the substitutability of the inside goods to the outside option. We make explicit use of the substitution elasticities to the outside option in identifying the scale effect of the ES/ETS policy. Given an appropriate measure of market size M (with all relevant brands in the data), we examine how the total sales quantity $M(1 - s_0)$ would respond to a counterfactual policy scenario. Hence, it is crucial to obtain consistent estimates of the substitution elasticities. The last column of Table 6 reports, à la BLP (1995), the estimated percentage of consumers who substitute to the outside good as a percentage of those who substitute away from a brand, given a price increase for that brand, for top-selling brands in 2011: i.e.,

$$\frac{ds_0/dp_j}{|ds_j/dp_j|} \times 100.$$

The number essentially indicates, given a small price increase for the brand j, of those who decided not to purchase the brand, what percentage of them would choose not to buy any of the brands. As in BLP (1995), the estimated substitution elasticities vary substantially across brands. We emphasize here that these numbers are roughly comparable to those in BLP (1995), yet are smaller than those in BLP (1995). We deem as evidence of our success in estimation — BLP (1995) note their numbers "still seem a bit large" (p.881).

Table 7 reports the estimated average own- and cross-price elasticities for these brands for 2011. Each entry (j, k) represents a percentage change of the market share for brand j with respect to a percentage change of the price of brand k. The estimated elasticities exhibit expected signs and magnitudes and are roughly comparable with those reported in BLP (1995) on U.S. counterparts. There is also substantial variation across brands, unlike with the standard logit model, which would display the identical elasticity for all entries in each column.[19]

[Table 6. Product Characteristics, Estimated Elasticities, and Price-Cost Margins of the Top 15 Sales Brands for Year 2011]

Many of the top-selling brands in the table had small or negligible cross-price elasticities, the

[19] Note that with the standard logit, the cross-price elasticity formula is $\varepsilon_{jk} = \alpha p_k s_k$ for all $j \neq k$, instead of Eq. (8).

magnitudes of which are roughly comparable to those reported in BLP (1995).[20] Yet, some of the top-selling brands had relatively large cross-price elasticities with respect to each other, particularly to brands with similar characteristics. For example, Corolla, Toyota's long-selling compact car, had relatively large elasticities with respect to the prices of Toyota's other compact cars, Vitz and Ractis. Note that these cross-price elasticities are highly asymmetric for some of the brands. For example, the demand for Toyota Prius is relatively sensitive to the price of Toyota Corolla, yet the demand for Corolla is not sensitive to the price of Prius. Interestingly, Honda Fit and Honda Fit Hybrid have negligible cross-price elasticities with each other, suggesting that they are not perceived as close substitutes despite the fact that the latter is simply a hybrid version of the same brand. This makes sense because these two models indeed have very different product attributes (see Table 6). Lastly, the estimated cross-price elasticities also seem to point to important sales or marketing channels. Though not reported in the table, Toyota Wish (a popular minivan, which comes at 16th in the sales ranking) has a cross-price elasticity of 0.09 with respect to the price of Toyota Vitz (a compact car). Though the two brands may appear to have no apparent similarities, both are sold exclusively in one of Toyota's sales channel "Netz" (with the original Logo "N"), and are popular among younger families. On the other hand, Toyota Vitz has a larger cross-price elasticity of 0.42 with respect to the price of Wish, which also makes sense because Wish's retail price is much higher (average at JPY1.9 million) than that of Vitz (average at JPY1.35 million).

[Table 7. Estimated Own- and Cross-Price Elasticities of the Top 15 Sales Brands for Year 2011]

7. Policy Evaluation

Our primary interest lies in translating these policy-induced demand responses into aggregate vehicle CO_2 emissions and social welfare. To that end, we consider three counterfactual scenarios. The first scenario assumes that the Japanese government implements no ES/ETC policy. The second scenario assumes that only the ETC program is implemented. In the third scenario, we examine the effect of an emissions-based vehicle tax (EVT) à la Fullerton and West (2002). To operationalize the idea of the EVT, we consider the following rebate/tax system, based on some reference tax and fuel efficiencies of cars:

$$T_{jt}^{EVT} = \tau_{jt}^{m} + \frac{A}{MPG_{jt}}, \tag{9}$$

where τ_{jt}^{m} is the amount of car tax under some reference tax system m for brand j in period t, MPG_{jt} is miles per gallon, and A is some constant that defines the tax/rebate rate per unit of fuel efficiency. As a benchmark, we consider $m =$ the pre-existing tax system and $A = -200$.[21] We also examine the case of $m =$ the ES/ETC policy and varying A, a rational for which is discussed below.

There are several advantages of formalizing the EVT this way. First, as shown in Appendix, this formulation closely follows the optimal vehicle tax in the spirit of Fullerton and West (2002), provided that an efficient gasoline tax is in place and there is no imperfect competition. With such

[20] In BLP (1995), even the brands that had the largest own- and cross-price elasticities exhibited cross-price elasticities that were in the order of 1/100 or smaller relative to their respective own-price elasticities.

[21] This value of A corresponds to the following values in eq. (A2) in Appendix: $VMT = 10,575$ km, $\sum_{l=1}^{L} \lambda^l EPM^l(\bar{\mathbf{x}}) = 50,000$ yen, and $\sum_{k=1}^{K} \frac{\partial MPG(\bar{\mathbf{x}})}{dx^k} \bar{x}_{jt}^{k}$ using estimated coefficients from the regression $\ln(MPG) = \mathbf{x}\boldsymbol{\beta}$.

an interpretation, $A < 0$ and the second component can be considered a rebate on choosing fuel-efficient cars for part of the external costs that is already internalized by a gasoline tax. Second, depending on the sign of A, this works as either a tax or a subsidy on fuel efficiency. For example, the expected annual CO_2 emissions from a car j in period t can be approximated by $(EPG \times VMT)/MPG_{jt}$ (see the discussion below). Then, we can interpret $A > 0$ as a vehicle carbon tax based on the expected vehicle CO_2 emissions. Third, because of other pre-existing distortions, the optimal EVT à la Fullerton and West (2002) may not be necessarily welfare-improving. Indeed, whether a rebate ($A < 0$) or a tax ($A < 0$) would work better is an empirical question. This formulation allows us to conveniently evaluate the effect of varying A from negative to positive values.

Because the ETC/ES policies were implemented after April, 2009 (except for auto tax cuts prior to that), we shall focus on the policy impacts after 2009. For each policy scenario, we simulate the consumption patters based on the estimated demand model, and estimate the changes in aggregate CO_2 emissions, compensating variation, industry profits, and tax revenues relative to the no-policy counterfactual, which would simulate the pre-existing market condition.

For aggregate CO_2 emissions, we adopt the following measure of (expected) aggregate emissions, in a manner analogous in spirit to Fullerton and Gan (2005) and Klier and Linn (2011). Let E_t be the aggregate CO_2 emissions generated via the consumption of gasoline in utilizing the cars purchased in each market t. Then, E_t can be approximated by:

$$E_t \simeq \sum\nolimits_{j \in J_t} q_{jt} \left(\frac{EPG_{jt} \times VMT_{jt}}{MPG_{jt}} \right),$$

where for each market t in each quarter, q_{jt} is the sales quantity of car model j, MPG_{jt} is the miles per gallon of gasoline for car model j, VMT_{jt} is the vehicle miles traveled for model j, and EPG_{jt} is the average CO_2 emissions per gallon of gasoline used in driving for model j.

