Abstract

Quantifying the Effect of Transaction Costs on Automobile Replacement

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This study extends the structural dynamic demand model for new and used durable goods proposed by Schiraldi (2011) and applies the random coefficients discrete choice approach to model consumer heterogeneity in demand and consumer forward-looking behavior. Specifically, I estimate the time- and product-specific transaction costs incurred in the purchase of automobiles with vehicle registration data from South Korea. A combination of the contraction mapping technique (Berry et al., 1995) and the nested fixed point algorithm (Rust, 1987) enables separate identification of the unobserved transaction costs and the unobserved product characteristics. Counterfactual experiments with arbitrary transaction costs as an input imply the significant impact of transaction costs on demand, which offers rich marketing implications.

Keywords: Durable Goods, Demand Estimation, Random Coefficients Discrete Choice Model, Used Good Market, Dynamic Programming, Transaction Costs

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1. Introduction

A market for durable goods is characterized by the infrequency of repeat purchase. In the case of automobiles, several years are needed for a vehicle to be replaced. This persistence of consumer holdings of vehicles, despite the depreciation of product quality, as Schiraldi (2011) explains, is attributed to the presence of transaction costs. Transaction costs include switching costs, search costs, taxes, and other financial and psychological costs incurred in purchase that are not captured by price. According to the utility theory, without these frictions, a rational consumer would evaluate available options in each time period and choose a quality net of price that maximizes utility given budget constraints, which would make replacements much more frequent than what is actually observed in the market. Since the transaction costs make replacement more costly and thus affect consumer decisions in purchase timing, estimating the transaction costs would play an important role in understanding automobile replacement behavior. If the variation of transaction costs across the available products and the effects of those frictions on sales can be measured, rich managerial implications can be drawn from the analysis.

Another important feature of the automobile market is that consumers are forward-looking, taking future expected market values into account to make purchase decisions. With the information on future market values such as expected price discounts, consumers are motivated to evaluate the current and future market value of each available option when they make replacement decisions. Along with the time-varying transaction costs incurred in purchase, consumer expectations on future market values result in substitutions across time periods, which shapes purchase decisions to be dynamic.

Recent expansion of the secondary market is also a significant factor that has changed the pattern of demand for automobiles. It has turned a used car at a relatively low price into a major substitute for new products. According to the 2010 report by the Korea Ministry of Land, Infrastructure, and Transport, trading volume of the used car market has become twice as large as that of the primary market. Given a larger choice set and greater chances for resale, consumers consider the current and future resale values of their holdings as well as the value of each available product to choose when and what to buy.

However, most empirical studies about automobile demand show limitations on accounting for transaction costs, dynamic nature of the demand, and used product purchases. Many studies focus on the static demand for new vehicles (Berry, Levinsohn, and Pakes, 1995, hereafter, BLP; Petrin, 2002). Also, most of the literature on durable goods demand do not model repeat purchases, ignoring the effect of a consumer's current holding on future purchase decision. As a result, the transaction costs, which can be characterized as a difference between the utility of purchase and the utility of holding,[1] cannot be identified in the studies using an optimal stopping model.

Schiraldi (2011) attempts to incorporate secondary market transactions into the dynamic demand model. The study sets consumer utility to depend on both current holdings and future expected market values, and estimates transaction costs by utilizing the model that combines the nested fixed point algorithm (Rust, 1987) with the market share inversion technique (BLP). The study uses individual primary

[1] Identification of the transaction costs is discussed in Section 5.4.

and secondary transaction data from the Province of Isernia in Italy. The data allows the author to separately track the shares of consumers who hold ownership of a product and the shares of consumers who purchase the same vehicle. With an insight that the difference between the two shares comes from the presence of transaction costs, he conducts two BLP-type contraction mappings on the two market shares and extracts time-varying product-specific transaction costs from unobservable car characteristics.

Employing the Schiraldi (2011) model, I investigate the effect of transaction costs on dynamic replacement behavior in the automobile market in South Korea (hereafter, Korea) when the used products are available. In particular, I use 2012-2014 vehicle registration data from Yangchun district, Seoul, and examine the patterns of car ownerships and car purchases for each car model and year. Model-specific and age-specific average prices of new and used vehicles assessed each year are obtained from the Korea Insurance Development Institute. I retrieve car characteristics including engine displacement (cc) and design (sedan, hatchback) from the vehicle identification numbers listed in the registration data, and supplement some information from NAVER Car, a major internet portal site in Korea. I focus on private passenger cars and exclude trucks and vans from the dataset. The dataset accounts for approximately 95% of the registered vehicles in the area.

Given the estimated utility parameters and the unobserved car characteristics, I run a set of counterfactual experiments by recalculating the market shares with arbitrary transaction costs. I investigate how change in the transaction costs might affect the market shares of consumer holdings and car purchases.

The intended contribution of this research is twofold. First, although the

model and estimation procedure that I use are almost the same with those of Schiraldi (2011), the research objective is not to measure the magnitude of the transaction cost itself, but to analyze the impact of the costs on sales generation. I apply an advantage of structural modeling, which enables policy evaluation, and quantify the potential effect of changes in consumer perceived transaction costs on market share and market size. These counterfactual experiments emphasize the importance of managing consumer perception on transaction costs, and thus suggest rich managerial implications to automobile manufacturers. Automobile manufacturers might investigate which type of products face high transaction costs and thus develop effective marketing plans accordingly to lower the transaction costs.

