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

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The dissertation develops a structural model where consumers can purchase up to two differentiated products, where I allow for flexible complementarities which depend on consumer attributes and product characteristics. In the model, firms set the prices for their products, given other firms' pricing strategies and consumer demand. I then estimate the model using two types of data: micro-level data on household automobile purchasing decisions and macro-level data on market share.

My estimates suggest that strong complementarities arise when households purchase a combination of one small automobile and one regular-sized automobile, or one small automobile and one minivan as their portfolio. The estimates also indicate that households are more likely to purchase two automobiles as their numbers of earners increase or if they are located in rural areas.

Ignoring such portfolio effects would lead to biased counterfactual analyses. For example, my results suggest that a policy proposal of repealing the current tax subsidies for eco-friendly small automobiles would decrease the demand for those automobiles by 12%, which is less than the 17% drop predicted by a standard single discrete choice model.

Similarly, model simulations indicate that the presence of positive portfolio effects significantly influences firms' pricing behavior: firms potentially have incentive to use a mixed bundling strategy when the number of products and firms in the market is small.

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PORTFOLIO CONSIDERATIONS IN AUTOMOBILE PURCHASES: AN APPLICATION TO THE JAPANESE MARKET

Naoki Wakamori

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To my grandparents

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ABSTRACT

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Naoki Wakamori

Elena Krasnokutskaya

This dissertation empirically studies demand complementarities in automobile purchases using newly collected Japanese household-level panel data, *Keio Household Panel Survey*. It is motivated by the observation that approximately one third of Japanese households own more than one automobile and they tend to hold particular combinations of products, which cannot be captured by the prevalent single choice model in this literature.

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Chapter 1

Introduction

In many differentiated product markets, such as the markets for automobiles and personal computers, consumers often purchase more than one product. They 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 three children might purchase one compact sedan to commute to work on the weekdays and one minivan to go camping on the weekends. This illustrative example suggests that, the utility from such a portfolio of products might not simply be the sum of the products' individual utilities due to complementarities between products, though most of the existing literatures ignore such effects.[1] In this paper, I call the extra utility that a household derives from purchasing combinations of products the "portfolio effect."

This dissertation develops an empirical framework to estimate a market equilibrium model that incorporates portfolio effects in consumer demand and applies the framework to the Japanese automobile market. The *Keio Household Panel Survey* (KHPS), a newly

[1] In single-discrete choice models, all choices are restricted a priori to be perfect substitutes.

collected household-level survey, suggests that of the households who purchase more than one automobile, more than half purchase at least one car from a category of small cars called *kei*-cars.[2] The popularity of kei-cars is partially due to government tax subsidies that were introduced in the 1960's 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 discussion about a potential repeal of these tax subsidies. The opposition claims that the demand for fuel efficient kei-cars would dramatically decrease. If there is a positive portfolio effect between kei-cars and other types of cars, however, those households who purchase one minivan and one kei-car under the current tax scheme might maintain their portfolio 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 subsidies for small automobiles might be limited.

The modeling framework developed in this dissertation extends previous models considered by Berry et al. (2004) (hereinafter referred to as "micro-BLP") and Gentzkow (2007). In my model, there are two types of agents - consumers and firms. Consumers choose to purchase one or two cars from a set of differentiated cars, or to purchase nothing. Each automobile is characterized by a bundle of characteristics, such as horsepower and fuel efficiency, and consumers derive utility from these characteristics. When they purchase two cars, consumers may potentially derive an extra utility, the portfolio effect, depending on household attributes and product types. Motivated by the data, I introduce portfolio effects that vary by car categories. I divide the set of automobiles into three categories,

[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 4.86ft, 6.56ft, and 11.15ft, respectively.

i.e., kei-cars, regular cars and minivans, and assume that consumers obtain the same portfolio effect for any set of two automobiles that belong to the same respective categories. Consumers maximize utility by consuming automobile and non-automobile goods subject to a budget constraint. The supply side of the model follows Berry, Levinsohn and Pakes (1995); oligopolistic multi-product firms simultaneously set the prices for their products to maximize profits, taking into account the pricing strategies of other firms.

To estimate the model, I draw on various sources of information including individual-level data on purchasing decisions, macro-level data on market shares, and data on product-level characteristics. 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. *New Motor Vehicle Registrations* provides aggregate annual market share data, which helps to improve the accuracy of estimated model parameters. I construct the product characteristics dataset using *Automotive Guidebook*, which lists all available automobile models in Japan every year.

The model predicts choice probabilities for each household given its attributes and yields the pricing first order conditions for firms. Following the estimation procedure suggested by Berry, Levinsohn and Pakes (1995) (hereinafter referred to as "BLP") and micro-BLP, I estimate the model by matching four sets of simulated moments to their data analogues: the macro market share of each product, the covariance between automobile characteristics and household attributes for those who purchased one automobile, the covariance between automobile characteristics for those who purchased two automobiles, and the firms' first order conditions. I minimize the distance between the predicted and empirical moments for the last three sets of moments derived from the micro-data, subject to the first set of moments derived from the macro-data matches exactly.

The estimation results show that positive portfolio effects exist between kei-cars and regular cars, and also between kei-cars and minivans. The estimates also indicate that households are more likely to purchase two automobiles as its number of earners increases and if they are located in rural areas. These results immediately suggest the following questions: Would ignoring portfolio effects lead to overestimation of the impact of repealing tax subsidies for small automobiles?

I use the estimated model to simulate the effect of eliminating the current tax subsidies for small automobiles. The results suggest that the total demand for kei-cars would decrease by 12%. To explore the importance of allowing for portfolio effects, I also estimate a standard single choice model, micro-BLP model. It predicts that the demand for kei-cars would decrease by 17%. This difference of about 5% can be accounted by the portfolio effect. My model also predicts that sales for cheaper minivans would increase under the new tax policy, while sales for expensive minivans would decrease. This can be explained by the fact that some households highly value a combination of one one kei-car and one minivan, and those households would purchase one kei-car and one relatively cheap minivan to maintain benefits from their portfolio under the new tax policy.

The simulation results also show that the profits of firms that primarily manufacture kei-cars would decrease by an average of 3.8%. Four out of seven manufacturers fall into this category. The remaining manufacturers would have, on average, 2.5% higher profits. One firm, which produces only one model of kei-car among its 28 models, would increase its profit by 3.3%. Industry-wide profits for Japanese automobile makers would not change. This result reflects two offsetting effects; an increase in profit from households purchasing slightly larger and more expensive cars than kei-cars, and a negative effect on profit from households purchasing no automobiles under the new tax scheme.

Given the finding of strong positive portfolio effects between kei-cars and minivans and between kei-cars and regular cars, I address a question of interest to firms and government; I consider how profits would change if firms used a bundling strategy in their pricing, and how social welfare would change as a consequence. This simulation is performed for a hypothetical market with two firms. In practice, I choose two firms and two products for each firm that were found to have strong portfolio effects and allow these two firms to price bundles of products as well as individual products. The simulation results show that there is an incentive for firms to use a mixed bundling strategy. Compared to the case where firms are banned from bundling, both the single-car prices and the bundle prices are higher.

Chapter 2

Related Literature

The modeling framework of this dissertation builds on earlier empirical studies on estimating discrete-choice demand and multiple-discrete choice models, because consumers in my model can choose at most two differentiated products from the choice set, taking into account the interaction between selected two products. Furthermore, this dissertation also builds on a literature on using both micro- and macro-level data. As an application point of view, this dissertation is related to literature on automobile industries and related policies, such as subsidies for purchasing new automobiles and gasoline taxes, because the Japanese automobile taxes work to promote purchase of particular types of automobiles.

Consequently, this chapter reviews literature on discrete-choice demand models and multiple-discrete choice models as a modeling framework, and automobile industry and related policies.

2.1 Modeling Framework

2.1.1 Random Coefficient Models

Estimating the demand functions is one of the central issues for empirical economists, because it enables us to study the sources of market power as in Bresnahan (1987), and BLP, measures the welfare effect from new products as in Petrin (2002), and answer many policy related questions as in Goldberg (1995). One of the most common approaches in this literature is characteristics approach, applied to differentiated product demand models by Lancaster (1971) and McFadden (1974), which considers products as bundles of characteristics, and consumers maximize their utility derived from these product characteristics.

Among them, BLP-type random coefficient model is one of the most attractive and convenient approaches, because it does not require micro-level data and allows us to have plausible substitution patterns by exploiting characteristics approach and introducing product specific unobservable terms. Suppose there are two products which have similar observed product characteristics but the market shares for those two products are totally different. Then, product specific unobservable terms can absorb the difference between market shares, and it allows us to have plausible substitution patterns. Due to these advantages, BLP-type random coefficient models are widely applied to estimate the differentiated product demand in various industries, such as Nevo (2001) for the ready-to-eat cereal industry, and Rysman (2004) for the Yellow Pages, and so on.

