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Portfolio Considerations in Differentiated Product Purchases: An Application to the Japanese Automobile Market*

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Abstract

Consumers often purchase more than one differentiated product, assembling a *portfolio*, which might potentially affect substitution patterns of demand and, as a consequence, oligopolistic firms' pricing strategies. To study such consumers' portfolio considerations, this paper develops and estimates a structural model that allows for flexible complementarities/substitutabilities, using Japanese household-level data on automobile purchases. My estimates suggest that complementarities arise when households purchase a combination of one small automobile and one minivan as their portfolio. Simulation results suggest that, due to such portfolio considerations, a policy proposal of repealing the current tax subsidies for small eco-friendly automobiles would not necessarily sharply decrease the demand.

Keywords: *Multiple Discrete Choices, Complementarities, Environmental Policy*
JEL Classification: D43, L13, L62, Q58

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1 Introduction

In many differentiated product markets, such as the markets for automobiles and personal computers, consumers often purchase more than one product. For instance, the U.S. Department of Transportation reports more than 55% of U.S. households owned more than one automobile in 2000. In such situations, consumers typically choose several different products rather than multiple units of an identical product, assembling a portfolio that meets their specific needs. For example, a married couple with two children might purchase one compact sedan to commute to work on the weekdays and one minivan to go camping on the weekends, instead of two midsize sedans. This illustrative example suggests that because of the complementarity between some products the utility from such a portfolio of products might not simply be the sum of the products' individual utilities, though most of the existing literature ignores such effects. In this paper, I call the extra utility that a household derives from purchasing combinations of products the "portfolio effect."[1]

This portfolio effect potentially plays an important role for evaluating government policies or examining firms' strategies which promote the consumption of particular types of products. For example, in the automotive industry, governments might subsidize fuel-efficient automobiles. Then, a household planning to purchase a midsize sedan and a minivan might instead purchase one compact car, which is eligible for the subsidy, and one slightly larger and more luxurious minivan than it was expected to purchase. The subsidy could therefore lead to an unintended consequence, because larger automobiles tend to be less fuel-efficient.

This paper develops an empirical framework for estimating a market equilibrium model that incorporates portfolio effects in consumer demand explicitly, building upon previous models considered by Berry, Levinsohn and Pakes (1995) (hereafter BLP) and Gentzkow (2007). In the model, there are two types of agents – consumers and firms. Consumers maximize utility by choosing one or two products, subject to a budget constraint. They can also choose to purchase nothing. Each product is characterized by a bundle of characteristics, and consumers derive utility from these characteristics. When they purchase two products, consumers may potentially derive an extra utility – the portfolio effect – depending on household attributes and product types. As suggested by the data, I introduce portfolio effects that vary by the product categories. I divide the set of automobiles into three categories (i.e., small cars, regular cars and minivans) and assume that consumers obtain the same

[1] In single discrete choice models, all choices are restricted a priori to be perfect substitutes. Moreover, even allowing for purchasing two products, such patterns cannot be generated unless the model takes into account the portfolio effects.

portfolio effect for any set of two automobiles that belong to the same respective categories. The supply side follows BLP where oligopolistic multi-product firms simultaneously set the prices for their products to maximize profits, taking into account the pricing strategies of other firms.

I apply the framework to the Japanese automobile market and estimate the model, drawing on various sources of information including individual-level data on purchasing decisions, in addition to macro-level data on market shares. Newly collected data from the Keio Household Panel Survey (KHPS) provides household-level data on annual automobile purchasing decisions, as well as basic household demographics, for 4,005 representative Japanese households. This micro-level dataset enables me to relate household attributes to the characteristics of purchased products and to identify the value of joint ownership of different categories of automobiles. I estimate the model by minimizing the distance between the empirical moments derived from the individual-household level data and the moments predicted by the model, as developed by Petrin (2002) and applied by Berry, Levinsohn and Pakes (2004) (hereafter micro-BLP). The estimation results show that there exists a positive portfolio effect between small cars and minivans. The estimates also indicate that households are more likely to purchase two automobiles as their number of income earners increases and if they are located in rural areas. These results immediately lead to the following question: Would ignoring portfolio effects lead to a biased counterfactual analysis?

I use the estimated structural model to simulate the effect of eliminating the current tax subsidies for small automobiles (commonly known in Japan as *kei-cars*).[2] In Japan, among households who purchase more than one automobile, more than half purchase at least one kei-car. The popularity of kei-cars is partially due to government tax subsidies that were introduced in the 1960s to make small cars more affordable for Japanese households, and that currently promote ownership of environmentally-friendly small cars. In recent years, there has been debate about repealing these tax subsidies. The opposition claims that the demand for fuel efficient kei-cars would dramatically decrease, which would have detrimental impact on the environment. However, if there is a positive portfolio effect between kei-cars and other types of cars, then those households who purchase one minivan and one kei-car under the current tax scheme might maintain their portfolios by purchasing more affordable minivans and kei-cars after the subsidies are repealed. As a consequence, the demand for kei-cars might not decrease as sharply, i.e., the environmental effect of the repeal of tax

[2] A kei-car is the smallest automobile classification in Japan. To be classified as a kei-car, an automobile must have an engine displacement of less than 660cc, and its exterior width, height, and length must be less than 4.86 ft., 6.56 ft., and 11.15 ft., respectively.

subsidies for small kei-cars might be limited.

This economic intuition is verified by the following two sets of simulation results. First of all, my model (hereinafter the portfolio-BLP model) predicts that the total demand for kei-cars would decrease by 9.0% and the total demand for other automobiles would increase by 3.9%. On the other hand, a standard single choice model, the micro-BLP model, predicts that the total demand for kei-cars would decrease by 14.0% and the demand for other automobiles would increase by 5.8%. Thus, by ignoring portfolio effects, the effects of repealing tax subsidies are overstated. Secondly, the portfolio-BLP model predicts that the demand for affordable minivans would increase and that for expensive minivans would decrease slightly. On the other hand, the micro-BLP model predicts that the demand for both types of minivans would increase. These two sets of results imply that some households highly value a combination of one kei-car and one minivan, and those households would purchase one kei-car and one relatively cheap minivan to maintain the benefits from their portfolios under the new tax policy.

In the interest of examining the environmental implications of allowing for the portfolio effect, I calculate the harmonic average of fuel efficiency of automobiles, which is commonly known as *Corporate Average Fuel Efficiency (CAFE) Standards* Index. Though both models predict a slight decrease in average fuel efficiency, the portfolio-BLP model still predicts higher average fuel efficiency than the micro-BLP model, implying that the environmental implications might be also overstated in the micro-BLP model. This difference between the predictions from two models can be explained by the same logic; some households giving up purchasing huge minivans and purchasing affordable minivans instead contribute to the higher average fuel efficiency, whereas this cannot happen in the micro-BLP model.[3] As a corollary of this result, when a government provides more subsidies for purchasing eco-friendly automobiles, we might not always be able to achieve the intended goal due to the portfolio effect.

2 The Model

Consider a differentiated product market. Each product is indexed by j, $j = 1, 2, \cdots, J$, and is expressed as a bundle of characteristics, such as horsepower and fuel efficiency. Let p_j and $\boldsymbol{x}_j$ denote the price and other characteristics of automobile j, respectively. As a matter of convention, let $j = 0$ denote the outside good, i.e., purchasing no products. This charac-

[3] Among the studies of implications for the incident of environmental taxes, West (2004) also emphasize the importance of household heterogeneity.

teristic approach is commonly employed in estimating discrete choice models, especially in studies of the automotive industry, such as BLP, Bresnahan (1987), and Goldberg (1995). This paper uses a BLP-type random coefficients model.

There are two types of agents: consumers and producers. I describe the consumers' and producers' maximization problems in the following sections.

2.1 Household Behavior

Let $i = 1, 2, \cdots, N$ denote the individual households. Each household is characterized by its observed characteristics, $(y_i, \boldsymbol{z}_i)$, where y_i denotes the income of households and $\boldsymbol{z}_i$ denotes other household characteristics such as such as family size, age of the household head, number of kids and so on. In the model, I assume that each household purchases up to two automobiles. Let $\boldsymbol{d}_i = (d_{i1}, d_{i2})$ denote an automobile purchase decision for household i, where each d_{ik} specifies the product, i.e., $d_{ik} = 0, 1, \cdots, J$ for $k = 1, 2$. The households maximize their utilities by choosing automobile purchases and levels of non-automobile consumption goods, C. Namely, each household i solves the following maximization problem;

$$\max_{C,(j,l)} u^c(C) u_i^a(j,l) \qquad \text{s.t.} \;\; C + p^c(p_j; \boldsymbol{\tau}) + p^c(p_l; \boldsymbol{\tau}) \leq y_i,$$

with

$$u^c(C) = C^\alpha, \quad \text{and} \quad \log(u_i^a(j,l)) = u_{ij} + u_{il} + \Gamma(j, l; z_i^c) + \varepsilon_{i,(j,l)},$$

where p_j is the price that firms charge for automobile j, $p^c(p_j; \boldsymbol{\tau})$ is the after-tax price for automobile j that consumers must pay under tax scheme $\boldsymbol{\tau}$, u_i^a is the utility from automobile consumption, which could be different for each household even if they choose the same automobiles, and u^c is the utility from non-automobile consumption.[4] This functional form is a Cobb-Douglas utility function in automobile and non-automobile consumption. I assume that the log of utility from automobile consumption is the sum of the following components; (i) the utilities from each automobile consumption, u_{ij} and u_{il}, (ii) an interaction term between two automobiles which I call the portfolio effect, $\Gamma(j, l; z_i^c)$, and (iii) idiosyncratic individual preference shock, $\varepsilon_{i,(j,l)}$, assumed to be independent of the product characteristics and of each other. In the following section, I explain the utilities from each automobile consumption and the portfolio effect term.

[4] To keep the notation for prices simple, I use p_j instead of $p^c(p_j; \boldsymbol{\tau})$ in this section, and will introduce detailed automobile taxes in Section 6.

Utility from Single Automobile Consumption For each automobile consumption, a household derives the following utility;

$$u_{ij} = \boldsymbol{x}_j \boldsymbol{\beta}_i' + \xi_j = \sum_{m=1}^{M} x_{jm} \beta_{im} + \xi_j, \tag{1}$$

with

$$\beta_{im} = \bar{\beta}_m + \sum_{r=1}^{R} z_{ir}^p \beta_{mr}^o + \beta_m^u \nu_{im}, \tag{2}$$

where $\boldsymbol{x}_j = [x_{j1}, \cdots, x_{jM}]$ and ξ_j represent the observed and unobserved characteristics for product j respectively, $\boldsymbol{\beta}_i = [\beta_{i1}, \cdots, \beta_{iM}]$ denotes household i's valuation for each product characteristic, $\boldsymbol{z}_i^p = [z_{i1}^p, \cdots, z_{iR}^p]$ and ν_i represent observed and unobserved household attributes, assumed to follow standard normal distributions. Furthermore, I interact these evaluations for each automobile's characteristics with household attributes. $\boldsymbol{\beta}^o$ and $\boldsymbol{\beta}^u$ denote the coefficients for the observable and unobservable household attributes.