As in the previous literature (e.g., Innes, 1996), we assume $EPG_{jt} = EPG$ and use the EPA estimate of 8.887 kilograms per gallon (EPA, 2011). The problem, however, is that unlike in the U.S. or elsewhere, there is no publicly available household survey data to correctly account for driving distance, which may vary either by consumer or by car model or both. Ideally, we would conduct a household survey to jointly estimate the car ownership and car utilization decisions in a manner analogous to Bento *et al.* (2009). Due to the data limitation, we assume $VMT_{ijt} = VMT$ and use the average annual driving distance per person of 10,575 km in Japan (MLITT, 2012). Then, the expected aggregate CO_2 emissions from the new cars sold can be approximated by:

$$\hat{E}_t = \sum_{j=1}^{J_t} q_{jt} \varphi_{jt}, \tag{10}$$

where $\varphi_{jt} = (EPG \times VMT)/MPG_{jt}$. This measure essentially asks, "How much of CO_2 emissions would be emitted from the cars sold during each period t if all consumers drive the same distance VMT?" Though this is not an ideal measure, it is not a bad approximation for the impact of the policy on CO_2 emissions, provided that no reliable estimates exist on the driving distance of every car sold during each period in Japan.[22]

Albeit its limitation, one advantage of the approximation (10) is that the impact of a policy

[22] The existing literature finds that elasticity of utilization with respect to car prices is small or negligible (e.g., Goldberg, 1998). Thus, the driving distance may not add much to our discussion unless we have detailed information on car utilization that differs in an important way by each car model.

change can be decomposed into two components:

$$\Delta \hat{E}_t = (Q_t^1 - Q_t^0)\bar{\varphi}_t^1 + Q_t^0(\bar{\varphi}_t^1 - \bar{\varphi}_t^0). \tag{11}$$

where $Q_t^m = \sum_j q_{jt}^m$ is the total sales quantity and $\bar{\varphi}_t^m = \sum_j s_{jt}^m \varphi_{jt}^m$ is the weighted average emissions under policy m in quarterly market t, with weight = sales share s_{jt}^m for each j. The first term is the *scale* effect, which measures the impact purely of the total sales quantity holding the average emissions rate constant. The second term is the *composition* effect, which measures the impact of changes in the composition of the total sales.

Making inferences about the policy impacts also requires us to obtain the standard errors of the estimated impacts. Doing so in our context is not easy. We could linearize the policy impacts in the parameters and use the "delta method." However, as the policy impacts are highly nonlinear in the parameters, this approach may not be appropriate. Berry *et al.* (1999) instead use a Monte Carlo approach, taking draws from the estimated asymptotic normal distribution of the parameters. We took 300 draws of parameters, and calculate the standard deviations of the policy impacts as the estimates of the standard errors.

We first report in Table 8 the estimated aggregate emissions under each policy scenario. We make several important observations. First, the estimated annual reduction in gasoline-consumption-related CO_2 emissions from the ETC/ES policy is 26,900 tons or only 0.5% of the annual emissions that would have occurred in the absence of the policy. Second, using Eq. (11), we can decompose the impacts into the scale and composition effects. We see that the policy indeed had substantial effects of both. The ETC/ES policy induced consumers into buying more fuel efficient cars. This substitution alone is estimated to have reduced 157,000 tons of CO_2 emissions or roughly 2.7%. However, this reduction is largely offset by the scale effect, which increased the total sales of cars by giving incentives for buying cars. The scale effect is estimated to have increased 130,100 tons of CO_2 emissions annually or roughly 2.3% relative to no policy. Third, a somewhat more encouraging observation is that the Japanese government's decision to add the ES policy on top of the ETC policy seemed to have induced a further reduction in aggregate emissions, rather than increasing it (Compare column 6 and column 8). Fourth, the EVT policy with a rebate on part of the external costs that are already internalized by the gasoline tax (the EVT-rebate policy henceforth) would have increased aggregate emissions by a large margin (9.2% relative to no policy), with the scale effect accounting for about 63% of the annual CO_2 increase.

[Table 8. Decomposition of the Simulated Impacts on Expected Aggregate Emissions from the New Car Sales]

We now evaluate the impacts on social welfare. Table 9 report the simulated impacts of three policy scenarios on aggregate vehicle CO_2 emissions, compensating variation, industry profits for domestic automakers, and tax revenues. The compensating variation does not include the negative externality cost of vehicle emissions, and is estimated using a standard formula (see Knittel and Metaxoglou, 2012). In this sense, in our calculation of total economic surplus, we only include consumer surplus, producer surplus, and tax revenues, and does not include the negative externality costs of vehicle CO_2 emissions. We do this because the estimates of the marginal economic damages associated with CO_2 emissions vary substantially across studies due to scientific uncertainty.

As expected, the ES/ETC policy had a positive impact on both consumer welfare and industry profits, with increases of 175.8 billion yen and 106.8 billion yen annually relative to no policy. The increase in industry profits and consumer welfare more than offset the decrease in tax revenues. Because it also induced a reduction in vehicle CO_2 emissions, the ES/ETC policy was indeed welfare-improving. The net effects of the ES program on top of the ETC program are estimated at about -40.1, 33.8, and 29.2 billion yen, respectively, for compensating variation, industry profits, and tax revenues. Hence, the net gain in total economic surplus, excluding that from environmental damages, is positive and estimated to be 22.8 billion yen annually. Hence, the Japanese government decision to subsidy ecofriendly cars was also welfare-improving.[23] By contrast, the EVT-rebate policy, with $A = -200$ in eq. (9), was also estimated to increase total economic surplus by 46.2 billion yen annually. However, the increase in total surplus is small because the rebate policy decreases tax revenues substantially. Because the policy would increase vehicle CO_2 emissions substantially, the pure EVT-rebate policy would not have been welfare-enhancing unless the negative externality damage per ton of CO_2 is 8,700 yen or lower.[24]

[Table 9. The Simulated Impacts of the ETC/ES Policy on Aggregate Emissions, Compensating Variation, Industry Profits, and Tax Revenues]

We now investigates the economic impacts of varying levels of A, from a rebate ($A < 0$) to a tax ($A > 0$) on fuel inefficiency, using two reference tax systems: $m = 0$ (the pre-existing tax system) and $m =$ the ES/ETC policy in (9). Figure 4 reports the changes in annual vehicle CO_2 emissions and total economic surplus.

The figure demonstrates that there is a clear trade-off between total surplus and vehicle emissions. With either reference system, an EVT-rebate policy would generally increase total surplus at the cost of also increasing vehicle emissions. An EVT-tax policy would generally have the opposite effects. As expected, however, the total surplus (excluding environmental damages) has a concave relationship to aggregate vehicle emissions. Aggregate vehicle emissions is monotonically decreasing in A, whereas there is a tradeoff between tax revenues and the sum of consumer welfare and industry profits. The figure demonstrates the two unique features of Japan's ES/ETC policy. First, unlike the EVT policy, the ES/ETC policy does not exhibit a simple tradeoff between the total surplus and the vehicle emissions. As a result, the policy outcome (the triangle marker) is far off any points along the EVT curve (the + marker). Second, the ES/ETC policy increased the total surplus with only a small change in vehicle emissions. This occurs presumably because tax rate reductions were varied not only by fuel efficiency but also by other product characteristics (i.e., they vary by sales prices, weights, and displacement levels). Indeed, with the ES/ETC policy as the reference tax system in (9), we see that it is possible to reduce vehicle CO_2 emissions substantially while *also* increasing total economic surplus relative to the pre-existing equilibrium. The result of the exercise is illustrated by the dot plot, which demonstrates that this version of the EVT policy exhibits the analogous tradeoff between vehicle emissions and total surplus, yet the trajectory lies strictly above that for the case of $m =$ the pre-existing tax system. These results suggest that tailoring vehicle taxes for all relevant dimensions may be the key to improving efficiency.

