Demand Estimation with Flexible Income Effect: An Application to Pass-through and Merger Analysis*

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Abstract

This paper proposes an empirical model of a discrete choice demand with a nonparametric income effect specification. The model allows for the flexible estimation of demand curvature, which has significant implications for pricing and policy analysis in oligopolistic markets. We adopt a sieve approximation method with shape restrictions from econometrics literature in a nested fixed-point algorithm. Applying this framework to the Japanese automobile market, we conduct a pass-through analysis of feebates and merger simulations. Our model predicts a higher pass-through rate and more significant merger effects than a simple logit model, highlighting the importance of flexibly estimating demand curvature.

JEL Classification: L1, L41, L62

Keywords: Discrete choice model, differentiated product, income effect, semiparametric model, aggregate data, sieve approximation, shape restriction, pass-through analysis, merger simulation, automobile

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1 Introduction

Estimating a consumer demand model is crucial for empirical research in industrial organization and related fields. Price elasticity and substitution patterns implied from the demand model are key when firms make pricing decisions in oligopolistic markets. Consumer demand is also essential for evaluating the welfare consequences of a firm's strategic behavior and policy changes. Therefore, accurate measurement of consumer demand is critical for various applications, including merger analysis (Nevo, 2000a), pass-through analysis of cost shocks and taxes (Weyl and Fabinger, 2013), and introducing new products (Petrin, 2002).

Given the practical importance of the demand model, a vast body of literature in empirical industrial organization proposes an econometric method for estimating consumer demand for differentiated products (Berry and Haile, 2021; Gandhi and Nevo, 2021). Most existing frameworks rely on parametric specifications because a fully flexible model of differentiated product demand has significantly many parameters.[1] However, this approach might be problematic because a parametric specification often leads to strong restrictions on the shape of the demand curve, which affects the implications of supply and demand analysis.

To address this concern, we propose a semiparametric framework for a discrete choice demand that accommodates an income effect in a flexible way. We demonstrate that a flexible specification for the income effect is vital for estimating the curvature of the demand function. Applying the proposed framework to data from the Japanese automobile industry, we conduct merger simulations and a pass-through analysis for a feebate policy (i.e., a subsidy for eco-friendly cars). These simulations demonstrate the practical value of our demand framework in policy-relevant applications.

In the spirit of previous works such as McFadden (1974), Berry (1994), and Berry et al. (1995) (henceforth BLP), we employ a random utility framework to model differentiated product demand. Our approach differs from prior research by incorporating income effects in a nonparametric manner, while maintaining parametric specifications of other primitives such as additive random utility shocks and utility from product characteristics. Previous studies often employ a quasi-linear specification of random utility without considering income effects or incorporate a parametric assumption

[1] Consider a log-log specification of the demand system with J products. The number of parameters required to estimate the own- and cross-price elasticity matrices is on the order of J^2. Consequently, to alleviate the burden of estimation, researchers must impose constraints on the demand system. Further details can be found in Berry (1994).

on the income effect. We demonstrate that allowing for greater flexibility in the functional form of the income effect term is critical to estimating demand curvature and the pattern of price elasticity. The framework also permits the estimation of welfare changes in the presence of the income effect (McFadden 1999; Dagsvik and Karlström 2005).

Our demand model is a semiparametric framework that includes both a parametric component of utility from product characteristics and a non-parametric function of the income effect. To estimate this model, we use a combination of a sieve approximation from semiparametric econometrics literature (Chen, 2007) and the nested fixed point algorithm proposed by BLP. First, we approximate a nonparametric function of the income effect using a sieve, a linear combination of known basis functions. We use Bernstein polynomials as a basis function because of the shape-preserving property we explain below. After adopting the sieve approximation, our model becomes similar to the standard parametric BLP framework. We then use a nested fixed-point approach in GMM estimation.

A novelty of our estimation method is to exploit a shape restriction on the nonparametric function of the income effect. In general, non- and semi-parametric estimation methods often suffer from the imprecision of the estimator. This issue is particularly crucial when the model has an endogeneity problem, which must be encountered in demand estimation.[2] To alleviate this issue, recent econometrics literature proposes using shape restrictions in non- and semi-parametric estimation.[3] As we show in Section 2.1, the specification of the income effect is weakly increasing, is implied from utility maximization of consumers. We incorporate this monotonicity restriction in our semiparametric estimation. Monte Carlo experiments in Section 4 shows that estimation with a shape restriction significantly reduces the variance of the estimated nonparametric function in our demand model.[4]

We apply our semiparametric framework to annual-level data from the automobile market in Japan. The dataset includes product- and market-level information on sales, prices, and characteristics from 2006 to 2013. Our estimation results show that the shape of the income effect and

[2] In a semiparametric setting, endogeneity leads to an ill-posed inverse problem and imprecise estimation of non-parametric components. See, e.g., Horowitz 2014 for the details.

[3] Chetverikov and Wilhelm (2017) demonstrate an improvement in estimation performance by shape restriction in the context of a nonparametric instrumental variable model.

[4] Previous literature (e.g., Blundell et al. 2017; Chetverikov and Wilhelm 2017) has demonstrated that shape restriction can improve the estimation performance in non- or semiparametric models that are linearly separable in the error term. Our simulation analysis indicates that the same insight can be applied to nonseparable models.

the resulting price elasticity exhibit significant nonlinearity. We then use the estimated model to conduct two counterfactual simulation exercises, a pass-through analysis and a merger simulation, in which the demand curvature plays a crucial role. We compare simulation results produced by our demand model with those from a simple logit model.

In our first counterfactual, we evaluate the pass-through of the Japanese government's subsidy for eco-friendly cars, which was introduced in 2009. Evaluation of this policy amounts to a pass-through analysis of a subsidy. In theory, Weyl and Fabinger (2013) show that the demand curvature determines the degree of pass-through to the final price. Our model predicts a higher pass-through rate than the standard logit model, which imposes a priori restriction on the pass-through rate.

Second, we perform a merger simulation using our demand model. This counterfactual simulation is motivated by the practical observation that a standard logit demand model often under-predicts the price effects of a merger due to its curvature property (see Crooke et al. 1999). Our simulation results support this observation. Given the level of own-price elasticity, the standard logit demand model predicts smaller price effects than our semiparametric demand model. Additionally, the simple logit model anticipates smaller price effects for more expensive products, which is due to a mechanically-induced pattern in the own-price elasticity. The prediction based on our flexible demand model does not exhibit such a pattern.

The remainder of this paper is structured as follows. First, we review the related literature to clarify the paper's intended contributions. In Section 2, we introduce a demand model for differentiated products with a nonparametric income effect. We then discuss the estimation of the model using aggregate (market-level) data in Section 3. In Section 4, Monte Carlo experiments are conducted to assess the performance of the proposed framework. The framework is then applied to Japanese automobile data, and the demand model is estimated in Section 5. Using the estimated model, we conduct two counterfactual simulations on the pass-through analysis and the merger analysis in Section 6. Finally, Section 7 concludes the paper.

Related Literature This paper makes contributions to three strands of literature. First, our paper relates to the literature on non- and semiparametric estimation of consumer demand models. Many prior works (e.g., Blundell et al. 2012, 2017) have focused on the case of homogenous goods demand. More recent studies have examined the demand for differentiated products in the discrete choice framework (e.g., Bhattacharya 2015; Tebaldi et al. 2019). These studies explore nonparametric identification and estimate demand and welfare when individual-level data is available. Our work, on the other hand, considers the case where only aggregate data (such as market-level data) is available, similar to the approach taken by BLP and subsequent studies.

Griffith et al. (2018) is the closest paper to ours. Their demand model incorporates a flexible and parametric form of the income effect into a discrete-choice demand model. The authors use the framework to estimate the demand for margarine in the UK and evaluate the tax on saturated fat content. Our paper complements Griffith et al. (2018) in both methodology and application. Regarding the methodology, we nonparametrically estimate income effect terms with shape restrictions using a sieve approximation, showing that a shape restriction can aid in precisely estimating the nonparametric term of the income effect. We also focus on the case where only aggregate data (i.e., market-level data) is available, as opposed to the individual-level choice data used by Griffith et al. (2018).[5] Moreover, we consider price endogeneity using instrumental variables. Note that our application is for automobile demand, where the income effect might play a crucial role in a purchase decision. We also analyze the implication of the flexible income effect in pass-through analysis and merger simulation.

Other related papers include Compiani (2021), Wang (2022), and Birchall and Verboven (2022). Compiani (2021) proposes a fully nonparametric estimation approach for differentiated product demand models. Although Compiani (2021) accommodates a wide array of demand models, it is difficult to directly apply the approach to a case with many products.[6] Our framework can manage such a case by relaxing a commonly imposed assumption on the functional form of the indirect utility function. Wang (2022) proposes a semiparametric model of differentiated products in a BLP framework that nonparametrically estimates the distribution of random coefficients. By contrast, our paper relaxes the assumption on the functional form of the income effect and estimates it nonparametrically. Finally, Birchall and Verboven (2022), whose work builds on Björnerstedt and Verboven (2016), apply a Box–Cox specification in the discrete choice model to relax the unit

[5] Herriges and Kling (1999) and Morey et al. (2003) also incorporate the nonlinear income effect in a parametric fashion to estimate discrete choice models using individual-level data.

[6] Berry and Haile (2014) and Compiani (2021) consider the identification and estimation of the inverse of mean utility as a function of the vectors of prices and market share, amounting to a $2J$ dimensional function where J is the number of products. In contrast, our approach estimates a one-dimensional nonparametric object of the income effect.

demand assumption and flexibly estimate the demand curvature. The authors apply the framework to estimate the demand for ready-to-eat cereals. Our approach is complementary to Birchall and Verboven (2022) in the sense that we provide a flexible specification for the case of unit demand, which can be applied to durable goods such as appliances and automobiles.

Second, our paper is related to the literature of empirical studies on pass-through (e.g., Nakamura and Zerom 2010; Goldberg and Hellerstein 2013; Fabra and Reguant 2014; Hollenbeck and Uetake 2021). We contribute to this literature by demonstrating the importance of flexibly estimating the demand curvature when evaluating the pass-through of tax and subsidies through supply-side simulation. Our empirical findings align with a theoretical study by Weyl and Fabinger (2013) showing the importance of the demand curvature as the determinant of the pass-through rate. While the simple logit model suffers from the restriction that the pass-through rate is capped by the unity, our demand model allows the pass-through rate to be larger than one.

Third, our paper contributes to the vast literature on the empirical analysis of horizontal mergers. Since the work of Nevo (2000a), there have been many empirical studies that conduct a simulation analysis in a differentiated product market to analyze the effects of horizontal mergers on price and social welfare.[7] Estimation of the demand model is crucial to accurately predict the price effects of a merger because oligopolistic firms consider the underlying demand structure in their pricing decisions. While the logit model or its variant random coefficient logit model are often used in such analyses, these models may suffer from a restrictive curvature property that impacts the simulated merger effects (see, e.g., Crooke et al. 1999). In response to this issue, we demonstrate that our demand model can flexibly estimate the demand curvature, thus offering an alternative demand model that can be used in antitrust analyses.

2 Demand Model

2.1 Utility Maximization Problem

This section introduces a model of differentiated product demand with a nonparametric income effect. We begin with a utility maximization problem incorporating both continuous and discrete

[7]See, e.g., Peters (2006) on airline mergers, Fan (2013) on newspaper mergers, Houde (2012) on gas stations, Gowrisankaran et al. (2015) on hospital mergers, Miller and Weinberg (2017) on beer mergers, Ohashi and Toyama (2017) on automobile mergers, and Björnerstedt and Verboven (2016) on pharmaceutical mergers.

choices (McFadden 1981). A consumer makes a discrete choice regarding differentiated goods and a continuous choice regarding all other bundles of goods. As assumed later, we can consider a continuous choice problem as the consumption of the numeraire.

Let $U(\mathbf{m}, j)$ be a direct utility function. $\mathbf{m}$ is a d_m-dimensional vector of consumption of continuous choice goods. The index $j \in \mathbf{J} \equiv \{0, 1, \cdots, J\}$ represents an alternative in the discrete choice decision. There are J products available in the market. The index $j = 0$ means that a consumer does not buy any of the discrete goods. We call this option "outside goods."

The utility maximization problem is given by the following:

$$\begin{aligned} \max_{(\mathbf{m},j)\in R_+^{d_m}\times \mathbf{J}} \quad & U(\mathbf{m}, j) \\ \text{s.t.} \quad & \mathbf{P_m}'\mathbf{m} + p_j \leq y_i, \end{aligned} \tag{2.1}$$

where $\mathbf{P_m}$ is a d_m dimensional vector of prices of continuous choice goods, p_j is the price of alternative j, and y_i is income.

Conditional on choice j in the discrete choice, we define the conditional indirect utility function as follows

$$V(\mathbf{P_m}, y - p_j, j) \equiv \max_{\mathbf{m}\in R_+^{d_m}} U(\mathbf{m}, j) \text{ s.t. } \mathbf{P_m}'\mathbf{m} \leq y_i - p_j. \tag{2.2}$$

Note that we define $p_0 = 0$ because choosing the outside good does not incur any costs.