The existing literature, however, is limited to analyzing a single discrete choice, i.e., decision makers can only choose one alternative from the choice set, because of difficulties in identification and computation. There are several exceptions, which are described in the following sections.

2.1.2 Multiple-Discrete Choice Models

This paper also contributes to the literature on estimating multiple-choice demand models. There are three approaches in the majority of the literature. Each approach needs to assume two differentiated products *ex-ante* are either substitutes as in Dube (2004) and Hendel (1999), independent as in Augereau, Greenstein and Rysman (2006), or complements as in Manski and Sherman (1980). 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. 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. Therefore, this dissertation builds on both Berry, Levinsohn and Pakes (1995) and Gentzkow (2007).

This dissertation is not the first article which is the hybrid of random coefficient models and multiple-discrete choice models. For example, Fan (2010) studies the U.S. newspaper industry using a multiple-discrete choice model. In her model, consumers can choose to subscribe to at most two newspapers, and the utility from the second newspapers is discounted by a constant number which is smaller than one, implying that two newspapers are substitutes.[1] Another article by Hendel (1999) measures the returns of computerization in firms by allowing firms to choose multiple units of differentiated computers to meet each employer's specific demands and aggregate their needs, implicitly assuming that computers

[1] Discounting the second newspaper's utility means that interaction term between first and second newspapers should be negative, when the utility from the second paper would not be discounted.

are substitutes. In my model, however, I would like to have flexible substitution patterns, which depend on household attributes. Therefore, I take Gentzkow (2007)'s modeling.

2.1.3 Combining Macro and Micro data

This empirical study is also related to the literature of dealing with micro- and macro-level data when both datasets are available. In many occasions, empirical economists face some difficulties in having individual-level data. That is why the BLP method is very convenient because it enables us to estimate the demand functions from only macro-level market share data. However, I have both levels of data, and would like to utilize both sets of information. As Imbens and Lancaster (1994) investigate and applied by Petrin (2002) and m-BLP, I construct the objective function from micro-level data and maximize it subject to the moment condition from macro-level data. In that way, I exploit both datasets.

Moreover, there is an advantage of using both types of datasets. Fan (2010) uses only macro-level market share data, while Hendel (1999) uses only micro-level market share data. Thus, macro-level data enable us to identify product specific unobservable terms and coefficient associated with random coefficient terms, while micro-level data enable us to identify combination specific unobservable terms and portfolio effect terms.[2]

2.2 Automobile Industry and Related Policies

Recent increasing environmental concerns have lead to a renewed policy focusing on automobile markets. One stream of literature analyzes the policy of promoting the retirement

[2]See Chapter 4 for more detailed discussion.

of old automobiles by subsidizing the scrappage of old atuomobiles and the purchase of new automobiles, such as Adda and Cooper (2000), Alberini, Harrington and McConnell (1995), Chen, Esteban and Shum (2010), Hahn (1995), and Schiraldi (2009). For example, Adda and Cooper (2000) and Schiraldi (2009) construct consumers' dynamic programming problem to describe the replacement behavior of automobiles.

In their models, however, one of the key features in automobile market is ignored: multiple-ownership. For example, suppose the government implements the policy of subsidizing the scrappage of old automobiles and the purchase of new eco-friendly automobiles. Consider a household which owns two automobiles, one of which is eligible to be subsidized while the other one is not, and is considering purchasing two new automobiles. In such a case, the household might replace those two cars with one eco-friendly automobile being subsidized and another larger displacement automobile. With a subsidy, the household may purchase even larger automobile that they would have in the absence of the subsidy. In this way, even in dynamic models, multiple-purchasing considerations might be important. And, ignoring those portfolio considerations, we might have biased counterfactual analyses. Therefore, in order to fully consider the automobile demand, both dynamic and

Table 2.1: Extending Direction of Automobile Demand

	Static	Dynamic
Single-purchase	BLP(1995)	Schiraldi (2009)
Multiple-purchase	Wakamori(2011)	

multiple-ownership aspects should be taken into account. However, such a dynamic and multiple-ownership model will be computationally expensive and data requirement will be demanding. As a result, this dissertation is devoted to understand the mechanism of multiple-ownership problem, and thus this empirical study complements the literature on dynamic demand models.[3]

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 automobile manufacturers when the average fuel economy of their annual fleet of automobile production falls below the standard. There are many papers that analyze CAFE standards using various approaches. These include Bento et al. (2009); Austin and Dinan (2005); Goldberg (1998); and Gramlich (2010). CAFE standards can be viewed as an implicit tax on large automobiles and a subsidy for eco-friendly small automobiles. However, the Japanese tax subsidies create a more direct consumer incentive to purchase eco-friendly automobiles. This empirical study complements aforementioned literature.

[3]Another reason why this dissertation focuses on multiple-ownership is to avoid an endogeneity problem. See Chapter 5 for more detailed discussion.

Chapter 3

The Model

3.1 Differentiated Product

In this chapter, I describe my model. Consider a differentiated product market with two types of agents: consumers and producers. Each differentiated product is indexed by j, $j = 0, 1, 2, \cdots, J$, and 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 product j. As a matter of convention, let $j = 0$ denote the outside good, i.e., purchasing no products. In the following sections, I describe consumers' and producers' maximization problems, respectively.

3.2 Household Behavior

Let $i = 1, 2, \cdots, N$ denote the individual households. Each household is characterized by its observed attributes, $(y_i, \boldsymbol{z}_i)$, where y_i denotes the income of households and $\boldsymbol{z}_i$ denotes other household attributes such as such as family size, age of the household head, number of kids and so on. In my model, I assume that each household purchase up to two automobiles. Let $d_i = (d_1, d_2)$ denote an automobile purchase decision for household i, where each d_k specify the product, i.e., $d_k \in \{0, 1, \cdots, J\}$ for $k = 1, 2$. The households maximize their utility by choosing automobile consumptions and level of non-automobile consumption goods, C. Namely, each household i solves the following maximization problem;

$$\max_{C,(j,l)} u^c(C) u^a_i(j, l) \qquad \text{s.t.} \;\; C + p^c_j + p^c_l \leq y_i,$$

with

$$\begin{aligned} u^c(C) &= C^\alpha, \\ \log(u^a_i(j, l)) &= u_{ij} + u_{il} + \Gamma(j, l; z^c_i) + \varepsilon_{i,(j,l)}, \end{aligned}$$

where p^c_j is a price for automobile j that consumers face, u^a_i 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. This functional form is a Cobb-Douglas utility function in automobile and non-automobile consumptions. I assume that the log of utility from automobile consumption as a sum of the following components; (i) utilities from each automobile consumption, u_{ij} and u_{il}, (ii) an interaction term between two automobiles which I call the portfolio effect, $\Gamma(j, l; z^c_i)$, 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 subsections, I explain the utilities from each automobile consumption and the portfolio effect term, after describing the automobile taxes in Japan.

Automobile Prices In Japan, three types of taxes are levied for purchasing automobiles.[1] First of all, based on acquisition prices, consumers must pay an *automobile acquisition tax*, depending on the engine displacement of automobiles, i.e.,

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

Second, consumers also must pay an *automobile weight tax*, which is approximately \$55 for any kei-cars per year, and \$79 for every 0.5 tons for other automobiles.

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

where $x_{j,1}$ is the weight of automobile j measured in kilo grams.[2] Finally, depending on the engine displacement of the purchased automobile, consumers must pay an *automobile tax* or *kei-car tax*, denoted by $\tau_{3,j}$. This tax is \$90 for any kei-cars, while the automobile tax is summarized in Table 7.2.

In summary, if the price for automobile j is p_j, consumers eventually need to pay the following price,

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

because consumers must pay these taxes for first three years at the time of the purchase.

[1] See Chapter 6 for more details.

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

3.2.1 Utility from Single Automobile Consumption

For each automobile consumption, each household derives the following utility;

$$u_{ij} = \boldsymbol{x}_j \boldsymbol{\beta}_i' + \xi_j = \sum_{m=1}^{M} x_{jm}\beta_{im} + \xi_j, \tag{3.1}$$

with

$$\beta_{im} = \bar{\beta}_m + \sum_{r=1}^{R} z_{ir}^p \beta_{mr}^o + \beta_m^u \nu_{im}, \tag{3.2}$$

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 characteristics with household attributes. $\boldsymbol{\beta}^o$ and the $\boldsymbol{\beta}^u$ denote the coefficient 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 to have different valuations for each product. For example, as the household size increases, the households valuation of seating capacity might increase. This trend will be captured by β^o. However, it still possible to have different valuations due to the unobserved household heterogeneity, ν_{im}, which is the last term in equation (3.2).

3.2.2 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. Thus, I introduce category-wise portfolio effects, motivated by the data showing that households are interested in having a particular combination of two different types of automobiles, such as one sedan and one minivan, not one specific sedan and one specific minivan. 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 $\mathcal{M}$. Then, I assume that the portfolio effect is the same, for all automobiles in the same category, respectively, i.e.,

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

Potentially, there are other possible ways to categorize automobiles. For example, I can categorize them by engine displacement, horsepower, or mileage. This classification is be viewed as the passenger capacity of the automobiles, because the average passenger capacity of kei-cars, regular cars, and minivans are four, five, and seven respectively. 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 taking the difference there is insufficient variation to estimate the coefficient. That it why I introduce the category-wise portfolio effect in this particular estimation.