[Figure 4. Simulated Impacts of Emissions-based Vehicle Tax Relative to Pre-existing Equilibrium, Avg. 2009-2012]

[23] Though not the primary objective of the paper, there were clear winners and losers in *all* policy scenarios. Toyota, the pioneer in production of hybrid cars, was the winner by large margins from the ES/ETC policy scenario whereas Honda and Nissan lost profits due to the ES/ETC policy.

[24] This calculation assumes an average year of use for the cars sold all years is approximately 10 years.

8. Concluding Remarks

Using detailed quarterly automobile sales data in Japan between 2004 and 2012, the random-coefficients logit model known as the BLP estimator was estimated. The estimated own- and cross-price elasticities of demand were then used to make inferences about the effects of the ETC and ES programs on aggregate vehicle CO_2 emissions and social welfare. We exploited the unique quasi-experimental setup created through a series of green car tax policies in the Japanese new car market in two ways. First, we took advantage of the large and persistent variation in the effective prices of cars that varied across models and over time in identifying the price elasticities. The estimated elasticities were then used to (i) simulate the counterfactual policies and (ii) decompose the scale and composition effects of the policies. Second, we constructed a new set of instrumental variables, arguing that the location of the tax rates over the product space is exogenous.

The results were much satisfying. The IVs seemed to work much better than the traditional product-location IVs. We found evidence of both strong scale and composition effects. The ES/ETC policy successfully shifted consumption toward fuel-efficient, ecofriendly cars, resulting in a large decline in the sales-weighted average emissions per vehicle (the composition effect). Yet, the policy also induced a higher level consumption of cars (the scale effect), which had largely offset the composition effect. As a result, the overall reduction in CO_2 emissions due to the policies was small. An alternative emissions-based vehicle tax would have reduced aggregate emissions substantially more. However, despite their negligible impacts on vehicle emissions, the ES/ETC policy was found to be substantially welfare-increasing, relative to both the no policy scenario, precisely due to the pre-existing market distortions. Most importantly, a version of the emissions-based vehicle tax would strictly improve social welfare, relative to both the no policy scenario and the ES/ETC policy scenario.

While our study offers several advantages over the previous studies, it also has several important limitations. Addressing them would define new and important agendas for future research. First, due to data limitation, we did not estimate the car ownership and utilization decisions jointly. Recent studies have shown that (i) combining the market-level data with household-level data (BLP, 2004; Petrin, 2004) and (ii) imposing cross-equation restrictions by imposing the Roy's identify for the demand for car utilization (Bento *et al.*, 2009) would improve the consistency and efficiency of the estimates. Second, we did not investigate the effects of the ES/ETC policy on used car and scrap markets. In theory, the policy must have had two counteracting effects. On one hand, the policy would induce consumers into buying new, fuel-efficient cars and, therefore, may facilitate retirement of old, fuel-inefficient cars.[25] On the other hand, the policy would also induce consumers into buying used cars because it would increase the supply of used cars, thereby decreasing the prices of used cars. Hence, it seems largely an empirical question whether inclusion of used car and scrap markets would increase or decrease the estimated impacts on aggregate emissions. Hence, collecting detailed household-level data on car ownership and utilization as well as detailed used car sales/scrap data and combining them with ours would further improve the accuracy of the estimated impacts of the green car tax reforms.

[25] An argument focusing only on this first effect is highly misleading at least in our context. Though we do not have detailed used car sales data by model (except for a small subset of the car models), we have data on aggregate used car sales and scrappage. The correlation between the aggregate new car sales and used car sales is a *positive* 0.16 during our study period (2004-2012). Moreover, the total scrappage *decreased* during the same period.

Appendix. Theoretical Underpinnings for the Emissions-based Vehicle Tax Policy

Consider the optimal combination of vehicle and gasoline taxes that would replicate the social optimum in the absence of imperfect competition. Fullerton and West (2002) show that given the efficient gasoline tax, the optimal vehicle tax rate for product attribute k for pollutant l is:

$$t^{lk} = \lambda^l VMT \left[\frac{\partial EPM^l}{\partial x^k} + \frac{EPM^l}{MPG} \frac{\partial MPG}{\partial x^k} \right], \tag{A1}$$

where λ^l is the negative external damage per unit of emissions, EPM^l is emissions per mile of driving, and MPG is milage per gallon of gasoline. As Fullerton and West (2002) note, the first term in the bracket times $\lambda^l VMT$ represents the environmental damage due to a per-unit increase of attribute k, and is positive for most product attributes (e.g., weight, size, and displacement). On the other hand, the second term in the bracket is often negative for most attributes because $\partial MPG/\partial x^k < 0$. This term is a 'rebate' for part of the external cost that is already internalized by the gasoline tax. Moreover, note that the expression inside the bracket can be rewritten as $\partial EPG^l/\partial x^k$, where EPG^l stands for emissions per gallon of gasoline. This means that there is no need for a separate vehicle tax if we care only about CO_2 emissions because $\partial EPG^{CO_2}/\partial x^k = 0$.

Summing over (A1) for all k and l, and evaluating it at the means of the product attributes, we obtain the amount of tax for an automobile with characteristics $\mathbf{x}_{jt}$:

$$T^{EVT}(\mathbf{x}_{jt}) = VMT \sum_{l=1}^{L} \sum_{k=1}^{K} \lambda^l \frac{\partial EPM^l(\bar{\mathbf{x}})}{\partial x^k} x_{jt}^k + VMT \sum_{l=1}^{L} \lambda^l \frac{EPM^l(\bar{\mathbf{x}})}{MPG(\mathbf{x}_{jt})} \left(\sum_{k=1}^{K} \frac{\partial MPG(\bar{\mathbf{x}})}{dx^k} x_{jt}^k \right),$$

where $\bar{\mathbf{x}}$ indicates a vector of the means of the attributes.

Note that the first term represents the (sum of) environmental damages from buying a car with attributes $\mathbf{x}_{jt}$. The second term is the rebate for buying a car with fuel efficiency $MPG(\mathbf{x}_{jt})$ that is already internalized by the gasoline tax. If we had product-specific emissions data for CO, HC, and NO_x, we would be able to estimate $\partial EPM^l/\partial x^k$ for each attribute k and replicate this tax perfectly. Unfortunately, we only have data on $MPG(\mathbf{x}_{jt})$. Under the pre-existing Japanese vehicle taxation, tax rates vary by vehicle weight and displacement because emissions per unit of fuel for CO, HC, and NO_x increase with these product attributes. Hence, the tax system may be already incorporating the first component. On the other hand, tax rates do not vary by fuel efficiency under the pre-existing tax system, and hence, it does not incorporate the second rebate component. Based on this observation, we approximate $T^{EVT}(\mathbf{x}_{jt})$ as follows:

$$\hat{T}^{EVT}(\mathbf{x}_{jt}) = \tau_{jt}^m + \frac{A(\boldsymbol{\lambda})}{MPG(\mathbf{x}_{jt})},$$

where τ_{jt}^m represent taxes under some benchmark taxation m and we evaluate $A(\boldsymbol{\lambda})$ at the means of the attributes, and therefore, is constant:

$$A(\boldsymbol{\lambda}) = VMT \sum_{l=1}^{L} \lambda^l EPM^l(\bar{\mathbf{x}}) \left(\sum_{k=1}^{K} \frac{\partial MPG(\bar{\mathbf{x}})}{dx^k} \bar{x}_{jt}^k \right). \tag{A2}$$

Indeed, the ES/ETC policy partly uses this idea because it gives subsidies and tax credits based on fuel efficiency.