The problem on the right-hand side of Equation (2.2) is a standard utility maximization problem. Hence, the conditional indirect utility function $V(\mathbf{P_m}, y - p_j, j)$ has the following standard properties: (1) homogeneous of degree 0 with respect to $\mathbf{P_m}$ and $(y - p_j)$, (2) increasing in $(y - p_j)$, (3) non-decreasing in $\mathbf{P_m}$, and (4) quasi-convex in $(y_i - p_j)$ and $\mathbf{P_m}$.

The following assumption is placed on the direct utility function:

$$U(\mathbf{m}, j) = v(j) + u(\mathbf{m}). \tag{2.3}$$

This assumption imposes that the utility from differentiated goods is independent of the one from all other goods. While it may seem restrictive, we show that most discrete-choice demand models implicitly impose this assumption.[8] Under this assumption, the conditional indirect utility function

[8] This restriction excludes the discrete-continuous choice model of Dubin and McFadden (1984), in which the choice

can be written as

$$V(\mathbf{P_m}, y - p_j, j) = v(j) + \tilde{V}(\mathbf{P_m}, y - p_j). \tag{2.4}$$

The function $\tilde{V}(\mathbf{P_m}, y - p_j)$ satisfies the above four properties implied by the utility maximization problem. In practice, however, we do not necessarily observe the prices of all other goods $\mathbf{P_m}$. We further assume that the continuous good is a numeraire and denote its price using P^m, which is considered to be the price index. We now have $\tilde{V}(P^m, y - p_j) = u\left(\frac{y-p_j}{P^m}\right)$. With a slight abuse of notation, we denote $f(y - p_j) \equiv \tilde{V}(P^m, y - p_j)$.

The function $f(y - p_j)$ is referred to as the income-effect term. Hereafter, we consider both income y and the price of discrete choice goods p_j as deflated by the price index P^n. This consideration imposes a restriction whereby $f(y - p_j)$ is a weekly increasing function.

2.2 Conditional Indirect Utility Function

Turning to the utility generated by consuming a discrete choice good $v(j)$ in Equation (2.3), we follow the standard specification in the literature. We add index i, representing a consumer, and denote the utility from a discrete choice good j as v_{ij}.

$$v_{ij} = \beta' X_j + \xi_j + \epsilon_{ij} \text{ for } j = 1, \ldots, J \tag{2.5}$$

$$v_{i0} = \epsilon_{i0} \tag{2.6}$$

X_j is a vector of observable characteristics of product j, and ξ_j represents unobservable characteristics. ϵ_{ij} is an independent and identically distributed (i.i.d.) idiosyncratic shock that follows the type I extreme-value distribution.

We now write the conditional indirect utility function of consumer i when she chooses j:

$$V_{ij} = \begin{cases} f(y_i - p_j) + \beta' X_j + \xi_j + \epsilon_{ij} & \text{for } j = 1, \cdots, J \\ f(y_i) + \epsilon_{i0}. & \text{for } j = 0 \end{cases}. \tag{2.7}$$

The resulting specification for the indirect utility function is standard except for the income-

of the appliance (i.e., discrete decision) affects the utility generated by electricity consumption (i.e., continuous decision). Newey (2007) considers a nonparametric identification of a discrete-continuous choice model when individual choice data is available. Extending our framework to such a case would be a fruitful direction in future research.

effect term $f(y-p)$. We do not impose any functional form but note that this function is weakly increasing, as implied by utility maximization in Equation (2.2).

Our specifications are now compared with the ones in previous studies. The quasi-linear form is a major specification in the literature, such as $V_{ij} = \alpha(y_i - p_j) + \beta' X_j + \xi_j + \epsilon_{ij}$. In this specification, the resulting demand function does not depend on income level y_i because the income term is canceled out when comparing two alternatives.[9] BLP specifies $V_{ij} = \alpha \ln(y_i - p_j) + \beta' X_j + \xi_j + \epsilon_{ij}$, which allows for a parametric form of the income effect.[10] In our approach, we do not place any parametric assumption on $f(\cdot)$, except that it is an increasing function. We discuss the advantage of such a flexible specification in Section 2.4 in various contexts in the industrial organization literature and applied microeconomics.

2.3 Individual Choice Probability and Market Share

In this subsection, we consider the discrete choice decision based on the conditional indirect utility function obtained above. We then derive the market share equation, which provides the basis for later estimation. Hereafter, we add the index t denoting the market, which is defined by geography, time, or both. The conditional indirect utility function is now denoted by V_{ijt}.

When considering the discrete choice decision, we must consider the budget constraint in the original utility maximization problem (2.1). The budget constraint implies that consumer i with income y_{it} cannot buy goods whose price p_{jt} is higher than their income. Previous literature mostly ignores this budget constraint because it has no impact under the common utility specification, such as a quasi-linear form. Recent papers (e.g., Xiao et al. 2017; Pesendorfer et al. 2023) discuss the bias associated with the omitted variable constraint. The budget constraint implies that each consumer i has a different choice set according to her income. Specifically, we define the choice set of consumers i as

$$\mathbf{J}_{it} = \{0\} \cup \{j \in \{1, \cdots, J_t\} : y_{it} - p_{jt} \geq 0\}, \tag{2.8}$$

where J_t is the total number of products available in market t.

Given the conditional indirect utility V_{ijt}, a consumer i chooses the alternative that provides

[9] Another common specification in the literature is $V_{ij} = \alpha_i(y_i - p_j) + \beta' X_j + \xi_j + \epsilon_{ij}, \alpha_i = g(z_i)$ where z_i is consumer i's characteristics such as income, age, household size, and other variables. See Nevo (2001).

[10] In practice, the term $\alpha \log(y_i - p_j)$ can be approximated by $\frac{\alpha}{y_i} p_j$ as a first-order Taylor expansion (see, e.g., Berry et al. 1999).

the highest utility from the choice set $\mathbf{J}_{it}$. The discrete choice problem is given as follows:

$$\max_{j \in \mathbf{J}_{it}} V_{ijt}. \tag{2.9}$$

The choice probability for consumer i selecting alternative j is derived as

$$s_{ijt}(y_{it}) = \frac{\mathbf{1}\{y_{it} \geq p_{jt}\} \cdot \exp\left(f(y_{it} - p_{jt}) + \beta' X_{jt} + \xi_{jt}\right)}{\exp(f(y_{it})) + \sum_{k=1}^{J_t} \mathbf{1}\{y_{it} \geq p_{kt}\} \cdot \exp\left(f(y_{it} - p_{kt}) + \beta' X_{kt} + \xi_{jt}\right)}. \tag{2.10}$$

Note that the indicator function $\mathbf{1}\{y_{it} \geq p_{jt}\}$ accounts for the budget constraint.

The market share of each product s_{jt} is now derived by aggregating the individual choice probability across consumers. In the current specification, consumer heterogeneity comes from individual income y_{it}.[11] Let y_{it} follow the distribution of income $G_t(y_{it})$. The market share is given by

$$s_{jt} = \int s_{ijt}(y_{it}) dG_t(y_{it}).$$

Market demand q_{jt} is calculated by multiplying the market share s_{jt} by the market size N_t, that is, $q_{jt} = N_t \times s_{jt}$.

2.4 Model Implications

This subsection evaluates the importance of the flexible income effect by illustrating its consequences for price elasticity. We also explore how the estimated shape of the demand function relates to the pass-through analysis and merger simulations.

Price Elasticity To highlight the novelty of our demand specification, we first review the price elasticity of the logit model under quasi-linear utility without consumer heterogeneity (i.e., $f(y - p) = \alpha(y - p)$). Omitting index t for notational simplicity, the own- and cross-price elasticity η_{jk} is given as follows

$$\eta_{jk} = \frac{\partial q_j}{\partial p_k} \frac{p_k}{q_j} = \begin{cases} -\alpha p_j (1 - s_j) & \text{if } k = j \\ \alpha p_k s_k & \text{if } k \neq j \end{cases} \tag{2.11}$$

[11] The model can also incorporate random coefficients on product characteristics, e.g., $u_{ijt} = f(y_{it} - p_{jt}) + \beta_i' X_{jt} + \xi_{jt} + \epsilon_{ijt}$, where $\beta_i \sim N(\bar{\beta}, \Sigma)$. This specification allows for a richer substitution pattern across products.

Price elasticity under the quasi-linear specification is known to be reasonably restrictive (e.g., see Nevo (2000b)). More specifically, the absolute value of own-price elasticity $|\eta_{jj}|$ increases in its own price p_j, which implies that more luxurious goods have higher own-price elasticity.

In our demand specification, the price elasticity is given as follows:

$$\eta_{jk} = \frac{\partial q_j}{\partial p_k}\frac{p_k}{q_j} = \begin{cases} -\frac{p_j}{s_j}\int f'(y_i - p_j)s_{ij}(1-s_{ij})dG(y_i) & \text{if } k = j \\ -\frac{p_k}{s_j}\int f'(y_i - p_k)s_{ij}s_{ik}dG(y_i) & \text{if } k \neq j \end{cases} \tag{2.12}$$

Price elasticity now depends on the income effect term $f(y-p)$. More specifically, the second-order derivative of the demand curve depends on the shape of $f(y-p)$, which we can flexibly estimate by employing a nonparametric approach. Thus, our method does not impose an a priori restriction on how own-price elasticity changes in relation to price.

It is worth discussing how our approach relates to the random coefficient logit model commonly used in practice. Nevo (2000b) notes that introducing heterogeneity in price sensitivity among consumers (i.e., the marginal utility from income) can flexibly estimate price elasticity even when prices enter linearly into the utility function. If consumers who purchase cheaper products have high price sensitivity, the own-price elasticity of that product may be high. Therefore, adding a random coefficient can help to address issues related to both cross- and own-price elasticity. In our demand model, price sensitivity $f'(y_i - p_j)$ is heterogeneous among consumers because it depends on income. In addition, price sensitivity $f'(y_i - p_j)$ depends on the price level in our model, which adds further flexibility in estimating own-price elasticity.[12]

Pass-Through Analysis The pass-through analysis measures how prices change according to an alteration in the production cost or tax (subsidy). Some theoretical studies have discussed the importance of demand curvature as a determinant of pass-through. Most notably, Weyl and Fabinger (2013) have shown that, in a symmetric oligopoly or monopoly, the pass-through rate is less than 1 if and only if the demand curve is log-concave (i.e., $\frac{d \log q(p)}{dp^2} < 0$).

With a quasi-linear specification in a simple logit model, demand is always log-concave. Even

[12] While our focus is on own-price elasticity, note that the income effect term also affects cross-price elasticity. The income effect term $f(y-p)$ introduces consumer heterogeneity in price sensitivity. Price-sensitive customers prefer to buy cheaper products than price-elastic consumers who are less concerned about price. This heterogeneity generates substitution patterns according to the product price.

if we do not adopt a simple quasi-linear specification, a function form on the income effect imposes an a priori restriction on the demand curvature, and thus the pass-through rate. This property highlights the importance of our flexible demand framework in analyzing the pass-through of cost shocks and tax policy.[13]

Merger Analysis Merger analysis is of immediate relevance to antitrust practice. The primary goal of merger analysis is to forecast the price increase resulting from the merger of two competing firms. One approach is to construct the measure of upward pricing pressure based on the diversion ratio of competing products and markup (Farrell and Shapiro 2010; Jaffe and Weyl 2013). This measure indicates the potential price impact of the merger. A more comprehensive approach is a merger simulation, in which one builds and estimates a demand and supply model of the market and performs a counterfactual simulation by solving the market equilibrium in which two firms jointly maximize profits.

The shape of the demand function is crucial in estimating the merger effect in both approaches. In the approach proposed by Farrell and Shapiro (2010) and Jaffe and Weyl (2013), the effect of a merger can be thought of as a cost pass-through in the first order because the merged firm now takes into account the opportunity cost of losing the profits of the partner.[14] The price effect of a merger is determined by the extent to which the increase in opportunity cost is reflected in the final price. Therefore, the significance of demand curvature in pass-through analysis can also be applied to this context. In a merger simulation approach, Crooke et al. (1999) has demonstrated that demand with the same elasticities but different curvature might lead to simulated merger effects that differ by orders of magnitude.

In our empirical application in Section 5 and 6, we illustrate the significance of the flexible income effect. Specifically, we perform numerical analysis to simulate the pass-through of a subsidy on eco-friendly cars and the price effects of a hypothetical merger. By comparing the results based on our demand model with those based on a simple logit model, we demonstrate the usefulness of

[13] Griffith et al. (2018) provides detailed discussions on how the flexible income effect specification is crucial in pass-through analysis.

[14] Consider a merger between two single-product firms. The new first-order condition for firm 1's price is $p_1 + \left(\frac{\partial q_1}{\partial p_1}\right)^{-1} q_1 = c_1 + \left(-\frac{\partial q_2}{\partial q_1}\right)^{-1} (p_2 - c_2)$. The left-hand side is the marginal revenue from firm 1's product. The second term on the right-hand side is the profit loss from firm 1's product due to the diversion from firm 2 to firm 1. This term is considered to be the opportunity cost for firm 1 to increase its production.

our demand framework in policy-relevant applications.

3 Estimation Approach

This section introduces an estimation method for our semiparametric model. The model contains the nonparametric function $f(y-p)$ and the linear parameter β in the utility function. To estimate these model primitives, we use a sieve approximation of the nonparametric function and incorporate it into the nested fixed-point algorithm proposed by BLP. We also impose a shape restriction on the nonparametric component to improve the precision of the parameter estimate.