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

$$\Gamma_r = \Gamma_0 + \zeta_r + \sum_{l=1}^{L} \gamma_{rl} z_{il}^c, \text{ for } \; r = KK, KR, KM, RR, RM, MM$$

where $\Gamma_0 = \gamma_0 z_{i0}^c$ is the constant utility shifters of owing two automobiles for all r, ζ_r is the combination specific unobserved term for combination r, $z_i^c = [z_{i1}^c, \cdots, z_{iL}^c]$ are the household i's attributes that affect the portfolio effect but not the base utility of each product $u_i(j)$, and $\gamma_r = [\gamma_r^1, \cdots, \gamma_r^L]$ are the coefficients for the household characteristics.[3]

The role of the first term, the Γ_0, captures the effect of having two automobiles, because this term does not depend on any particular combination of automobiles. The combination specific unobserved terms play a similar role to that of the unobserved characteristics for each product, the ξ_j. The last term captures any patterns of holding a particular combination which might be driven by a particular households attributes. For example, if the household includes any children, the choice probabilities for combinations which

[3]This is necessary for the identification condition. To achieve identification, the household attributes included in the portfolio effect are different from the household attributes included in the random coefficient parts.

include one minivan are typically high. It captures such trends.

3.2.3 Choice Probabilities

Substituting (3.2) into (3.1) and putting them together with the original maximization problem, the utility of household i choosing j can be given by the following simple equation:

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

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 except ε_{ij}. When a household chooses the outside option, it will obtain $\delta_0 = 0$ and $\mu_{i0} = \alpha \ln(y_i)$.

Assuming that ε follows a Type I extreme value distribution, the probability of choosing product j and l conditional on household i's attributes, all product characteristics, and parameter values is given by

$$\begin{aligned} &\Pr[d_i = (j,l) | \boldsymbol{z}_i, y_i, \boldsymbol{\nu}_i, \boldsymbol{x}, \boldsymbol{p}, \boldsymbol{\delta}, \boldsymbol{\theta}] \\ &\quad = \frac{1}{F_i} \exp[\delta_j + \mu_{ij} + \delta_l + \mu_{il} + \alpha \log(y_i - p_j - p_l) + \Gamma(j,l; \boldsymbol{z}_i)], \qquad (3.3) \end{aligned}$$

where F_i is defined as

$$
\begin{aligned}
F_i &= \exp[\alpha \log(y_i)] + \\
&\quad \sum_{k=m+1}^{J} \sum_{m=0}^{J-1} \exp[\delta_k + \mu_{ik} + \delta_m + \mu_{im} + \alpha \log(y_i - p_k - p_m) + \Gamma(k, m; \boldsymbol{z}_i)],
\end{aligned}
$$

and $\boldsymbol{\theta}$ is the set of parameters. Moreover, let q_{ij} denote the sum of probabilities of choosing product j for household i. Then, q_{ij} will be given by

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

Notice that this q_{ij} might exceed one, because household $'$ purchase more than one product in my model.

3.3 Firm Behavior

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

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

with

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

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 potential market size, $s_j^p(\boldsymbol{p}; \boldsymbol{x}, \boldsymbol{\theta})$ 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 in Japan. 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, I can obtain the following Bertrand-Nash equilibrium condition;

$$D_j(\boldsymbol{p};\boldsymbol{\tau}) + \sum_{k\in\mathscr{F}_f}(p_k - \mathrm{mc}_k)\frac{\partial D_k(\boldsymbol{p})}{\partial p_j} = 0, \tag{3.4}$$

where $D_j(\boldsymbol{p};\boldsymbol{\tau}) = Ms_j^p(\boldsymbol{p};\boldsymbol{x},\boldsymbol{\theta\tau})$.[4] 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 $\mathbf{c}$ represent vectors of demand, price, and marginal cost, and $\boldsymbol{\Delta}$ denotes

[4] I use this equation (3.4) for counterfactual analyses, when I find Bertrand-Nash equilibrium under new price vectors.

a $J \times J$ matrix with (k, m) element defined by

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

Furthermore, the system of first order conditions can be solved for the vector of the marginal costs, **mc**, i.e.,

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

Chapter 4

Estimation

4.1 Overview

If there is no unobservable term, $\boldsymbol{\xi}$ nor $\boldsymbol{\zeta}$, in the utility function, then the estimation can be done in a straight forward way, such as maximum likelihood, so that we can match the market share for each product to that observed in the macro data, or the individual choice probabilities to those observed in the micro data. In my model, however, there is an unobservable term, $\boldsymbol{\xi}$, in the utility function. Thus, 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.[1] Intuitively, I minimize the set of moment conditions from micro-level data subject to the moment conditions from

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

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, the $\boldsymbol{\delta}$, 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, the $\boldsymbol{\delta}$, which together satisfies the moment conditions for the macro data.

4.2 Objective Function

I estimate the parameters, $\boldsymbol{\theta} = (\alpha, \{\bar{\beta}_m, \boldsymbol{\beta}^o_m, \beta^u_m\}_{m=1}^M, \{\xi_r, \gamma_r\}_{r=1}^R, \boldsymbol{\gamma}_0, \boldsymbol{\psi})$, 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 $\boldsymbol{z}^p_i$ and the observed product characteristics, $\boldsymbol{x}_j$ which are 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.

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

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

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 calculate this market share vector, I use the simulation methods. Households are characterized by their attributes, $(\boldsymbol{z}_i, y_i)$. Thus, I draw 10,000 households from the joint distribution of $\boldsymbol{z}_i$ using Census data, and I simulate income for these households based on $\boldsymbol{z}_i$ and KHPS.[2] For these simulated households, I calculate the choice probabilities for possible choices each product in order to integrate out the heterogeneity at the individual household level. Then, I sum up these probabilities to obtain the theoretical market share. In other words, I approximate the market shares by

$$s_j^p(\boldsymbol{\delta}(\boldsymbol{\theta})) \quad = \quad \frac{1}{2N} \sum_{i=1}^{N} \left\{ \sum_{l=j+1}^{J} \sum_{j=0}^{J-1} \Pr(d_{i1} = j, d_{i2} = l | \boldsymbol{z}_i, y_i, \boldsymbol{\nu}_i, \boldsymbol{x}, \boldsymbol{\theta}, \boldsymbol{\delta}) \right\}$$

where N represents the number of households in Japan. The choice probabilities are given by equation (3.3) in the previous section. The reason why I divide the sum of probabilities by 2 is potential market share for product j can be more than one. I define the first set of moments by taking a difference between empirical and predicted market shares for each

[2]This procedure relies on the representativeness of KHPS. I disccss in detail in Section 4.

product j:

$$\mathbf{G}_j^1(\boldsymbol{\theta}) = s_j - s_j^p(\boldsymbol{\delta}(\boldsymbol{\theta}))$$

where s_j denote the empirical market share.

After obtaining the predicted market shares, I utilize the contraction mapping method developed by Berry et al. (1995). Until the difference between the predicted market shares and the empirical market shares is small, I iterate this procedure by updating the mean utilities, $\boldsymbol{\delta}$. By doing so, I can exactly match the product-level market shares, i.e., $\mathbf{G}^1(\boldsymbol{\theta}) = \mathbf{0}$, and obtain the vector of mean utilities, the $\boldsymbol{\delta}(\boldsymbol{\theta})$, which satisfies the first moment, given the parameter values, the $\boldsymbol{\theta}$.

4.2.2 Covariance between Households Attributes and Product Characteristics

The second set of moments is derived from the micro data. Having obtained $\boldsymbol{\delta}$, it is straightforward to calculate the choice probabilities for each household in the KHPS samples by using the household characteristics via equation (3.3). Now, because I know $\boldsymbol{z}_i$ exactly, so I do not need to integrate them out, though I still need to integrate $\boldsymbol{\nu}_i$ out. After obtaining these 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. More precisely, I can obtain it as

$$\boldsymbol{G}^2(\boldsymbol{\theta}) = \frac{1}{|B_1|}\sum_{i\in B_1}\left[z_i\left\{\sum_{j=1}^{J}(\boldsymbol{x}_j\mathbf{1}_{\{d_i=j\}} - \boldsymbol{x}_j\Pr[d_{i1}=0, d_{i2}=j|\boldsymbol{x}, \boldsymbol{z}_i, \boldsymbol{\theta}])\right\}\right],$$

where B_1 denotes the set of households who purchase one product in the KHPS. This set of moment conditions is useful to identify $\boldsymbol{\beta}^o$, since it enables us to predict the kinds of household attributes that incline them to purchase a particular product.