Second, while Schiraldi (2011) constructs a single probability matrix for each of the two stated variables, I construct different transition probability matrices for different types of products. Schiraldi (2011) assumes that, no matter which product *j* a consumer holds or considers to purchase, the net augmented utility flow ϕ_{ijt} evolves according to the same first-order Markov process.[2] However, in the automobile market in Korea, price depreciation rates are expected to be different across brand, size, or other physical product characteristics. In particular, according to market research conducted in 2010 by the used car website *Cars*,[3] the brands that released new models more frequently face higher price depreciation rates, which led Hyundai products to depreciate more rapidly than Renault Samsung products. To reflect this market feature, I allow that consumers expect the net augmented utility

[2] The net augmented utility flow refers to the utility earned from the product net of the per-period price, which is discussed in Section 4.2. Construction of the transition probability matrices is discussed in Section 4.3.
[3] "How much would my car cost after 2 years?" *AutoM*, November 23, 2010.

flow to depreciate differently across brands. I divide the brands into three groups: brands with frequent model changes (e.g., Hyundai), brands with less frequent changes (e.g., other domestic brands), and foreign brands. Then, I construct a distinct transition probability matrix with different Markov coefficients for each group. This process reflects the consumer's awareness of different depreciation ratio across the brands.

An additional minor change is applied in the data grouping process. Different from what Schiraldi (2011) proposes, I categorize the vehicles in a way more consistent with consumer perceptions by using survey data about choice criteria in automobile purchase (Figure 1).

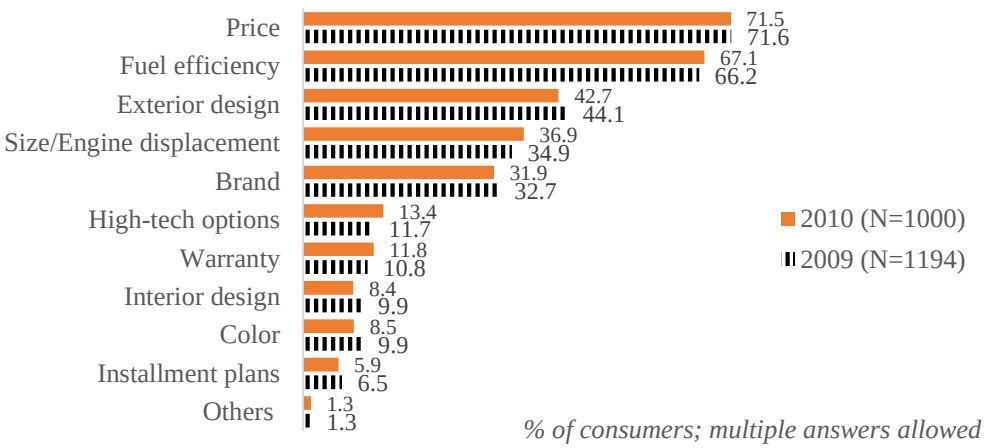


Figure 1. Survey results on automobile selection criteria[4]

Considering the consumer choice criteria, I group the data into 720 categories based on brand (Hyundai, other domestic brands, or foreign brands), type of fuel (gasoline or others), design (sedan or others), engine displacement (less than

[4] The data is from an annual survey conducted by Trend Monitor, a Korean consumer research company. http://www.zdnet.co.kr/news/news_view.asp?artice_id=20100729113646, July 29, 2010.

1000cc, less than 1500cc, less than 2000cc, less than 2500cc, less than 3000cc, 3000cc or more), and the vehicle age (0, …,9), where 0 is a new car and 9 is a car 9 years or older. The inclusion of fuel type and engine displacement together well reflects fuel efficiency, which is the second-most important selection criterion. Although this different categorization may not have significant implications, different results generated by different data management suggest the need for efficient and realistic aggregation of the data.

Table 1. Automobile Product Categorization

	Schiraldi (2011)	Current study
Brand	3 levels	3 levels
Engine	3 levels	6 levels
Exterior design	Not included	2 levels
Fuel type	2 levels	2 levels
Age	10 levels	10 levels

The rest of the paper is organized as follows. Section 2 reviews the existing literature about durable goods demand. Section 3 describes the data and provides snapshots of the market features. Section 4 discusses the model, and Section 5 outlines the estimation procedure and identification issue. Section 6 reports the estimation results and the insights from counterfactual experiments. Section 7 concludes the article and discusses future research directions.

2. Literature review

2.1. Static discrete choice model

Many empirical studies about durable goods market focus on estimating heterogeneous demand of differentiated products in static setting. Berry (1994) proposes a market share inversion technique that retrieves mean utility level of each differentiated product from aggregate sales data and uses linear instrumental variables method to account for price endogeneity. Extending the idea, BLP (1995) introduce generalized method of moments estimation procedure that accounts for unobserved product characteristics and consumer heterogeneity, and obtain supply and demand parameters of the U.S. automobile industry given aggregate level data. Petrin (2002) supplements BLP's method by adding a set of micro-moments with consumer survey data. Although BLP's framework and its variation explicitly consider the price endogeneity and consumer heterogeneity that allow for consistent estimates and richer implications, most of them ignore the option of purchasing used vehicles and lump it into an outside good. Goldberg (1995) employs a nested logit model to include consumer decision between purchasing new and used vehicles, but it abstracts the option of used car purchase by modeling "average" used car instead of individual models as an alternative. Another shortcoming of the literature using a static model, as Goldberg (1995) points out, is that it ignores the effect of consumer expectations about future market conditions on purchase decisions and thus fails to take inter-temporal substitution patterns into account. Failure to address these two issues – the secondary market transactions and the time-dependent purchase decisions – is critical especially in automobile demand analysis because of the durability of the products and the wide availability of various used good options.