3.1 Sieve Approximation with Shape Restriction

We first explain the method of sieve approximation proposed by Chen (2007) and Blundell et al. (2007). In the sieve method, we approximate a nonparametric function by a linear combination of known basis functions. While there are many candidates of basis functions, we use the Bernstein polynomial as it allows us to incorporate the shape restriction easily. More specifically, we approximate function $f(\cdot)$ by the K-th order Bernstein polynomial $B_K(x)$:

$$f(x) \approx B_K(x) = \sum_{k=0}^{K} \pi_k b_k^K(x) \equiv \psi^K(x)'\Pi \tag{3.1}$$

where

$$b_k^K(x) = \begin{pmatrix} K \\ k \end{pmatrix} x^k (1-x)^{K-k}, \tag{3.2}$$

$\psi^K(x) = \left(b_0^K(x), b_1^K(x), \ldots, b_K^K(x)\right)'$, and $\Pi = (\pi_0, \pi_1, \ldots, \pi_K)'$. The nonparametric function $f(\cdot)$ is now approximated by a linear function of the basis function $\psi^K(x)$ and coefficients Π.

An advantage of using the Bernstein polynomial as a basis function is that we can easily incorporate the shape restriction on the nonparameric function. As we saw in Section 2.1, the nonparametric income-effect term $f(y-p)$ is weakly increasing. We incorporate this shape restriction in our estimation by imposing constraints on coefficient Π. Under the approximation by the

Bernstein polynomial, the derivative can be written as

$$B'_K(x) = K \sum_{k=0}^{K-1} (\pi_{k+1} - \pi_k)\, b_k^{K-1}(x)$$

Thus, the monotonicity restriction (i.e., $B'_K(x) \geq 0$) can be imposed by $\pi_k \leq \pi_{k+1}$ for all k.

Lastly, we need to normalize the function by setting $\pi_0 = 0$, so that we have $f(0) = 0$. This normalization is needed because we cannot identify the level of the income effect term $f(\cdot)$. More clearly, if $f(\cdot)$ in Equation (2.10) is replaced with $\tilde{f}(\cdot) = f(\cdot) + C$, the constant term C will be canceled out.

3.2 Sieve GMM Estimation with Nested Fixed-Point Algorithm

We incorporate the sieve approximation into the nested fixed point algorithm of BLP to estimate the model parameters. With sieve approximation, the model can be written as

$$s_{jt} = \int \frac{\mathbf{1}\{y_{it} \geq p_{jt}\} \cdot \exp\left(\psi^K(y_{it} - p_{jt})'\Pi + \beta' X_{jt} + \xi_{jt}\right)}{\exp(\psi^K(y_{it})'\Pi) + \sum_{k=1}^{J_t} \mathbf{1}\{y_{it} \geq p_{jt}\} \cdot \exp\left(\psi^K(y_{it} - p_{jt})'\Pi + \beta' X_{kt} + \xi_{jt}\right)} dG_t(y_{it}). \quad (3.3)$$

In the model, unobserved product characteristics ξ_{jt} represent an econometric error term. The parameters we estimate are summarized by (β, Π).

As is common in the estimation of consumer demand models, our model is subject to an endogeneity problem. The source of endogeneity is the correlation between the product price p_{jt} and the unobserved product characteristics ξ_{jt}, which is an econometric error term. Although econometricians lack data on unobserved product characteristics ξ_{jt}, oligopolistic firms might have some information. Firms may select their product prices while considering product characteristics that are unobservable for econometricians. This asymmetry then leads to the endogeneity problem associated with product prices.

We address this endogeneity problem by using instrumental variables. We impose the following conditional mean restrictions:

$$\mathbb{E}\left[\xi_{jt} | Z_{jt}\right] = 0 \text{ for all } j = 1, 2, ...J_t, \text{ and } t = 1, 2, ...T, \quad (3.4)$$

where Z_{jt} is a vector of exogenous variables in the utility function (X_{jt}) and additional instruments

(W_{jt}). We specify additional instruments W_{jt} in our empirical application later.

In the estimation, we adopt a sieve generalized method of moments (GMM) estimator (Chen (2007)), which utilizes the following unconditional moment restrictions:[15]

$$\mathbb{E}\left[\xi_{jt}(\theta)p_b(X_{jt}, W_{jt})\right] = 0, b = 1, \ldots, B, \tag{3.5}$$

where $\theta \equiv (\beta, \Pi)$ denotes a set of model parameters and $\{p_b(X_{jt}, W_{jt})\}_{b=1,\ldots,B}$ is a sequence of known functions that can approximate any real-valued square-integrable functions of X_{jt} and W_{jt} as $B \to \infty$.

The sieve GMM criterion function is given as follows: [16]

$$\xi(\beta, \Pi)'\tilde{\mathbf{P}}(\tilde{\mathbf{P}}'\tilde{\mathbf{P}})^{-}\tilde{\mathbf{P}}'\xi(\beta, \Pi), \tag{3.6}$$

where ξ is a vector that stacks unobserved demand shock ξ_{jt} for $j = 1, \cdots, J_t$ and $t = 1, \cdots, T$. The matrix $\tilde{\mathbf{P}} = [\mathbf{P}, \mathbf{P} \otimes \mathbf{X}]$ denotes a matrix of instruments. We follow Chetverikov et al. (2018) for our choice of matrix $\tilde{\mathbf{P}}$. We first consider a linear span of additional instruments W_{jt} by a known basis function and denote it as $p(W_{jt}) = (p_1(W_{jt}), \cdots, p_B(W_{jt}))'$. Then the matrix $\mathbf{P}$ is defined as $\mathbf{P} = (p(W_{11}), \cdots, p(W_{J_T,T}))'$. We also include the tensor product of the columns of two matrices $\mathbf{P}$ and $\mathbf{X} = (X_{11}, \cdots, X_{J_T,T})'$, denoted by $\mathbf{P} \otimes \mathbf{X}$.

In implementing the estimation method introduced above, we must obtain the econometric error term ξ_{jt} given the parameter (β, Π). Since this term enters the demand function (3.3) nonlinearly, we need to the nested fixed-point algorithm to calculate ξ_{jt}. We define the mean utility as $\delta_{jt} = \beta' X_{jt} + \xi_{jt}$, which is the common component of the utility of product j in market t. BLP have shown that there exists a unique vector of $\delta_t = \{\delta_{1,t}, \cdots, \delta_{J_t,t}\}$ such that the observed market share

[15] The sieve GMM estimation is considered to be a sieve minimum distance estimation in which the conditional expectation is estimated using a series estimator with an identity weighting matrix (see, e.g., Chen (2007)).

[16] Some of the sieve estimation methods for non- and semiparametric models with endogeneity propose a penalization term on the higher derivative of the nonparametric function to alleviate the ill-posed inverse problem (see, e.g., Chen (2007)). In practice, this penalization term is not necessarily used in implementation, as discussed in Chetverikov and Wilhelm (2017). Our approach aligns with this practice for several reasons. First, penalization requires choosing a tuning parameter that governs the strength of penalization. Second and more importantly, our approach incorporates a monotonicity restriction on a nonparametric function, which has a similar effect to penalization. Chetverikov and Wilhelm (2017) demonstrated in their empirical application that the penalization term does not affect the result once they impose a shape restriction in the estimation. See Appendix B.3 in Chetverikov and Wilhelm (2017) for further discussion.

$\{s_{jt}\}_{j=1,\cdots,J_t}$ is equal to the predicted market share in the model. The vector of mean utility δ_t can be obtained by a contraction mapping.

We calculate the value of the objective function given a candidate parameter value of Π, as follows: (1) calculate the vector of mean utility δ by applying a contraction-mapping algorithm;[17] (2) run a linear regression of δ on $\mathbf{X}$ to obtain $\hat{\beta}$ and the residual ξ_{jt}; and (3) calculate the value of the objective function: (3.6).

We then run a numerical optimization to minimize the objective function. Note that the parameter β appearing in the mean utility function can be obtained by employing a linear GMM.[18] Thus, we only need to run a nonlinear optimization routine over Π. This property circumvents the computational costs and allows us to incorporate a rich set of covariates and fixed effects in the mean utility component δ_{jt}.

To calculate the confidence interval of the linear parameter β and the nonparametric function $f(y-p)$, we use a generalized residual bootstrap proposed by Chen and Pouzo (2015) (specifically Theorem 5.2 of their paper).

4 Monte Carlo Simulation

Before applying our estimation approach to real-world data, we conduct Monte Carlo experiments to evaluate the efficacy of our approach. Specifically, we investigate the extent to which our estimation method can accurately recover the income effect term, denoted by $f(y-p)$, and the linear coefficients, represented by β, in the utility function. Additionally, we deliberate on the significance of shape restrictions in achieving the precise estimation of the non-parametric component.

4.1 Data Generating Process

We consider a market t where the total number of products is J_t. In our simulations, we set $J_t = 100$ for all market t and $T = 10$. We consider the following utility specification:

$$V_{ijt} = \begin{cases} \beta_0 + \beta_1 x_{jt} + \xi_{jt} + f(y_{it} - p_{jt}) + \epsilon_{ijt} & \text{for } j = 1, \cdots, J \\ f(y_{it}) + \epsilon_{i0t}. & \text{for } j = 0 \end{cases}, \tag{4.1}$$

[17] We set the tolerance level of the algorithm at 1E-12 .

[18] This estimation trick is called "concentration out." See, e.g., Nevo (2001).

where ϵ_{ijt} follows an i.i.d. type I extreme-value distribution. The observed product characteristic x_{jt} follows the uniform distribution $U(0,1)$. The unobserved product characteristic ξ_{jt} is assumed to follow the normal distribution with mean 0 and standard deviation 0.1 (i.e., $\xi_{jt} \sim N(0, 0.1^2)$.)

The product price p_{jt} is given by the following:[19]

$$p_{jt} = 0.2 + 0.3x_{jt} + w_{jt} + \xi_{jt}, \tag{4.2}$$

where we include the term ξ_{jt} in the product price to consider the endogeneity between the price and the unobservable product characteristics. We add the "cost shifter" w_{jt} following the uniform distribution $U(0,1)$, which will serve as an instrument for the product price.

The market share of each product s_{jt} is given by Equation (2.3). To compute s_{jt} in the simulation, we use a numerical integration with a quasi-randomly drawn 1000 units from the Halton sequence. The income is drawn from the log-normal distribution. Specifically, we assume that $y_{jt} \sim LN(0, 0.25^2)$. Given the data-generating process, the variable $y - p$ has the support of approximately from -1.5 to 2.5.

The model primitives we estimate are β_0, β_1, and $f(y-p)$. We set $\beta_0 = -5$ and $\beta_1 = 3$, and consider the three different specifications for the income effect term $f(\cdot)$ as follows;

DGP 1 $f(a) = \sinh^{-1}(a)$

DGP 2 $f(a) = \ln(2) + \ln(|a-1|+1)sgn(a-1)$

DGP 3 $f(a) = a$

Note that the second function is less smooth than the other two functions because it is not differentiable at $a = 1$. Moreover, the function is convex if $a \in [0,1]$ and concave if $a \geq 1$. Therefore, after we standardize positive $y - p$ to the range of $[0,1]$, the curvature of the second income function changes at approximately the 40th percentile point. See the footnote 21 for more detail on the standardization procedure.

[19] The data-generating process of the price assumes that the price is competitively determined by the marginal costs. We do not incorporate Bertrand competition into the supply side in our Monte Carlo experiments.

4.2 Implementation

To estimate the income function $f(\cdot)$ nonparametrically, we use the sieve approximation method introduced in Section 3.1 with Kth order Bernstein polynomials. We set $K = 3, 4$, and 5 and compare the results across the different choices of order.

The cost shifter w_{jt} is used to construct an instrument for the price. More specifically, we set $p(w_{jt}) = (1, w_{jt}, \cdots, w_{jt}^3)'$ as the basis function. Thus, each row of the matrix $\mathbf{P} \otimes \mathbf{X}$ comprises all products of the forms: $p(w_{jt})'x_{jt} = (x_{jt}, w_{jt}x_{jt}, w_{jt}^2 x_{jt}, w_{jt}^3 x_{jt})$ for all $j = 1, 2, ...J_t,$ and $t = 1, 2, ...T$. We then apply sieve GMM estimation along with the nested fixed-point algorithm.[20]

To measure the precision of estimation for the nonparametric income function, we compute the mean integrated squared error (MISE) by $MISE = \frac{1}{NS}\sum_{r=1}^{NS}\left(\int_0^1 \left(f(z) - \hat{f}^r(z)\right)^2 dz\right)$, where z is the standardized value of $y - p$ ranging from 0 to 1.[21]. The subscript r denotes the index for a simulation. The total number of simulations NS is set to 100. Regarding the linear parameters (β_0, β_1), we calculate the mean bias and root mean square error (RMSE) given by $Bias(\beta_j) = \frac{1}{NS}\sum_{r=1}^{NS}\hat{\beta}_j^r - \beta_j$ and $RMSE(\beta_j) = \frac{1}{NS}\sum_{r=1}^{NS}(\hat{\beta}_j^r - \beta_j)^2$.

4.3 Results

The simulation results are reported in Table 1 and Figure 1 for DGP 1, Table 2 and Figure 2 for DGP 2, and Table 3 and Figure 3 for DGP 3. The first point to note is that the overall simulation results with shape restriction substantially outperform those without shape restriction. Specifically, the MISE of nonparametric function $f(y-p)$ is much smaller when shape restriction is applied to the income effect. This finding is consistent with Chetverikov and Wilhelm (2017), who demonstrate a large performance gain from the monotonicity restriction under a semiparametric partially linear model with endogeneity. Our simulation results demonstrate that their finding can also be applied to a setting where the model is non-separable.