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Figure 1. Data Coverage and Policy Periods

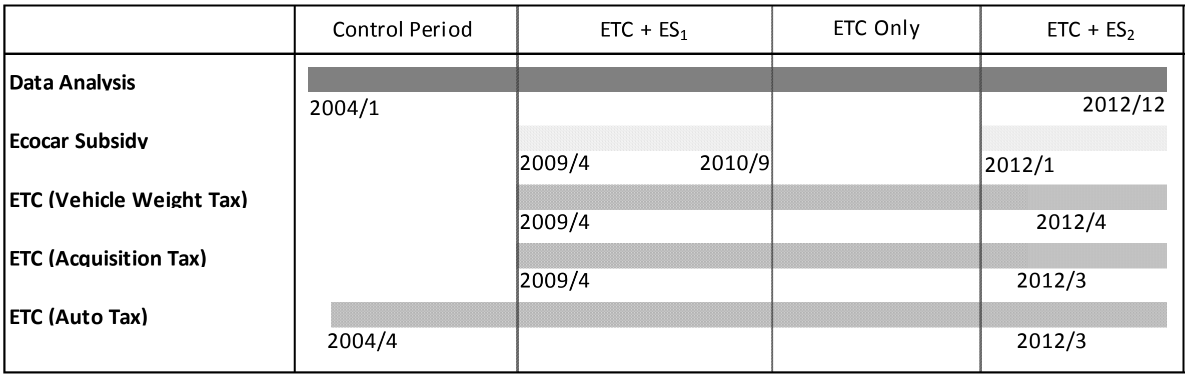
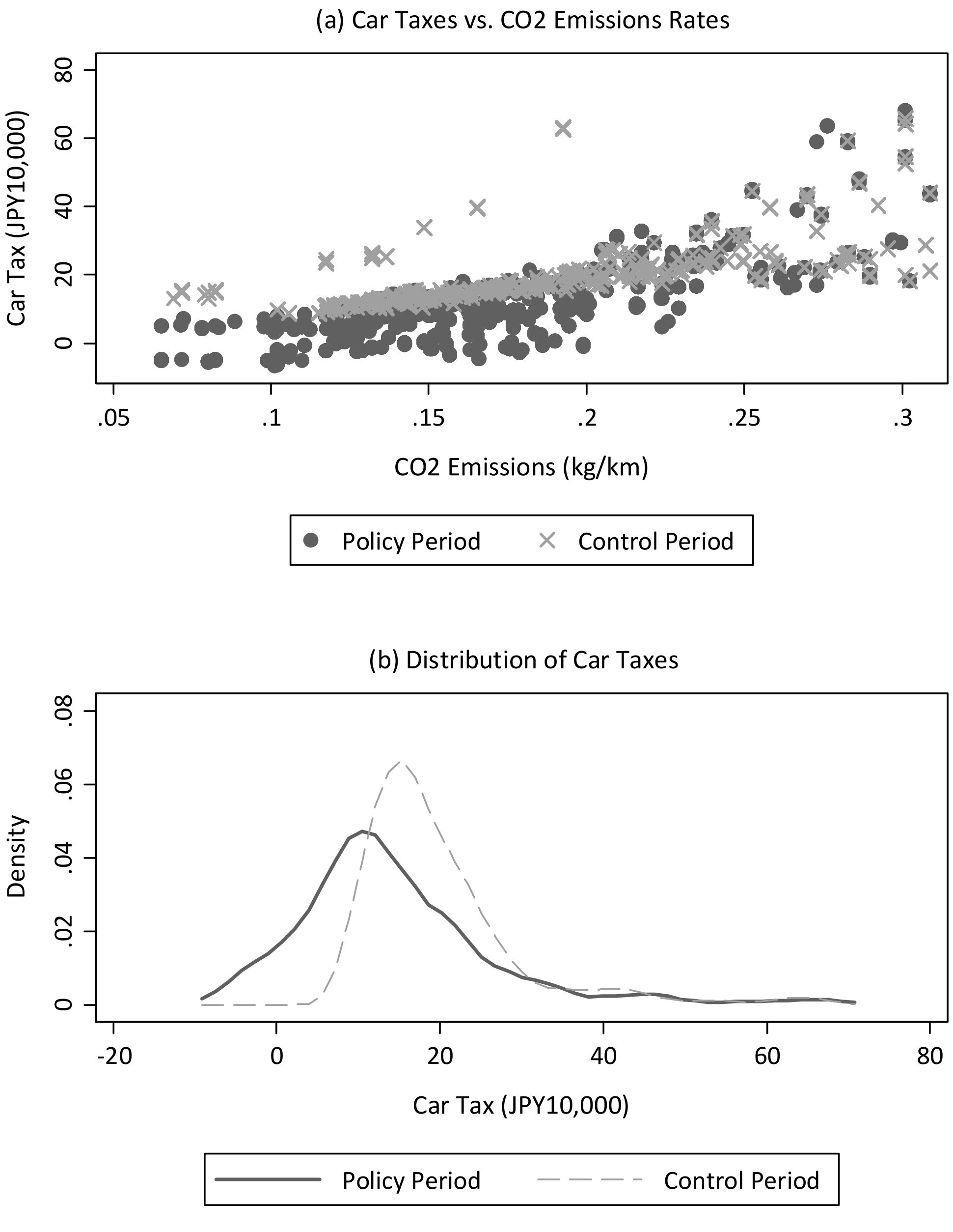


Figure 2. Regulatory Changes in Car Taxes in Japan



Note 1: CO_2 emissions for each model = Average CO_2 emissions per liters of gasoline/mileage per liter of gasoline. Average CO_2 emissions per liters of gasoline are taken from EPA (2012).
Note 2: Kernel density estimation used the Epanechnikov kernel and the bandwidth of 2.5.