2.2. Dynamic discrete choice model with no repeat purchases

Starting from Erdem amd Keane (1996), there have been studies about various industries that take structural approaches to incorporate dynamic nature of consumer purchase decision. The key assumption that most of these researches share is that consumers believe the state variables to evolve in the first-order Markov process, which means that the state at time *t* depends only on the state at time *t-1*. Works on dynamic demand of consumption goods include Gönül and Srinivasan (1996), which models consumer expectation on coupon availability and estimates its effect on sales using scanner panel data of disposable diaper products. Researches about dynamic demand of durable goods mainly focus on new product diffusion. Song and Chintagunta (2003) measure the impact of consumer expectation about future prices on new product diffusion in the digital camera market; Melnikov (2013) uses the logit inclusive value as a sufficient statistic for the distribution of future payoffs to analyze the new product purchase pattern in the U.S. computer printer market.

These papers suggest significant evidence of consumer forward-looking behavior and the inter-temporal substitution in demand, which emphasizes the appropriateness of dynamic structural modeling in demand estimation. However, as in the static model literature, most of the researches ignore the presence of used goods market. Since the trading volume of used vehicles almost doubles that of new products in Korea, the demand model needs to be extended to treat used cars as available substitutes.

Also, many papers on durable goods demand do not consider repeat purchases and assume that consumers leave the market as soon as they make purchases. However, in the actual market, consumers take into account not only the

future values of possible alternatives but also the future values of their current holdings to decide when to replace. Since consumers continue to evaluate the market even after purchase to optimize on their replacement, the optimal stopping model that presumes an immediate exit of a consumer after purchase should be modified to analyze the automobile demand.

2.3. Dynamic discrete choice model of durable goods in the presence of repeat purchases and used good markets

There have been much fewer empirical studies on dynamic demand that model repeat purchases in durable goods markets. Extending Melnikov (2013)'s idea that uses the logit inclusive value as a one-dimensional state variable, Gowrisankaran and Rysman (2012) construct a model that allows for consumer heterogeneity and repeat purchases by defining consumer-specific utility to depend on what consumers currently own. The study combines BLP technique which estimates static demand with Rust (1987)'s nested fixed point algorithm to account for forward-looking behavior of consumers.

Using a similar technique that ,Gowrisankaran and Rysman (2012) propose, Schiraldi (2011) develops a more generalized model that allows for used good purchases and product-specific transaction costs. It identifies the transaction costs – a term that includes search costs, switching costs, taxes, and other kinds of costs not accounted by the prices – from unobserved product characteristics by using two different market shares data: market shares for purchases and those for holdings. With an insight that the difference between the two shares come from the presence of frictions, it conducts two BLP-type contraction mappings on the two market shares to extract the transaction costs from unobservable car characteristics.

Limitations of his model lies on the Independence of Irrelevant Alternatives (IIA) property of a simple logit model; instead of nesting the product choice decision under the purchase decision, he models no purchase option parallel with other product choice options.

Ishihara (2012) estimates the transaction costs with the presence of used products in the Japanese video game market, but using the Bayesian Markov Chain Monte Carlo (MCMC) algorithm instead of BLP technique. Using a nested logit model, he employs the Bayesian method with simulated draws to derive the posterior distribution of parameter vectors.

3. Data

I use monthly vehicle registration data of Yangchun district from 2012 to 2014 provided by the Korea Ministry of Land, Infrastructure, and Transport. The dataset contains information on car model, year of production, and whether the transaction was primary or secondary. I observe the initial set of 115,820 registered vehicles in the district and subsequent 70,168 transactions excluding dealer transactions. Information on car characteristics including brand, size, type (sedan or hatchback), and engine displacement are collected either from the vehicle identification numbers or from NAVER Car, a website operated by a major portal in Korea. Model- and age-specific average prices of used vehicles, assessed each year, are obtained from the Korea Insurance Development Institute.

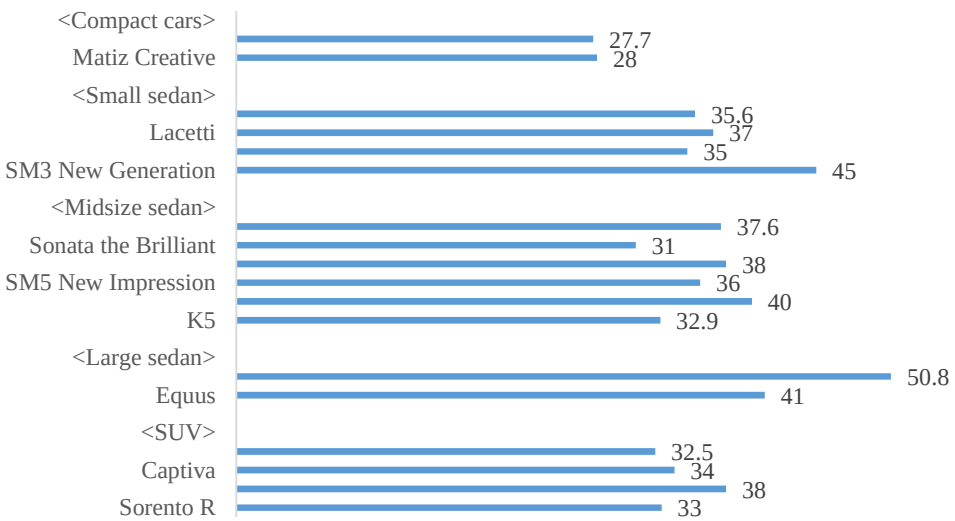


Figure 2. Time spent for a used vehicle to be sold[5]

Figure 2 shows the average time spent for a used car to be sold. This

[5] The data is obtained from the SK Encar website, an online used car market operated by one of the large conglomerates in Korea. (http://www.encar.com)

snapshot shows that the time spent for resale varies across the products, indicating that product-specific transaction costs are present in the market. Comparison between NF Sonata transform and Sonata the Brilliant, the two (old and new) models from the same product line, implies that the transaction costs can also be time-varying.