4.2.3 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, I can obtain it as

$$\begin{aligned}\boldsymbol{G}^3(\boldsymbol{\theta}) = \frac{1}{|B_2|} = \sum_{i\in B_2}\Bigg[\sum_{l=j+1}^{J}\sum_{j=0}^{J-1}\Big\{&\boldsymbol{x}_j\boldsymbol{x}_l\mathbf{1}_{\{d_i^1=j\}}\mathbf{1}_{\{d_i^2=j'\}}\\ &-\boldsymbol{x}_j\boldsymbol{x}_l\Pr(d_{i1}=j, d_{i2}=l|\boldsymbol{z}_i, \boldsymbol{\nu}_i, \boldsymbol{x}, \boldsymbol{\theta}, \boldsymbol{\delta})\Big\}\Bigg],\end{aligned}$$

where B_2 denotes the set of households who purchase two products in the KHPS. These moment conditions are particularly important for identifying the coefficients in the portfolio effect terms, such as $\boldsymbol{\gamma}_r$. This is because that these moment conditions enable us to predict the kinds of household attributes that incline them to purchase a particular combination of products.

First order conditions for firms Finally, the fourth set of moments comes from the first order conditions for firms. The first order conditions derived in Section 3 is

$$\mathbf{mc} = \boldsymbol{p} - \boldsymbol{\Delta}^{-1}\mathbf{D},$$

and I can solve for the unobserved product specific costs, ω_j for each product j. As a matter of convention, as sets of instrument 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) characteristics of product j. Thus, defining $\boldsymbol{Z}_4$ as the sets of instrument explained above, the fourth set of moments can be expressed as follows:

$$\mathbf{G}^4(\boldsymbol{\theta}) = \mathbf{E}[\boldsymbol{Z}_4\boldsymbol{\omega}].$$

4.2.4 The GMM Estimator

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

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

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

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

This minimization problem illustrates that I minimize the sets of moment conditions from micro data, $\mathbf{G}^2(\boldsymbol{\theta})$, $\mathbf{G}^3(\boldsymbol{\theta})$, and $\mathbf{G}^4(\boldsymbol{\theta})$, given the set of moment conditions from macro data, $\mathbf{G}^1(\boldsymbol{\theta})$ being equal to zero. I use Nelder and Mead (1965) simplex method to find $\hat{\boldsymbol{\theta}}$.

4.2.5 Variances of Parameter Estimates

The variance-covariance of the parameters can be decomposed into two parts: (1) the derivative matrix of the first order conditions evaluated at the true parameter values, and (2) the variance-covariance of the first order conditions evaluated at the true parameter values, as shown in Hansen (1982).

As for (1), it can be consistently estimated by taking derivative of the sample moment's first order condition, which is given by

$$\hat{\boldsymbol{\Gamma}}_{ij} = \left.\frac{\partial G_j(\boldsymbol{\theta})}{\partial \theta_i}\right|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}},$$

where G_j is the j-th element defined in the previous section. Notice that this $\hat{\Gamma}$ is different from the portfolio effect term.[3]

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

[3] In order to follow the standard notation in this literature, I use $\hat{\Gamma}$ to denote the derivative matrix in this section.

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.

As a consequence, the asymptotic variance of $\sqrt{n}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})$ is given by

$$(\hat{\boldsymbol{\Gamma}}'\hat{\boldsymbol{\Gamma}})^{-1}\hat{\boldsymbol{\Gamma}}'(\hat{\boldsymbol{V}})\hat{\boldsymbol{\Gamma}}(\hat{\boldsymbol{\Gamma}}'\hat{\boldsymbol{\Gamma}})^{-1}.$$

where $\hat{\boldsymbol{V}}$ is the sum of three sources of randomness, because those are independent of each other.

Chapter 5

The Data

For this empirical study, I mainly use three 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. I describe the characteristics of these datasets and show some summary statistics in this section.

5.1 Dataset

5.1.1 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 the 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.[1] In terms of

[1]Starting from 2007, the sample size increased by 1,400 households with 2,500 individuals. Thus we currently have 5,400 households with 9,500 individuals in total.

automobile ownership, KHPS inquires 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 after 2004, KHPS inquires (1) whether the household purchases automobiles or not up to two cars; and (2) whether the household discards automobiles or not up to two cars. I extract information from these three years of data.

5.1.2 New Motor Vehicle Registrations

The *New Motor Vehicle Registrations* series issued by Japan Automobile Dealers Association provides the number of automobiles sold in a given year under the supervision of Ministry of Land, Infrastructure, Transportation, and Tourism. Because all Japanese automobiles must be registered with the government, the exact numbers of each automobile sold in a given year is available.[2]

5.1.3 Automotive Guidebook: Micro Data for Products

The *Automotive Guidebook* series is issued by 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 exterior dimensions, seating capacity, and engine displacement. Table 5.1 shows the average characteristics of automobiles sold in 2004 to 2006.

[2] As for the sales of used automobiles, however, it is difficult to know the exact number of automobile sales since there are so many companies which deal with used cars and it is difficult to collect and aggregate this decentralized market information. I will discuss this issue later.

5.2 Deciding on a Choice Set

Foreign Automobiles I decided not to use foreign automobiles. There are two reasons for this. First of all, Foreign automobiles hold tiny market shares in Japan. Domestic automobiles are dominant in Japan and about 94% of the market share is held by automobiles produced by domestic automobile manufacturers. Second, compared to Japan's domestic automobiles, information about foreign automobiles is mis-reported often in my micro data. Therefore, I chose to use only domestic automobiles in this empirical study.

Secondary Markets I do not use the secondary market data for this empirical exercise. There are two reasons for this. Most importantly, the secondary market is not big in Japan, and more than 65% of them purchase new automobiles in KHPS. This is partially because of the costly automobile inspection system and owning old automobiles is costly in Japan. Second, the total sales data for secondary market is not available in Japan. Compared to the sales of brand 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 cars are sold/purchased, because in these statistics, we must count the number of trades as two when someone sells an automobile to a used car dealer and the used car dealer then sells it to another person. On the other hand, if someone sells an automobile directly to a friend, we only need count it as one trade. In other words, one transfer of ownership counts as one trade, which makes counting the actual sales difficult. In addition to this problem in macro data issue, micro data, *KHPS*, does not include details about automobile models, nor does it include used car sales prices. Therefore, I ignore used car purchases, because it is not possible to use the information from the macro- and micro-data correctly.

The Choice Set To finalize the choice set, I also eliminate several discontinued domestic automobile models during 2004 to 2006 and whose sales are less than 1,000 per year. This leaves 154 automobiles that I use in 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.

5.3 Descriptive Statistics

In this section, using the datasets introduced above, I summarize some descriptive statistics for automobiles included in the choice set. Table 5.1 displays means, standard deviations, and the max and min 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. This is 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 sport utility vehicles (SUVs).

Table 5.2 lists all domestic automobile manufacturers included in my estimation. It 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 huge 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 than other types of automobiles, on average. 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 numbers of kei-cars. In particular, Mazda's kei-cars represent only 16.5 % of its sales, even though Mazda produces five models of kei-car.

5.4 Data Implementation

5.4.1 Decision Period

I chose the three years from 2003 to 2005 as one decision period.[3] That is, as long as a household purchases automobiles within that period, I assume that the household purchases 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 quick. This is because the Japanese government has implemented a costly automobile inspection system for car owners. If a consumer purchases an brand new automobile, that car must get inspected after three years of purchase, and every other year after that. The cost of

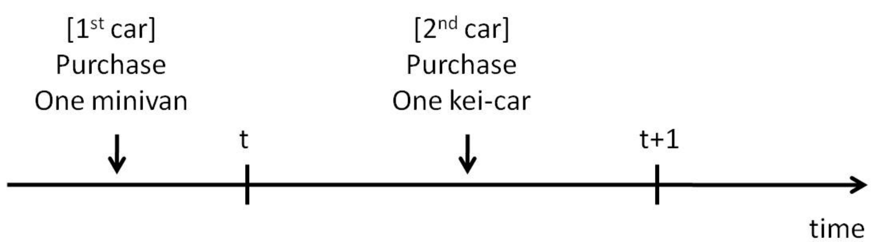
[3]Hendel (1999) also uses three years as one decision period to studies the demand of personal computers for firms.

automobile inspection is about $1,000 to $2,500 USD per inspection. Many households discard their automobiles at the end of three, or five 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 high accuracy.

5.4.2 Alternative Data Implementation

It is also possible to model consumers' utility based on the current automobile holding, taking advantage of panel structure of the data. For example, suppose a household purchased one minivan before 2002, and one kei-car during the decision period, as described in Figure 7.3. An alternative way of using data would be to estimate demand parameters

Figure 5.1: Alternative Modeling of Consumers Decision



depending on the category of current automobile, or specifying different utility functions depending on the current automobile holding. 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 would eliminate tax subsidies for small automobiles in the near future, they might not purchase a combination of one minivan and one kei-car that they would purchase. In order to avoid this issue, my model does not allow utility to vary by the current automobile holdings.