Figure 3. Trends in New Car Sales, Hybrid Shares, Prices, and Car Tax Rates

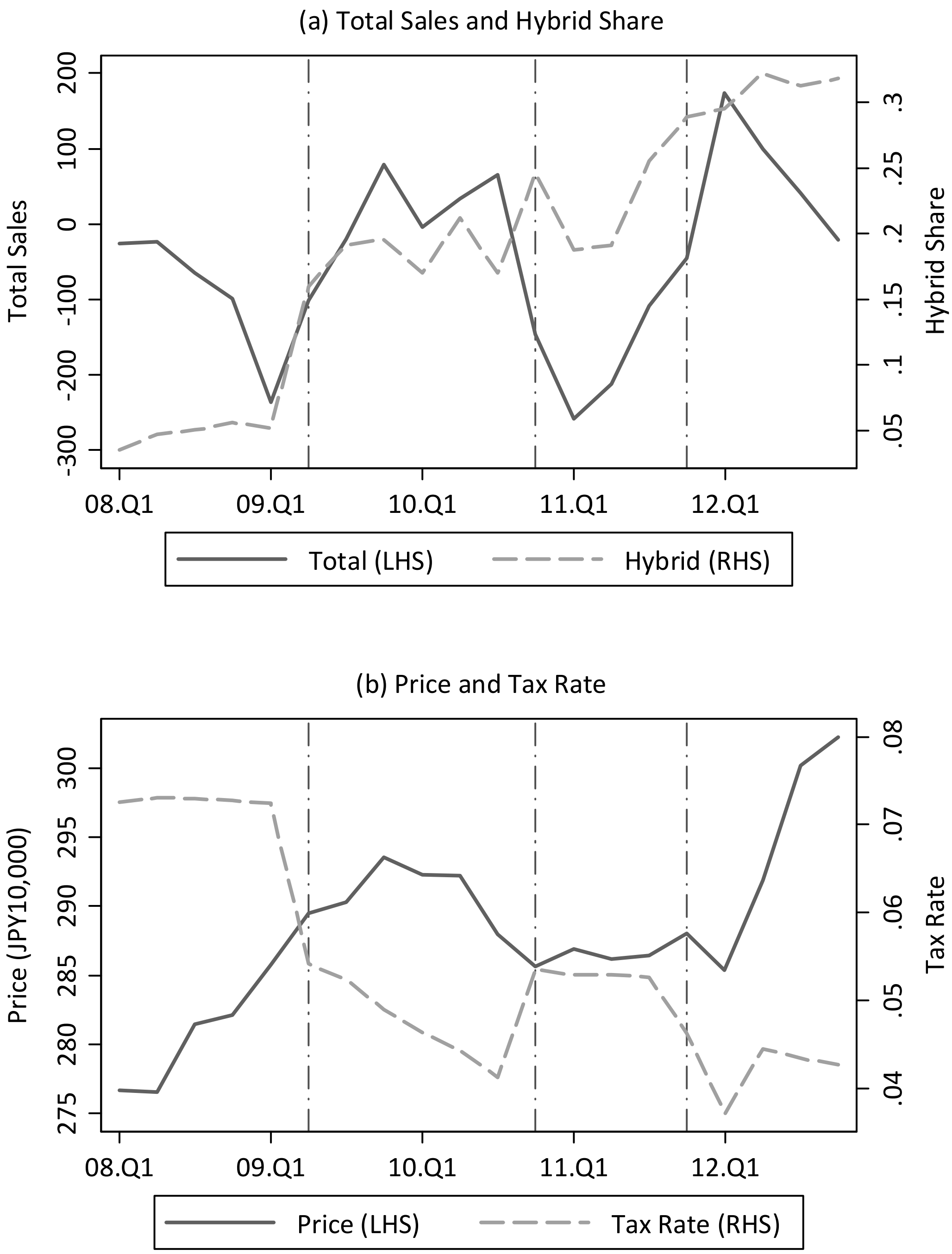


Figure 4. Trends in Monthly New Car Sales from 2006 to 2010

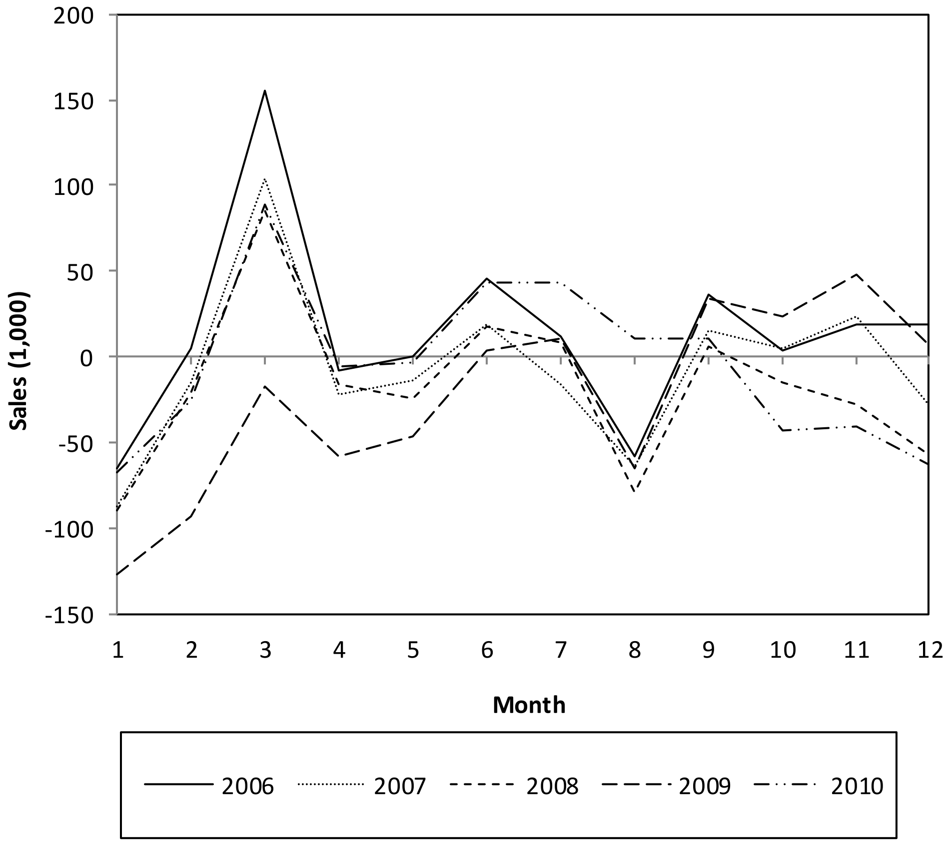


Figure 5. Simulated Impacts of Emissions-based Vehicle Tax
Relative to Pre-existing Equilibrium, Avg. 2009-2012

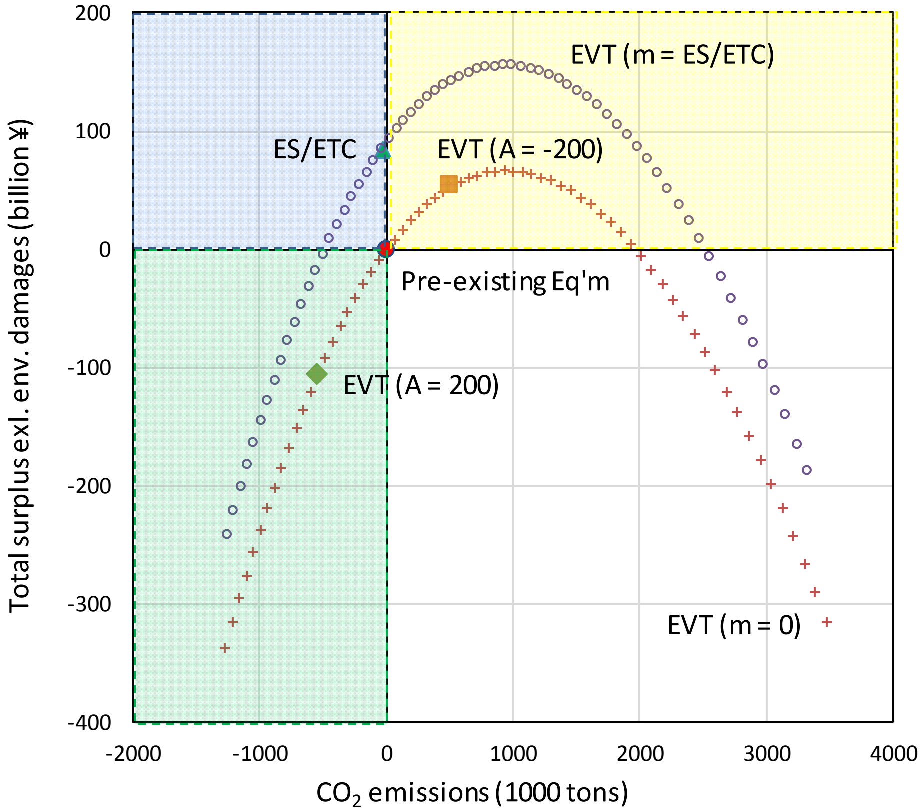


Table 1. Model Eligibility Requirements for ES and ETC during the Policy Period

	2010 Fuel Efficiency Standard				2005 Emissions Standard
	115% or above	Incentives	125% or above	Incentives	4 Stars
ES_1	✓	JPY100,000	✓	JPY100,000	✓
ES_2	---	---	✓	JPY100,000	✓
ETC (Vehicle Weight Tax)	✓	50% tax cut	✓	75% tax cut	✓
ETC (Acquisition Tax)	✓	50% tax cut	✓	75% tax cut	✓
ETC (Auto Tax)	✓	25% tax cut	✓	50% tax cut	✓

Note: The subsidy amount would increase to JPY 250,000 if it replaces the old car owned. The eligibility requirements for tax credits vary over the study period. The requirements in this table refer to those in 2009.