Table 2 and 3 show the descriptive statistics. Both tables suggest that the number of used car purchases is almost twice as large as that of new car purchases, which is consistent with the 2010 report by the Korea Ministry of Land, Infrastructure, and Transport (Table 3). The significant volume of secondary transactions implies that including used good purchases to the dataset is crucial for proper estimation of automobile replacement behavior.

Table 2. Descriptive statistics (2012 – 2014)

		Quantity sold			
	Quarter	New	Used	Scrappage	Total
2012	1	2327	3700	1464	7491
	2	2116	3640	1442	7198
	3	1972	2575	1347	5894
	4	2049	3575	1295	6919
2013	1	2031	3949	1241	7221
	2	2047	4043	1348	7438
	3	2022	4139	1211	7372
	4	1778	4208	1143	7129
2014	1	2798	5512	1600	9910

Table 3. Ratio of new and used good purchases across the brands

	Domestic	Imported
New	16762	3010
Used	33097	4694
Total	49859	7704
Used/New	**1.97**	**1.56**

Figure 3 illustrates the variations in sales volume of used cars in 2012. Foreign brands show a higher purchase rate of "new used" cars than domestic brands do, which indicates that the popularity of used cars varies across the brands and across the car age. Distinct patterns of purchase shares and holding shares of different products in Figure 4 suggest the existence of product-specific transaction costs which affect consumers' purchase and ownership decisions. Table 4 and 5 describe the demographics of Yangchun district.

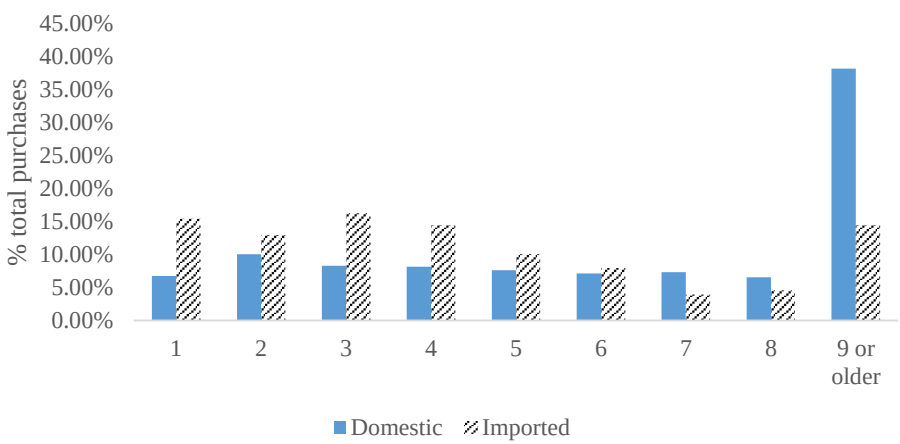


Figure 3.Purchase of used cars (2012)

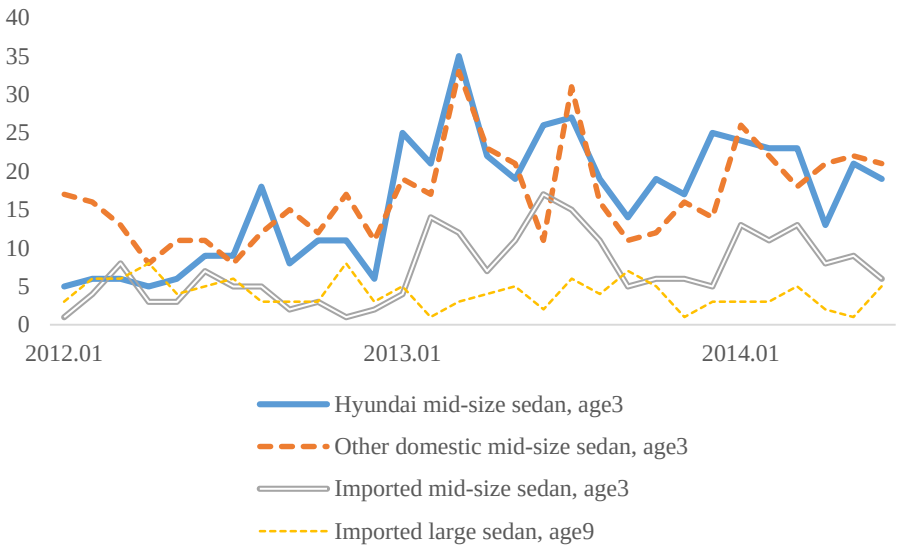


Figure 4. Number of monthly purchases

Table 4. Vehicles per person

	Number of vehicles (per person)		
	2011	2012	2013
Yangchun, Seoul	0.29	0.30	0.30
Seoul	0.29	0.29	0.29

Table 5. Income distribution

	Average income	less than ₩1M	less than ₩2M	less than ₩3M	less than ₩4M	less than ₩5M	₩5M or more
Yangchun, Seoul	₩3.62M	5.9%	13.7%	21.6%	27.1%	15.3%	16.4%
Seoul	₩3.24M	7.7%	12.6%	20.3%	21.4%	13.0%	25.0%

*Seoul Survey, 2008

4. Model

The model setting is mostly the same with that of Schiraldi (2011). Following are the terms used in the model.

t subscript indexes time period.

i subscript indexes consumer.

k, j subscript indexes product. *k* often refers to the initial endowment, and *j* refers to the product after replacement. $j = 0$ refers to the outside option, which means no purchase.