5.4.3 Potential Market Share

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. As Berry et al. (1995) dealt with this problem and Nevo (2000) suggested, 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 the households to choose more than one alternative. Thus, I set the potential market share as the sum of the doubled number of households, i.e., 83,669,000.

Table 5.1: Mean and Std. Dev. 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	1096	4494
Minivan	29	2130	495.2	1297	3498
All	154	1797	829.0	656	4494
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 5.2: List of Automobile Makers and Product Lineups

	Number of models			Units sold (Q)		
Manufacturers	Kei-car	Regular	Minivan	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.

Chapter 6

Estimation Results

6.1 Estimates

Tables 6.1 and 6.2 present the demand side estimates. Table 6.1 displays the parameters associated with random coefficients, while Table 6.2 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 75% percentile income households than for slightly wealthy 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 underestimate 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 because by the fact that some large-family households purchase small capacity automobiles such as kei-cars, and vice versa, because they have already owned one minivan and they do not purchase any cars during this period.

The rest of the parameters also can 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 6.2. 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.[1] The estimation results show that households in less populated areas are more likely to purchase two automobiles. This is largely because public transportations in rural area are not well And thus, households living in rural area tend to demand two automobiles.

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

The combination specific unobserved terms, listed in the next five rows, shows 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. According to the results, the presence of children might also be a driving force in the purchase of at least one kei-car, because any combinations that include at least one kei-car are higher than other combinations that do not include any kei-cars.

Finally, the estimation results on the supply side are summarized in Table 6.3. The negative coefficient for 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 probably decreasing in sales. In fact, Berry et al. (1995) encounter the same problem, and explain and solve this problem by including sales data as an explanatory variable.[2]

6.2 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

[2] For more detail, see Berry, Levinsohn and Pakes (1995), pp.876-877.

micro samples. Table 6.4 demonstrates the fit of my model using the data for households purchasing one automobile in the KHPS. I calculate the probability of choosing SUVs, sport cars, and minivans, which are not directly targeted in the estimation procedure, using the household attributes found in the micro data. My 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 SUVs is 0.0390, whereas the empirical data shows 0.0335. Predicted average expenditure's can be computed by summing up prices weighted by the choice probabilities. My model indicates an average expenditure of $21,369, which is almost identical to the average expenditure in the data ($21,286). Overall, the results show that the model fits well.

Furthermore, I also report similar results for limiting the samples to those having family size equal to four. This helps to clarify the extent of my model fit. The predicted choice probabilities and average expenditures are reported in the fourth column, and their empirical counterparts are reported in the fifth column. Excepting the choice probabilities for sport cars, the results show that the model fits well. The reason I underestimate the choice probabilities for sports cars is that my model does not include any variables that distinguish sports cars from other automobiles. Although it might be possible to enhance the fit of my model by including a sport car dummy in my model, I hesitate to take the approach that far because the choice probabilities for sports cars are so small.

Table 6.5 demonstrates the model fit using only the households purchasing two automobiles in the KHPS. 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, 280, respectively. (from Table 5.1). Thus, comparing the predicted average horsepower, 97.21, with the empirical average horsepower, 97.68, I conclude the model also fits well for those households that purchase two automobiles.

I also summarize the model fit for some targeted moments in Table **??**, using the data from households purchasing two automobiles. In the table, I report the predicted and empirical choice probabilities for each combination. I slightly overestimate the choice probabilities for the combination of a kei-car and a minivan, while I slightly underestimate the choice probabilities for the combination of a regular-size car and a minivan. Overall, however, these probabilities are close to each other, which enables me to use this estimated model for counterfactual analyses in the next section.

Table 6.1: Estimated Parameters of the Demand Sides

Product Characteristics	Parameter Estimate	Standard Error
Term on Price (α)		
Income $\leq$ 50 percentile (α_1)	**14.98****	0.450
Income $\in$ [50,75] (α_2)	**44.78****	2.368
Income $\geq$ 75 percentile (α_3)	**42.11****	2.063
Seating Capacity (β_1)		
Mean ($\bar{\beta}_1$)	**0.242****	0.003
Family Size ($\beta^o_{1,1}$)	**0.010****	0.003
Std. Deviation (β^u_1)	**1.397****	0.034
Miles Per Gallon (β_2)		
Mean ($\bar{\beta}_2$)	**0.159****	0.036
Std. Deviation (β^u_2)	**0.688****	0.026
log(HP) (β_3)		
Mean ($\bar{\beta}_3$)	**0.240***	0.151
Age of Household Head ($\beta^o_{3,1}$)	**1.69E-04****	1.52E-06
Std. Deviation (β^u_3)	**0.030****	0.002
log(Weight) (β_4)		
Mean ($\bar{\beta}_4$)	**0.418****	0.030
Std. Deviation (β^u_4)	**2.395****	0.307

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

Table 6.2: Estimated Parameters for Portfolio Term

	Parameter Estimate	Standard Error
Fixed effect of having two cars (Γ_0)		
Number of earns	**3.157****	0.318
City dummy	**3.674****	0.758
Village dummy	**3.548****	0.113
Combination specific unobserved terms (ζ_r)		
Kei-Kei	**-2.667****	0.591
Kei-Regular	**6.816****	1.324
Kei-Minivan	**9.446****	1.310
Regular-Regular	**7.361****	1.032
Regular-Minivan	**6.430****	0.270
Presence of children interacted with combinations (γ_r)		
Kei-Kei	**9.260****	0.517
Kei-Regular	**5.234****	0.335
Kei-Minivan	**4.117****	0.288
Regular-Regular	**3.496****	0.300
Regular-Minivan	**3.544****	0.244

Note: The first three columns display the variables included in the fixed effect of having two automobiles, Γ_0. The next five columns display the estimation results for combination specific unobserved terms. The last five columns display the interaction terms between combinations of automobiles and the presence of children. ** and * indicate 95% and 90% level of significance, respectively.

Table 6.3: Estimated Parameters for Supply Side

	Estimates	S.E.
MPG	**-0.3100****	0.0010
log(HP)	**0.4202****	0.0924
log(Weight)	**0.2582****	0.0278

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

Table 6.4: Model Fit 1 - Households Purchasing One Automobile

	All Samples		Family Size = 4	
	Predicted	Data	Predicted	Data
Probability of choosing SUV	0.0390	0.0335	0.0375	0.0376
Probability of choosing Sport	0.0038	0.0094	0.0055	0.0150
Probability of choosing Minivan	0.2600	0.2890	0.1845	0.1654
Average Expenditure ($)	21,369	21,286	19,622	19,846

Note: 'All samples' means that I include all households that purchase 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 6.5: Model Fit 2 - Households purchasing two automobiles

	Predicted	Data
Average Capacity	5.313	5.313
Average MPG	14.67	14.52
Average Horsepower	97.21	97.86

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

Chapter 7

Counterfactual Analyses

Using the estimated model, I conduct two counterfactual analyses. The first experiment compares the effects of repealing current tax subsidies for small automobiles to the results from a standard single choice model, micro-BLP. In the second experiment, to illustrate the effectiveness of a bundling strategy in the presence of the portfolio effect, I explicitly allow firms to use a bundling strategy. I describe these analyses in this chapter.

7.1 Repeal of Tax Subsidies

In this subsection, I examine the effects of repealing the tax subsidies for kei-cars. The estimation results show that a positive portfolio effect exists between kei-cars and regular cars or minivans. Thus, by ignoring a strong portfolio effect, we might overestimate the effect of repealing tax subsidies for small automobiles. First, I describe the details of the tax subsidies in Japan. Then I show the results of the simulation using an estimated model. At the same time, I also show the results from a standard single-choice model as a benchmark.

7.1.1 Details of Tax Subsidies

When consumers purchase automobiles in Japan, there are three types of taxes. Table 7.1 summarizes these taxes. First of all, based on acquisition prices, consumers must pay an *automobile acquisition tax* of 3% of the purchase price for any kei-cars and 5% for any other automobiles. Second, consumers also must pay an *automobile weight tax*, which is $55 for any kei-cars per year, 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, multiplying by three, the difference will 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.[1]

To see how large these tax subsidies are, Table 7.3 summarizes tax payment for a selected 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.

[1]Detail tax scheme is summarized in Table 7.2.

Later, the goal of this policy shifted to promote consumption 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 claims that the demand for ekei-cars (which are eco-friendly automobiles) would dramatically decrease. However, considering the strong positive portfolio effects, it 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.

7.1.2 Simulation Results

Table 7.4 summarizes by automobile category the predicted effects of repealing tax subsidies. If subsidies were eliminated, the total demand for kei-cars would decrease by 12.2%, and total demand for regular cars and minivans would increase 5.7% and 0.6%, respectively. In order to compare these results to the case where there is no portfolio effect, I also estimate micro-BLP model using the same dataset. The estimation results from micro-BLP model are summarized in the middle column of Table 7.4, and the simulation results suggest that the total demand for kei-cars (ignoring portfolio effects) would decrease by 16.7%. Thus, this difference of about 5% can be accounted by the portfolio effect.