Figures 1, 2, and 3 show the estimated function and its 95% confidence interval (CI). Without the shape restriction, the function is estimated poorly near the endpoint of the support. On the other hand, the confidence band remains narrower when we impose the restriction. Regarding

[20] We set the tolerance level of the nested fixed-point algorithm as 1E-12 and employ the constrained minimization procedure in the Knitro solver.

[21] We standardize the generated $y_i - p_j$ as follows. Let $z_{max} = \max\{y_i - p_j\}$ and $z_{min} = \min\{y_i - p_j | y_i - p_j > 0\}$. Next, we define $z \equiv \frac{y_i - p_j}{z_{max} - z_{min}}$ so that z ranges in $[0, 1]$ if $y_i - p_j$ is positive.

the linear parameter β, the RMSE of the estimated β_0 under the restriction is much smaller than that without the restriction. However, the estimation precision of β_1 is similar regardless of the restriction.

Table 1: Results of Monte Carlo Simulation (DGP 1)

(i) MISE of $f(y-p)$

	Without SR	With SR
$K=3$	0.0141	0.0022
$K=4$	0.0202	0.0052
$K=5$	0.5886	0.0064

(ii) β_0

	Without SR		With SR	
	Bias	RMSE	Bias	RMSE
$K=3$	0.0212	0.0760	-0.0028	0.0222
$K=4$	0.0253	0.0991	0.0034	0.0403
$K=5$	0.0014	0.3093	0.0027	0.0452

(iii) β_1

	Without SR		With SR	
	Bias	RMSE	Bias	RMSE
$K=3$	-0.0002	0.0119	-0.0008	0.0118
$K=4$	-0.0003	0.0119	-0.0005	0.0119
$K=5$	0.0026	0.0135	-0.0004	0.0119

Figure 1: Median and 95% CI for DGP 1

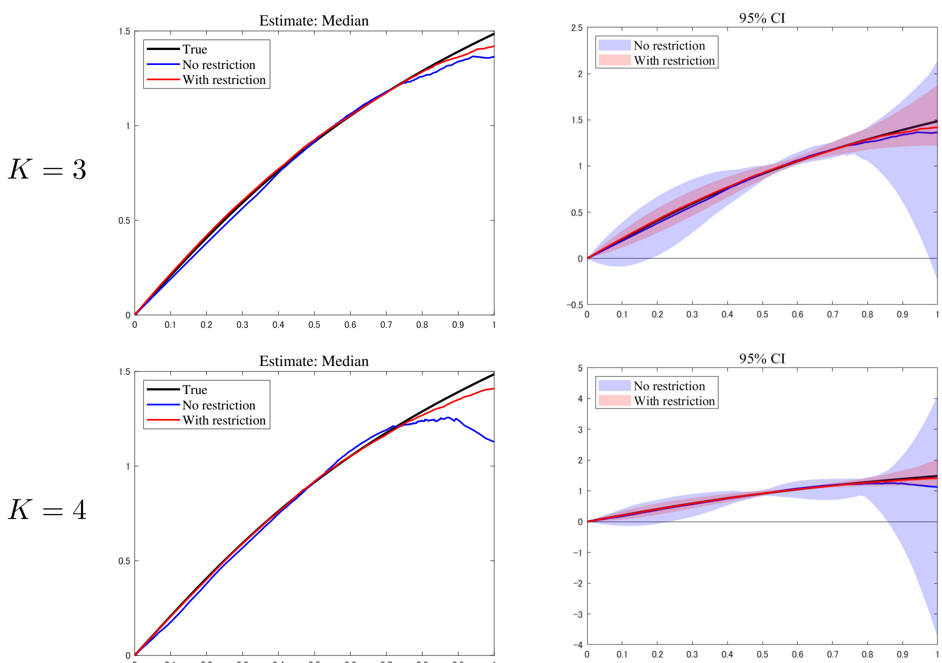


Table 2: Results of Monte Carlo Simulations (DGP 2)

(i) MISE of $f(y-p)$

	Without SR	With SR
$K=3$	0.0124	0.0033
$K=4$	0.0169	0.0044
$K=5$	0.5191	0.0054

(ii) β_0

	Without SR		With SR	
	Bias	RMSE	Bias	RMSE
$K=3$	0.0027	0.0754	-0.0166	0.0291
$K=4$	0.0167	0.0938	-0.0170	0.0361
$K=5$	-0.0060	0.3106	-0.0153	0.0436

(iii) β_1

	Without SR		With SR	
	Bias	RMSE	Bias	RMSE
$K=3$	0.0002	0.0120	-0.0003	0.0119
$K=4$	-0.0004	0.0119	-0.0003	0.0119
$K=5$	0.0027	0.0136	-0.0004	0.0119

Figure 2: Median and 95% CI for DGP 2

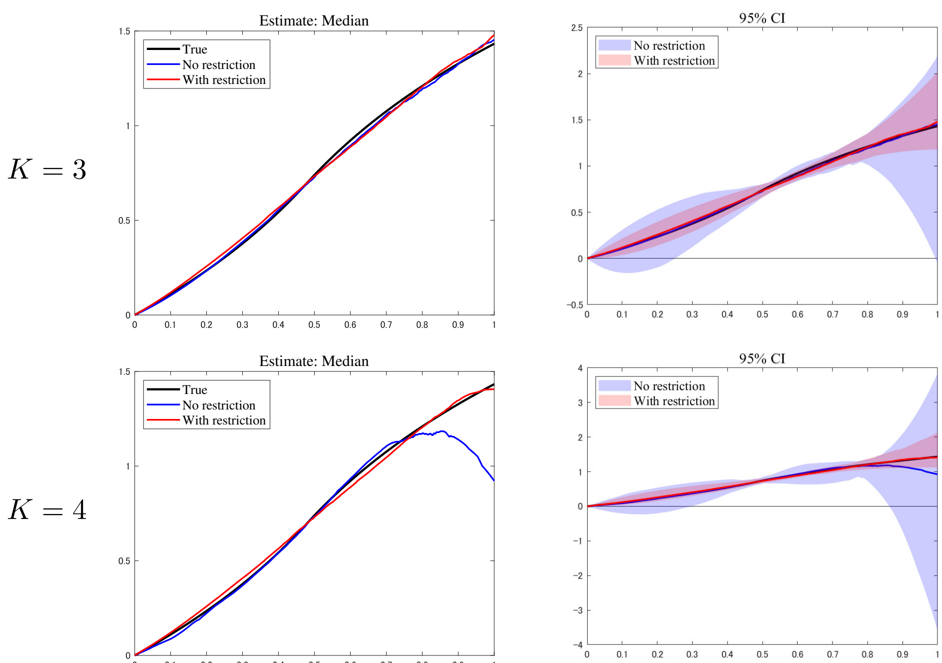


Table 3: Results of Monte Carlo Simulation (DGP 3)

(i) MISE of $f(y-p)$

	Without SR	With SR
$K=3$	0.0157	0.0037
$K=4$	0.0189	0.0063
$K=5$	0.5222	0.0076

(ii) β_0

	Without SR		With SR	
	Bias	RMSE	Bias	RMSE
$K=3$	0.0217	0.0791	0.0053	0.0352
$K=4$	0.0225	0.0912	0.0070	0.0468
$K=5$	0.0019	0.3024	0.0074	0.0538

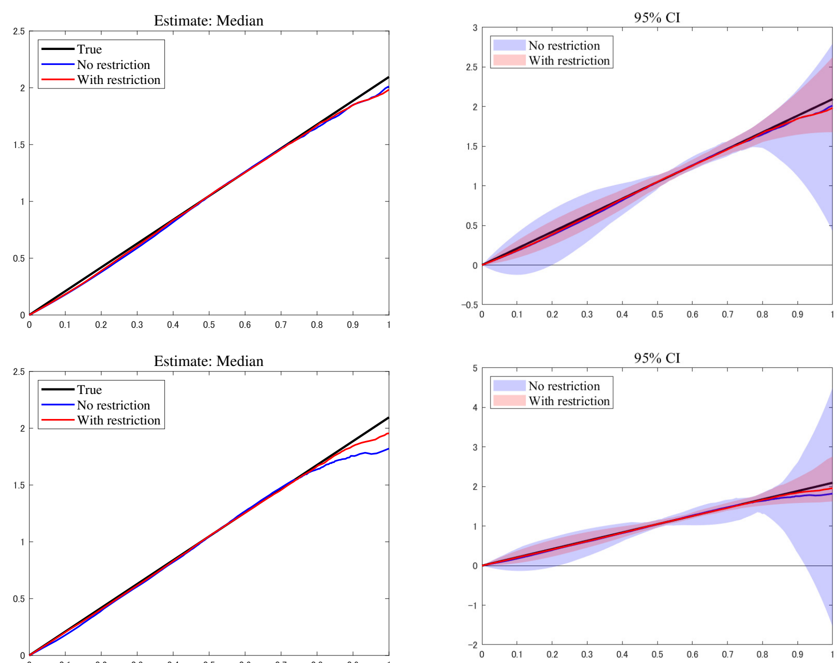
(iii) β_1

	Without SR		With SR	
	Bias	RMSE	Bias	RMSE
$K=3$	-0.0002	0.0119	-0.0005	0.0118
$K=4$	-0.0004	0.0119	-0.0004	0.0119
$K=5$	0.0024	0.0134	-0.0004	0.0119

Figure 3: Median and 95% CI for DGP 3

$K=3$

$K=4$



5 Empirical Application: Automobile Demand

We now apply our semiparametric demand model to the Japanese automobile market to demonstrate the practical relevance of our framework. In Section 5.1, we briefly explain the data and relevant background of the industry. Then, we report the preliminary results estimated by the linear logit model of Berry (1994) and discuss the potential issues of this approach in Section 5.2. The semiparametric specification of the demand model, as a remedy to the issues raised in the linear logit model, is introduced in Section 5.3. The estimation results of the semiparametric model are discussed in Section 5.4. We then use the estimated demand model to conduct counterfactual simulations in Section 6. Specifically, we evaluate (1) the impact of the feebate policy for eco-friendly cars in Japan and (2) the effect of a hypothetical merger between two major Japanese automobile manufacturers: Toyota and Honda.

5.1 Data

Two types of datasets are constructed. The first contains information on the Japanese automobile market for the period 2006–2013, including product-level information on sales, prices, and product characteristics for each year. Second, we construct the income distribution of Japanese households as a source of consumer heterogeneity in the demand model (see Appendix A for details).

To construct the former dataset on the Japanese automobile market, we combine the catalog information of car models and the registration of newly purchased cars.[22] The dataset is an unbalanced panel at the model-and-year level.

We define the share of each car model in each year (s_{jt}) as the fraction of the total number of new car registrations (see footnote 22) over the total number of households in Japan, which is sourced from annual reports of *Population, demographics, and the number of households based on the Basic Resident Register* conducted by the Ministry of Internal Affairs and Communications[23].

[22] The catalog information is obtained from the website *CarView!*, which provides the specifications of car models and their list prices. Registrations of standard and compact cars are obtained from the *Annual Report of New Car Registrations* (*Shinsha Touroku Daisu Nempou*) issued by the Japan Automobile Dealers Association. Registrations for minicars are obtained from a report published by the Japan Mini Vehicle Association (see `https://www.zenkeijikyo.or.jp/statistics/tushokaku`; in Japanese. Accessed on January 6, 2023.). Finally, we source information on registrations for 20 top-selling imported cars from a report published by the Japan Automobile Importers Association (see `http://www.jaia-jp.org/english-transition/`. Accessed on January 6, 2023).

[23] See `https://www.soumu.go.jp/main_sosiki/jichi_gyousei/daityo/jinkou_jinkoudoutai-setaisuu.html` for details (In Japanese. Accessed on January 6, 2023).

The share of households not purchasing any automobile is defined as $s_{0t} = 1 - \sum_{j \in J_t} s_{jt}$, where J_t represents all the available car models in market t (i.e., year t).

The observable product characteristics (X_{jt}) include (1) the ratio of horsepower to the weight of the car (HP/WT), (2) car size (Size), (3) fuel efficiency (miles per gallon [MPG]), and (4) a dummy variable that indicates whether the model has an automatic/continuously variable transmission system (AT/CVT). [24] We also use dummy variables for minicar, foreign cars, and hybrid cars.[25]

The data also include the list price p_{jt} offered by manufacturers. We construct an effective price p^e_{jt} that reflects the tax and subsidy. The effective price p^e_{jt} is defined as follows

$$p^e_{jt} = (1 + \rho_{jt})p_{jt} + T_{jt} - ES_{jt}, \tag{5.1}$$

where ρ_{jt} is the rate of the ad-valorem tax, including consumption tax (5% during the sample period), T_{jt} is the specific tax, and ES_{jt} is a subsidy for eco-friendly cars. All prices and taxes are deflated by the 2015 consumer price index (CPI).