$\boldsymbol{j_t}$ refers to the set of new cars available in period t.

$J_t = \{j : j \in \{\cup_{\tau=1}^{t} \boldsymbol{j_\tau}\}\}$ refers to the set of all products purchasable in period t in the primary or secondary market.

p_{jt} refers to the price of the product j at time t. $p_{0t} = 0$.

x_{jt} refers to the vector of observed product characteristics including price.

ξ_{jt} refers to the unobserved (by researchers) product characteristics. This term can also be interpreted as the unobserved demand shocks.

τ_{jt} refers to the unobserved (by researchers) transaction cost. The transaction cost captures the presence of search costs, switching costs, financial costs, and other types of costs not characterized by price; it is assumed to be paid by consumers (along with the price) every time they purchase the product j at time t.

$\epsilon_{it} = \left(\epsilon_{i0t}, \epsilon_{i1t}, \dots, \epsilon_{iJ_t t}\right)$ refers to the vector of idiosyncratic demand shocks, which are assumed to follow type 1 extreme-value distribution and to be *i.i.d.* across *i*, *j*, and *t*.

s_{it} refers to the set of state variables.

$\beta \in (0,1)$ refers to the discount factor. Here, β is set to be 0.8.

4.1 Consumer utility

Consider an infinite horizon stationary dynamic model with finite types of products. Consumers maximize their expected lifetime utility given a discount factor. A single-period utility of consumer *i* at time *t* is the following:

1) If the consumer *i* keeps her holding *k* $(k \in J_{t-1} \cup \{0\})$

$$u_{it}^{k} = x_{kt}\alpha_i^x + \xi_{kt} + \epsilon_{ikt},$$
$$u_{it}^{0} = \epsilon_{i0t}. \tag{1}$$

2) If the consumer *i* replaces her holding *k* to a different car $j \in J_t$

$$u_{it}^{kj} = x_{jt}\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \alpha_i^p p_{kt} + \epsilon_{ijt}. \tag{2}$$

3) If the consumer *i* sells her holding *k* and does not make any purchase

$$u_{it}^{k0} = \alpha_i^p p_{kt} + \epsilon_{i0t}. \tag{3}$$

Then, the time invariant value function of consumer *i* with endowment *k* is the maximum of the present discounted sum of expected utility,

$$\max_{\{a_t\}_{t=0}^{\infty}} E\left\{\sum_{t=0}^{\infty} \beta^t R_i(k, a_t) | s_{it}, \epsilon_{it}\right\},$$

where $a_t = \{d, j\}$ is the set of possible actions that a consumer can take at time *t*, *d* = 0 (keep), *d* =1 (replace), $j \in J_t \cup \{0\}$ is the optimal replacement at time *t* if *d* = 1, and s_{it} is the set of state variables including product characteristics of available cars and any other market value that affect consumer utility. s_{it} is assumed to evolve according to the first-order Markov process $Pr(s_{it+1}|s_{it})$. The return function *R* is

given by

$$R_i(k, a_t) = \begin{cases} u_{it}^{k} & \text{if } d = 0 \\ u_{it}^{kj} & \text{if } d = 1 \text{ and } j \in J_t \cup \{0\}. \end{cases}$$

If R is bounded, then a consumer's value function of being in the car market can be expressed as the following Bellman equation:

$$\widehat{V}_i(k, \epsilon_{it}, s_{it}) = \max \left\{ \begin{array}{c} u_{it}^{k} + \beta \mathrm{E}\left[\widehat{V}_i(k, \epsilon_{it+1}, s_{it+1}) \middle| s_{it}, \epsilon_{it}\right], \\ \max_{j \in J_t}\left(u_{it}^{kj} + \beta \mathrm{E}\left[\widehat{V}_i(j, \epsilon_{it+1}, s_{it+1}) \middle| s_{it}, \epsilon_{it}\right]\right), \\ 1[k \neq 0] \cdot \left(u_{it}^{k0} + \beta \mathrm{E}\left[\widehat{V}_i(0, \epsilon_{it+1}, s_{it+1}) \middle| s_{it}, \epsilon_{it}\right]\right) \end{array} \right\}. \tag{4}$$

4.2 Definition of the state space and the expected value function

Since the state space includes all the variables that affect consumer utility, its large dimension requires heavy computational costs. To reduce the dimension to make the model computationally tractable, following Schiarldi (2011), I first subtract the term $\alpha_i^p p_{kt}$ from (4) and substitute (1), (2), and (3) to rewrite the Bellman equation:

$$V_i(k, \epsilon_{it}, s_{it}) = \max \left\{ \begin{array}{c} x_{kt}\alpha_i^x + \xi_{kt} + \epsilon_{ikt} - \alpha_i^p p_{kt} + \beta \mathrm{E}\left[\alpha_i^p p_{kt+1} + V_i(k, \epsilon_{it+1}, s_{it+1}) \middle| s_{it}, \epsilon_{it}\right], \\ \max_{j \in J_t}\left(x_{jt}\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \epsilon_{ijt} + \beta \mathrm{E}\left[\alpha_i^p p_{jt+1} + V_i(j, \epsilon_{it+1}, s_{it+1}) \middle| s_{it}, \epsilon_{it}\right]\right), \\ \epsilon_{i0t} + \beta \mathrm{E}[V_i(0, \epsilon_{it+1}, s_{it+1}) | s_{it}, \epsilon_{it}] \end{array} \right\} \tag{5}$$

where the first line is the alternative-specific value function for keeping endowment k, the second line is the alternative-specific value function for replacing k with j, and the last line is the alternative-specific value function of selling k and making no

purchase.