Table 2. Sales, Price and Product Characteristics of All Brands over Time

Quarter	Models	Sales	Price		HP/Weight		MPY		Size		AT	
			Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2004.1	127	923,562	199	72	0.101	0.018	15.0	3.9	7,637	480	0.685	0.311
2004.2	128	610,273	199	74	0.100	0.019	14.0	4.1	7,646	495	0.691	0.325
2004.3	125	756,844	194	68	0.100	0.018	13.2	3.6	7,622	518	0.686	0.327
2004.4	126	688,013	197	74	0.102	0.019	12.9	3.5	7,634	496	0.640	0.369
2005.1	126	898,849	193	71	0.101	0.018	13.0	3.3	7,618	491	0.638	0.351
2005.2	126	657,441	194	71	0.100	0.018	12.5	3.3	7,642	499	0.640	0.366
2005.3	131	727,971	196	70	0.100	0.018	11.8	3.1	7,666	496	0.611	0.378
2005.4	127	624,927	199	77	0.100	0.019	11.7	3.1	7,661	483	0.595	0.376
2006.1	116	879,339	196	72	0.100	0.018	11.7	2.9	7,651	483	0.575	0.371
2006.2	117	582,717	198	77	0.100	0.019	11.6	3.1	7,645	489	0.579	0.373
2006.3	115	651,025	197	75	0.099	0.018	11.1	3.0	7,641	481	0.569	0.371
2006.4	118	602,192	198	71	0.099	0.019	11.5	3.2	7,649	463	0.532	0.367
2007.1	119	784,087	201	72	0.100	0.020	11.9	3.2	7,648	484	0.535	0.377
2007.2	116	528,120	201	86	0.099	0.020	11.8	3.3	7,636	483	0.521	0.377
2007.3	111	596,774	202	90	0.099	0.019	11.1	3.0	7,639	482	0.461	0.389
2007.4	113	561,911	205	87	0.100	0.021	10.6	3.0	7,649	477	0.463	0.374
2008.1	114	758,085	204	90	0.100	0.022	10.4	2.9	7,638	481	0.466	0.371
2008.2	117	520,908	208	96	0.100	0.022	10.7	3.1	7,643	493	0.466	0.365
2008.3	117	596,323	205	88	0.099	0.020	9.3	2.6	7,650	499	0.445	0.354
2008.4	119	462,284	208	90	0.098	0.020	12.3	3.7	7,640	514	0.431	0.355
2009.1	121	546,509	198	79	0.097	0.020	15.5	4.4	7,577	518	0.440	0.368
2009.2	123	442,627	204	85	0.095	0.020	15.9	5.9	7,597	496	0.368	0.357
2009.3	123	640,969	201	78	0.094	0.019	15.2	6.1	7,604	481	0.341	0.343
2009.4	121	639,553	209	85	0.094	0.019	14.8	6.0	7,646	489	0.319	0.331
2010.1	122	779,417	213	92	0.096	0.020	14.2	5.6	7,657	492	0.310	0.312
2010.2	122	578,088	209	82	0.094	0.019	14.2	5.8	7,635	476	0.273	0.308
2010.3	123	726,562	210	82	0.095	0.018	13.7	5.4	7,657	481	0.276	0.301
2010.4	122	414,843	216	89	0.095	0.021	15.0	6.3	7,669	499	0.257	0.318
2011.1	122	525,429	209	87	0.095	0.020	13.6	5.2	7,624	499	0.245	0.325
2011.2	123	332,096	206	81	0.094	0.020	12.8	4.5	7,614	471	0.229	0.312
2011.3	124	553,094	209	83	0.092	0.020	13.6	4.8	7,638	446	0.198	0.305
2011.4	126	515,609	220	85	0.092	0.021	14.1	5.2	7,698	462	0.205	0.311
2012.1	127	957,250	225	82	0.088	0.021	18.0	11.3	7,670	448	0.157	0.279
2012.2	126	643,284	226	88	0.087	0.020	17.8	10.8	7,653	463	0.141	0.271
2012.3	126	702,075	224	86	0.088	0.021	18.6	11.3	7,648	444	0.131	0.268
2012.4	126	540,448	224	102	0.088	0.023	18.3	10.8	7,638	445	0.127	0.272

Note: A hybrid version of the same car brand is treated as a separate brand, so the sales and other product characteristics exclude those of the hybrid model. Price = average retail price in 10,000 JPY; HP/Weight = HP/weight in kw/kg; MPY = mileage in km per JPY; Size = the sum of length, width and height; AT = the fraction of the car grades that have automatic transmission.

Table 3. Sales, Price and Product Characteristics of Hybrid Cars over Time

Quarter	Models	Sales		Price		HP/Weight		MPY		Size		AT	
		Total	Share	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2004.1	4	16,035	0.017	224	28	0.060	0.002	32.0	2.7	7,689	144	0	0
2004.2	4	18,241	0.030	222	24	0.059	0.002	29.8	2.1	7,680	121	0	0
2004.3	3	15,320	0.020	226	32	0.060	0.002	27.7	2.7	7,698	159	0	0
2004.4	4	13,405	0.019	225	31	0.060	0.003	27.0	2.6	7,694	162	0	0
2005.1	6	14,368	0.016	239	57	0.064	0.014	26.2	4.0	7,737	214	0	0
2005.2	6	13,303	0.020	243	62	0.065	0.015	24.8	4.0	7,748	227	0	0
2005.3	6	14,092	0.019	246	65	0.065	0.015	23.4	4.0	7,761	242	0	0
2005.4	6	11,499	0.018	249	60	0.065	0.014	23.6	4.0	7,757	235	0	0
2006.1	5	11,866	0.013	254	80	0.069	0.019	23.6	4.1	7,752	208	0	0
2006.2	8	15,172	0.026	273	109	0.070	0.023	22.4	4.7	7,789	261	0	0
2006.3	7	21,340	0.033	289	111	0.070	0.022	20.4	4.8	7,866	315	0	0
2006.4	7	23,747	0.039	267	83	0.066	0.016	21.9	4.3	7,818	298	0	0
2007.1	7	23,628	0.030	275	85	0.067	0.016	22.5	4.8	7,852	316	0	0
2007.2	7	19,125	0.036	328	230	0.073	0.031	21.5	5.5	7,864	327	0	0
2007.3	7	21,309	0.036	362	279	0.077	0.037	19.7	5.5	7,880	338	0	0
2007.4	7	21,187	0.038	316	223	0.071	0.030	19.8	4.7	7,825	307	0	0
2008.1	8	26,634	0.035	321	223	0.072	0.031	19.0	4.7	7,843	318	0	0
2008.2	8	24,644	0.047	329	210	0.078	0.037	19.2	5.0	7,839	286	0	0
2008.3	7	29,963	0.050	323	173	0.079	0.036	16.2	4.2	7,856	286	0	0
2008.4	7	25,832	0.056	299	160	0.071	0.029	22.5	4.8	7,802	266	0	0
2009.1	8	28,426	0.052	245	99	0.068	0.018	28.6	4.1	7,676	221	0	0
2009.2	9	70,575	0.159	239	101	0.074	0.016	27.2	4.4	7,680	230	0	0
2009.3	10	122,798	0.192	233	86	0.074	0.013	26.2	4.2	7,704	204	0	0
2009.4	11	124,989	0.195	245	103	0.075	0.014	25.2	4.4	7,715	204	0	0
2010.1	12	132,374	0.170	264	130	0.079	0.018	24.5	5.1	7,742	217	0	0
2010.2	12	122,369	0.212	242	92	0.077	0.015	23.8	4.3	7,689	205	0	0
2010.3	12	123,358	0.170	248	107	0.077	0.017	23.8	4.5	7,703	219	0	0
2010.4	14	102,012	0.246	227	99	0.076	0.016	24.6	3.8	7,580	306	0.011	0.106
2011.1	14	98,710	0.188	235	103	0.076	0.016	22.6	3.6	7,562	313	0.010	0.101
2011.2	14	63,359	0.191	244	93	0.075	0.016	20.6	2.6	7,623	298	0.013	0.114
2011.3	15	141,087	0.255	254	96	0.073	0.015	20.6	2.4	7,748	235	0.005	0.073
2011.4	19	148,781	0.289	254	86	0.073	0.015	20.9	2.9	7,782	239	0.005	0.068
2012.1	19	282,623	0.295	231	81	0.071	0.012	21.3	3.5	7,636	371	0.003	0.057
2012.2	21	207,197	0.322	233	99	0.073	0.014	20.9	3.8	7,594	406	0.006	0.076
2012.3	24	219,347	0.312	234	98	0.074	0.015	21.6	4.4	7,619	424	0.007	0.084
2012.4	24	171,833	0.318	229	120	0.073	0.015	21.7	4.4	7,557	430	0.013	0.113