In Table 7.5, 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 7.5 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 a strange 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 a large number of competitors.

There is one more interesting pattern in Table 7.5: the percentage changes in prices for MR WAGON, KEI, and ALTO are almost zero, though other automobiles' prices increase in my model's prediction. This is because these three automobiles are produced by Suzuki, which mainly produces kei-cars. As Table 5.2 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 7.6. 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 is because in 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 minivan decreases, as the automobile prices increase. On the other hand, my model predicts that the demand for expensive minivans would decrease. This can be explained by the fact that there are some households highly value a combination of one one kei-car and one minivan. Those households would purchase one kei-car and one slightly cheap 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.

Economic intuition behind these results are also confirmed by Figures 7.1, 7.2, and 7.3. In Figure 7.1, I show the simulated changes in units sold from my model and micro-BLP model, depending on engine displacement. It is clear that the demand for kei-cars decrease sharply in both my model and micro-BLP model, while the demand for other automobiles increase in both models. In particular, as automobiles' engine displacement increases, the change is getting smaller. Moreover, I decompose these results depending on the category of automobiles: regular cars and minivans. In Figure 7.2, the patterns are preserved. However, in Figure 7.3, the The reason why I have smaller increase in the class of less than 1500cc minivans is there are only few number of minivans.

In Table 7.7, 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 3.3%. This is largely because Nissan produces only one model of kei-car among its 27 models. Mazda would also get higher profits, even though it produces five models of kei-car. This 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 5.2. In Figure 7.4, I show the simulated changes in units sold for each manufacturers from my model and micro-BLP.

Finally, Table 7.8 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 9%, 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 ratio causes social welfare to decrease, and creates a dead-weight loss.

7.2 Mixed Bundling

The discovery of the strong portfolio effects between kei-cars and other categories of automobiles immediately raises the following questions: How would profits change if firms used a bundling strategy? And, how would social welfare change as a consequence of these firms' behavior? To answer the questions, I allow firms to use a particular bundling strategy in this counterfactual analysis.

7.2.1 Competitive Mixed Bundling

In the following counterfactual analysis, I allow the use of mixed bundling strategy, where firms are able to price the bundle of the products, as well as each product. To empirically examine this mixed bundling strategy, I first choose two firms and two products for each firm. Then, I simulate the Bertrand-Nash equilibrium of this game.

The framework I use in this hypothetical bundling experiment is quite close to the model used in Thanassoulis (2007).[2] In Thanassoulis (2007), there are two firms and each firm sells two products. These firms are competing in prices. There are consumers who want to have only product A or B, and there are consumers who want to have both A and B. Therefore, his model is similar to this hypothetical bundling setting. However, there are

[2]For more comprehensive discussion on price discrimination including bundling, see the recent survey by Armstrong (2007).

two differences. First of all, consumers in my model are not limited to purchasing one or two products, whereas consumers in his model are explicitly assumed to purchase a specific number of products, exogenously. Second, when consumers purchase two products in my model, they might purchase two same types of products, say two A's, whereas consumers must purchase a combination of A and B in his model.

Most empirical literature on product bundling that use structural approach focus on channel bundling in Cable TV industries, where bundles include more than ten products.[3] The mixed bundling strategy this paper applies is also closely related to second degree price discrimination, because firms can price discriminate consumers by charging different prices when they purchase more than one product, i.e., quantity discount. This is because that this strategy can be viewed as a coupon which can be obtained at the first purchase and redeemed at the second purchase. There are several papers that empirically study second degree price discrimination. For example, Cohen (2008) develop an equilibrium model to examine whether second degree price discrimination occurs in paper towel industry, and welfare effect under counterfactual pricing scheme.[4]

7.2.2 Simulation Results

As described above, I choose two firms, namely Honda and Toyota, and two products for each firm. For Honda, I choose one kei-car, LIFE (Product H1), and one regular car, FIT (Product H2). For Toyota, I choose one kei-car, MOVE (Product T1), and one regular car, VITZ (Product T2). Thus, there are only four available automobiles in this hypothetical

[3] For example, see Crawford (2000), Crawford and Shum (2006), Crawford and Yurukoglu (2009) and Goolsbee and Petrin (2004).

[4] Other examples include, Verboven (2002) and McManus (2007).

setting, though the demand structure is the same as before. Then, I find the Bertrand-Nash equilibrium for each case where firms are banned from bundling as a benchmark to compare the case where firms can use the mixed bundling strategy.

More precisely, in the case where firms are banned from bundling, each firm f, $f = H, T$, solves the following maximization problem:

$$\max_{p_1^f, p_2^f} \sum_{i=1}^{2} \left[p_i^f D_i^f(\boldsymbol{p}) - C_i^f(D_i^f(\boldsymbol{p})) \right],$$

while, in the case where firms can use the mixed bundling strategy, each firm f, $f = H, T$, solves the following maximization problem:

$$\max_{p_1^f, p_2^f, p_B^f} \sum_{i=1}^{2} \left[p_i^f D_i^f(\boldsymbol{p}) - C_i^f(D_i^f(\boldsymbol{p})) \right] - p_B^f \int_E \mathscr{P}_w d(w),$$

where

$$E = \{w | u(f1, f2) \geq u(j, l) \quad \text{for} \forall (j, l)\}.$$

The set E denotes a set of consumers who purchase both types of product from the same firm f, and they are eligible to get discount of p_B^f. And thus, firms' profit should be subtracted by $p_B^f \int_E \mathscr{P}_w d(w)$, as firms need to give discount for those who purchase two products. Therefore, this mixed bundling strategy can be seen as one of the form of bundle-size pricing or volume discounting.[5]

Table 7.9 summarizes all of the simulation results. The second column shows the prices

[5] Chu, Leslie and Sorensen (2011) empirically shows that the mixed bundling strategy can be approximated by the bundle-size pricing strategy.

for automobiles and profits for firms when these firms are banned from bundling, while the third column shows the prices for automobiles and profits for firms when they use bundling strategies. First of all, the results shows that both firms have an incentive to use a mixed bundling strategy, yielding higher profits for both firms. By observing that prices for bundles are strictly less than the sum of two products for each firm, one can confirm the validity of this result.

To interpret the results, suppose firms are banned from using bundling. In that case, their prices should be the same as in the second column. When firms can use bundling, both firms set the price of the product bundle to the sum of the prices of the kei-car and the regular car in the bundle. Then, these firms would obtain the same profit. Now, most consumers who want one automobile would purchase one automobile, even if firms charge higher prices for separate automobiles, because they are less price elastic than consumers who want to have two automobiles. Moreover, as long as both firms are charging the same prices for their bundles, neither firm would lose profits. Thus, the firms can charge higher prices for separate, non-bundled automobiles. However, these firms are also competing in prices at the same time, and cannot increase their prices much.

According to Thanassoulis (2007), the prices for bundles should be less than the sum of the component prices of no bundling case. That is, p_{HB} and p_{TB} should be less than $15,962 + 18,667$ and $14,372 + 15,713$, respectively. However, as mentioned before, this model setting is slightly different from his model. In particular, all four automobiles in this experiment are differentiated, implying that the bundles offered by the two firms are also differentiated. This mechanism drives up these bundling prices.

Table 7.1: List of Taxes Associated with Automobile Purchases

	Kei-cars	Full-size cars
Automobile Acquisition Tax	3% of acquisition price	5% of acquisition price
Automobile Weight Tax	¥ 4,400 ($55.00) for any kei-cars	¥ 6,300/500kg ($78.75/0.5t)
Automobile Tax/ Kei-car Tax	¥ 7,200 ($90.00) for any kei-cars	See Table 7.2

Note: Listed prices 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 7.2: 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 7.3: 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 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 7.4: Tax Elimination Effect on Automobile Sales

	Current	micro BLP (w/o P.E.)		my Model (w P.E.)	
	Sales	After	%	After	%
Kei-cars	3,942,028	3,282,371	-16.73	3,461,484	-12.19
Regular	6,216,555	6,802,675	9.43	6,571,925	5.72
Minivan	2,660,215	2,686,029	0.97	2,675,633	0.58
Total	12,818,798	12,771,075	-0.37	12,709,042	-0.86