Let ϕ_{ijt} define the net augmented utility of consumer *i* with endowment *j* which consists of utility from product characteristics (both observed and unobserved) and disutility from per-period price:

$$\phi_{ijt} \equiv x_{jt}\alpha_i^x + \xi_{jt} - \alpha_i^p\left(p_{jt} - \beta \mathrm{E}\left[p_{jt+1}\right]\right). \tag{6}$$

$(p_{jt} - \beta \mathrm{E}[p_{jt+1}])$ can be viewed as a "rental price" – the cost of using product *j* for one period. Note that $\phi_{i0t} = 0$. Also, I define the mean net augmented utility as $\hat{\phi}_{jt} \equiv x_{jt}\alpha^x + \xi_{jt}$, which is a product- and time-specific mean net augmented utility without consumer-specific elements. $\hat{\phi}_{jt}$ is used in the contraction mapping like δ in BLP (1995), which is discussed in Section 5. It is useful for estimation to rewrite the individual net augmented utility ϕ_{ijt} using the mean utility:

$$\phi_{ijt} \equiv \hat{\phi}_{jt} + foreign_{jt}\sigma_f\omega_i - \sigma_p\nu_i\left(p_{jt} - \beta \mathrm{E}\left[p_{jt+1}\right]\right) \tag{6'}$$

Following Melnikov (2012) and Schiraldi (2011)'s approach, I define consumer *i*'s maximum expected utility from buying one of the J_t products and use it as a state variable that represents the distribution of future payoffs. Since ϵ_{it} is assumed to follow *i.i.d.* type 1 extreme-value distribution, this maximum expected utility, called logit inclusive value, can be written as the logarithm of the sum of the mean expected discounted utility of each option:

$$\delta_{it} = \ln\left(\sum_{j\in J_t} \exp\left(\phi_{ijt} - \tau_{jt} + \beta \mathrm{E}_s[\mathrm{E}_\epsilon V_i(j, s_{it+1})|s_{it}]\right)\right). \tag{7}$$

To reduce the dimension of the state space, I assume that consumers predict

the market values in the next period only based on limited information provided in the current state, which is the assumption used by most literature on dynamic demand (Hendel and Nevo, 2006; Gowrisankaran and Rysman, 2012; and Schilardi, 2011).

Assumption 1. Consumer i perceives $(\phi_{ijt}, \delta_{it})$ as a representative information of the market which evolves according to a first-order Markov process:

$$G_i\left(\phi_{ijt+1}, \delta_{it+1} \middle| s_{it}\right) = G_i(\phi_{ijt+1}, \delta_{it+1} | \phi_{ijt}, \delta_{it})$$

The assumption implies that $(\phi_{ijt}, \delta_{it})$ contains all the relevant information that consumers use to evaluate the market conditions. It conforms to the bounded rationality assumption, which suggests that consumers use only a subset of available information to make evaluations. Expression of the state space only with the two variables can be restrictive since different combinations of market and product characteristics can be expressed as the same value of $(\phi_{ijt}, \delta_{it})$. However, this dramatic reduction of the state space relieves the computational burden and makes the estimation tractable.

Given the property of type 1 extreme-value distribution and the previous assumptions, the expected value function can be written as follows:

$$\begin{aligned} EV_i(\phi_{ikt}, \delta_{it}) &\equiv E_{\epsilon'} V_i(s_{it}) = E_{\epsilon'} V_i(\phi_{ikt}, \delta_{it}) \\ &= \ln(\exp(\delta_{it}) + 1[k \neq 0] \cdot \exp(\phi_{ikt} + \beta E_{s'}[EV_i(\phi_{ikt+1}, \delta_{it+1} | \phi_{ikt}, \delta_{it})] \\ &+ \exp(\beta E_{s'}[EV_i(0, \delta_{it+1} | \phi_{ikt}, \delta_{it})])) \end{aligned} \tag{8}$$

4.3. Construction of transition probability matrix

Simplifying Schiraldi (2011)'s assumption, I assume that the Markov processes of $(\phi_{ijt}, \delta_{it})$ are expressed in the linear functional form:

$$\delta_{it+1} = \rho_{1i} + \rho_{2i}\delta_{it} + \eta_{it} \tag{9}$$

$$\phi_{ijt+1} = \gamma_{1i} + \gamma_{2i}\phi_{ijt} + \upsilon_{ijt} \quad \text{(for each brand)} \tag{10}$$

I discretize the state space $(\phi_{ijt}, \delta_{it})$ by dividing each variable into 20 evenly dispersed grid points. Using the Markov coefficients obtained via linear regression of (9) and (10), I compute the transition probability matrix in the following way.

i. Let δ denote one of the discretized value of δ_{it} and δ' denote the next period (discretized) logit inclusive value.

ii. Given δ, the mean of δ' is $\mu(\delta) = \rho_{1i} + \rho_{2i}\delta$.