A unique feature of the Japanese automobile market in the sample period is the presence of various tax and subsidy policies. The Japanese government introduced a feebate policy called the eco-car subsidy (ES) program in 2009 as part of the economic stimulus measures in the wake of the Great Recession. Table 4 provides an overview of the policy.[26] The program has two phases. The first phase of the ES program took place from April 2009 to September 2010.[27] In this phase, cash rebates of JPY $100,000$ (approximately USD 1,000) and JPY $50,000$ (approximately USD 500) were offered to normal cars and minicars that exceeded the 2010 fuel efficiency standard by 15%, respectively.[28] In December 2011, the second phase of the ES program began, continuing until January 2013. In the second phase, the eligibility to receive a cash rebate was made stricter than in the first phase. JPY 100,000 and JPY 70,000 were subsidized to normal cars and minicars exceeding the 2015 fuel efficiency standard, which is equivalent to 125% of the 2010 standard.

Table 5 shows the descriptive statistics of our dataset. A slight increase is seen in effective

[24] Given that the fuel efficiency is measured in kilometers per liter, we convert it to miles per gallon using mpg = (fuelefficiency/1.60934) $\times$ 3.78541.

[25] A minicar is a category of automobile models with a length of 3.4 m or less, a width of 1.48 m or less, and a height of 2.0 m or less, as well as a displacement level of 660 cc or less.

[26] The details of the tax policy are relegated to Appendix B.

[27] In the first phase of the ES policy, consumers had the option to apply for the ES program with a higher amount of subsidy conditional on scrapping their existing vehicle if it was older than 13. See Kitano (2022) for details.

[28] We use an exchange rate of 100 JPY/USD throughout the paper.

Table 4: Details of the Eco-car Subsidy

	Phase 1	Phase 2
Period	April 2009 to September 2010	December 2011 to January 2013
Subsidy to normal cars	JPY 100,000	JPY 100,000
Subsidy to minicars	JPY 50,000	JPY 70,000
Requirement	exceeding the 2010 fuel efficiency standard by 15%	exceeding the 2015 fuel efficiency standard

automobile prices after introducing the subsidy, and a substantial (approximately 24%) decrease is shown in the total amount of taxes. This observation suggests that automakers respond to the change in the tax policy (See Appendix B for the detail). The average amount of ES is JPY 19,000 during the policy periods. Regarding the automobile characteristics, while we do not find significant differences in HP/WT, car size, and AT/CVT, we did observe an improvement in the average MPG (fuel efficiency).

Table 5: Descriptive Statistics of Japanese Automobile Market Data

	(1) 2006-2008				(2) 2009-2013			
	Mean	SD	Min	Max	Mean	SD	Min	Max
$\log(s_{jt}/s_{0t})$	-8.446	1.563	-13.766	-5.347	-8.860	1.782	-15.435	-5.052
p^e_{jt} (JPY 1 Million)	2.731	1.966	0.780	12.870	2.772	1.973	0.771	13.946
Total Tax (JPY 1 Million)	0.186	0.113	0.030	0.682	0.144	0.120	0.008	0.707
ES (JPY 1 Million)	0.000	0.000	0.000	0.000	0.019	0.039	0.000	0.104
HP/WT	0.099	0.033	0.047	0.276	0.099	0.036	0.045	0.318
MPG	34.595	10.600	12.937	83.501	37.142	11.974	15.524	83.266
Car Size	7.485	0.676	6.115	8.855	7.520	0.673	6.115	8.825
AT/CVT	0.978	0.148	0.000	1.000	0.987	0.115	0.000	1.000
Minicar Dummy	0.202	0.402	0.000	1.000	0.198	0.399	0.000	1.000
Hybrid Car Dummy	0.008	0.090	0.000	1.000	0.042	0.201	0.000	1.000
N	495				827			

Notes: s_{jt} and s_{0t} represent the market share of product j and outside good in market t . p^e_{jt} indicates the effective price that consumers face. "Total Tax" denotes the sum of automobile acquisition tax, automobile weight tax, and automobile tax. "ES" is an abbreviation of "eco-car subsidy". All the price and tax variables are deflated by the 2015 CPI. Product attribute variables include the ratio of horsepower to car weight (HP/WT), millage per gallon (MPG), car size (Size), dummy variables indicating whether the model has an automatic or continuously variable transmission (AT/CVT Dummy), and minicar and hybrid car (minicar and hybrid car dummy).

5.2 Preliminary Analysis based on Berry (1994)'s Logit Model

As a benchmark, we first estimate the parametric version of the demand model. Specifically, we estimate the quasi-linear specification given by $f(y-p) = \alpha(y-p)$, where α is a parameter to be estimated. Given that the income term y is canceled out, the model is reduced to the linear logit model of Berry (1994) as follows:[29]

$$\ln\left(\frac{s_{jt}}{s_{0t}}\right) = \alpha p^e_{jt} + \beta' X_{jt} + \theta_j + \theta_t + \xi_{jt}, \tag{5.2}$$

where s_{jt} is the market share of the automobile j at year t, s_{0t} is the market share of outside option (i.e., not purchasing any car) at year t, p^e_{jt} is the effective price of the automobile j at year t, the vector X_{jt} includes HP/WT, MPG, car size, AC/CVT dummy, minicar dummy, and hybrid car dummy. Furthermore, the maker fixed effects (θ_j) and year (market) fixed effects (θ_t) are controlled. ξ_{jt} stands for the econometric error term.

We estimate this equation using ordinary least squares (OLS) and two-stage least squares (2SLS) in which the set of instrumental variables (IV) are employed to deal with the endogeneity of effective price p^e_{jt}. We construct the instruments based on tax and subsidy policy by following Konishi and Zhao (2017).[30] Specifically, our instruments are defined by (1) the sum of the tax amount of other products produced by the firm $\sum_{k\in J_f, k\neq j}(Tax)_{kt}$ and (2) the sum of the tax amount of competitors' products $\sum_{k\notin J_f}(Tax)_{kt}$. Note that Tax_{jt} represents the sum of automobile acquisition tax, automobile weight tax, and automobile tax of car model j in year t. This variable does not include the eco-car subsidy.

We discuss the relevance of these instruments based on the first-stage regression in Table 6. Regarding the independence of IVs, we should note some identification concerns. For instance, the types of cars produced by automakers might be correlated with the policy design and, thus, with our instrument. Specifically, the total amount of hybrid car production might have increased after introducing the policy. To address this issue, we include dummies for minicars, foreign cars, and hybrid cars as a covariate in the utility specification.

Table 6 shows the estimation results of Equation (5.2). Column (1) reports the results of OLS estimation, in which the price is treated as an exogenous attribute. The results of the IV estimation are then summarized in columns (2)–(4). Estimated coefficients have the expected signs. By

[29] To be precise, we also omit the budget constraint so we can derive the linear logit model of Berry (1994). Even if the quasi-linear specification is assumed in our model, the presence of the budget constraint is a source of consumer heterogeneity. Thus, the budget constraint does not allow us to use a linear regression model, as in Berry (1994).

[30] We also use differentiation instruments proposed by Gandhi and Houde (2019) to assess its performance. Moreover, we attempted to use traditional BLP instruments for car characteristics, though the first-stage regression of a parametric IV logit model was substantially weaker than differentiation IV. The result of using traditional BLP IV is not reported. This finding is consistent with results obtained by Konishi and Zhao (2017) (see Appendix D in their paper).

comparing the results of OLS and IV estimation, the price coefficient seems to be underestimated in OLS (i.e., the OLS estimate is biased towards zero). Regarding the validity of the instruments, the result shown in column (3) suggests that the tax-based instrument has the highest value of Kleibergen–Paap F statistics in the first stage. Based on the above results, we use a tax-based instrument to estimate the semiparametric demand model. We also use column (3) as a parameter of the simple logit model in simulation analysis in Section 6.

While the estimation of the linear logit model is useful as a preliminary analysis, the model has several issues for applications. First, as discussed in Section 2.4, the quasi-linear assumption imposes a strict restriction on the pattern of price elasticity. The relationship between the own-price elasticity and price is linear under a simple logit model. We will revisit this point when we estimate the price elasticity in a semiparametric demand model. In addition, since the demand curve is always log-concave in price under a simple logit model, the pass-through rate is bounded by 1 (Weyl and Fabinger 2013). Such property may imply an underestimation of the pass-through rate of the subsidy.

Table 6: Preliminary Estimation Results of Equation (5.2)

	(1)	(2)	(3)	(4)
	OLS	IV	IV	IV
Effective Price (p^e_{jt})	-0.402	-0.646	-0.519	-0.480
	(0.030)	(0.119)	(0.052)	(0.045)
HP/WT	5.898	13.598	9.596	8.382
	(1.578)	(3.830)	(1.992)	(1.881)
MPG	0.105	0.100	0.103	0.103
	(0.006)	(0.007)	(0.006)	(0.006)
Car Size	1.686	1.976	1.826	1.780
	(0.115)	(0.163)	(0.120)	(0.117)
AT/CVT	0.257	0.437	0.343	0.315
	(0.385)	(0.385)	(0.381)	(0.381)
Differentiation IV on car attribute	No	Yes	No	Yes
Tax-based IV	No	No	Yes	Yes
Kleibergen–Paap F statistic		21.650	**74.359**	33.830
Hansen J statistics		25.702	**2.249**	27.792
N	1322	1322	1322	1322

Notes: All regression includes year fixed effects, firm fixed effects, minicar dummy and hybrid car dummy. The robust standard error is reported in parentheses.

5.3 Semiparametric Demand Specification

We now take the semiparametric approach introduced in Section 2 to overcome the potential issues of the simple logit model we discussed. The following specification is considered for the conditional indirect utility:

$$V_{ijt} = f(y_{it} - p^e_{jt}) + \beta' X_{jt} + \theta_j + \theta_t + \xi_{jt} + \epsilon_{ijt}, \ (\forall j \in \{1, \cdots, J_t\}) \tag{5.3}$$

$$V_{i0t} = f(y_{it}) + \epsilon_{i0t} \tag{5.4}$$

where $f(\cdot)$ is a weakly increasing continuous function, y_{it} stands for the real income for individual i at year t[31], and ϵ_{ijt} is idiosyncratic shock following Type-I extreme value distribution. The definition of all the other components is the same as in Equation (5.2). We make use of tax-based IV defined in the previous section (i.e., $w_{1,kt} \equiv \sum_{k \in J_f, k \neq j} (Tax)_{kt}$, and $w_{2,kt} \equiv \sum_{k \notin J_f} (Tax)_{kt}$) to estimate $f(.)$ and β in the model. Specifically, the matrix of IVs defined in equation (3.6) is based on $p(w) = (1, w_{1,kt}, w_{2,kt}, w^2_{1,kt}, w^2_{2,kt}, w^3_{1,kt}, w^3_{2,kt})$ and the tensor products of $p(w)$ and X_{jt}.

The income effect term $f(y - p)$ is approximated using the following:

$$f(y - p) = \frac{-1}{\sum_{k=1}^{K} \pi_k b^K_k (y - p)},$$

where $b^K_k(x)$ is a Bernstein polynomial defined in (3.2). We set $K = 4$ in estimation. The above approximation imposes the condition that $\lim_{x \to 0} f(x) = -\infty$. This restriction makes the demand model continuous regarding prices, which is critical when subsequently simulating a pricing equilibrium.

Due to the presence of the budget constraint in the optimization problem, the individual choice probability $s_{ijt}(\cdot)$ defined in Equation (2.10) can be discontinuous with respect to the price at $p_{jt} = y_{it}$, as $s_{ijt} = 0$ when $p_{jt} > y_{it}$. Given that we approximate aggregate demand by simulating a finite number of consumers, the resulting demand function may also have a range of discontinuous points. While such discontinuity is not detrimental to estimation where prices are fixed as a covariate, it makes the supply-side analysis (i.e., solving the Bertrand pricing equilibrium) numerically challenging.

[31] See the last paragraph of this section for the data generating process of real income.

To avoid this issue, we imposed a restriction whereby $\lim_{p \to y} f(y-p) = -\infty$ so that the individual choice probability $s_{ijt}(\cdot)$ converges to zero as the price gets closer to the income level. This property ensures the continuity of the demand function.

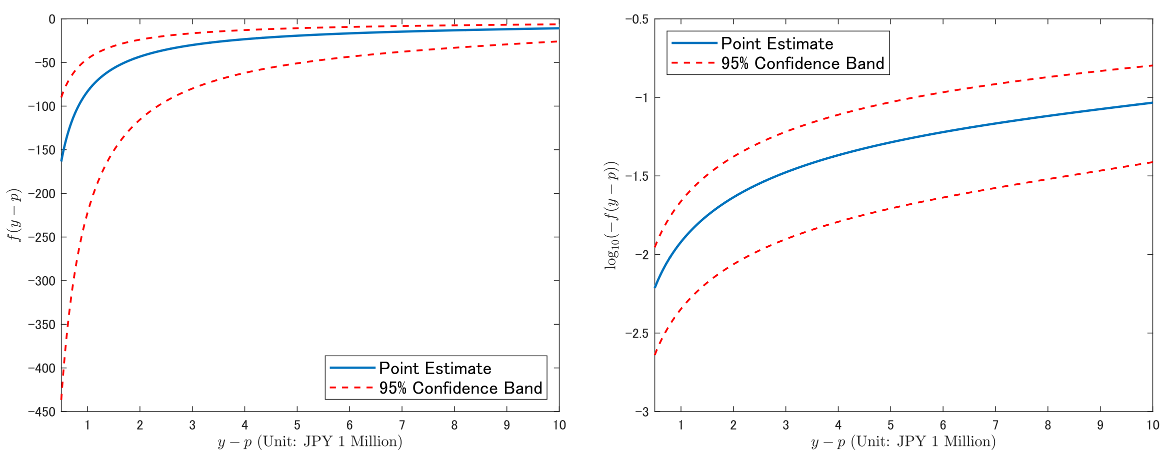
The aggregate demand is determined by integrating the individual choice probability with income distribution. We assume the income distribution to be the log-normal distribution with mean μ_t and standard deviation σ_t: $LN(\mu_t, \sigma_t^2)$. We estimate these two parameters (μ_t, σ_t) for each year using the data from *the Comprehensive Survey of Living Conditions.* See Appendix A for the details. To numerically compute the integral, we use quasi-random sampling. We draw 1,000 consumers from the estimated distribution by a Halton sequence.