Note: Price = average retail price in 10,000 JPY; HP/Weight = HP/weight in kw/kg; MPY = mileage in km per JPY; Size = the sum of length, width and height; AT = the fraction of the car grades that have automatic transmission.

Table 4. Estimation Results: OLS Logit and IV Logit

	OLS Logit		IV Logit					
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Constant	-18.0849 ***	-18.3645 ***	-13.5998 ***	-17.5838 ***	-20.0887 ***	-15.2705 ***	-18.1825 ***	-20.4922 ***
	(0.6399)	(0.6434)	(3.4256)	(1.2504)	(1.0059)	(3.4008)	(1.2512)	(1.0085)
Price	-0.0052 ***	-0.0052 ***	-0.0021	-0.0048 ***	-0.0066 ***	-0.0031	-0.0051 ***	-0.0066 ***
	(0.0002)	(0.0002)	(0.0023)	(0.0008)	(0.0006)	(0.0023)	(0.0008)	(0.0006)
HP/Weight	0.5218	0.6767	-10.4556	-0.7047	5.4263 **	-6.8799	0.2322	5.8732 ***
	(0.9919)	(0.9913)	(8.2914)	(2.8116)	(2.1406)	(8.2139)	(2.8037)	(2.1375)
MPY	0.0924 ***	0.0996 ***	0.0708 ***	0.0900 ***	0.1020 ***	0.0810 ***	0.0950 ***	0.1062 ***
	(0.0087)	(0.0087)	(0.0184)	(0.0101)	(0.0095)	(0.0184)	(0.0101)	(0.0095)
Size	0.0007 ***	0.0007 ***	0.0002	0.0007 ***	0.0009 ***	0.0004	0.0007 ***	0.0010 ***
	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)
AutoTransmission	-0.4361 ***	-0.4245 ***	-0.4672 ***	-0.4395 ***	-0.4221 ***	-0.4463 ***	-0.4258 ***	-0.4095 ***
	(0.0616)	(0.0135)	(0.0675)	(0.0619)	(0.0621)	(0.0666)	(0.0619)	(0.0621)
Maker Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Quarter Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Macroecon. Var.	---	✓	---	---	---	✓	✓	✓
Location IVs used	---	---	Characteristics	Taxes	Taxes + Characteristics	Characteristics	Taxes	Taxes + Characteristics
R^2	0.4593	0.461	0.4256	0.4588	0.4525	0.4450	0.4609	0.4534
Overidentification Tests								
Sargan χ^2	---	---	27.1428	13.8833	49.1259	17.6110	4.5628	35.4057
(p-values)			(0.0003)	(0.0031)	(0.0000)	(0.0139)	(0.2068)	(0.0002)
Basmann χ^2	---	---	27.1124	13.8383	49.2751	17.5488	4.5373	35.3927
(p-values)			(0.0003)	(0.0031)	(0.0000)	(0.0142)	(0.2090)	(0.0002)
# of Obs.	4,371	4,371	4,371	4,371	4,371	4,371	4,371	4,371

Note: In parentheses are standard errors.

Table 5. Estimation Results: Full Random-Coefficients Logit

	RC Logit (IX)		RC Logit (X)	
	Mean	St. Dev.	Mean	St. Dev.
Constant	14.9950	-17.2590 **	-68.8420 ***	-15.7900 ***
	(14.0580)	(9.9639)	(5.7565)	(1.4125)
Price	0.0175 **	-0.0074	-0.0406 ***	-0.0047 *
	(0.0094)	(0.0498)	(0.0036)	(0.0033)
HP/Weight	-109.8000 ***	12.0190	106.5500 ***	10.5630 ***
	(33.3990)	(55.3300)	(12.9110)	(0.6198)
MPY	-0.2913 ***	0.1342	0.1154 ***	0.1180
	(0.0793)	(0.5717)	(0.0492)	(0.1695)
Size	-0.0043 ***	0.0002	0.0052 ***	0.0000
	(0.0015)	(0.0008)	(0.0006)	(0.0007)
AutoTransmission	-1.1842 ***	-0.4779	-0.6259 **	-0.5051
	(0.3100)	(27.5530)	(0.2848)	(9.8557)
Maker Dummies	✓		✓	
Year Dummies	✓		✓	
Quarter Dummies	✓		✓	
Macroecon. Var.	✓		✓	
Location IVs used	Characteristics		Taxes	
# of Obs.	4,371		4,371	
GMM Obj.	7,288.9		15.8	

Note: In parentheses are standard errors. Inner-loop tolerance for NFP = 1E-14. Outer-loop tolerance for GMM = 1E-3.

Table 6. Product Characteristics, Estimated Elasticities, and Implied Price-cost Margins of the Top 15 Sales Brands for 2011

Brand Name	Sales	Price	HP/Weight	MPY	Size	AT	Own-price elasticities	Price-cost Margin	Outside Substitution
1 Toyota Prius	252,232	239	0.069	22.9	7,822	0.000	-0.177	0.25	8.00
2 Toyota Vitz	128,725	135	0.092	15.2	7,094	0.000	-1.087	0.43	8.23
3 Honda Fit	105,310	140	0.098	13.3	7,211	0.359	-0.237	0.17	8.34
4 Honda Fit Hybrid	102,386	173	0.075	20.4	7,314	0.000	-0.064	0.15	7.67
5 Mazda Demio	61,902	126	0.098	14.1	7,066	0.216	-0.120	0.18	8.59
6 Toyota Ractis	58,964	152	0.090	13.3	7,282	0.000	-1.877	0.39	7.97
7 Honda Freed	56,345	183	0.088	10.7	7,634	0.396	-0.168	0.13	7.36
8 Toyota Passo	53,973	117	0.079	14.5	6,844	0.000	-0.240	0.48	8.66
9 Honda StepWgn	48,765	258	0.089	9.1	8,208	0.500	-0.253	0.11	6.09
10 Toyota Corolla	48,038	177	0.097	11.7	7,590	0.000	-6.497	0.33	7.51
11 Nissan Note	46,448	147	0.096	12.0	7,249	0.286	-0.824	0.17	8.14
12 Nissan Serena	38,433	241	0.086	10.0	8,304	0.000	-1.776	0.11	6.26
13 Suzuki Solio	36,875	146	0.086	14.9	7,095	0.000	-0.253	0.17	8.00
14 Nissan Cube	35,643	158	0.088	12.4	7,244	0.000	-0.472	0.16	7.87
15 Suzuki Swift	31,339	129	0.088	14.6	7,064	0.000	-0.512	0.18	8.36