Given δ, the variance of δ is $\sigma^2(\delta) = var(\eta_{it})$.

iii. I assume $\delta' \sim N(\mu(\delta), \sigma^2(\delta))$.

iv. Then, the transition probability of δ' conditional on δ_{it} is given by

$$\Pr(\delta'|\delta) = p = \frac{1}{\sigma(\delta)\sqrt{2\pi}}\, e^{-\frac{\left(\delta' - \mu(\delta)\right)^2}{2\sigma^2}}$$

v. I construct the transition probability matrix by normalizing sum of each row to be equal to 1.

Similarly, three transition probability matrices for ϕ_{ijt} (Hyundai, other domestic brands, foreign brands) are computed. These transition probability matrices are used to calculate the expected value function in which expectation is taken over the state variables. To be more specific, I compute four distinct alternative-specific

value functions via iteration given four transition probability matrices.[6]

4.4 Individual choice probability

For the estimation of market demand, I first calculate the individual-specific probability of holding the endowment and probability of making purchase for each product at each time period using the state variables $(\phi_{ijt}, \delta_{it})$ and the expected value function $EV_i(\phi_{ikt}, \delta_{it})$.

The probability that consumer *i* with endowment $k \in J_{t-1} \cup \{0\}$ makes a replacement to product $j \in J_t \cup \{0\}$ at time *t* is given by

$$d_{it}^{kj} = \frac{\exp\left(\phi_{ijt} - \tau_{jt} + \beta E_{s'}\left[EV_i\left(\phi_{ijt+1}, \delta_{it+1}\right)\middle|\delta_{it}, \phi_{ijt}\right]\right)}{\exp(\delta_{it}) + \exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}]) + 1[k \neq 0] \cdot \exp(\phi_{ikt} + \beta E_{s'}[EV_i(\phi_{ikt+1}, \delta_{it+1})|\delta_{it}, \phi_{ikt}])}. \tag{11}$$

For clear illustration, I write the replacement probability when the initial endowment is the outside good (k= 0) and when the replacement is no purchase option (j= 0) respectively:

$$d_{it}^{0j} = \frac{\exp\left(\phi_{ijt} - \tau_{jt} + \beta E_{s'}\left[EV_i\left(\phi_{ijt+1}, \delta_{it+1}\right)\middle|\delta_{it}, \phi_{ijt}\right]\right)}{\exp(\delta_{it}) + \exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}])}, \quad (j \neq 0)$$

$$d_{it}^{k0} \quad (k \neq 0)$$

$$= \frac{\exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}])}{\exp(\delta_{it}) + \exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}]) + 1[k \neq 0] \cdot \exp(\phi_{ikt} + \beta E_{s'}[EV_i(\phi_{ikt+1}, \delta_{it+1})|\delta_{it}, \phi_{ikt}])}.$$

[6] $EV_i(0, \delta_{it})$, $EV_i(\phi_{ikt}, \delta_{it}|k \in J_{Hyundai})$, $EV_i(\phi_{ikt}, \delta_{it}|k \in J_{Other\ domesic\ brands})$, $EV_i(\phi_{ikt}, \delta_{it}|k \in J_{Foreign})$

The probability that consumer *i* with endowment $k \in J_{t-1} \cup \{0\}$ decides to keep her ownership at time *t* is given by

$$\tilde{d}_{it}^{k} = \frac{\exp\left(\phi_{ikt} + \beta E_{s'}\left[EV_i(\phi_{ikt+1}, \delta_{it+1}) \middle| \delta_{it}, \phi_{ijt}\right]\right)}{\exp(\delta_{it}) + \exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}]) + 1[k \neq 0] \cdot \exp(\phi_{ikt} + \beta E_{s'}[EV_i(\phi_{ikt+1}, \delta_{it+1})|\delta_{it}, \phi_{ikt}])}. \tag{12}$$

For illustrative purpose, I write the holding probability when the initial endowment is the outside good (*k=0*):

$$\tilde{d}_{it}^{0} = \frac{\exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}])}{\exp(\delta_{it}) + \exp(\beta E_{s'}[EV_i(0, \delta_{it+1})|\delta_{it}])}.$$

According to the definition of probabilities, given any endowment *k*, the sum of probabilities of all possible choices is equal to 1.

$$\sum_{j \in J_t \cup \{0\}} d_{it}^{kj} + \widetilde{d_{it}^{k}} = 1.$$

4.5 Aggregate demand

Let ms_{ikt-1} refer to the share of type-*i* consumers who own *k* at time *t-1*. Then, the share of type-*i* consumers with endowment *k* who buy *j* at time *t* is given by

$$ms_{ijt}^{B} = \sum_{k \in J_{t-1} \cup \{0\}} d_{it}^{kj} ms_{ikt-1}.$$

The share of type-*i* consumers who hold the endowment *k* at time *t* is given by

$$\widetilde{ms}_{ijt}^{H} = \tilde{d}_{it}^{k} ms_{ikt-1}.$$

Iteratively, ms_{ijt}, the total share of type-*i* consumers who have *j* at period *t*, is computed as the sum of the two shares above:

$$ms_{ijt} = ms_{ijt}^{B} + \widetilde{ms}_{ijt}^{H}.$$

The unconditional share of consumers who buy *j* at time *t*, denoted by s_{jt}^{B}, is obtained by integrating out s_{ijt}^{B} over consumer preferences:

$$ms_{jt}^{B} = \int_{\nu_i} \sum_{k \in J_{t-1} \cup \{0\}} d_{it}^{kj} ms_{ikt-1} dP_{\nu} \tag{13}$$

Similarly, the unconditional share of consumers who hold *k* at time *t* is given by

$$\widetilde{ms}_{kt}^{H} = \int_{\nu_i} d_{it}^{k} ms_{ikt-1} dP_{\nu}. \tag{14}$$

The total unconditional market share of product *j* at time *t* is

$$ms_{jt} = ms_{jt}^{B} + \widetilde{ms}_{jt}^{H}$$

These predicted market shares of consumer purchases and ownerships, which are constructed by aggregating individual choice probabilities defined in the previous section, are used to identify the unobserved product characteristics ξ_{it} and the unobserved transaction costs τ_{jt}.