One key feature of this specification is that each household is able to have a different valuation for each product. Moreover, even if the household characteristics are the same, it is still possible for them to have different valuations for each product. For example, as the household size increases, the household's valuation of seating capacity might increase. This trend will be captured by β^o. Such parameters are identified by adding micro-level moments, as developed by Petrin (2002) and applied by micro-BLP. Moreover, it is still possible to have different valuations due to the unobserved household heterogeneity, ν_{im}, which is the last term in equation (2).

Portfolio Effects The most straightforward way to capture portfolio effects between two automobiles is by defining them pair-wise, i.e., defining them for each possible combination of j and l. It is, however, almost impossible to estimate these pair-wise portfolio effects due to difficulties in computation and identification. Motivated by the data which shows that households are interested in owning particular combinations of different types of automobiles, such as one sedan and one minivan (and not one specific sedan and one specific minivan), I introduce category-wise portfolio effects. I categorize automobiles into three mutually exclusive sets, the set of *kei*-cars denoted by $\mathcal{K}$, the set of regular cars denoted by $\mathcal{R}$, and the set of minivans denoted by $\mathcal{M}$. I assume that the portfolio effect is the same for all automobiles in the same category:

$$\Gamma(j,l;z_i^c) = \begin{cases} \Gamma_{KK}, & \text{if } (j,l) \in (\mathcal{K} \times \mathcal{K}) \\ \Gamma_{KR}, & \text{if } (j,l) \in (\mathcal{K} \times \mathcal{R}) \cup (\mathcal{R} \times \mathcal{K}) \\ \Gamma_{KM}, & \text{if } (j,l) \in (\mathcal{K} \times \mathcal{M}) \cup (\mathcal{M} \times \mathcal{K}) \\ \Gamma_{RR}, & \text{if } (j,l) \in (\mathcal{R} \times \mathcal{R}) \\ \Gamma_{RM}, & \text{if } (j,l) \in (\mathcal{R} \times \mathcal{M}) \cup (\mathcal{M} \times \mathcal{R}) \\ \Gamma_{MM}, & \text{if } (j,l) \in (\mathcal{M} \times \mathcal{M}) \\ 0, & \text{otherwise.} \end{cases}$$

This classification can be viewed as the passenger capacities of the automobiles, because the average passenger capacity of kei-cars, regular cars, and minivans are four, five, and seven respectively.[5] Moreover, it is also possible to include the difference of capacities between the two automobiles in the portfolio effect. However, this method offers too little variation, because the seating capacities do not vary enough and even considering the difference there is insufficient variation to estimate the coefficient. That it why I introduce the category-wise portfolio effect in this particular estimation. There are other possible ways to categorize automobiles, e.g., I can categorize them by engine displacement or horsepower. I discuss this issue in Section 4.

Moreover, I impose the following parametric assumption on the functional form of the portfolio effect, Γ, for each combination r;

$$\Gamma_r = \sum_{l=1}^{L} \gamma_{rl} z_{il}^c + \zeta_r, \text{ for } \ r = KK, KR, KM, RR, RM, MM,$$

where $z_i^c = [z_{i1}^c, \cdots, z_{iL}^c]$ are the household i's attributes that affect the portfolio effect, $\gamma_r = [\gamma_{r1}, \cdots, \gamma_{rL}]$ are the combination-specific coefficients vectors for the household characteristics, and ζ_r is the combination specific unobserved term for combination r. The first term captures any patterns of holding a particular combination which might be driven by a particular household's attributes. For example, if the household includes any children, the choice probabilities for combinations which include one minivan are typically high. It captures such trends. For some characteristics, $\hat{l}$, I restrict $\gamma_{r\hat{l}} \equiv \gamma_{\hat{l}}$ for all r, in order to capture the pure effect of having two automobiles, because such $\hat{l}$ does not depend any particular combination of automobiles. The second term, the combination specific unobserved terms ζ_r, play a similar role to that of the unobserved characteristics for each product, ξ_j.

[5] See Table 1.

There are three alternative approaches in the literature. Each approach needs to assume two differentiated products *ex-ante* are either substitutes as in Hendel (1999), Dube (2004), and Fan (2010), independent as in Augereau, Greenstein and Rysman (2006), or complements as in Manski and Sherman (1980) and Train, McFadden and Ben-Akiva (1987).[6][7] However, Gentzkow (2007), who studies the complementarities among print and online newspapers, allows for more flexibility in the sense that the two differentiated products could be substitutes, independent, or complements. Therefore, this paper extends Gentzkow (2007)'s method, allowing the portfolio effect to depend on household attributes in order to obtain flexible complementarity patterns, which are likely of importance in the empirical setting.

Portfolio Effects vs. Complementarities In Gentzkow (2007), as his model assumes a quasi-linear utility function which has no income effects, the sign of Γ implies whether two products are complements, independent, or substitutes. However, as this model assumes a Cobb-Douglas utility function, which has an income effect, the sign of Γ cannot be interpreted straightforwardly; even though the portfolio effect term for a particular combination of two automobiles is positive, it could be possible that these two products are complements. To see this point, consider the market with two products j and l. The condition for judging the relationship between two products is given by

$$\Gamma(j, l; z_i^c) \gtreqless \alpha \log \left[\frac{(y_i - p_j)(y_i - p_l)}{y_i(y_i - p_j - p_l)} \right]. \tag{3}$$

If $\Gamma(j, l)$ is greater than the right hand side, it means that these two products are complements. If equality holds, then the two products are independent. Otherwise, they are substitutes. More importantly, the right hand side should be a positive number for any income level, as $(y_i - p_j)(y_i - p_l)/[y_i(y_i - p_j - p_l)] > 1$. Therefore, $\Gamma > 0$ does not nessessarily mean that two products are complements. Moreover, condition (3) also tells us that the determinant of complementarities/substitutabilities largely depends on the magnitude of income relative to the automobile prices. As income level y_i becomes relatively large compared to p_j and p_l, the right hand side approaches zero, as in the Gentzkow (2007) model.

Although condition (3) enables us to judge whether each combination of products are complements, substitutes, or independent, the goal of this paper is to examine the role portfo-

[6] For more comprehensive discussion, see Gentzkow (2007).

[7] I also build on Manski and Sherman (1980) who allow consumers to purchase two automobiles, but assume that any two automobiles are complements. Instead, I allow for flexible portfolio effects, not restricting them to be complementarities ex-ante and allowing them to vary by household attributes and automobile categories.

lio effects play in the demand structure and counterfactual experiments. Therefore, I will use this portfolio effect term notation instead of translating them into complements/substitutes.

Choice Probabilities Substituting (2) into (1) and plugging them into the original maximization problem, the utility of household i choosing j can be given by the following equation:

$$u_{ij} = \underbrace{\sum_{m=1}^{M} x_{jm}\bar{\beta}_m + \xi_j}_{\delta_j=\delta_j(\boldsymbol{\beta})} + \underbrace{\sum_{m=1}^{M} x_{jm}\left[\sum_{r=1}^{R} z_{ir}^{P}\beta_{mr}^{o} + \beta_m^{u}\nu_{im}\right]}_{\mu_{ij}=\mu_{ij}(\boldsymbol{x}_j,\boldsymbol{\beta},\boldsymbol{\nu}_i,\boldsymbol{z}_i,)}.$$

For notational simplicity, let δ_j denote the mean utility derived from product j, which is the same for every household, and $\mu_{ij} = \mu(\boldsymbol{x}_j, \boldsymbol{\beta}, \boldsymbol{\nu}_i, \boldsymbol{z}_i)$ denote the remaining part, excluding ε_{ij}. When a household chooses the outside option, it obtains $\delta_0 = 0$ and $\mu_{i0} = \alpha \ln(y_i)$. Assuming that ε follows a Type I extreme value distribution, the probability of choosing products j and l conditional on household i's attributes, all product characteristics, and parameter values is given by:

$$\begin{aligned}&\Pr[\boldsymbol{d}_i = (j,l)|\boldsymbol{H}_i, \boldsymbol{\nu}_i, \boldsymbol{X}, \boldsymbol{\delta}, \boldsymbol{\theta}]\\ &= \frac{\exp[\delta_j + \mu_{ij} + \delta_l + \mu_{il} + \alpha\log(y_i - p_j - p_l) + \Gamma(j,l)]}{y_i\exp[\alpha] + \sum_{m=0}^{J-1}\sum_{k=m+1}^{J}\exp[\delta_k + \mu_{ik} + \delta_m + \mu_{im} + \alpha\log(y_i - p_k - p_m) + \Gamma(k,m)]},\end{aligned} \tag{4}$$

where $\boldsymbol{H}_i = (\boldsymbol{z}, y_i)$, $\boldsymbol{X} = \{\boldsymbol{x}_j, p_j\}_{j=1}^{J}$, and $\boldsymbol{\theta}$ is the set of parameters. Moreover, let $\tilde{s}_{ij}$ denote the sum of probabilities of choosing product j for household i.[8] Then, $\tilde{s}_{ij}$ will be given by:

$$\tilde{s}_{ij} = \frac{1}{F_i}\sum_{l\in(J\setminus\{j\})\cup\{0\}} \exp[\delta_j + \mu_{ij} + \delta_l + \mu_{il} + \alpha\log(y_i - p_j - p_l) + \Gamma(j,l;\boldsymbol{z}_i)], \tag{5}$$

where F_i is defined as the denominator of equation (4).

2.2 Firm Behavior

Each firm f, $f = 1, 2, \cdots, F$, maximizes the following profit function;

$$\max_{\{p_j\}_{j\in\mathscr{F}_f}} \sum_{j\in\mathscr{F}_f} (p_j - mc_j)Ms_j(\boldsymbol{p};\boldsymbol{x},\boldsymbol{\theta},\boldsymbol{\tau}),$$

[8] Notice that this $\tilde{s}_{ij}$ can be one at its maximum, because each household purchases more than one product, but they are not allowed to pucahse two identical automobiles in my model.

with

$$\ln(mc_j) = \boldsymbol{x}_j \boldsymbol{\psi}' + \omega_j, \tag{6}$$

where $\mathscr{F}_f$ is the set of products produced by firm f, mc_j denotes the cost function of product j, M denotes the market size, $s_j(\boldsymbol{p};\boldsymbol{x},\boldsymbol{\theta})$ denotes the market share for product j, $\boldsymbol{\psi}$ denotes the cost parameters for the product characteristics, and ω_j represents the unobservable cost factors. This formulation is able to capture not only the strategic interaction among firms, but also the pricing strategy within a single firm. Due to the fact that there are only seven manufacturers in the Japanese automobile market, it is natural to assume that their price setting behaviors are affected by other firms' strategies. Moreover, all firms produce multiple products. Thus, when setting prices, the firms need to consider not only other firms' strategies, but also the effect of their own pricing strategies on other products they produce.