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

Table 7.5: Tax Reduction Effects for Selected Kei-cars

		% change in Demand			Price (Before Tax)			Car Characteristics			
Name	Maker	Original	m-BLP	My Model	Original	m-BLP	My Model	Disp.	SUV	Sport	Weight
MAX	Daihatsu	110,842	-18.5%	-14.0%	14,806	0.20%	0.95%	659	0	0	930
TERIOS KID	Daihatsu	49,353	-19.0%	-14.0%	16,090	0.16%	0.61%	659	1	0	990
PAJERO Mini	Mitsubishi	41,942	-19.3%	-12.9%	17,150	-0.06%	0.02%	659	1	0	1,000
LIFE	Honda	455,705	-17.0%	-12.3%	15,081	0.00%	0.38%	657	0	0	910
MOCO	Nissan	133,389	-17.1%	-12.0%	13,054	0.29%	0.66%	658	0	0	850
THAT'S	Honda	80,958	-17.1%	-11.9%	15,052	-0.05%	0.11%	656	0	0	920
EK	Mitsubishi	329,863	-16.6%	-11.8%	14,224	-0.08%	0.33%	657	0	0	860
NAKED	Daihatsu	24,105	-18.1%	-11.4%	14,577	0.28%	0.15%	659	0	0	840
MR WAGON	Suzuki	165,552	-15.6%	-11.2%	14,681	-0.31%	-0.02%	658	0	0	890
SUBARU R2	Subaru	61,152	-16.5%	-10.5%	13,125	0.01%	0.03%	658	0	0	830
SPIANO	Mazda	22,429	-16.7%	-10.3%	13,558	0.01%	0.02%	658	0	0	790
KEI	Suzuki	86,818	-14.3%	-10.2%	11,926	-0.40%	-0.01%	658	0	0	780
ALTO	Suzuki	342,567	-13.7%	-9.6%	11,282	-0.63%	0.00%	658	0	0	800
COPEN	Daihatsu	24,232	-9.4%	-6.8%	18,725	-1.09%	-0.01%	659	0	1	840

Note: Daihatsu, in the second column, is one of the companies in Toyota group. The third and sixth columns show the original units sold and the original prices for each automobile. The fourth and seventh columns show the predicted demand changes and price changes for each automobile calculated by micro-BLP model. The fifth and eighth columns show the predicted demand changes and price changes for each automobile calculated by my model. 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 7.6: Tax Reduction Effects for Selected Minivans

		Original	m-BLP		My Model		Car Characteristics		
Name	Maker	Unit Sold	Units	%	Units	%	Price	Disp.	Weight
ALPHARD	Toyota	222,910	223,333	0.18%	221,996	-0.41%	46,438	2,804	2,080
ELYSION	Honda	30,274	30,337	0.21%	30,160	-0.38%	43,056	2,676	1,940
ESTIMA	Toyota	130,768	130,991	0.17%	130,276	-0.38%	46,943	2,764	1,950
ELGRAND	Nissan	107,618	107,761	0.13%	107,233	-0.36%	43,583	3,498	2,020
DELICA SG*	Mitsubishi	10,790	10,805	0.14%	10,758	-0.30%	36,813	2,972	2,060
BONGO F**	Mazda	10,940	10,963	0.21%	10,918	-0.20%	31,340	2,075	1,940
PRESAGE	Nissan	57,693	57,865	0.30%	57,648	-0.08%	30,525	2,488	1,740
NOAH	Toyota	261,156	262,094	0.36%	261,063	-0.04%	32,834	1,998	1,600
SERENA	Nissan	146,151	146,635	0.33%	146,104	-0.03%	31,406	1,998	1,640
VOXY	Toyota	196,672	197,476	0.41%	196,633	-0.02%	31,397	1,998	1,560
STEP WAGON	Honda	131,739	132,154	0.32%	131,778	0.03%	28,155	2,087	1,620

Note: The third column shows the units sold in data. The fourth and sixth columns show the predicted units sold based on micro-BLP model and my model, respectively, The fifth and seventh columns show the percentage changes in units sold for micro-BLP and my model. Price figures are measured in USD, and I use the following exchange rate: $1.00 = ¥ 80. Engine displacement and weight are measured in cc and kg, respectively.
*DELICA SG stands for DELICA SPACE GEAR
**BONGO F stands for BONGO FRIENDEE