5.4 Estimation Results of Semiparametric Model

Figure 4 and Table 7 report estimates of the income-effect term $f(y-p)$ and linear parameters β, respectively. Figure 4 shows that the income effect term $f(y_{it} - p_{jt})$ is nonlinear and concave. The marginal utility from the disposable income after purchasing an automobile is higher for low-income households. Table 7 reports the estimation results of linear parameters in Equation (5.3). The point estimates are comparable with the simple logit model, except for the HP/WT. The coefficient for HP/WT is approximately 1.5 times larger when we employ the semiparametric estimation (see column (3) of Table 6).

Figure 4: Estimation of $f(y_{it} - p_{jt})$

(i) $f(y-p)$ is plotted. (ii) $-\log_{10}(-f(y-p))$ is plotted.



Note: Point estimate and 95% confidence band based on 200 times bootstrap sampling are reported. The range of $y-p$ plotted is JPY 0.5 to 10 Million.

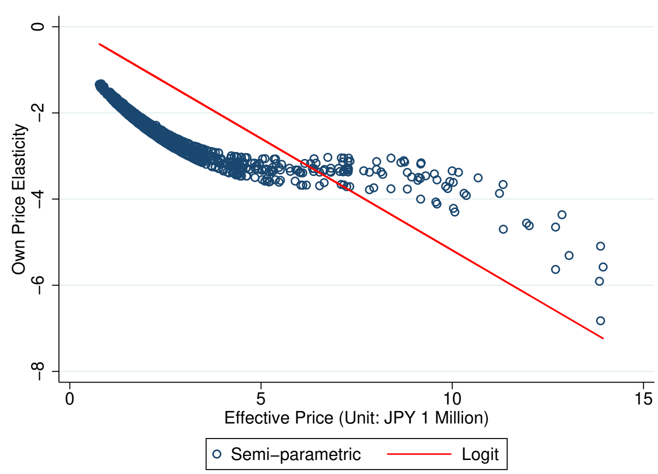
Table 7: Estimation of Linear Parameters

	Estimate	95% CI
Constant	-24.705	[-26.655, -21.355]
HP/WT	13.635	[7.931, 20.102]
MPG	0.086	[0.052, 0.105]
Car Size	2.178	[1.781, 2.704]
AT/CVT	0.143	[-0.802, 1.328]
N		1322

Note: The point estimate of selected linear parameters and 95% confidence interval are reported. The confidence interval is constructed using 200 bootstrap samples. See Theorem 5.2 of Chen and Pouzo (2015) for the details. Minicar dummy, hybrid car dummy, year fixed effects, and market fixed effects are also included but not reported.

Based on the estimated demand function, we calculate the own-price elasticity. Figure 5 shows the estimated own-price elasticity as a function of the effective price of automobiles. We compare the own-price elasticity based on our demand with that from a simple logit model (column (3) of Table 6). As we have discussed in Section 5.2, the simple logit model implies a linear relationship between elasticity and price (See Equation (2.11) in Section 2.4). However, our semiparametric model reveals a nonlinear relationship where the estimated elasticity is relatively constant in the range of JPY 2 to 10 million. As a result, the elasticity estimated by simple logit suffers from underestimation for inexpensive cars (such as mini-car) and from overestimation for luxury cars.

Figure 5: Estimated Own-Price Elasticity



6 Policy Simulations: Pass-Through and Merger Analysis

We conduct two counterfactual simulations using our estimated semiparametric model. In the first simulation, the eco-car subsidy program is evaluated by assessing the pass-through of the subsidy and its welfare impacts. As discussed in Section 2.4, our demand model can flexibly capture the curvature of the demand function, which has key implications for the pass-through. Second, we conduct a merger simulation between two automobile manufacturers.

Below, we begin by introducing a supply model in Section 6.1 to estimate the marginal costs of car models and simulate counterfactual equilibria. We then conduct counterfactual simulations in Sections 6.2 and 6.3.

6.1 Supply Model

To predict a counterfactual equilibrium, we introduce a supply model for automobile manufacturers. We adopt a model of Bertrand competition with differentiated products, as in BLP and Nevo (2001).

Automobile manufacturers are multiproduct oligopolists that compete in prices. The profit for manufacturer f in year t is given as follows:

$$\pi_{ft} = \sum_{j \in \mathbf{J}_{ft}} (p_{jt} - mc_{jt}) q_{jt} \left(\mathbf{p}_t^e\right), \tag{6.1}$$

where mc_{jt} is the marginal cost of car model j in year t. We assume a constant marginal cost. The variable $\mathbf{p}_t^e$ is a vector of effective prices in market t and defined as $\mathbf{p}_t^e = \{p_{jt}^e\}_{j \in J_t}$. Note that we distinguish between the price charged by a firm p_{jt} and the effective price p_{jt}^e that reflects the tax and subsidy. Remember that the effective price is given by $p_{jt}^e = (1 + \rho_{jt}) p_{jt} + T_{jt} - ES_{jt}$. Lastly, $\mathbf{J}_{ft}$ denotes the set of car models produced by manufacturer f in year t.

The first-order condition (FOC) of the profit maximization problem is as follows:

$$\frac{\partial \pi_{ft}}{\partial p_{jt}} = q_{jt} \left(\mathbf{p}_t^e\right) + (1 + \rho_{jt}) \sum_{l \in \mathbf{J}_{ft}} (p_{lt} - mc_{lt}) \frac{\partial q_{lt}}{\partial p_{jt}^e} = 0, \ \forall j \in \mathbf{J}_{ft} \tag{6.2}$$

By stacking the FOCs across all products, we obtain the equilibrium conditions for year t in the following matrix notation:

$$\tilde{\mathbf{q}}_t(\mathbf{p}_t^e) - D_t(\mathbf{p}_t^e)(\mathbf{p}_t - \mathbf{mc}_t) = \mathbf{0}, \tag{6.3}$$

where $\tilde{\mathbf{q}}_t = (\frac{q_{1,t}}{1+\rho_{1t}}, \cdots, \frac{q_{J_t,t}}{1+\rho_{J_t,t}})'$, $\mathbf{p}_t = (p_{1,t}, \cdots, p_{J_t,t})'$, and $\mathbf{mc}_t = (mc_{1,t}, \cdots, mc_{J_t,t})'$. The matrix D_t is a $J_t \times J_t$ matrix defined as $D_t(\mathbf{p}_t^e) = \Omega_t \odot S(\mathbf{p}_t^e)$. Here the operator $\odot$ denotes the element-by-element multiplication of matrices. Ω_t, meanwhile, denotes the ownership structure of car models sold in market t. More specifically, the (i, j) element of the matrix Ω_t takes a value of 1 if product i and j are sold by the same manufacturer and 0 otherwise. Lastly, the (i, j) element of matrix $S(\mathbf{p}_t^e)$ is defined as $-\frac{\partial q_{jt}(\mathbf{p}_t^e)}{\partial p_{it}^e}$.

To use this supply model for simulations, we must first estimate the model primitives, namely the demand function and marginal costs. The demand function is estimated in Section 5. To estimate the vector of marginal cost $\mathbf{mc}_t$, we use the equilibrium conditions derived above. To be precise, given that the matrix $S(\mathbf{p}_t^e)$ can be calculated from the demand estimates, we can invert Equation (6.3) to back out the marginal costs $\mathbf{mc}_t$.

Given the estimated model primitives, we conduct a simulation analysis by numerically solving Equation (6.3) for a vector of equilibrium prices. To do so, we use the algorithm proposed by Morrow and Skerlos (2011).[32]

6.2 Simulation 1: Pass-through Analysis of Feebate Policy

In this subsection, we conduct a pass-through analysis of eco-car subsidies. To do this, we simulate the market equilibrium if the subsidy for eligible automobile models that satisfy the fuel efficiency requirements is removed (i.e., $ES_{jt} = 0$ for all j in Equation (5.1)). We then calculate how much of the subsidy amount was attributed to consumers and producers. Note that our simulation analysis aims to highlight the value of our demand framework in the pass-through analysis rather than fully evaluating the Japanese feebate policy.[33]

[32] The algorithm of Morrow and Skerlos (2011) is used in pyBLP package provided by Conlon and Gortmaker (2020)

[33] We abstract away several institutional features in our analysis. First, the actual policy started in the middle of the year, i.e., in April, but our data is annual, so we cannot fully account for this point. Thus, we assume that the first phase of the ES policy was implemented from April 2009 to September 2010 and that the second phase ran from December 2011 to January 2013. See Konishi and Zhao (2017), who analyze the policy using quarterly data. Second, in the first phase of the ES policy, consumers can apply for the ES program with a higher amount of subsidy if they scrap an existing vehicle that is older than 13. To analyze the scrap subsidy, we must incorporate consumer heterogeneity for the age of the owned vehicle. See Kitano (2022) for an evaluation of the feebate policy with full consideration of the scrap subsidy.

First, we report the pass-through rate in Table 8. We define the pass-through rate (PTR_{jt}) as the ratio of changes in effective price that consumers face to the amount of ES:

$$PTR_{jt} = \frac{p_{jt}^{e'} - p_{jt}^{e}}{ES_{jt}},$$

where $p_{jt}^{e'}$ indicates the simulated price in the counterfactual case without ES. We find that the average pass-through rate under our semiparametric model is 1.282, while the rate implied by a simple logit model is 0.991. In terms of price reduction, the ES policy decreased the effective price of eligible car models by 6.4% on average.

Table 8: Price Change Due to Ecocar Subsidy

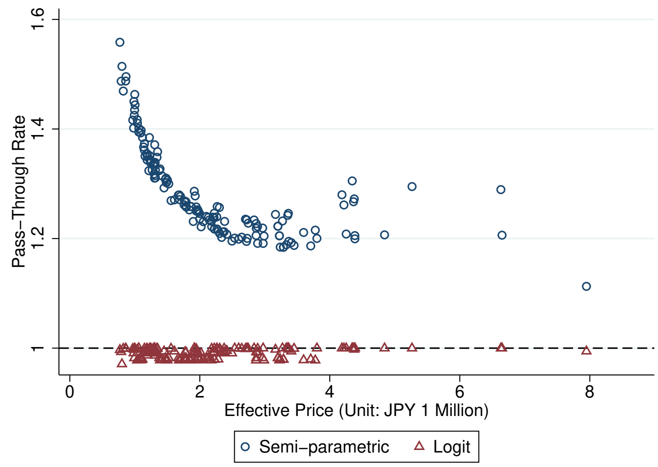
	Mean	SD	P25	Median	P75
			A: PTR_{jt}		
Semi-parametric	1.282	0.080	1.221	1.259	1.335
Logit	0.991	0.009	0.980	0.993	0.999
			B: Percentage Change in Effective Price		
Semi-parametric	-6.36%	2.56%	-4.29%	-6.09%	-7.96%
Logit	-4.93%	1.79%	-3.50%	-4.85%	-5.93%

Note: $PTR_{jt} = (p_{jt}^{e'} - p_{jt}^{e})/ES_{jt}$. Percentage change in effective price due to ecocar subsidy is defined as $100 * (p_{jt}^{e'} - p_{jt}^{e})/p_{jt}^{e'}$. P25 and P75 represent the 25th and 75th percentiles, respectively.

Figure 6 shows the relationship between the pass-through rate and the effective price for our semiparametric model and a simple logit model. It indicates significant heterogeneity in the estimated pass-through rate in the semiparametric specification. A less expensive car shows a higher pass-through rate. In comparison, the pass-through rate under a quasi-linear logit model is bounded by 1. This result supports the argument put forth by Weyl and Fabinger (2013) that log-concave demand always predicts an incomplete pass-through (i.e., the pass-through rate is below 1) in a symmetric oligopoly model. Our semiparametric model does not suffer from such an a priori restriction on the demand curvature and the pass-through rate.

To further compare our demand model to a simple logit model, we create a binned scatter plot of the pass-through rate against the own-price elasticity in Figure 7. For a given price elasticity, our semiparametric model predicts a higher pass-through rate than a simple logit model. These differences can be attributed to the difference in demand curvature (i.e., the second-order derivative) across the two demand models.

Figure 6: Pass-Through Rate of the Eco-Car Subsidy



Note: The car models whose effective price is less than JPY 8 million are plotted.

Next, we quantify the policy impact on social welfare. We calculate the changes in producer surplus (PS_t), tax revenues (TR_t), and the consumer's aggregate compensating variation (CV_t).[34] To calculate the compensating variation (CV), we use the result of Dagsvik and Karlström (2005).[35] Table 9 reports the results. Overall, the eco-car subsidy policy improves the total welfare by JPY 230 billion (around 2.3 billion USD) annually. This improvement is likely due to the subsidy mitigating the preexisting distortion caused by market power (Buchanan 1969; Fowlie et al. 2016).