Taking the first order condition with respect to p_j, we can obtain the following Bertrand-Nash equilibrium condition;

$$D_j(\boldsymbol{p};\boldsymbol{\tau}) + \sum_{k \in \mathscr{F}_f} (p_k - \mathrm{mc}_k) \frac{\partial D_k(\boldsymbol{p})}{\partial p_j} = 0, \tag{7}$$

where $D_j(\boldsymbol{p};\boldsymbol{\tau}) = M s_j^p(\boldsymbol{p};\boldsymbol{x},\boldsymbol{\theta}\boldsymbol{\tau})$.[9] The first order conditions can be written in the following matrix form;

$$\mathbf{D}(\boldsymbol{p};\boldsymbol{\tau}) + \boldsymbol{\Delta}(\mathbf{p} - \mathbf{mc}) = \mathbf{0},$$

where $\mathbf{D}$, $\mathbf{p}$, and $\mathbf{mc}$ represent vectors of demand, price, marginal cost, and $\boldsymbol{\Delta}$ denotes a $J \times J$ matrix with (k,m) element defined by:

$$\Delta_{km} = \begin{cases} \frac{\partial D_k}{\partial p_m}, & \text{if } k \text{ and } m \text{ are produced by the same firm,} \\ 0, & \text{otherwise.} \end{cases}$$

Notice that the price elasticities are different from single-choice models, given the portfolio effects.[10] Furthermore, the system of first order conditions can be solved for the vector of

[9] This equilibrium condition (7) is useful in the counterfactual analyses, when I find the Bertrand-Nash equilibrium under new price vectors.

[10] See own and cross price elasticities summaried in Section 3.

the marginal costs, **mc**, i.e.,

$$\mathbf{mc} = \boldsymbol{p} - \boldsymbol{\Delta}^{-1}\mathbf{D}(\boldsymbol{p}; \boldsymbol{\tau}). \tag{8}$$

3 Estimation and Identification

Given the unobservable term $\boldsymbol{\xi}$ in the utility function, I apply the strategy developed by Berry (1994) and commonly used in other papers such as Berry et al. (1995) and Petrin (2002). Although Berry et al. (1995) uses only macro-level market share data, I have both micro-level decision data and macro-level market share data. In this situation, as Petrin (2002) developed and Berry et al. (2004) applied, I construct the GMM objective function from both micro- and macro-level data as moment conditions.[11] Intuitively, I minimize the set of moment conditions from micro-level data subject to the moment conditions from macro-level data being equal to zero. In particular, given a set of parameter values, I match the macro market share for each product by changing the mean utilities, $\boldsymbol{\delta}$, in the first stage. Then, after matching the market shares, I evaluate the other moments using the set of parameter values and the mean utilities, which together satisfy the moment conditions for the macro data.

3.1 Estimation

I estimate the parameters, $\boldsymbol{\theta} = (\alpha, \{\bar{\beta}_m, \boldsymbol{\beta}^o_m, \beta^u_m\}_{m=1}^M, \{\zeta_r, \{\gamma_{rl}\}_{l=1}^L\}_{r=1}^R, \boldsymbol{\psi})$, by matching four "sets" of predicted moments to their data analogues: (i) the market share of each product; (ii) the covariance between the observed consumer attributes $\boldsymbol{z}_i^p$ and the observed product characteristics $\boldsymbol{x}_j$ chosen by the households that purchase only one automobile; (iii) the covariance between the observed product characteristics of two automobiles for those households purchasing two automobiles; and (iv) the first order conditions from the Bertrand-Nash equilibrium condition. In this section, I define these sets of moments, explaining the algorithm and procedure of my estimation.

3.1.1 Macro Market Share

The first set of moments, the market shares of the J products, can be derived by the following procedure. Let $\boldsymbol{w}$ denote the vector of observed and unobserved individual heterogeneity, i.e., $\boldsymbol{w} = (\boldsymbol{z}_i, \boldsymbol{\nu}_i, \boldsymbol{\varepsilon}_i,)$. Moreover, let $\mathscr{P}_w$ denote the distribution of $\boldsymbol{w}$ in the population.

[11] The theoretical background is given by Imbens and Lancaster (1994).

Then, given an initial guess of mean utilities, $\boldsymbol{\delta}^0$, and a set of parameters, $\boldsymbol{\theta}$, the model predicts the market share for product j as

$$s_j^p(\boldsymbol{\delta}, \boldsymbol{\theta}) \;\; = \;\; \int_{A_j(\boldsymbol{\delta}, \boldsymbol{\theta})} \mathscr{P}_w d(\boldsymbol{w}),$$

where

$$A_j(\boldsymbol{\delta}, \boldsymbol{\theta}) = \{\boldsymbol{w} | \max_{k,m}[u_{i,(k,m)}] = u_{i,(j,l)} \text{ for } j \leq l\}.$$

This expression means that the demand for product j is generated by households who purchase product j. In order to obtain this market share vector, the joint distribution of household demographic characteristics is needed. I use survey data from KHPS to calculate this joint distribution, relying on the representativeness of KHPS.[12] I sum up choice probabilities for each simulated household's to obtain the theoretical market share. In other words, I approximate the market shares by:

$$s_j^p(\boldsymbol{\delta}(\boldsymbol{\theta})) \;\; \approx \;\; \frac{1}{2N} \sum_{i=1}^{N} \left\{ \sum_{j=0}^{J-1} \sum_{l=j+1}^{J} \Pr[\boldsymbol{d}_i = (j,l) | \boldsymbol{H}_i, \boldsymbol{\nu}_i, \boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{\theta})] \right\},$$

where N represents the number of households. The choice probabilities are given by equation (4) in the previous section. The reason why I divide the sum of probabilities by 2 is that each household can purchase up to two automobiles. Here, I define the 'zeroth' set of moments by taking the difference between empirical and predicted market shares for each product j:

$$G_j^0(\boldsymbol{\theta}) = s_j - s_j^p(\boldsymbol{\delta}(\boldsymbol{\theta})), \tag{9}$$

where s_j denotes the empirical market share, and $\mathbf{G}^0 = [G_1^0(\boldsymbol{\theta}), \cdots, G_J^0(\boldsymbol{\theta})]'$. After obtaining the predicted market shares, I utilize the contraction mapping method developed by Berry et al. (1995).[13] Until the difference between the predicted market shares and the empirical market shares is small, I iterate this procedure by updating the mean utilities via:

$$\boldsymbol{\delta}^{T+1} = \boldsymbol{\delta}^T + \log(\boldsymbol{s}) - \log(\boldsymbol{s}^p(\boldsymbol{\delta}(\boldsymbol{\theta}))).$$

[12] This usage is partially due to the absence of the joint distributions of household characteristics in the Japanese Census data.

[13] In this setting, the applicability of BLP-type contraction mapping is not straightforward, because the substitutability plays an important role in making this method work. Typically, this inversion technique requires the products being gross substitutes. In this particular application, though some products might be complements at the individual-level, the products are gross substitutes at the market-level judging from the market share. Thus, the inversion works in this case. See also discussion in Berry, Gandhi and Haile (2013).

By doing so, I can exactly match the product-level market shares, i.e., $\mathbf{G}^0(\boldsymbol{\theta}) = \mathbf{0}$, and obtain the vector of mean utilities, $\boldsymbol{\delta}^*(\boldsymbol{\theta})$, which satisfies the first moment, given the parameter values of $\boldsymbol{\theta}$.

3.1.2 Covariance Between Household Attributes and Product Characteristics

The second set of moments is derived from the micro data. In particular, in order to construct this moment, I use the households that purchased exactly one automobile during the period in the KHPS. Having obtained $\boldsymbol{\delta}$, it is straightforward to calculate the choice probabilities for each household by using the household characteristics via equation (4). Now, I prepare ns times of $\boldsymbol{\nu}_i$ for each household, and integrate them out to obtain the predicted choice probabilities for micro samples:

$$\hat{\Pr}[\boldsymbol{d}_i = (j,l)|\boldsymbol{H}_i, \boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{\theta})] = \frac{1}{ns}\sum_{k=1}^{ns} \Pr[d_i = (j,l)|\boldsymbol{Z}_i, \boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{\theta}), \boldsymbol{\nu}_i^k].$$

After obtaining these simulated choice probabilities, I construct the covariance of the observed consumer attributes $\boldsymbol{z}_i^p$ with the observed product characteristics $\boldsymbol{x}_j$ which are chosen by the households. Conceptually, it should be $E[zx^D - zx^P]$ where x^D and x^P denote the product characteristics of the empirical data and model prediction, respectively. This set of moments enables us to predict the kinds of household attributes that incline them to purchase a particular product. More precisely:

$$\boldsymbol{G}^2(\boldsymbol{\theta}) = \frac{1}{|B_1|}\sum_{i \in B_1}\left[z_i \left\{ \sum_{j=1}^{J} (\boldsymbol{x}_j \mathbf{1}_{\{d_i = j\}} - \boldsymbol{x}_j \Pr[\boldsymbol{d}_i = (0,j)|\boldsymbol{H}_i, \boldsymbol{X}, \boldsymbol{\theta}, d_{i1} = 0]) \right\} \right],$$

where B_1 denotes the set of households who purchase one automobile. Notice that the probability is a conditional choice probability, as I know which households purchased exactly one automobile during the period. And, these conditional choice probabilities should be given as:

$$\hat{\Pr}[\boldsymbol{d}_i = (0,j)|d_{i1} = 0] = \frac{\hat{\Pr}[\boldsymbol{d}_i = (0,j)]}{\sum_{l \in J} \hat{\Pr}[\boldsymbol{d}_i = (0,l)]},$$

where every choice probability is given $(\boldsymbol{H}_i, \boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{\theta}))$.

3.1.3 Covariance Between Observed Characteristics for Two Automobiles

Next, I set the third set of moments as the covariance of the observed product characteristics for two automobiles, given that the households eventually own two automobiles. Conceptually, it should be $\mathrm{E}[x_1^D x_2^D - x_1^P x_2^P]$, where x_l^P and x_l^D denote the l-th automobile's characteristics of the model prediction and actual data, respectively. More precisely:

$$G^3(\boldsymbol{\theta}) = \frac{1}{|B_2|}\sum_{i \in B_2}\left[\sum_{l=j+1}^{J}\sum_{j=0}^{J-1}\Big\{\boldsymbol{x}_j\boldsymbol{x}_l\mathbf{1}_{\{d_i^1=j\}}\mathbf{1}_{\{d_i^2=j'\}} - \boldsymbol{x}_j\boldsymbol{x}_l\Pr[\boldsymbol{d}_i = (j,l)|\boldsymbol{H}_i, \boldsymbol{\nu}_i, \boldsymbol{x}, \boldsymbol{\theta}, \boldsymbol{\delta}, d_{i1} \neq 0]\Big\}\right],$$

where B_2 denotes the set of households who purchase two automobiles, and the conditional choice probability is given by:

$$\hat{\Pr}[\boldsymbol{d}_i = (0,j)|d_{i1} \neq 0] = \frac{\hat{\Pr}[\boldsymbol{d}_i = (j,l)]}{\sum_k\sum_m \hat{\Pr}[\boldsymbol{d}_i = (k,m)|k \neq 0]}.$$

These moment conditions are particularly important for identifying the coefficients in the portfolio effect terms, such as $\boldsymbol{\gamma}_r$, because these moment conditions enable us to predict the kinds of household attributes that incline them to purchase a particular combination of products.