Figure 7.1: Change in Units Sold for All Automobiles

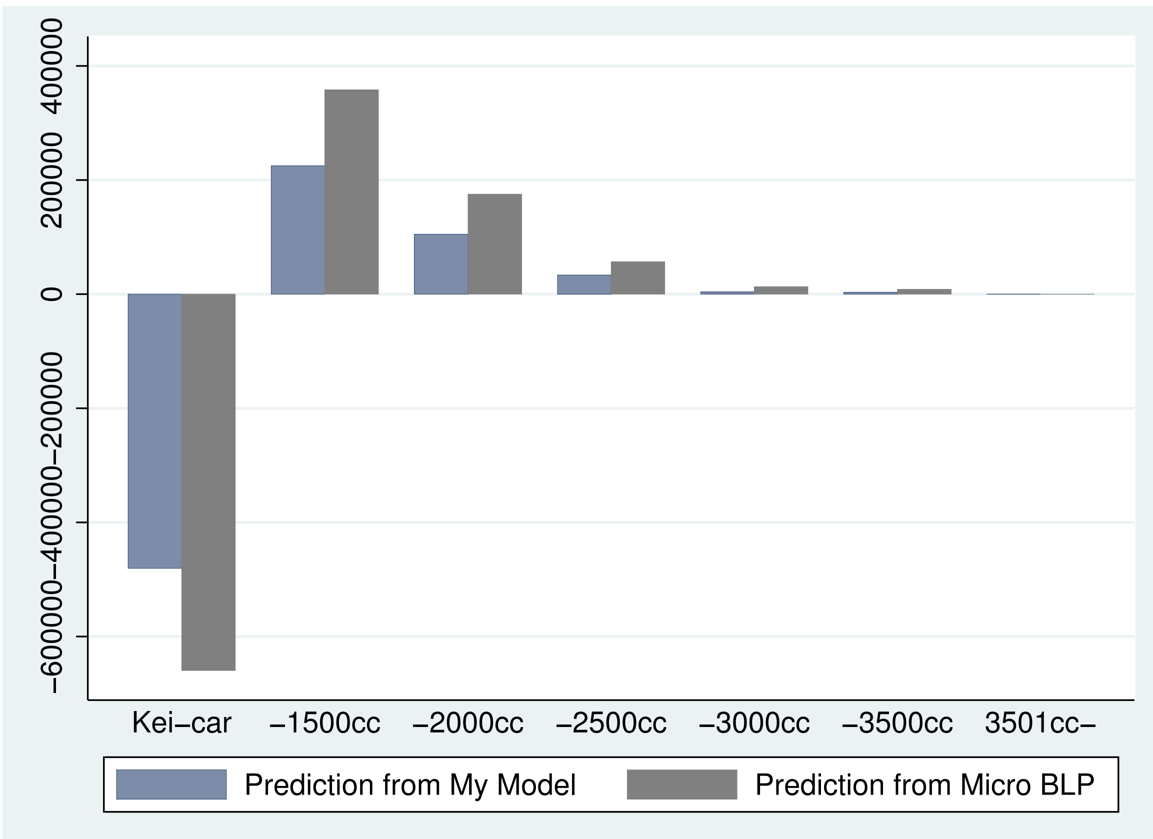


Figure 7.2: Change in Units Sold for Regular Cars

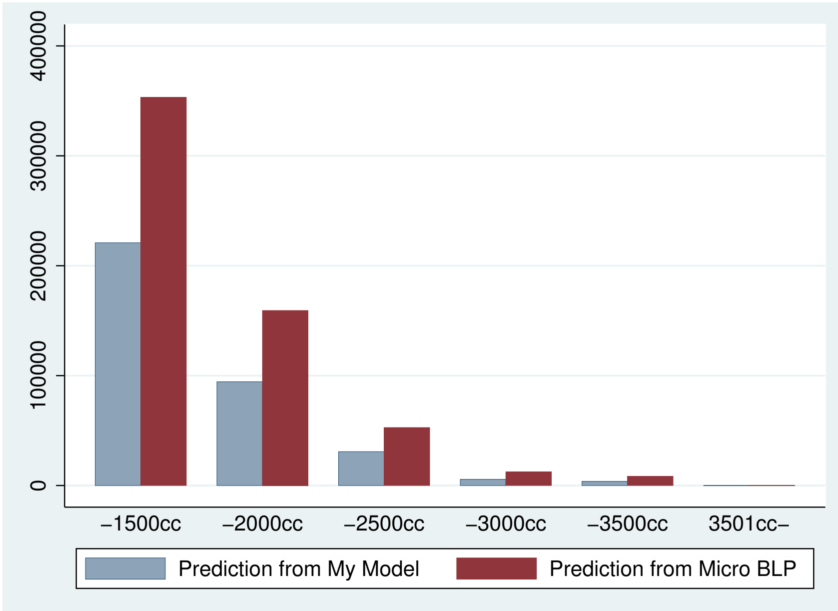


Figure 7.3: Change in Units Sold for Minivans

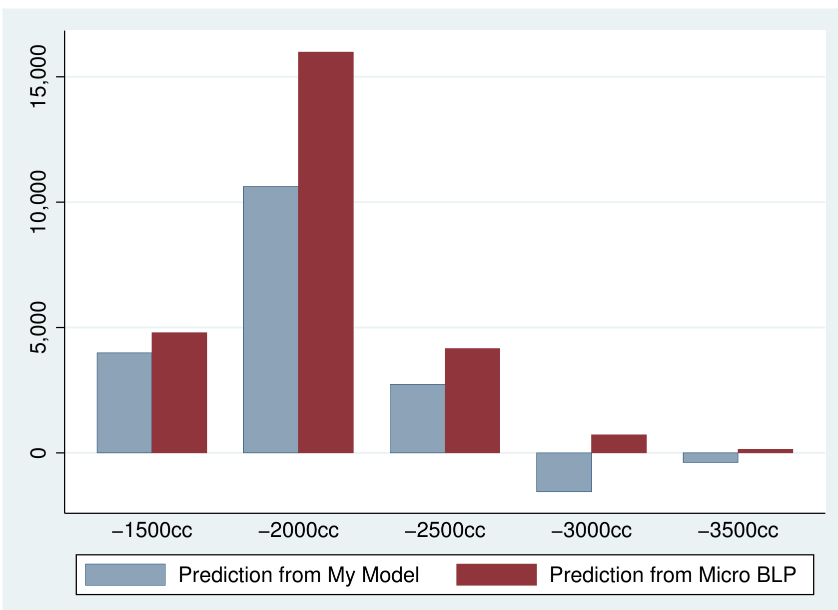


Figure 7.4: Change in Units Sold for Manufacturers

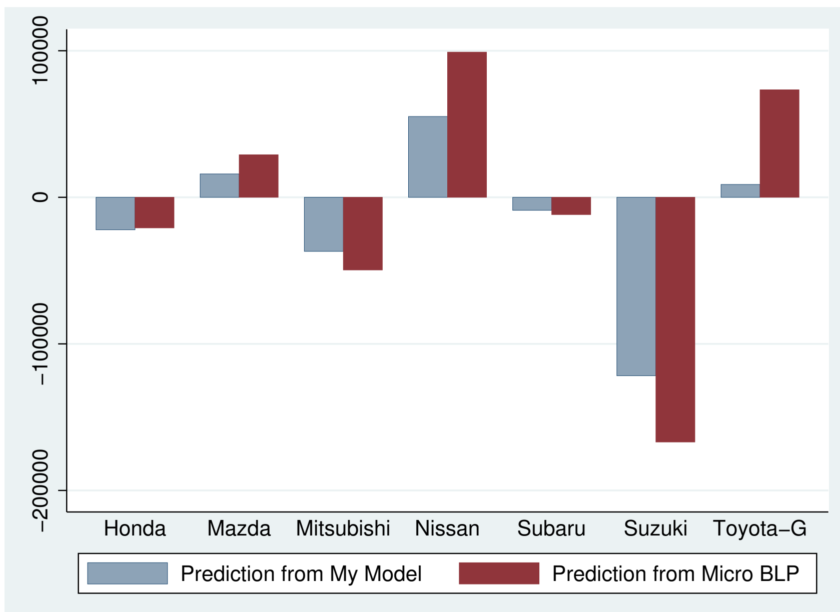


Table 7.7: Tax Elimination Effect on Producer Surplus

	Profit			Product Lineup		
	Before	After	%	Kei	Reg.	Mini.
Daihatsu/Toyota	61,701	62,340	+1.04	8	44	11
Honda	15,166	15,063	−0.67	3	8	6
Mazda	4,524	4,661	+3.02	5	8	3
Mitsubishi	4,565	4,338	−4.96	4	5	3
Nissan	15,508	16,021	+3.30	1	21	5
Subaru	3,158	3,120	−1.21	3	3	0
Suzuki	10,787	9,876	−8.45	7	5	1
Total	115,409	115,418	+0.01	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 7.8: Welfare Implication in Million Dollars

Δ(Consumer Surplus)	−7,106
Δ(Producer Surplus)	+9
Δ(Tax Revenues)	+5,934

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.

Table 7.9: Mixed Bundling Strategy

	No Bundling	Bundling
Honda		
Price for Kei (p_1^H)	15,962	19,085
Price for Regular (p_2^H)	18,667	20,485
Price for Bundle (p_B^H)	–	35,565
Profit for Honda	57,509	62,797
Toyota		
Price for Kei (p_1^T)	14,372	14,602
Price for Regular (p_2^T)	15,713	19,154
Price for Bundle (p_B^T)	–	31,455
Profit for Toyota	48,973	50,348

Note: Profit figures are measured in millions of dollars. The second and third columns display the simulation results where two firms are banned from bundling and where two firms can use bundling, respectively. I use the following exchange rate: \$1.00 = ¥ 80.

Chapter 8

Conclusion

In this paper, I develop a market equilibrium model where consumers can purchase up to two automobiles taking into account portfolio effects which depend on household attributes and product characteristics, and firms strategically set the prices for their products. I then estimate the model using unique Japanese household level panel data on automobile purchases, as well as macro data on market shares, in order to examine the role these portfolio effects play. My estimates suggest that strong positive portfolio effects exist between kei-cars and regular cars, or kei-cars and minivans. Moreover, those portfolio effects are stronger, if a household lives in an rural area or if a household has multiple earners.

Ignoring such portfolio effects leads to biased counterfactual analyses. For example, I conduct a counterfactual experiment where the Japanese government repeals current tax subsidies for kei-cars. My model suggests that a repeal of the current tax subsidies for small automobiles would decrease the demand for small automobiles by 12%, which is smaller than the 17% drop predicted by a standard discrete choice model, i.e., micro-BLP model. The simulation results from my 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 micro-BIL model.

I also conduct another counterfactual experiment where firms are explicitly allowed to use a bundling strategy. More specifically, I chose two firms and two products for each firm, and I simulate the Nash equilibrium where (i) firms are banned from using a mixed bundling strategy, and (ii) firms are explicitly allowed to use a mixed bundling strategy. My simulation results show that firms do have an incentive to use a mixed bundling strategy. Compared to the case where firms are banned from using a mixed bundling strategy, both the single-car prices and the bundle prices are higher.

Appendix A

Description of Variables

A.1 Household Attributes

Table A.1 summarizes the variables for household attributes. Except the variable 'Income', I use household attributes reported in 2004. As for income, I calculate it by

$$z_{i,income} = \sum_{t=2003}^{2005} \sum_{h=1}^{NH_i} z_{i,t,h,income},$$

where NH_i is the number of earners in household i. Thus, this definition is the total income of household i over the decision period.

A.2 Product Characteristics

In this dissertation, I use three years as one decision period, and within that period, product characteristics might change by year. Therefore, I define product j's characteristics by taking averages for three years. More precisely,

$$x_{j,l} = \frac{1}{n_l} \sum_{t=2003}^{2005} x_{j,l,t},$$

where

$$n_l = \sum_{t=2003}^{2005} \mathbf{1}_{\{\text{if product } l \text{ exists in } t\}}.$$

Table A.1: Description of Variables for Household Attributes

Variables	Description
Income	Total income of the household
Family Size	The number of individuals who live together in a household
Age of HH Head	The age of the household head
Number of Earners	The number of people who have any income within the household
Presence of Children	The dummy variable for whether the household has any children
Living Area	The dummy variable for whether the household lives in the
	the following categories:
14 Biggest Cities	Metropolitan areas in Japan
Cities	Cities whose population is more than 50,000
Villages	Remaining areas

Note: 14 biggest cities include Tokyo, Sapporo, Sendai, Saitama, Chiba, Yokohama, Kawasaki, Nagoya, Kyoto, Osaka, Kobe, Hiroshima, Kita-Kyushu, and Fukuoka.

Table A.2: Description of Variables for Automobile Characteristics

Variables	Description
Capacity	Seating capacity measured by the number of people
Miles Per Gallon	Fuel efficiency measured in km/l
Horsepower	Horsepower measured in PS/rpm
Weight	Weight measured in kg
Size	Exterior Width $\times$ Length measured in cm^2

Appendix B

Technical Appendix

B.1 Substitution Matrix

In Section 3, I define the sum of the probability that a household i choose product j in its portfolio as

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

where

$$\begin{aligned} F_i &= \exp[\alpha \log(y_i)] + \\ &\quad \sum_{k=m+1}^{J} \sum_{m=0}^{J-1} \exp[\delta_k + \mu_{ik} + \delta_m + \mu_{im} + \alpha \log(y_i - p_k - p_m) + \Gamma(k, m; \boldsymbol{z}_i)], \end{aligned}$$

Then, each own price elasticity for product j is given by

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

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

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

Therefore, summing over i, I can obtain the market level price elasticities:

$$\frac{\partial s_k}{\partial p_m} = \sum_{i=1}^{N} \frac{\partial q_{ik}}{\partial p_n}.$$

Appendix C

Computational Appendix

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, $\mathbf{G}^1$, 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 shares is small. This step enable to find a vector of the mean utilities, $\delta_j^*(\theta_0)$, which satisfies the first moment being equal to zero, i.e., $G^1(\theta_0) = 0$.
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 $\boldsymbol{\Delta}$ by

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

Given this $\boldsymbol{\Delta}$, 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.

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