Table 9: Welfare Impact of Ecocar Subsidy

	2009	2010	2012	Average
(i) Semi-parametric				
Consumer Surplus	199.9	277.6	379.1	285.5
Profit	110.0	147.6	201.0	152.9
Tax Revenue	-143.3	-197.6	-274.7	-205.2
Total Welfare	166.5	227.5	305.4	233.2
(ii) Simple Logit				
Consumer Surplus	156.0	215.5	299.0	223.5
Profit	141.6	195.3	268.3	201.7
Tax Revenue	-152.1	-209.6	-291.7	-217.8
Total Welfare	145.5	201.3	275.5	207.5

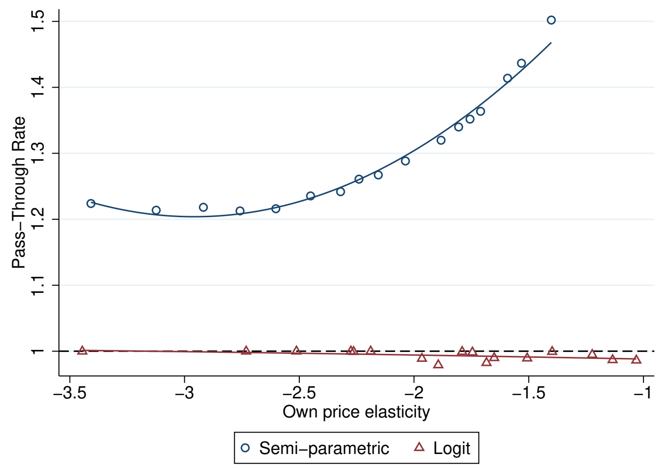
Note: The unit is JPY 1 Billion. The average of 2009, 2010, and 2012 is reported in the final column.

While a simple quasi-linear logit model assumes the same consumer surplus among consumers,

[34] The producer surplus is $PS_t = \sum_{f \in F} \sum_{j \in \mathbf{J}_{ft}} (p_{jt} - \widehat{mc}_{jt}) q_{jt}(\mathbf{p_t^e})$ and the tax revenue is given by $TR_t = \sum_{f \in F} \sum_{j \in \mathbf{J}_{ft}} (p_{jt}\rho_{jt} + T_{jt} - ES_{jt}) q_{jt}(\mathbf{p_t^e})$.

[35] See Appendix C for more detail on how CV is calculated.

Figure 7: Relationship between Pass-Through Rate of the Eco-Car Subsidy and Own-Price Elasticity



Note: The car models whose estimated own price elasticity is less than -1 and more than -4 are plotted.

a semiparametric specification can factor in the heterogeneity of compensating variation. We apply the results from Dagsvik and Karlström (2005) to calculate the distribution of CV in Table 10. We find a large standard deviation, which implies significant heterogeneity among consumers. The table further suggests that while almost half of the consumers are unaffected by the eco-car subsidy, a large CV is observed at the right tail of the distribution, from approximately JPY 15,500 (around USD 155) in 2009 to JPY 28,600 (around USD 286) in 2012 at the 90th percentile. Such heterogeneity is attributed to the observations that (i) the eco-car subsidy only affects the welfare of consumers who have the potential to purchase eco-cars, and (ii) more than 90% of consumers do not buy cars in any year (i.e., s_{0t} is larger than 0.9). Meanwhile, the CV implied by the simple logit model is between the median and the 75th percentile of the distribution under our model with a nonparametric income effect. This result suggests the importance of incorporating the income effect when analyzing the distributional effects of the policy on consumers.

6.3 Simulation 2: Merger Simulation

We conduct a merger simulation analysis by applying our demand model to a hypothetical merger between Toyota and Honda. As we did in the pass-through analysis, we compare the price effects of a merger predicted by our demand model and the quasi-linear logit model.

To do this, we simulate the outcome of the merger by solving the equilibrium conditions under a

Table 10: The Distribution of CV by Year (Ecocar Subsidy)

	Semiparametric							Logit
Year	Mean	SD	P10	P25	Median	P75	P90	Mean
2009	3779	7353	0	0	56	3289	15480	2951
2010	5201	10507	0	0	80	4114	20911	4039
2012	6998	12798	0	0	164	7230	28639	5519

Note: The unit is JPY. P10, P25, P75, and P90 represent the 10th, 25th, 75th, and 90th percentile points respectively. Under a simple logit, there is no heterogeneity in CV.

counterfactual ownership structure. Specifically, we set the ownership matrix Ω_t such that the car models produced by Toyota and Honda are owned by the same firm. The hypothetical merged firm chooses prices to maximize joint profit. We use the estimated marginal costs and do not consider efficiency gains from the merger. Our focus in this work is on the anti-competitive effects, which are of primary interest in the antitrust practice and are determined by the demand structure.

Table 11 presents the simulation results. The price effects of a merger are higher in our semiparametric model than in a simple logit model. While the product prices increase by 2.5% for Toyota and 6.8% for Honda under our demand specification, a simple logit demand predicts increases of 1.0% for Toyota and 2.4% for Honda.

Table 11: Descriptive Statistics of Merger Simulation

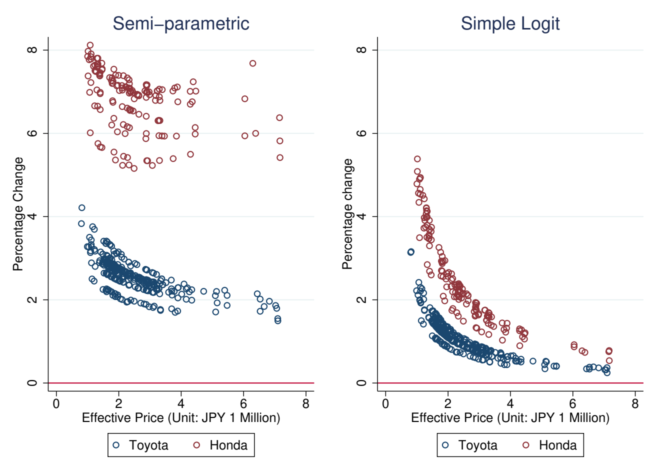
	Mean	SD	P25	Median	P75
A: Observed Effective Price (Unit: JPY 1 Million)					
(1) Toyota	2.76	2.01	1.77	2.18	2.98
(2) Honda	2.51	1.27	1.46	2.33	2.99
B: Effective price change in percentage (Semi-parametric)					
(1) Toyota	2.52%	0.50%	2.26%	2.53%	2.83%
(2) Honda	6.80%	0.70%	6.31%	6.99%	7.27%
C: Effective price change in percentage (Logit)					
(1) Toyota	1.05%	0.45%	0.76%	1.02%	1.32%
(2) Honda	2.45%	1.11%	1.63%	2.19%	3.26%

Note: P25 and P75 represent the 25th and 75th percentiles.

One of the most notable differences between the semiparametric model and the simple logit model is how the merger effect varies across products. Figure 8 plots the relationship between the merger effect and product prices. In the right panel of Figure 8 for a simple logit model, we observe a negative relationship, implying that the merger effect is larger for cheaper products. This correlation is due to the functional form restriction on price elasticity discussed in Section 2.4. Products are less elastic for less expensive products in the simple logit model, which suggests that the merged company can easily increase the prices of its less expensive products. However, the price effects under our demand model (left panel of Figure 8) do not display such a monotonic relationship. This observation is partly because the price elasticity in our demand model does not show such a mechanical pattern created in the simple logit model.

In addition to price elasticity, demand curvature also plays a significant role in determining the price effects of mergers. Figure 9 illustrates the relationship between the price effect and the own-price elasticity. Conditional on the price elasticity, our demand model predicts higher price effects of the merger. It is worth noting that this finding aligns with the argument regarding the pass-through rate in Figure 7.

Figure 8: Price Effect of Merger Between Toyota and Honda



Note: The car models whose effective price is less than JPY 8 million are plotted.

Lastly, Table 12 shows the welfare effects of the merger. Our semiparametric model predicts that the merger will result in a larger loss of consumer surplus and total welfare, which reflects the larger price effects in the semiparametric specification.

7 Conclusion

This paper proposes a new empirical framework for a differentiated product demand model with a nonparametric income effect. The proposed model is a semiparametric model with endogeneity.

Figure 9: Relationship between Price Effect of Merger and Own Price Elasticity

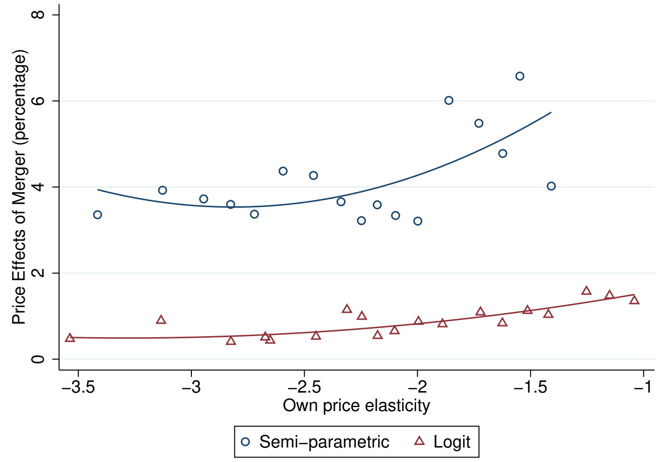


Table 12: Welfare Impact of Merger

	Semiparametric	Logit
Consumer Surplus	-144.7	-60.6
Profit	23.3	2.8
Tax Revenue	-9.4	-0.4
Total Welfare	-130.8	-58.1

Note: The average welfare impact from 2006 to 2013 is reported, as measured in Billion JPY.

We estimate the model by combining the nested fixed-point algorithm proposed by BLP and a sieve approximation with shape restriction. Notably, our Monte Carlo simulations suggest significant gains in estimating the nonparametric term of the income effect by incorporating the shape restriction.

Furthermore, our empirical application using Japanese automobile data demonstrates the importance of a flexible income effect. A quasi-linear specification greatly restricts the estimated own-price elasticity, yet our demand model does not suffer from such a restriction. In the pass-through analysis and the merger simulation, our demand model offers qualitatively and quantitatively different results than the parametric specification.

Appendix

A Income Distribution

Income distribution is obtained from *the Comprehensive Survey of Living Conditions (CSLC)*, which is conducted annually in Japan by the Ministry of Health, Labor, and Welfare (MHLW). Specifically, we used the summary of CSLC annual data circulated by MHLW in which the median and the average income of the surveyed population are reported. In our analysis, we assume that the annual income follows a log-normal distribution ($= LN(\mu_t, \sigma_t^2)$). The parameters are calibrated using the property that $\mathbb{E}(y) = \exp(\mu + \sigma^2/2)$ and $Median(y) = \exp(\mu)$. Table A1 shows the nominal and real (i.e., deflated by 2015 CPI) average and median income and the parameters of income distribution from 2006 to 2013.

Table A1: Descriptive Statistics of Annual Income Data from CSLC

Year	Average[(a)]	Median[(a)]	Average (Deflated)	Median (Deflated)	μ_t[(b)]	σ_t[(b)]
2006	566.8	451	583.1276	463.9918	6.1399	0.6761
2007	556.2	448	572.2222	460.9053	6.1332	0.6578
2008	547.5	427	555.2738	433.0629	6.0709	0.7051
2009	549.6	438	565.4321	450.6173	6.1106	0.6738
2010	538.0	427	557.5130	442.4870	6.0924	0.6798
2011	548.2	432	569.2627	448.5981	6.1061	0.6902
2012	537.2	432	558.4200	449.0644	6.1072	0.6602
2013	528.9	415	547.5155	429.6066	6.0629	0.6964

Notes: The unit used in columns 2–5 is JPY 10 thousands. (a): Average and median income are sourced from the summary of CSLC circulated by MHLW. (b) The parameters of the log-normal distribution is calculated based on deflated average/median income.

B Tax Policy in Japanese Automobile Market

This appendix explains the tax system in the Japanese automobile market. Under the Japanese vehicle tax system, consumers must pay three types of car tax: (1) acquisition tax, (2) weight tax, and (3) automobile tax. The acquisition tax is an ad valorem tax, while the other two are specific taxes that depend on the weight and engine displacement of the car model.

First, the automobile acquisition tax is an ad valorem tax collected by each prefecture, which charges 5% (3%) of the purchase price before March 2014 (after April 2014). Note that the automobile acquisition tax was abolished in October 2019, with a new taxation system called the environmental performance discount (*Kankyo-Seino-Wari* in Japanese) being rolled out in October 2019. Under this new system, at most 3% of the purchase price is imposed depending on the automobile's fuel efficiency.

Second, the rate of the automobile weight tax was JPY $12,600$ per 0.5 tons of vehicle weight before April 2010, JPY 10,000 per ton from April 2010 to April 2012, and JPY 8,200 per ton after May 2012.

Third, the automobile tax is an additional tax collected by each prefecture. In recent years, the size of the automobile tax has been modified several times. For instance, the automobile tax on minicars was hiked from JPY $7,200$ to JPY $10,800$, while the range of the automobile tax on normal cars was raised from JPY $29,500$–$111,000$ to JPY $25,000$–$110,000$ in October 2019.