3.1.4 The Berry et al. (1995) Moments

Finally, the first and the fourth sets of moments come from the orthogonality condition of $\mathbf{E}[\boldsymbol{\xi}|(\boldsymbol{X}, \boldsymbol{W})] = 0$ and $\mathbf{E}[\boldsymbol{\omega}|(\boldsymbol{X}, \boldsymbol{W})] = 0$. Mean utilities vector will give us $\boldsymbol{\xi}$ as:

$$\boldsymbol{\xi} = \boldsymbol{\delta}^*(\boldsymbol{\theta}) - \boldsymbol{X}\hat{\beta}.$$

Similarly, the first order conditions given by equation equation (8), and the functional form assumption of marginal cost given by equation (6) yield:

$$\boldsymbol{\omega} = \log(\boldsymbol{p} - \boldsymbol{\Delta}^{-1}\mathbf{D}) - \boldsymbol{X}\boldsymbol{\psi}'.$$

Here, as previously mentioned, because of the portfolio effects, I need to compute $\mathbf{\Delta}$ by integrating individual-price elasticities over population;

$$\frac{\partial D_k}{\partial p_m} = \int \frac{\partial \tilde{s}_{ik}}{\partial p_m} d\mathscr{P}_w,$$

where individual-level own-price elasticity for product j is given by

$$\frac{\partial \tilde{s}_{ij}}{\partial p_j} = -\frac{1-\tilde{s}_{ij}}{F_i} \sum_{l \in J \cup \{0\}} \frac{\alpha \exp[\delta_j + \mu_{ij} + \delta_l + \mu_{il} + \alpha \log(y_i - p_j - p_l) + \Gamma(j, l; \boldsymbol{z}_i)]}{y_i - p_j - p_l}, \tag{10}$$

whereas cross-price elasticity for product j with respect to product $n \neq j$, is given by

$$\begin{aligned} \frac{\partial \tilde{s}_{ij}}{\partial p_n} &= \frac{\tilde{s}_{ij}}{F_i} \sum_{l \in J \cup \{0\}} \frac{\alpha \exp[\delta_n + \mu_{in} + \delta_l + \mu_{il} + \alpha \log(y_i - p_n - p_l) + \Gamma(n, l; \boldsymbol{z}_i)]}{y_i - p_n - p_l} \\ &\quad - \frac{1}{F_i} \frac{\alpha \exp[\delta_j + \mu_{ij} + \delta_n + \mu_{in} + \alpha \log(y_i - p_j - p_n) + \Gamma(n, j; \boldsymbol{z}_i)]}{y_i - p_j - p_n}. \end{aligned} \tag{11}$$

The economic intuition behind this complexity is as follows: In the BLP model, products are gross substitutes, implying that an increase in price j would increase the choice probabilities for other products. However, in this model, as equation (11) indicates, the change in price of product n can be decomposed into two parts; (i) the choice probability of product j will increase as the relative price of p_j/p_n decreases, and (ii) the choice probability of jointly purchasing j and n will decrease as p_n increases.

As a matter of convention, as sets of instruments for this set of moments, I use (i) the average product characteristics produced by other firms, (ii) the average characteristics of products other than j produced by the same firm, and (iii) the characteristics of product j. I also add the number of products that firm f produces in order to identify the constant terms in both utility and cost functions. Thus, defining $\boldsymbol{Z}_1$ and $\boldsymbol{Z}_4$ as the sets of instruments explained above, the first and fourth sets of moments can be expressed as follows:

$$\mathbf{G}^1(\boldsymbol{\theta}) = \frac{1}{J} \sum_{j=1}^{J} Z_{1,j} \xi_j, \quad \text{and } \mathbf{G}^4(\boldsymbol{\theta}) = \frac{1}{J} \sum_{j=1}^{J} Z_{4,j} \omega_j.$$

3.1.5 The GMM Estimator

I use the Method of Simulated Moments (MSM) to estimate this model, i.e., I solve the following minimization problem;

$$\min_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \mathbf{G}(\boldsymbol{\theta})'\mathbf{S}^{-1}\mathbf{G}(\boldsymbol{\theta}) \text{ subject to } \quad \mathbf{G^0}(\boldsymbol{\theta}) = 0,$$

where $\mathbf{S}$ is a weighting matrix which is a consistent estimate of $E[\mathbf{G}(\boldsymbol{\theta})\mathbf{G}(\boldsymbol{\theta})']$ and

$$\mathbf{G}(\boldsymbol{\theta}) = [\mathbf{G}^1(\boldsymbol{\theta})\ \mathbf{G}^2(\boldsymbol{\theta})\ \mathbf{G}^3(\boldsymbol{\theta})\ \mathbf{G}^4(\boldsymbol{\theta})]',$$

where each $\mathbf{G}^m(\boldsymbol{\theta})$, for $m = 1, \cdots 4$, is defined above. To solve this problem, I use the method suggested by Nevo (2001) and applied by Goeree (2008) to ease the computational burden. Namely, the mean utilities do not depend on the parameter values of $\{\bar{\boldsymbol{\beta}}_m\}_{m=1}^M$, and they only depend on $\boldsymbol{\alpha}$'s, $\{\boldsymbol{\beta}_m^o, \boldsymbol{\beta}_m^u\}_{m=1}^M$ and the parameters in the portfolio effects term. Thus, I can restrict the non-linear search to a subset of the parameters. The estimator is consistent and asymptotically normal (Pakes and Pollard (1989)).

3.2 Identification

In order to discuss identification issue in this model, consider the following example. Suppose there are three products, A, B, and C, and assume that A and B are regular cars, whereas C is a minivan. The mean utility and unobserved taste for product j are denoted by δ_j and ν_j, respectively. Moreover, assume that when purchasing two products i and j jointly, consumers obtain an additional utility, denoted by $\Gamma(i, j)$, which is unobserved:

$$\begin{aligned} u_A &= \delta_A + \nu_A, & u_{AB} &= \delta_A + \delta_B + \Gamma(A, B) + \nu_A + \nu_B, \\ u_B &= \delta_B + \nu_B, & u_{AC} &= \delta_A + \delta_C + \Gamma(A, C) + \nu_A + \nu_C, \\ u_C &= \delta_C + \nu_C, & u_{BC} &= \delta_B + \delta_C + \Gamma(B, C) + \nu_B + \nu_C, \end{aligned}$$

where

$$\begin{bmatrix} \nu_A \\ \nu_B \\ \nu_C \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} 1 & \sigma_{AB} & \sigma_{AC} \\ \sigma_{AB} & 1 & \sigma_{BC} \\ \sigma_{AC} & \sigma_{BC} & 1 \end{bmatrix}\right).$$

One of the difficulties of a multiple discrete choice model is separating "correlated preference" and "complementarities." When an individual purchases products A and C, for example, the model cannot tell whether σ_{AC} is high (correlated preference) or $\Gamma(A, C)$ is high (complementarities). Gentzkow (2007) takes advantage of the panel data structure and decomposes unobserved preference into fixed effect terms and random utility shocks:

$$\nu_j = \tilde{\nu}_j + \varepsilon_j,$$

which enables him to achieve identification. On the other hand, I take a different approach – imposing categorical complementarities. In this example, A and B belong a set of regular cars and C belongs to a set of minivans, and thus this paper assumes $\Gamma(A, C) = \Gamma(B, C) = \Gamma_{RM}$. This assumption leads to:

$$\begin{aligned} u_{AC} &= \delta_A + \delta_C + \Gamma_{RM} + \nu_A + \nu_C, \\ u_{BC} &= \delta_B + \delta_C + \Gamma_{RM} + \nu_B + \nu_C. \end{aligned}$$

From this expression it is easy to see that σ_{AC} and σ_{BC} are identified by comparing the number of households that purchase (i) a combination of A and C, and (ii) a combination of B and C, after controlling for individual automobile utilities. If these two numbers are totally different, the difference should be resulted from either the difference in mean utilities or the difference in correlated preference, because complementarities arising from both combinations are identical. Thus, after controlling for individual automobile utilities, the difference should be explained by correlated preference.

Of course, Γ_{RM} might not be enough to explain $\Gamma(A, C)$ or $\Gamma(B, C)$. In other words, it might be possible to decompose $\Gamma(\cdot, \cdot)$ into two parts:

$$\begin{aligned} \Gamma(A, C) &= \Gamma_{RM} + \mu_{AC}, \\ \Gamma(B, C) &= \Gamma_{RM} + \mu_{BC}. \end{aligned}$$

where μ_{AC} and μ_{BC} are, again, unobserved complementarities, depending on a specific combination of the products. I rule out such further unobserved complementarities. However, in this application, it is hard to imagine that the complementarities coming from (i) a Toyota Camry (regular) and a Mazda 5 (minivan), and (ii) a Honda Accord (regular) and a Mazda 5 are so different. Therefore, I believe this will not restrict the results in this particular application.

4 The Data

I mainly use three Japanese datasets; *Keio Household Panel Survey* which contains household-level data on purchasing decisions, *New Motor Vehicle Registrations* which gives the aggregate sales number of automobiles in a given year, and *Automotive Guidebook* which provides the product-level panel data. In this section, I describe the characteristics of these datasets and present some summary statistics.[14]

Keio Household Panel Survey The *Keio Household Panel Survey* is provided by Keio University, a private research university in Tokyo, Japan. One of the main goals of KHPS is to provide Japanese household-level micro panel data in order to promote empirical research about Japan. The sample size of KHPS was approximately 4,000 households from 2004 to 2006. In terms of automobile ownership, KHPS inquired in 2004 about: (1) month and year of purchase; (2) maker, brand, and model of each automobile; and (3) whether it was purchased as a new car or a used car, for up to three cars. Every year since 2004, KHPS has inquired (1) whether each household purchased automobiles or not up to two cars; and (2) whether each household discarded automobiles or not up to two cars. I extract information from the data gathered in 2004 to 2006.

New Motor Vehicle Registrations The *New Motor Vehicle Registrations* series issued by the Japan Automobile Dealers Association provides the number of units sold for each model in a given year under the supervision of the Ministry of Land, Infrastructure, Transportation, and Tourism.[15] Thus, this registration data can serve as empirical macro-level market share, which is used in the "zeroth" set of moments in equation (9).

Automotive Guidebook: Micro Data for Products The *Automotive Guidebook* series is issued by the Japan Automobile Manufactures Association (JAMA) every year. I construct the product-level panel data from this series of books, since each edition provides the set of available automobile models and the characteristics for each, such as price, interior and

[14] The reasons why I choose the Japanese automobile market are the following: (i) its relatively small used car market compared to the market for brand new automobiles, and (2) its quick purchasing cycle. As for the first reason, it enables us to ignore the used car markets, which provides close substitutes for new automobiles, and makes the choice set for consumers bigger. As for the second reason, I will discuss later in this section.

[15] As for the sales of used automobiles, it is difficult to know the exact number of automobile sales since there are many companies which deal with used cars and it is difficult to collect and aggregate this decentralized market information.

exterior dimensions, seating capacity, and engine displacement. Table 1 shows the average characteristics of automobiles sold from 2004 to 2006.