Note: A hybrid version of the same car brand is treated as a separate brand, so the sales and other product characteristics exclude those of the hybrid model. Price = average retail price in 10,000 JPY; HP/Weight = HP/weight in kw/kg; MPY = mileage in km per JPY; Size = the sum of length, width and height; AT = the fraction of the car grades that have automatic transmission; Outside substitution = estimated percentage of consumers who substitute to the outside good as a percentage of those who substitute away from the good, given a price increase of the good. All quantities are simple averages, except for sales, which is the sum of sales for 2011.

Table 7. Estimated Own- and Cross-Price Elasticities for a Sample of 15 Brands in 2011

	Brand Name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Honda StepWgn	-0.253	0.001	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001
2	Nissan Serena	0.001	-1.776	0.026	0.001	0.001	0.000	0.001	0.001	0.002	0.004	0.003	0.001	0.006	0.001	0.009
3	Toyota Corolla	0.003	0.024	-6.497	0.002	0.006	0.001	0.003	0.003	0.011	0.020	0.016	0.007	0.032	0.008	0.048
4	Toyota Prius	0.000	0.003	0.016	-0.177	0.001	0.000	0.000	0.000	0.001	0.002	0.002	0.001	0.004	0.001	0.006
5	Honda Fit	0.000	0.002	0.011	0.000	-0.237	0.000	0.000	0.000	0.001	0.002	0.001	0.001	0.003	0.001	0.004
6	Honda Fit Hybrid	0.000	0.001	0.003	0.000	0.000	-0.064	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001
7	Honda Freed	0.000	0.001	0.004	0.000	0.000	0.000	-0.168	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001
8	Mazda Demio	0.000	0.001	0.004	0.000	0.000	0.000	0.000	-0.120	0.000	0.001	0.000	0.000	0.001	0.000	0.001
9	Nissan Cube	0.000	0.001	0.007	0.000	0.000	0.000	0.000	0.000	-0.472	0.001	0.001	0.000	0.002	0.000	0.003
10	Nissan Note	0.000	0.003	0.016	0.000	0.001	0.000	0.000	0.000	0.001	-0.824	0.002	0.001	0.004	0.001	0.006
11	Suzuki Swift	0.000	0.001	0.007	0.000	0.000	0.000	0.000	0.000	0.001	0.001	-0.512	0.000	0.002	0.000	0.002
12	Suzuki Solio	0.000	0.001	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	-0.253	0.001	0.000	0.001
13	Toyota Vitz	0.001	0.010	0.060	0.001	0.003	0.001	0.001	0.002	0.005	0.009	0.007	0.003	-1.087	0.004	0.022
14	Toyota Passo	0.000	0.001	0.006	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.001	-0.240	0.002
15	Toyota Ractis	0.001	0.008	0.048	0.001	0.002	0.000	0.001	0.001	0.004	0.007	0.006	0.002	0.012	0.003	-1.877

Note : Each entry (j,k) indicates a percentage change in market share of brand j with respect to a percentage change in price of brand k .

Table 8. Decomposition of the Simulated Impacts on Expected Aggregate Emissions from the New Car Sales

	No Policy (1)	ETC Only (2)	ES/ETC (3)	EVT (4)		Diff. (2) - (1)	S.E. of Diff.	Diff. (3) - (1)	S.E. of Diff.	Diff. (4) - (1)	S.E. of Diff.
2009	5,652	5,661	5,673	6,151	Total Effect:	9.1	(101.5)	20.5	(66.5)	498.5	(296.0)
					Scale	47.9		104.5		328.4	
					Compotition	-38.9		-84.0		170.1	
2010	5,625	5,637	5,637	6,125	Total Effect:	11.5	(57.6)	12.0	(25.0)	499.5	(84.0)
					Scale	97.4		196.2		341.7	
					Compotition	-85.9		-184.2		157.8	
2011	4,765	4,718	4,712	5,170	Total Effect:	-47.0	(107.5)	-52.8	(107.5)	405.3	(158.7)
					Scale	64.9		65.5		222.2	
					Compotition	-111.8		-118.3		183.1	
2012	7,009	6,963	6,922	7,715	Total Effect:	-45.7	(132.4)	-87.3	(83.7)	706.2	(455.0)
					Scale	74.7		154.1		442.4	
					Compotition	-120.4		-241.4		263.8	
Annual	5,763	5,745	5,736	6,290	Total Effect:	-18.0	(69.3)	-26.9	(52.9)	527.4	(169.2)
					Scale	71.2		130.1		333.7	
					Compotition	-89.2		-157.0		193.7	

Note: All numbers are in 1000 tons of carbon dioxides emissions. In parentheses are standard errors.

Table 9. Simulated Impacts of the ETC/ES Policy on Aggregate Emissions, Compensating Variation, Industry Profits, and Tax Revenues

	Changes to vehicle emissions (relative to no policy) due to:			Changes to compensating variation (relative to no policy) due to:			Changes to industry profits (relative to no policy) due to:			Changes to tax revenues (relative to no policy) due to:		
	ES/ETC	ETC Only	EVT	ES/ETC	ETC Only	EVT	ES/ETC	ETC Only	EVT	ES/ETC	ETC Only	EVT
	(1000 tons of CO_2)			(billion ¥)			(billion ¥)			(billion ¥)		
2009	20.51	9.07	498.54	144.98	63.82	457.15	100.40	46.30	65.30	-168.36	-69.34	-476.80
	(101.5)	(66.5)	(296.0)	(78.5)	(27.4)	(71.7)	(48.3)	(19.2)	(78.4)	(91.0)	(26.3)	(95.7)
2010	12.03	11.47	499.53	254.85	123.20	455.24	183.26	89.59	68.41	-287.85	-131.88	-474.79
	(57.6)	(25.0)	(84.0)	(91.9)	(15.5)	(81.9)	(40.8)	(20.0)	(23.2)	(106.2)	(19.1)	(84.4)
2011	-52.78	-46.96	405.34	110.43	106.30	384.72	44.37	42.44	52.23	-118.71	-113.75	-400.82
	(107.5)	(107.5)	(158.7)	(43.5)	(13.3)	(84.7)	(13.3)	(9.8)	(43.2)	(47.8)	(15.4)	(87.6)
2012	-87.28	-45.66	706.20	192.84	570.21	466.83	98.97	113.60	74.89	-221.52	-598.07	-487.62
	(132.4)	(83.7)	(455.0)	(117.1)	(44.9)	(84.4)	(74.1)	(12.6)	(123.4)	(136.9)	(46.2)	(106.3)
Avg.	-26.88	-18.02	527.40	175.77	215.88	440.99	106.75	72.98	65.21	-199.11	-228.26	-460.01
	(69.3)	(52.9)	(169.2)	(79.0)	(22.3)	(73.3)	(27.3)	(9.4)	(47.2)	(91.2)	(23.1)	(82.9)

Note: In parentheses are standard errors.