Furthermore, in 2009, a tax reduction was introduced for car models that satisfy criteria based on fuel efficiency and emissions standards. This tax reduction scheme is called the eco-car tax reduction (hereafter ETR). The changes in the tax reduction rates and the criteria of the ETR program are described in Table A2. The eligibility for the tax reduction was revised in 2012, 2014, and 2015. For instance, from 2009 to 2011, the acquisition tax on new cars that met the 2010 fuel efficiency standards by 15% or better and received a four-star rating for the emission standard in 2005 was cut by 50%, while the automobile tax on these cars was reduced by 25%.

Table A2: Eligibility for Tax Reduction Under the ETR program

	Acquisition tax	Weight tax	Automobile tax	
			Normal	Minicar
(1) 2009−2011				
EV, FCV, Plug-in Hybrid, etc.	Exempted	Exempted	50% cut	No exemption
125% or above 2010 standard	75% cut	75% cut	50% cut	
115% or above 2010 standard	50% cut	50% cut	25% cut	
(2) 2012−2013				
EV, FCV, Plug-in Hybrid, etc.	Exempted	Exempted	50% cut	No exemption
120% or above 2015 standard	Exempted	Exempted	50% cut	
110% or above 2015 standard	75% cut	75% cut	50% cut	
100% or above 2015 standard	50% cut	50% cut	25% cut	
(3) 2014				
EV, FCV, Plug-in Hybrid, etc.	Exempted	Exempted	75% cut	No exemption
120% or above 2015 standard	Exempted	Exempted	75% cut	
110% or above 2015 standard	80% cut	75% cut	50% cut	
100% or above 2015 standard	60% cut	50% cut	50% cut	
(4) 2015−2016				
EV, FCV, Plug-in Hybrid, etc.	Exempted	Exempted	75% cut	75% cut
120% or above 2020 standard	Exempted	Exempted	75% cut	50% cut
110% or above 2020 standard	80% cut	75% cut	75% cut	25% cut
100% of above 2020 standard	60% cut	50% cut	75% cut	25% cut
110% above 2015 standard	40% cut	25% cut	50% cut	No exemption
105% above 2015 standard	20% cut	25% cut	50% cut	

Notes: For all tax reductions, automobiles must receive a four-star rating for the emission standards in 2005. ETR: Eco-car Tax Reduction, ES: Eco-Car Subsidy, EV: Electronic Vehicle, FCV: Fuel-Cell Vehicle.

C Measurement of Compensating Variation

C.1 Overview

We measure changes in consumer welfare associated with a price change using compensating variation (hereafter CV), which is the amount of money a consumer would need to be indifferent to the change. Let the baseline price be $\mathbf{p}$ and the counterfactual price $\mathbf{p}'$. The indirect utility is defined as follows:

$$W(\mathbf{p}, y) = \max_{j \in J_i} V_{ij}, \tag{C.1}$$

where $V_{ij} = v_j(p_j, y) + \epsilon_{ij}$ and ϵ_{ij} has the joint cumulative distribution $F(\epsilon_1, \cdots, \epsilon_{J_t})$. In our application, $v_j(p_j, y) = f(y - p_j) + \beta X_j + \xi_j$ holds.

We denote the individual-level CV using cv, which is defined as

$$W(\mathbf{p}, y) = W(\mathbf{p'}, y - cv). \tag{C.2}$$

CV should be interpreted as a random variable because it depends on the idiosyncratic shock $(\epsilon_1, \cdots, \epsilon_{J_t})$. Consequently, we focus on the mean CV $\mathbb{E}(cv)$ as a welfare measure.

If ones assume the linear utility, measuring CV can be relatively straightforward when using the log-sum formula proposed by Small and Rosen (1981). In our paper, we use the theoretical results produced by Dagsvik and Karlström (2005) to calculate $\mathbb{E}(cv)$.[36] Using their method, the computation of CV reduces to a sum of a one-dimensional integral, which can be easily calculated using numerical methods. Moreover, when the idiosyncratic shock $\boldsymbol{\epsilon}$ follows the i.i.d. Type I extreme-value distribution, the calculation of the integral becomes much simpler.

To explain the method proposed by Dagsvik and Karlström (2005), we first define the random expenditure function $Y(\mathbf{p}, u)$ by using the following equation:

$$u = W(\mathbf{p}, Y(\mathbf{p}, u)). \tag{C.3}$$

The expenditure function $Y(\mathbf{p}, u)$ is interpreted as the income level under which the consumer can achieve the utility level of u when the price vector is $\mathbf{p}$.

The CV can be defined as

$$cv = y - Y(\mathbf{p'}, W(\mathbf{p}, y)). \tag{C.4}$$

Using this equation, the expected CV $\mathbb{E}(cv)$ can be obtained by calculating $\mathbb{E}[Y(\mathbf{p'}, W(\mathbf{p}, y))]$.[37] Dagsvik and Karlström (2005) formulates useful theorems to derive the distribution function of the random variable $Y(\mathbf{p}, u)$. Below, we present an overview of this derivation.

[36]Griffith et al. (2018) also use this method to derive the mean CV in their application.

[37]This is because by substituting (C.4) to (C.2), we get $W(\mathbf{p}, y) = W(\mathbf{p'}, Y(\mathbf{p'}, W(\mathbf{p}, y)))$, where the equality must hold by the definition of the expenditure function.

C.2 Derivation of the general case

First, we consider the joint distribution of the random expenditure $Y(\mathbf{p}, u)$ and the optimal choice $J(\mathbf{p}, y)$, which is defined by

$$J(\mathbf{p}, y) = \arg\max_{j \in J} v_j(p_j, y) + \epsilon_{ij}.$$

Theorem 3 of Dagsvik and Karlström (2005) derives the formal expression of this joint distribution:

$$\begin{aligned}\mathbb{P}\left(Y(\mathbf{p}', W(\mathbf{p}, y))\right. &> z, J(\mathbf{p}, y) = i) \\ &= \begin{cases} \int F_i(u - h_1(p_1, y, p_1', z), \cdots, u - h_J(p_J, y, p_J', z))du & \text{if } 0 < z < y_i(p_i, y, p_i') \\ 0 & \text{if } z \geq y_i(p_i, y, p_i') \end{cases}\end{aligned}$$

where F_i denotes the partial derivative of the cumulative distribution $F(\epsilon_1, \cdots, \epsilon_{J_t})$ with respect to i-th input. $h_j(p_j, y, p_j', z)$ is defined by

$$h_j(p_j, y, p_j', z) \equiv \max\left\{v_j(p_j, y), v_j(p_j', z)\right\}$$

and $y_j(p_j, y, p_j')$ is defined by the following equation.

$$v_j(p_j, y) = v_j(p_j', y_j(p_j, y, p_j')).$$

Intuitively speaking, $y_j(p_j, y, p_j')$ is the income level needed to obtain the utility level of $v_j(p_j, y)$ when the price is p_j'.

We now derive the marginal distribution of the random expenditure $Y(\mathbf{p}, u)$, which will be used to calculate $\mathbb{E}[Y(\mathbf{p}', W(\mathbf{p}, y))]$. Corollary 2 of Dagsvik and Karlström (2005) has shown that the marginal distribution is derived as follows:[38]

$$\mathbb{P}(Y(\mathbf{p}', W(\mathbf{p}, y)) > z) = \sum_{i \in \mathbf{J}} I_i(p_i, y, p_i', z) \times \int F_i(u - h_1(p_1, y, p_1', z), \cdots, u - h_J(p_J, y, p_J', z))du.$$

[38] The marginal distribution can be obtained by adding up the joint distribution for goods i, thus satisfying $I_j(p_i, y, p_i', z) = 1$. Note that $z < y_i(p_i, y, p_i')$ is equivalent to $v_j(p_j, y) > v_j(p_j', z)$.

where the indicator function $I_i(p_i, y, p'_i, z)$ is defined as

$$I_i(p_i, y, p'_i, z) = \begin{cases} 1 & \text{if } v_i(p_i, y) > v_i(p'_i, z) \\ 0 & \text{otherwise} \end{cases} \tag{C.5}$$

Using the marginal distribution, we now calculate the expectation $\mathbb{E}(Y(\mathbf{p}', W(\mathbf{p}, y)))$ by

$$\begin{aligned}
\mathbb{E}(Y(\mathbf{p}', W(\mathbf{p}, y))) &= \int_0^\infty Y(\mathbf{p}', W(\mathbf{p}, y)) \cdot d\mathbb{P}(Y(\mathbf{p}', W(\mathbf{p}, y)) \leq z) \\
&= \int_0^\infty \mathbb{P}(Y(\mathbf{p}', W(\mathbf{p}, y)) > z) dz && \text{(C.6)} \\
&= \sum_{i \in \mathbf{J}} \int_0^{y_i(p_i, y, p'_i)} \int F_i(u - h_1(p_1, y, p'_1, z), \cdots, u - h_J(p_J, y, p'_J, z)) du dz && \text{(C.7)}
\end{aligned}$$

The second equality uses Lemma 1 of Dagsvik and Karlström (2005).[39]

C.3 Special Case: i.i.d. Type-1 Extreme Value Distribution

When the idiosyncratic shock follows Type-I extreme value distribution, the integral of choice probability has a closed form expression (McFadden, 1981) [40]. Therefore, in this case, the joint distribution of expenditure function and the choice can be rewritten as, for $z < y_i(p_i, y, p'_i)$,

$$\begin{aligned}
&\mathbb{P}(Y(\mathbf{p}', W(\mathbf{p}, y)) > z, J(\mathbf{p}, y) = i) \\
&= \int F_i(u - h_1(p_1, y, p'_1, z), u - h_2(p_2, y, p'_2, z), \cdots, u - h_J(p_J, y, p'_J, z)) du \\
&= \frac{\exp(h_i(p_i, y, p'_i, z))}{\sum_{k \in \mathbf{J}} \exp(h_k(p_k, y, p'_k, z))} \\
&= \frac{\exp(v_i(p_i, y))}{\sum_{k \in \mathbf{J}} \exp(\max\{v_k(p'_k, z), v_k(p_k, y)\})}
\end{aligned}$$

The final equality holds by the definition of $h_i(p_i, y, p'_i, z)$ and the restriction of $z < y_i(p_i, y, p'_i)$.[41]

[39] Let G be the cumulative distribution function of a random variable x. Lemma 1 of Dagsvik and Karlström (2005) shows that, for any $\alpha \geq 1$, $\int_0^\infty x^\alpha dG(x) = \alpha \int_0^\infty x^{\alpha-1}(1 - G(x))dx$. We apply this lemma when $\alpha = 1$.

[40] This is a special case of the Generalized Extreme Value (GEV) model in which the choice probability of j-th alternative can be expressed as $P_j = \int_{-\infty}^{+\infty} F_j(v_j + \epsilon_j - v_1, \cdots, v_j + \epsilon_j - v_J) d\epsilon_j = y_j G_j / G$ using some function $G(e^{v_1}, e^{v_2}, \cdots, e^{v_J})$ having the following properties: (i) $G(e^{v_1}, e^{v_2}, \cdots, e^{v_J}) \geq 0$ for all j, (ii) G is linearly homogeneous (i.e. $G(\rho e^{v_1}, \rho e^{v_2}, \cdots, \rho e^{v_J}) = \rho G(e^{v_1}, e^{v_2}, \cdots, e^{v_J})$), (iii) $\lim_{v_k \to \infty} G = +\infty$ for all k, and (iv) n-th order derivative is non-negative if n is odd, and non-positive if n is even. When the error term follows Type-I extreme value distribution, the function G corresponds to $G = \sum_{j \in \mathbf{J}} e^{v_j}$. See McFadden (1981) for details.

[41] $z < y_i(p_i, y, p'_i)$ is equivalent to $v_i(p_i, y) > v_i(p'_i, z)$. Thus, $h_i(p_i, y, p'_i, z) = \max\{v_i(p_i, y), v_i(p'_i, z)\} = v_i(p_i, y)$.

Based on this result, the probability distribution of the expenditure function can be derived as follows:

$$\mathbb{P}(Y(\mathbf{p}', W(\mathbf{p}, y)) > z) = \sum_{i \in \mathbf{J}} I_i(p_i, y, p_i', z) \frac{\exp(v_i(p, y))}{\sum_{k \in \mathbf{J}} \exp(\max\{v_k(p_k', z), v_k(p_k, y)\})}$$

Finally, by (C.7), the expectation of expenditure function is

$$\mathbb{E}(Y(\mathbf{p}', W(\mathbf{p}, y)) = \sum_{i \in \mathbf{J}} \int_0^{y_i(p_i, y, p_i')} \frac{\exp(v_i(p_i, y))}{\sum_{k \in \mathbf{J}} \exp(\max\{v_k(p_k', z), v_k(p_k, y)\})} dz,$$

which is the final result of Corollary 5 of Dagsvik and Karlström (2005).

As we argued at the beginning of this section, the computation of $\mathbb{E}(cv)$ reduces to the sum of a one-dimensional integral under the standard assumptions (i.e. the error term follows Type-I extreme value distribution). Furthermore, in our counterfactual analysis, because none of the automobile characteristics change except for the price, $y_i(p_i, y, p_i')$ can be derived by $y_i(p_i, y, p_i') = y + p_i' - p_i$. Finally, by applying the technique of numerical integration (e.g., Gauss-Legendre quadrature), we can compute the expectation of expenditure function and the expectation of CV.

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