4.1 Consumer Choice Set

Domestic automobiles are dominant in Japan – about 94% of the market share is held by domestic automobile manufacturers. Moreover, compared to Japan's domestic automobiles, information about foreign automobiles is misreported often in my micro data. I thereby exclude foreign automobiles.

Second of all, like BLP, I do not use the secondary market data for this empirical exercise. There are two reasons. First and most importantly, the secondary market is small in Japan – more than 65% of consumers in KHPS purchase new automobiles. This popularity of new automobiles is partially because of the costly automobile inspection system and partially because owning old automobiles is expensive in Japan. Moreover, the total sales data for the secondary market is not available in Japan. Compared to the sales of new cars, the secondary market is not well monitored by the government. Even though statistics on total automobile "trading" exist, it is hard to know how many used cars are sold/purchased. In addition to this problem in the macro data, the micro data (KHPS), does not include details about automobile models, nor does it include used car sale prices. Therefore, I ignore used car purchases, because it is not possible to use the information from the macro and micro data consistently.

To finalize the choice set, I also eliminate several discontinued domestic automobile models having annual sales of fewer than 1,000 units each during 2004-2006. This leaves 154 automobiles for this study. Also, because very few households purchased two minivans and none of them purchased two exactly identical automobiles, I exclude the combinations of two minivans and two identical products from the potential choice set.

4.2 Descriptive Statistics

In this section, using the datasets introduced above, I summarize some descriptive statistics for automobiles included in the choice set. Table 1 displays means, standard deviations, and the maximum and minimum of several automobile characteristics for each category. Compared to other automobiles, it is clear that kei-cars have less seating capacity, horsepower, and polluting gas emissions, but are more fuel-efficient and affordable. Also, within the categories of kei-car and minivan, the standard deviations for each characteristic are much smaller than for regular cars, because regular cars include all automobiles, except kei-cars and minivans, i.e., the regular car category includes hatchbacks, sedans, station wagons, sport cars, and sports utility vehicles (SUVs).

Table 2 lists all domestic automobile manufacturers included in my estimation. Table 2 also shows the number of models and aggregate sales for each category by these manufacturers. The table clearly indicates that the total sales for kei-cars and minivans are indeed substantial in Japan, accounting for about 31% and 21% of total automobile sales, respectively. In particular, while kei-car models represent only about 20% of all considered automobile models, the total number of kei-car sales accounts for 30% of the total automobile sales, implying that each kei-car model has more sales, on average than other types of automobiles. It is also clear that several firms, such as Mitsubishi and Suzuki, rely heavily on kei-car production, because kei-cars represent 63% and 88% of their unit sales, respectively. Mazda and Nissan, on the other hand, sold significantly fewer kei-cars. In particular, Mazda's kei-cars represent only 16.5% of its sales, even though Mazda produces five kei-car models.

4.3 Data Implementation

Similar to Hendel (1999), I chose the three years from 2003 to 2005 as one decision period. That is, as long as a household purchased automobiles within that period, I assume that the household purchased automobiles in a decision period. Three years might not be long enough, because some fraction of households that eventually purchase two automobiles might not purchase both of them within the decision period. They might purchase just one automobile within these three years and purchase another automobile later. Thus, the longer the decision period, the better the estimation.

However, interestingly, the automobile purchase cycle of Japanese households is short. This short cycle is because the Japanese government has implemented a costly automobile inspection system for car owners. If a consumer purchases a new automobile, that car must be inspected three years after purchase, and every other year after that. The cost is about \$1,000 to \$2,500 USD per inspection, which could be about 8% to 20% of the average kei-car price. Many households discard their automobiles at the end of three, five, or seven years in order to avoid the inspection costs. Therefore, by observing their purchasing behavior for three years, I can predict their eventual number of automobile purchases with relatively high accuracy.

Alternatively, it might be also possible to model consumers' utility based on their current automobile holdings, taking advantage of the panel structure of the data. For example, suppose a household purchased one minivan before 2002, and one kei-car during the decision period. An alternative way of using the data would be to estimate demand parameters depending on the category of the current automobile, or specifying different utility functions depending on the current automobile holdings. In that way, I might be able to take advantage of information from the data. However, these alternative ways of modeling have endogeneity problems. If a household expects that the government will eliminate tax subsidies for small automobiles in the near future, they might not purchase a combination of one minivan and one kei-car as they otherwise would. In order to avoid this issue, I do not allow utility to vary by the current automobile holdings.

As Nevo (2000) notes, the potential market size is one of the big issues in this Berry et al. (1995) style random coefficient model, because the potential market size is crucial for the market share of outside options. The most common way of setting the potential market size is to use the number of households in the market. However, in this study, I allow each household to choose more than one alternative. Thus, I set the potential market share as the sum of the number of single-person households, and the doubled number of multiple-person households, i.e., 83,669,000.

5 Estimation Results

Structural Estimates Tables 3 and 4 present the demand side estimates. Table 3 displays the parameters associated with random coefficients, while Table 4 lists the parameters in the portfolio effect term. As one can see from these tables, most of the estimates are statistically significant.

For the parameter estimates associated with random coefficients, I first show the coefficients for the log of the income term, $\log(y_i - p_j)$, which are interacted with the percentile income. These are listed in the top three rows. As household-level income increases, α becomes larger. Similar results can be observed in Petrin (2002). I have a larger coefficient α for 50% to 95% percentile income households than for wealthier households. This might be a result of dropping expensive domestic automobiles and foreign automobiles from the choice set. The average prices for foreign automobiles are much higher than those of domestic automobiles. Thus, by dropping them from the choice set, I might be underestimating their marginal utility of automobile consumption.

The next three rows show the estimates associated with seating capacity. I include the family size as one of the variables for explaining the valuation of seating capacity, because a reduced form analysis indicates that family size is one of the most important determinants for seating capacity. Not surprisingly, the result shows that a household with more members is more likely to purchase an automobile with larger seating capacity, showing high statistical significance. The reason I have a relatively large standard deviation for seating capacity may be caused by the fact that some large-family households purchase small-capacity automobiles such as kei-cars, and vice versa. The rest of the parameters can also be interpreted in the same way. I include the age of the household's head as one of the variables for explaining the valuation of horsepower. Again, not surprisingly, the result shows that a higher head-of-household age contributes to the purchase of automobiles with higher horsepower.

The estimation results for portfolio effects are presented in Table 4. The first three rows show the fixed effect of having two automobiles. As one might expect, the larger the number of earners within a household, the higher the probability of purchasing two automobiles. In Japan, cities are classified by population, and the government categorizes them into the following three groups: the 14 biggest cities, other cities, and villages.[16] The estimation results show that households in less-populated areas are more likely to purchase two automobiles.

According to the results, the presence of children might also be a driving force in the purchase of at least one kei-car, because all combinations that include at least one kei-car are higher than other combinations that do not include any kei-cars. The combination specific unobserved terms, listed in the last five rows, show that combinations of kei-cars and minivans create the highest portfolio effect, whereas combinations of two kei-cars give the lowest portfolio effect. The combination of two regular cars also shows a positive portfolio effect, because the category of regular cars includes all automobiles except kei-cars and minivans and households might enjoy the combination of one sedan and one SUV, for example.

Finally, the estimation results on the supply side are summarized in Table 5. The negative coefficient for miles-per-gallon (MPG) may be a result of the constant returns to scale assumption. The reason is as follows: the best selling automobiles tend to have high MPG, and the model predicts that these best selling automobiles should have a smaller marginal cost than they actually do by assuming the constant returns to scale. Thus, by omitting sales or production from the model, we might underestimate the coefficient for MPG, because sales and MPG are positively correlated and marginal cost is likely decreasing in sales. In fact, Berry et al. (1995) encounter the same problem, and solve this problem by including

[16] Recently, the categorization was changed because of municipal amalgamations that occurred between 2000 and 2005.

sales data as an explanatory variable.[17]

Model Fit The predicted macro market shares are exactly the same as the empirical market shares, due to the first step in the estimation procedure. Thus, I show the model fit using my micro samples. Table 6 demonstrates the fitness of the model using data for households purchasing one automobile in the KHPS. I calculate the probability of choosing passenger cars with a seating capacity of 5, and sports cars, which are not directly targeted in the estimation procedure, using the household attributes found in the micro data. The model also predicts the average expenditure for automobiles. These numbers are reported in the second column, while empirical probabilities and expenditures are reported in the third column. For example, my model suggests that the choice probability for sport cars is 0.009, whereas the empirical data shows also 0.009. Predicted average expenditures can be computed by summing up prices weighted by the choice probabilities. My model indicates an average expenditure of $23,435, which is almost identical to the average expenditure in the data ($23,678), when I use 1 USD is equal to 80 JPY.

Table 7 demonstrates the model fit using only the households in KHPS purchasing two automobiles. I report the predicted average characteristics for all automobiles purchased by these households in the second column, and empirical averages in the third column. Notice that the average, standard error, minimum and maximum of horsepower are 134.5, 61.2, 43, and 280, respectively (from Table 1). Thus, comparing the predicted averages with the empirical averages, I conclude the model predicts the non-targeted moments well for those households that purchase two automobiles.

6 Counterfactual Analysis: Repealing Tax Subsidies

The estimation results show that a positive portfolio effect exists between kei-cars and minivans. Thus, by ignoring a strong portfolio effect, we might have biased counterfactual analyses. In this subsection, to emphasize the importance of consumers' portfolio considerations and potential bias in counterfactual experiments, I examine the effects of repealing the tax subsidies for kei-cars, comparing the results from a standard single discrete choice model, i.e., micro-BLP. First, I describe the details of the tax subsidies for automobiles in Japan. Then I show the results of the simulation using an estimated model with and without portfolio considerations.

[17] For more detail, see Berry et al. (1995), pp.876-877.

A: Details of Tax Subsidies

When consumers purchase automobiles in Japan, there are three types of taxes. Table 8 summarizes these taxes. First, based on acquisition prices, consumers must pay an *automobile acquisition tax* of 3% of the purchase price for any kei-car and 5% for any other automobile. Second, consumers must also pay an *automobile weight tax*, which is \$55 per year for any kei-car, and \$79 for every 0.5 tons for other automobiles. Although it seems the difference between kei-cars and other cars is small, the Japanese government requires consumers to pay the automobile weight tax for three years. Thus, the full cost difference is be more than \$300. Finally, depending on the engine displacement of the purchased automobile, consumers must pay an *automobile tax* or *kei-car tax*. This tax is \$90 for any kei-cars, while the automobile tax is at least \$369 for other automobiles and about \$62 for every additional 500cc of engine displacement.[18]

More precisely, I use the following tax structure in my estimation. The *automobile acquisition tax* ratio is defined as

$$\tau_{1,j} = \begin{cases} 0.03, & \text{if } j\text{'s displacement is less than 660cc,} \\ 0.05, & \text{otherwise.} \end{cases}$$

Second, the *automobile weight tax* is specified as

$$\tau_{2,j} = \begin{cases} 55, & \text{if } j \text{ is a kei-car,} \\ 79\lfloor x_{j,1}/500 \rfloor, & \text{otherwise,} \end{cases}$$

where $x_{j,1}$ is the weight of automobile j measured in kilograms.[19] Finally the *automobile tax* or *kei-car tax*, denoted by $\tau_{3,j}$, is \$90 for any kei-cars. The automobile tax for other cars is summarized in Table 9. In summary, if the price for automobile j is p_j, consumers eventually pay the following price;

$$p^c(p_j, \boldsymbol{\tau}) = (1 + \tau_{1,j})\, p_j + 3\tau_{2,j} + 3\tau_{3,j}.$$

The reason why $\tau_{2,j}$ and $\tau_{3,j}$ are multiplied by 3 is that consumers must pay these taxes for the first three years after purchase.

To show how large these tax subsidies are, Table 10 summarizes tax payment for a selected

[18] Detail tax scheme is summarized in Table 9.

[19] A definition of the floor function is $\lfloor x \rfloor = \max\{n \in \mathbb{Z} | n \le x\}$.

kei-car, the Nissan MOCO, as an example. The price, displacement and weight of MOCO are \$13,054, 658cc, and 850kg, respectively, Based on this information, we can calculate the total tax with and without these tax subsidies. I find that the difference would be more than \$1,400, which is more than 10 percent of the original price. This difference might be large enough to change consumers' purchasing behavior.

These tax subsidies were introduced in the 1960s to make small automobiles more affordable for Japanese households that could not afford to purchase regular-size automobiles. Later, the goal of this policy shifted to promote purchasing of eco-friendly automobiles. Recently, there has been discussion over whether these tax subsidies should be repealed or not, and those who oppose the repeal claim that the demand for kei-cars (which are eco-friendly automobiles) would dramatically decrease. However, considering the strong positive portfolio effects, this argument might not be the case. To examine the effects of repealing these tax subsidies, I set the same tax scheme for small cars as regular automobiles.

B: Related Literature

Recent increasing environmental concerns have led to a replacement policy focusing on automobile markets. One stream of literature analyzes the policy of promoting the retirement of old automobiles by subsidizing the scrappage of old atuomobiles or the purchase of new automobiles, such as Adda and Cooper (2000), Alberini et al. (1995), Chen et al. (2010), Hahn (1995), and Schiraldi (2011). Such dynamic replacement behavior is one of the critical aspects in examining the effectiveness of a renewed policy. At the same time, however, it is also important to take into account the portfolio considerations of consumers. For example, a household can own one small enviromentally friendly car and one minivan, and plan to replace the minivan with a new car. Then, even though the household can purchase small cars at discounted prices due to the subsidies, it would not purchase one more small car because of the portfolio effect. Therefore, this empirical study complements the aforementioned literature.

Another literature on the effects of Corporate Average Fuel Economy (CAFE) Standards is also closely related to my paper. CAFE Standards are U.S. regulations intended to improve automobile fuel efficiency by charging penalty fees to any automobile manufacturer having an average fuel economy (calculated across its entire fleet) that falls below the standards. There are many papers that analyze CAFE Standards using various approaches. These include Austin and Dinan (2005); Bento et al. (2009); Goldberg (1998); and Gramlich (2010). CAFE standards, in general, can be viewed as an implicit tax on large automobiles and a subsidy for eco-friendly small automobiles. The Japanese tax subsidies, however, create a more direct consumer side incentive to purchase eco-friendly automobiles. Thus, this empirical study also complements the literature.

C: Simulation Results

Aggregate-level and Brand-level Effects Table 11 summarizes by automobile category the predicted effects of repealing tax subsidies. If subsidies were eliminated, the total demand for kei-cars would decrease by 9.04%, and total demand for regular cars and minivans would increase 5.02% and 1.13%, respectively. In order to compare these results to the case where there is no portfolio effect, I also estimate the micro-BLP model using the same dataset. The estimation results from micro-BLP model are summarized in the middle column of Table 11, and the simulation results suggest that the total demand for kei-cars (ignoring portfolio effects) would decrease by 13.95%. Thus, this difference of about 4.9% can be accounted by the portfolio effect.

In Table 12, I show more detailed results for some selected kei-cars. Comparing the fourth and fifth columns (which display the percentage change in demand predicted by micro-BLP and my model) one can see that the standard single choice model overestimates the effects of repealing tax subsidies. Most automobiles are overestimated by 5%. Table 12 indicates that demand for more expensive cars would tend to decrease, because consumers would give up purchasing expensive kei-cars and would purchase relatively affordable regular cars instead. However, those households that purchase cheap automobiles would not change their choices, because there is no cheaper class of automobiles available. The COPEN, produced by Daihatsu, shows an interesting pattern. Even though it is expensive, the demand would not decrease much because the COPEN is a sport type kei-car, and there is no suitable substitute for this automobile, while other automobiles have many competing substitutes.

There is one more interesting pattern in Table 12: the percentage changes in prices for EVERY WAGON, WAGON R, and MR WAGON are almost zero, though other automobiles' prices increase in micro-BLP's prediction. These differences are largely because these three automobiles are produced by Suzuki, which mainly produces kei-cars. As Table 2 suggests, other manufacturers have many substitutes for kei-cars, and thus they charge higher prices for kei-cars to shift the demand toward their other automobiles. Suzuki, however, cannot do so.

I also display more detailed results for some selected minivans in Table 13. The micro-BLP model predicts that demand for minivans would slightly increase, while my model predicts that demand for expensive minivans would decrease while demand for affordable minivans would increase. This difference is because in the micro-BLP model, all automobiles are substitutes and thus choice probabilities for other automobiles increase when kei-cars' prices are increased by repealing tax subsidies. Thus, the changes in demand for minivans decrease as the automobile prices increase. On the other hand, my model predicts that only the demand for expensive minivans would decrease. This difference can be explained by the fact that there are some households that highly value a combination of one kei-car and one minivan. Those households would purchase one kei-car and one slightly cheaper minivan to maintain their portfolios under the new tax policy. Thus, the demand for expensive minivans would decrease. At the same time, the demand for affordable minivans would increase.

The economic intuition behind these results is also confirmed by Figures 1 and 2. In Figure 1, I show the simulated changes in units sold from micro-BLP model and my model, depending on engine displacement. It is clear that the demand for kei-cars decreases sharply in both my model and micro-BLP model, while the demand for other automobiles increases in both models. In particular, as automobiles' engine displacement increases, the change gets smaller. Moreover, I decompose these results for regular cars and minivans, and show the results for minivans in Figure 2. Again, it can be confirmed that the demand for expensive minivans would decrease slightly, while the demand for affordable minivans would increase.

Fuel Consumption and Environmental Implication Policy makers might be interested in the environmental implications of this repeal of tax subsidies. Thus, I calculate an index, commonly known as Corporate Average Fuel Economy (CAFE) Standards in the U.S., which is given by the following sales-weighted harmonic mean of fuel efficiency:

$$\mathrm{CAFE} = \frac{\sum_{j=1}^{J} n_j}{\sum_{j=1}^{J} n_j / f_j},$$

where n_j and e_j denote the sales and fuel efficiency of automobile j, respectively. As mentioned in the previous section, CAFE Standards are intended to improve average automobile fuel efficiency by charging penalty fees to automobile producers when this index of their annual fleet of automobile sales falls below a certain number. Thus, if this index decreases by repealing tax subsidies, it implies that the repeal promotes the purchasing of less fuel-efficient automobiles.

The results summarized in Table 14 show that in both models the CAFE Standards decrease slightly. This overall small impact is because many households will purchase compact cars, close substitutes for kei-cars which are almost as fuel efficient as kei-cars, after eliminating tax subsidies. Thus, the effect of eliminating tax subsidies is quite limited. The small difference between two models might be explained by the same logic as before; some households might purchase affordable minivans under the new policy, giving up purchasing huge minivans, whereas this cannot happen in the micro-BLP model. However, notice that this index cannot reflect the actual number of automobiles sold. As Table 11 suggests, the total number of automobiles decreases more in the micro-BLP model. Therefore, even though this CAFE Standards index decreases more in the micro-BLP model, it does not neccessary mean that the total environmental implications is worse in the micro-BLP model.

Effects on Producer In Table 15, I show the simulated profits for automobile manufacturers in Japan. Repealing the tax subsidies would cause lower profits for four out of seven manufacturers, because those four firms rely heavily on profits from kei-cars. The other firms, however, would achieve higher profits. One of the firms, Nissan, would increase its profit by 3.87%, as Nissan produces only one model of kei-car among its 27 models. Mazda would also have higher profits, even though it produces five models of kei-car. This large increase is because Mazda's kei-cars are not its best-selling automobiles, and its total sales of kei-cars account for only 16.5% of its profit, as seen in Table 2.

Welfare Implication Finally, Table 16 presents the changes in consumer surplus, producer surplus, and tax revenue. The results show that repealing tax subsidies would force consumers to spend their money for purchasing automobiles, and thus their surplus would decrease remarkably. Although the profits of Suzuki, one of the most famous manufacturers producing kei-cars, would decrease by 7.2%, total producer surplus would remain nearly the same, as mentioned above. Lastly, tax revenue for the Japanese government would increase, because repealing tax subsidies implies that the government keeps more money. Moreover, raising tax rates causes social welfare to decrease, and creates a dead-weight loss.

7 Conclusion

This paper develops a structural model which accounts for the portfolio effect, building upon the previous papers by BLP and Gentzkow (2007). I estimate the model using a unique set of Japanese household-level data on automobile purchases to examine the role these portfolio effects play. My estimates suggest that positive portfolio effects exist between kei-cars and minivans. Ignoring such portfolio effects might lead to a biased counterfactual analysis. In particular, I conduct a counterfactual experiment where the Japanese government repeals current tax subsidies for kei-cars. The portfolio-BLP model suggests that a repeal of the current tax subsidies for small automobiles would decrease the demand for small automobiles by 9%, which is smaller than the 14% drop predicted by a standard discrete choice model, i.e., the micro-BLP model. The simulation results from the portfolio-BLP model also show that the demand for expensive minivans would decrease and the demand for affordable minivans would increase, whereas the demand for all automobiles except kei-cars would increase in the micro-BLP model.

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Tables and Figures

Table 1: Descriptive Statistics of Product Characteristics for Each Category

	Obs.	Mean	S.D.	Min	Max
Capacity (person)					
Kei-car	31	3.87	0.50	2	4
Regular	94	5.09	1.04	2	8
Minivan	29	7.27	0.65	6	8
All	154	5.25	1.40	2	8
Fuel Efficiency (km/l)					
Kei-car	31	16.4	2.22	10	22
Regular	94	12.9	3.88	6	30
Minivan	29	12.2	2.82	7	19
All	154	13.5	3.72	6	30
Horsepower (PS/rpm)					
Kei-car	31	57.6	4.99	43	67
Regular	94	154.6	57.9	76	280
Minivan	29	151.6	33.5	86	240
All	154	134.5	61.2	43	280
Displacement (cc)					
Kei-car	31	658	0.85	656	659
Regular	94	2068	720.2	1,096	4,494
Minivan	29	2130	495.2	1,297	3,498
All	154	1797	829.0	656	4,494
Price ($)					
Kei-car	31	14,487	2,125	10,643	18,725
Regular	94	28,265	10,778	12,250	57,125
Minivan	29	29,760	7,813	17,130	46,943
All	154	25,741	10,733	10,643	57,125

Note: For each product characteristic and each automobile category, I report the mean, standard deviation, minimum, and maximum. For price calculation, I use the following exchange rate: $1.00 = ¥ 80.0.

Table 2: List of Automobile Makers and Product Lineups

Manufacturers	Number of models: Kei-car	Regular	Minivan	Units sold (Q): Kei-car	Regular	Minivan
Daihatsu/Toyota	8	44	11	1,173,235	2,924,224	1,372,277
	(12.7%)	(69.8%)	(17.5%)	(21.4%)	(53.5%)	(25.1%)
Honda	3	8	6	652,333	763,918	688,781
	(17.6%)	(47.1%)	(35.3%)	(31.0%)	(36.3%)	(32.7%)
Mazda	5	8	3	112,458	410,603	157,422
	(31.3%)	(50.0%)	(18.8%)	(16.5%)	(60.3%)	(23.1%)
Mitsubishi	4	5	3	430,059	198,724	56,752
	(33.3%)	(41.7%)	(25.0%)	(62.7%)	(29.0%)	(8.3%)
Nissan	1	21	5	133,389	1,485,896	380,199
	(3.7%)	(77.8%)	(18.5%)	(6.7%)	(74.3%)	(19.0%)
Subaru	3	3	0	194,459	267,932	0
	(50.0%)	(50.0%)	(0.0%)	(42.1%)	(57.9%)	(0.0%)
Suzuki	7	5	1	1,246,095	165,258	4,784
	(53.8%)	(38.5%)	(7.7%)	(88.0%)	(11.7%)	(0.3%)
Total	31	94	29	3,942,028	6,216,555	1,372,277
	(20.1%)	(61.0%)	(18.8%)	(30.8%)	(48.5%)	(20.8%)

Note: The first three columns show the number of products which fall into each category for each firm. The next three columns show the total sales of products in each category. The numbers in parentheses display the percentage of models and units sold for each category within a firm.

Table 3: Estimated Parameters of the Demand Sides

Product Characteristics	Micro-BLP: Estimates	Std. Err.	Portfolio-BLP: Estimates	Std. Err.
Term on Price (α)				
Income $\leq$ 50 percentile (α_1)	16.71**	6.013	12.59**	3.70
Income $\in$ [50,90] (α_2)	68.61**	4.163	65.12**	1.41
Income $\geq$ 90 percentile (α_3)	76.89**	4.504	59.52**	9.40
Constant Term				
Mean ($\bar{\beta}_1$)	-130.2**	18.17	-132.5**	7.92
Std. Deviation (β_1^u)	0.032	0.015	2.081**	0.60
Seating Capacity				
Mean ($\bar{\beta}_2$)	4.985**	1.082	5.170**	0.412
Family Size ($\beta_{2,1}^o$)	0.615**	0.218	0.791**	0.100
Std. Deviation (β_2^u)	0.191	0.392	0.360	0.347
Miles Per Gallon				
Mean ($\bar{\beta}_3$)	-6.18**	0.493	-0.317	0.199
Std. Deviation (β_3^u)	0.469	0.225	0.043	0.044
log(HP/Weight)				
Mean ($\bar{\beta}_4$)	9.200**	1.379	7.694**	0.382
Age of Household Head ($\beta_{4,1}^o$)	0.023	0.015	3.46E-04**	0.000
Std. Deviation (β_4^u)	0.261**	0.050	0.013**	0.004

Note: For horsepower and weight of automobiles, I use logarithms. ** and * indicate 95% and 90% level of significance, respectively.

Table 4: Estimated Parameters for Portfolio Term

	Estimates	Std. Err.
Fixed effect of having two cars		
Number of earners	1.377**	0.085
City dummy	1.494**	0.308
Village dummy	2.305**	0.159
Presence of children interacted with combinations (γ_r)		
Kei-Kei	6.617**	0.024
Kei-Regular	3.227**	0.055
Kei-Minivan	3.061**	0.070
Regular-Regular	2.912**	0.067
Regular-Minivan	1.950**	0.088
Combination specific unobserved terms (ζ_r)		
Kei-Kei	-1.248**	0.212
Kei-Regular	1.145**	0.194
Kei-Minivan	2.246**	0.042
Regular-Regular	1.461**	0.062
Regular-Minivan	1.467**	0.244

Note: The first three rows display the variables included in the fixed effect of having two automobiles (γ_r is the same for all categories). The next five rows display the interaction terms between combinations of automobiles and the presence of children. The last five rows display the estimation results for combination specific unobserved terms. ** and * indicate 95% and 90% level of significance, respectively.

Table 5: Estimates for Supply Side Parameters

	Micro-BLP		Portfolio-BLP	
	Estimate	Std. Err.	Estimate	Std. Err.
Constant	14.52**	0.055	14.81**	0.014
Miles Per Gallon	-2.447**	0.084	-4.003**	0.019
Horsepower/Weight	1.348**	0.030	1.129**	0.041
Toyota Dummy	-0.065**	0.020	-0.031**	0.011

Note: ** and * indicate 95% and 90% level of significance, respectively.

Table 6: Model Fit 1 - Households Purchasing One Automobile

	All Samples	
	Predicted	Data
Probability of choosing a 5-passengers car	0.398	0.392
Probability of choosing a sports car	0.009	0.009
Average Expenditure ($)	23,435	23,678

Note: 'All samples' means that I include all households that purchased one automobile during the decision period. Probabilities of choosing particular categories of automobiles are aggregated with the probabilities of choosing each automobile that falls into the category. Average expenditures are calculated by summing up prices weighted by choice probabilities.

Table 7: Model Fit 2 - Households Purchasing Two Automobiles

	Predicted	Data
Average Capacity	5.310	5.313
Average MPG	14.29	14.52
Average Horsepower	97.28	97.86

Note: Average characteristics were computed by summing up characteristics for all automobiles weighted by choice probabilities.

Table 8: List of Taxes Associated with Automobile Purchases

	Kei-cars	Full-size cars
(i) Automobile Acquisition Tax	3% of acquisition price	5% of acquisition price
(ii) Automobile Weight Tax	¥ 4,400 ($55.00)	¥ 6,300/500kg ($78.75/0.5t)
(iii) Automobile/Kei-car Tax	¥ 7,200 ($90.00)	See Table 9

Note: Listed costs for automobile weight tax and automobile/kei-car tax are annual rates, and consumers are required to pay these taxes for three years. I use the following exchange rate: $1.00 = ¥ 80.

Table 9: Annual Automobile Tax

Displacement (cc)	Fee ($)
less than 1000	369
1001-1500	431
1501-2000	494
2001-2500	563
2501-3000	638
3001-3500	725
3501-4000	831
4001-4500	956
4501-6000	1,100
more than 6000	1,375

Note: I use the following exchange rate: $1.00 = ¥ 80.

Table 10: Example of Tax Subsidies for a Selected Kei-car, MOCO

	With Tax Subsidies	Without Tax Subsidies
Original Price	$13,054	$13,054
Tax		
Acquisition Tax	$392	$653
Automobile Weight Tax	$165	$473
Automobile/Kei-car Tax	$270	$1,106
Tax sub-total	$827	$2,232

Note: MOCO is produced by Nissan. MOCO's engine displacement is 658cc and its weight is 850kg. Because automobile weight tax must be paid for three years, I multiply the numbers by three. Although the automobile/kei-car tax must be paid annually, most Japanese households do not discard an automobile within three years, thus I also multiplied them by three. For prices, I use the following exchange rate: $1.00 = ¥ 80.

Table 11: Tax Elimination Effect on Automobile Sales

	Current	Micro-BLP (w/o P.E.)		P-BLP (w P.E.)	
	Sales	After	%	After	%
Kei-cars	3,942,028	3,392,034	-13.95	3,585,812	-9.04
Regular	6,216,555	6,693,223	7.67	6,528,402	5.02
Minivan	2,660,215	2,699,055	1.46	2,690,298	1.13
Total	12,818,798	12,784,312	-0.27	12,804,512	-0.11

Note: The third and fifth columns show the total units sold for each category after repealing tax subsidies as predicted by Micro-BLP and the Portfolio BLP, respectively. The fourth and sixth columns show the % changes from the current sales to the predicted sales.

Figure 1: Change in Units Sold for All Automobiles by Engine Displacement

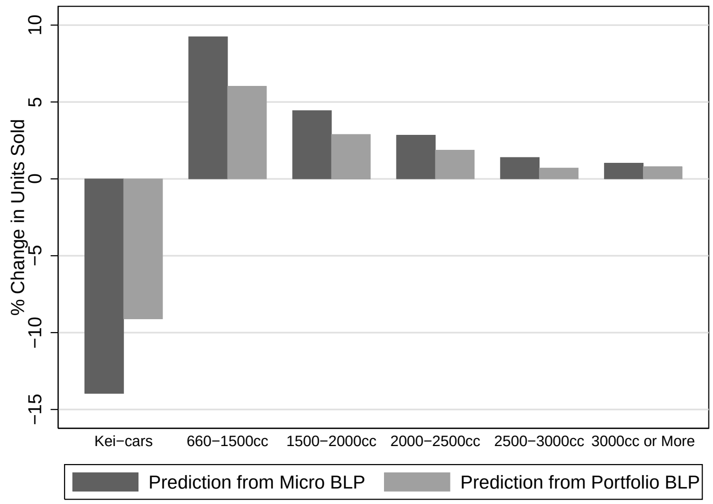

Figure 2: Change in Units Sold for Minivans by Engine Displacement

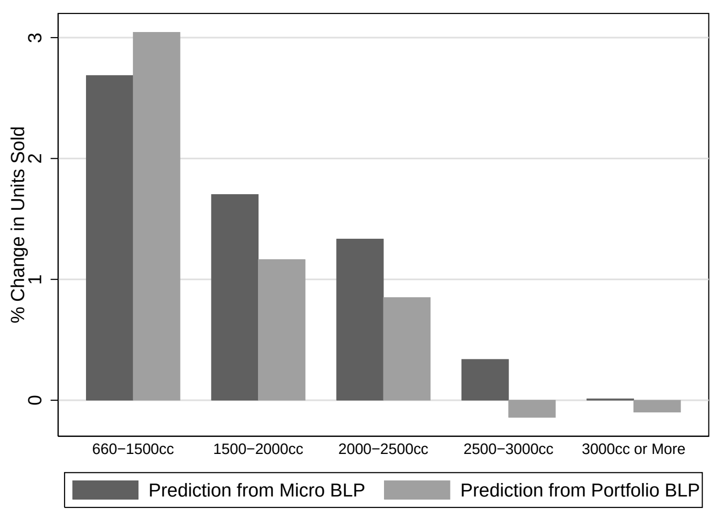

TABLE 12: Tax Reduction Effects for Selected Kei-cars

		% change in Demand			Price (Before Tax)			Car Characteristics			
Name	Maker	Original	M-BLP	P-BLP	Original	M-BLP	P-BLP	Disp.	SUV	Sport	Weight
VAMOS	Honda	115,759	-18.11%	-12.21%	16,925	0.21%	0.06%	656	0	0	1060
SAMBAR	Subaru	13,644	-16.68%	-11.75%	16,850	0.06%	0.01%	658	0	0	1100
AZ WAGON	Mazda	62,466	-15.27%	-10.41%	14,877	0.34%	0.71%	658	0	0	860
EK	Mitsubishi	330,119	-13.53%	-10.38%	14,224	0.10%	0.93%	657	0	0	860
PAJERO MINI	Mitsubishi	41,974	-14.06%	-10.09%	17,150	0.08%	0.29%	659	1	0	1000
MOCO	Nissan	133,493	-13.86%	-9.80%	13,054	0.34%	0.88%	658	0	0	850
PLEO	Subaru	119,766	-12.54%	-9.71%	13,052	0.07%	0.91%	658	0	0	900
EVERY WAGON	Suzuki	61,033	-14.34%	-9.63%	15,938	-0.04%	0.15%	658	0	0	950
SCRUM WAGON	Mazda	4,073	-14.72%	-9.62%	17,021	0.00%	0.00%	658	0	0	950
MOVE	Daihatsu	523,941	-16.00%	-9.46%	15,158	0.52%	0.22%	659	0	0	880
WAGON R	Suzuki	549,406	-12.84%	-9.20%	14,043	-0.23%	0.33%	658	0	0	890
TERIOS KID	Daihatsu	49,391	-15.03%	-9.18%	16,090	0.35%	0.01%	659	1	0	990
MR WAGON	Suzuki	165,681	-13.00%	-9.10%	14,681	-0.18%	0.18%	658	0	0	890
LIFE	Honda	456,060	-14.00%	-9.09%	15,081	0.20%	0.16%	657	0	0	910
NAKED	Daihatsu	24,123	-16.08%	-8.99%	14,577	0.39%	0.00%	659	0	0	840
SPIANO	Mazda	22,446	-14.30%	-8.59%	13,558	0.19%	0.03%	658	0	0	790
COPEN	Daihatsu	24,250	-6.97%	-7.42%	18,725	-0.15%	0.01%	659	0	1	840

Note: Daihatsu, in the second column, is one of the companies in the Toyota group. The third and sixth columns show the original units sold and the original prices for each automobile. The fourth and fifth columns show the predicted demand changes for each automobile calculated by the Micro-BLP model and the Portfolio-BLP model. The seventh and eighth columns show the predicted price changes for each automobile calculated by M-BLP and P-BLP. The ninth to twelfth columns show the engine displacement, SUV dummy, Sport dummy and weight of automobiles, respectively . For prices, I use the following exchange rate: \$1.00 = ¥ 80.

TABLE 13: Tax Reduction Effects for Selected Minivans

		% change in Demand			Price (Before Tax)			Car Characteristics		
Name	Maker	Original	M-BLP	P-BLP	Original	M-BLP	P-BLP	Disp.	Capacity	Weight
ESTIMA	Toyota	130,869	0.29%	-0.27%	46,943	-0.01%	-0.04%	2764	8	1950
GRANDIS	Mitsubishi	33,717	1.58%	-0.07%	31,317	-0.02%	-0.02%	2378	7	1685
ALPHARD	Toyota	223,082	0.39%	0.00%	46,438	-0.02%	-0.09%	2804	8	2080
STEP WGN	Honda	131,839	0.43%	0.17%	28,155	0.00%	-0.12%	2087	8	1620
EDIX	Honda	19,006	4.62%	0.55%	22,625	-0.04%	-0.01%	1833	6	1440
NOAH	Toyota	261,357	0.52%	0.66%	32,834	-0.03%	-0.26%	1998	8	1600
VOXY	Toyota	196,823	0.45%	0.71%	31,397	-0.02%	-0.29%	1998	8	1560
IPSUM	Toyota	105,277	1.91%	0.94%	30,875	-0.08%	-0.26%	2362	7	1590
ODYSSEY	Honda	195,738	1.72%	1.23%	33,095	-0.05%	-0.29%	2408	7	1720
MPV	Mazda	110,389	1.60%	1.69%	31,428	-0.01%	-0.37%	2407	7	1740
STREAM	Honda	122,671	2.37%	1.94%	24,800	-0.05%	-0.48%	1792	7	1480
WISH	Toyota	261,770	3.84%	2.11%	27,475	-0.14%	-0.50%	1998	6	1430
MOBILIO	Honda	189,756	3.22%	3.83%	20,486	-0.05%	-0.96%	1496	7	1330

Note: The third and sixth columns show the original units sold and the original prices for each automobile. The fourth and fifth columns show the predicted demand changes for each automobile calculated by the Micro-BLP model and the Portfolio-BLP model, respectively. The seventh and eighth columns show the predicted price price changes for each automobile calculated by Micro-BLP and Portfolio-BLP model, respectively. The ninth to eleventh columns show the engine displacement, capacity, and weight of automobiles, respectively . Price figures are measured in USD, and I use the following exchange rate: \$1.00 = ¥ 80. Engine displacement, capacity and weight are measured in cc, person, and kg, respectively.

Table 14: Tax Elimination Effect on CAFE Standards

Current CAFE Standards	After Repealing	
	Micro-BLP	Portfolio-BLP
32.551	32.488 (-0.194%)	32.500 (-0.157%)

Table 15: Tax Elimination Effect on Producer Surplus

	Profit			Product Lineup		
	Before	After	%	Kei	Reg.	Mini.
Daihatsu/Toyota	73,723	74,294	+0.76	8	44	11
Honda	21,196	21,083	−0.53	3	8	6
Mazda	6,238	6,352	+1.83	5	8	3
Mitsubishi	6,592	6,288	−4.62	4	5	3
Nissan	20,217	20,720	+2.49	1	21	5
Subaru	4,188	4,089	−2.35	3	3	0
Suzuki	15,347	14,242	−7.20	7	5	1
Total	147,510	147,068	−0.30	31	94	29

Note: The second and third columns show the estimated profits under the current tax policy, and the simulated profits under the new tax policy where there are no tax subsidies for kei-cars. The fourth column displays the percentage change for firms' profit. The remaining columns show the number of models that each manufacturer produces. Profit figures are measured in millions of dollars, and I use the following exchange rate: $1.00 = ¥ 80.

Table 16: Welfare Implication in Million Dollars

Δ(Consumer Surplus)	−6,997
Δ(Producer Surplus)	−442
Δ(Tax Revenues)	+5,887

Note: For consumer surplus, I use compensation variations (CV). Figures are expressed in millions of dollars, and I use the following exchange rate: $1.00 = ¥ 80.

Appendix (Not for Publication)

A1: Computational Details

In this technical appendix section, I explain the simulation and estimation procedure.

1. Prepare random draws, which do not change throughout estimation, for the macro moment and the micro moments, $\mathbf{G}^2$ and $\mathbf{G}^3$.

   (a) Draw $i = 1, \cdots, n_M$ consumers from the joint distribution of characteristics given by the Census data, $F_{M1}(\boldsymbol{z})$. And, we also need to draw corresponding unobserved consumer characteristics from multivariate normal distribution, $F_{M2}(\boldsymbol{\nu})$.

   (b) For each consumer $i = 1, \cdots, n_m$ in KHPS, draw n_s times from multivariate normal distribution, $F_m(\boldsymbol{\nu})$ of unobserved consumer characteristics vector.

2. Choose an initial guess of parameters, θ_0.

3. Calculate the predicted market share for each product, s_j^P, by summing up choice probabilities for each consumer $i = 1, \cdots, n_M$. Using the contraction mapping developed by Berry et al. (1995),

$$\delta_j^{t+1} = \delta_j^t + \ln(s_j) - \ln(s_j^P(\theta)),$$

   iterate until the difference between the predicted market share and the empirical market share is small. This step enables us to find a vector of the mean utilities, $\delta_j^*(\theta_0)$, which satisfies the first moment being equal to zero, i.e., $G^0(\theta_0) = 0$.

4. Find the objective value by calculating the following three moments:

   (a) For each consumer in KHPS, calculate the average choice probabilities for each product given the parameters value, i.e.,

$$\hat{q}_{ij} = \frac{1}{n_s} \sum_{k=1}^{n_s} q_{ijk}$$

   which is the approximated choice probabilities of product j for each household i. It is straightforward to calculate the moment conditions $\mathbf{G}^2(\boldsymbol{\theta})$ and $\mathbf{G}^3(\boldsymbol{\theta})$.

(b) Because of the household heterogeneity, we need to approximate $\mathbf{\Delta}$ by

$$\Delta_{km} = \frac{1}{n_M}\sum_{i=1}^{n_M}\frac{\partial q_{ik}}{\partial p_m}$$

Given this $\mathbf{\Delta}$, we can compute the inverse matrix, which enables us to obtain the firms' first order conditions, i.e., $\mathbf{G}^4(\boldsymbol{\theta})$.

5. Go back to step 2, until the objective function is minimized.

A2: Standard Errors

The asymptotic variance of $\sqrt{n}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})$ is given by

$$(\boldsymbol{\Psi}'\boldsymbol{\Psi})^{-1}\boldsymbol{\Psi}'\boldsymbol{V}\boldsymbol{\Psi}(\boldsymbol{\Psi}'\boldsymbol{\Psi})^{-1}. \tag{12}$$

where

$$\boldsymbol{\Psi}_{ij} = \mathbf{E}\left[\left.\frac{\partial G_j(\boldsymbol{\theta})}{\partial \theta_i}\right|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}}\right],$$

and G_j is the j-th element defined in the previous section. The variance-covariance of the parameters can be decomposed into two parts: (i) the derivative matrix of the first order conditions evaluated at the true parameter values, $\hat{\mathbf{\Gamma}}$ in (12), and (ii) the variance-covariance of the first order conditions evaluated at the true parameter values, $\hat{\boldsymbol{V}}$ in (12), as shown in Hansen (1982). As for (1), it can be consistently estimated by taking the derivative of the sample moment's first order condition, $\hat{\Gamma}$, explained above. As for (2), there are three sources of randomness: (i) the standard GMM variance term given by $\hat{\boldsymbol{V}}_1 = \boldsymbol{S}(\hat{\boldsymbol{\theta}})$, (ii) the difference between observed market shares and true market shares which is zero in my case, i.e., $\hat{\boldsymbol{V}}_2 = 0$, and (iii) simulation error in my calculations. The variance term due to simulation error can be given by:

$$\hat{\boldsymbol{V}}_3 = \frac{1}{H}\sum_{h=1}^{H}\left[\boldsymbol{G}(\hat{\theta}, P_{ns}^h) - \frac{1}{H}\sum_{h=1}^{H}\boldsymbol{G}(\hat{\theta}, P_{ns}^h)\right]\left[\boldsymbol{G}(\hat{\theta}, P_{ns}^h) - \frac{1}{H}\sum_{h=1}^{H}\boldsymbol{G}(\hat{\theta}, P_{ns}^h)\right]',$$

where P_{ns}^h is independently redrawn H times. These three randomness factors are independent of each other, and thus $\hat{\boldsymbol{V}}$ will be the sum of these three $\hat{\boldsymbol{V}}_i$, for $i = 1, 2, 3$.