5. Estimation

The main idea of identifying the transaction costs is the following. From the monthly registration data of each car model at each car age, I can derive the two distinct market shares: the share of product *j* held by its owner from time *t-1* to time *t*, and the share of the same product *j* purchased at time *t*. Given that all the *j*'s in the market have the same observed car characteristics, the only source of difference between the two market shares – the incentive that makes consumers stick to their products rather than purchase different goods – is the transaction costs; while consumers who decide to keep their endowment *j* at time *t* would have the net augmented utility flow ϕ_{ijt}, consumers who buy *j* at *t* would earn the net augmented utility flow net of the transaction cost, $\phi_{ijt} - \tau_{jt}$. So, after Schiraldi (2011), I conduct two BLP contraction mappings with the two market shares to separately identify unobserved product characteristics and the transaction costs.

For comparison, I estimate both static and dynamic models with and without transaction costs. Description of the static models is in Appendix.

5.1. Parameters to be estimated

I set the total market size *M* to be equal to the number of households in Yangchun district. I model the price coefficient α_i^p to be independently and normally distributed with mean α_p and standard deviation σ_p. The Foreign brand dummy coefficient $\alpha_i^{foreign}$ is assumed to be normally distributed with mean $\alpha^{foreign}$ and standard deviation σ_f. Because of computational issue, I assume that consumers are homogeneous in preferences over other product characteristics.

Table 6 summarizes the parameters to be estimated.

Table 6. List of parameters to be estimated

Nonlinear parameters, θ_1	Description
σ_p	Price coefficient. $\alpha_i^p = \alpha^p + \sigma_p \nu_i$, where $\nu_i \sim N(0,1)$.
σ_f	Foreign brand coefficient. $\alpha_i^{foreign} = \alpha^{foreign} + \sigma_f \omega_i$, where $\omega_i \sim N(0,1)$.
Linear parameters, θ_2	**Description**
α^x	$= (\alpha^p, \alpha^{age}, \alpha^{deisgn}, \alpha^{fuel}, \alpha^{domestic}, \alpha^{foreign}, \alpha^{engine})$

Following Schiraldi (2011), given a nonlinear parameter vector θ_1 in each iteration, I retrieve the unobserved product characteristics and the transaction costs (ξ_{jt}, τ_{jt}) that match the predicted market shares with the actual data via contraction mapping. As (ξ_{jt}, τ_{jt}) converge, the set of linear parameters θ_2 is recovered via linear regression, and the generalized method of moments (GMM) objective function is calculated. If the objective function value is not minimized, the new iteration starts with a new set of nonlinear parameters θ_1'.

5.2. Moment conditions

In this study, I set the moment conditions to be different from those in the BLP model. The traditional BLP approach uses instrument variables which are not correlated with the demand side but correlated with the supply side, since those variables are expected to be correlated with price p_{jt} but orthogonal to the unobservable demand shocks ξ_{jt}. However, this intuition does not hold with the presence of used goods in the market, since no second-hand products are directly

produced by manufacturers. Also, Rossi (2014), in his in-depth investigation of Instrumental Variable (IV) method, points out that an IV estimator can generate large finite sample bias and substantial variability in the case of small samples even if the instruments are not weak because of the methods' reliance on asymptotic properties. The author also suggests that, in many marketing applications in which conditional prediction rather than hypothesis testing is the main focus, it would be better not to adjust for endogeneity and choose a simple Ordinary Least Squares estimator which has much lower variability. I follow Rossi's (2014) argument and use OLS rather than IV GMM, because 1) it is hard to find strong and valid instruments in case of used vehicles, which would worsen the sampling bias and variability issue of the IV estimator, and 2) the main objective of this study is not to estimate the utility parameters but to decompose the transaction costs with observed variables,

So the error terms ξ_{jt} and the observed product characteristics X_{jt} are used to construct the moment conditions.

$$\mathrm{E}\left[X_{jt}\xi_{jt}\right] = 0.$$

In matrix notation, I write the moment conditions as $G(\theta) = \mathrm{E}[X'\xi(\theta)]$ where $\theta = (\theta_1, \theta_2)$. Using total $\Sigma_{\mathrm{t}} J_t$ moment conditions, I obtain the GMM estimator of θ which is given by

$$\hat{\theta} = \arg\min_{\theta} G(\theta)' W^{-1} G(\theta),$$

where W is the weighting matrix: $W = (E(X'\xi(\theta)\xi(\theta)'X))^{-1}$. To calculate the weighting matrix, consistent estimates of θ is needed. So I start with $W = I$ to get the initial estimate of θ and use $W = (E(X'\xi(\theta)\xi(\theta)'X))^{-1}$ to obtain the new

estimate in the next iteration.

5.3. Computation

Figure 5 gives an overview of the estimation procedure.

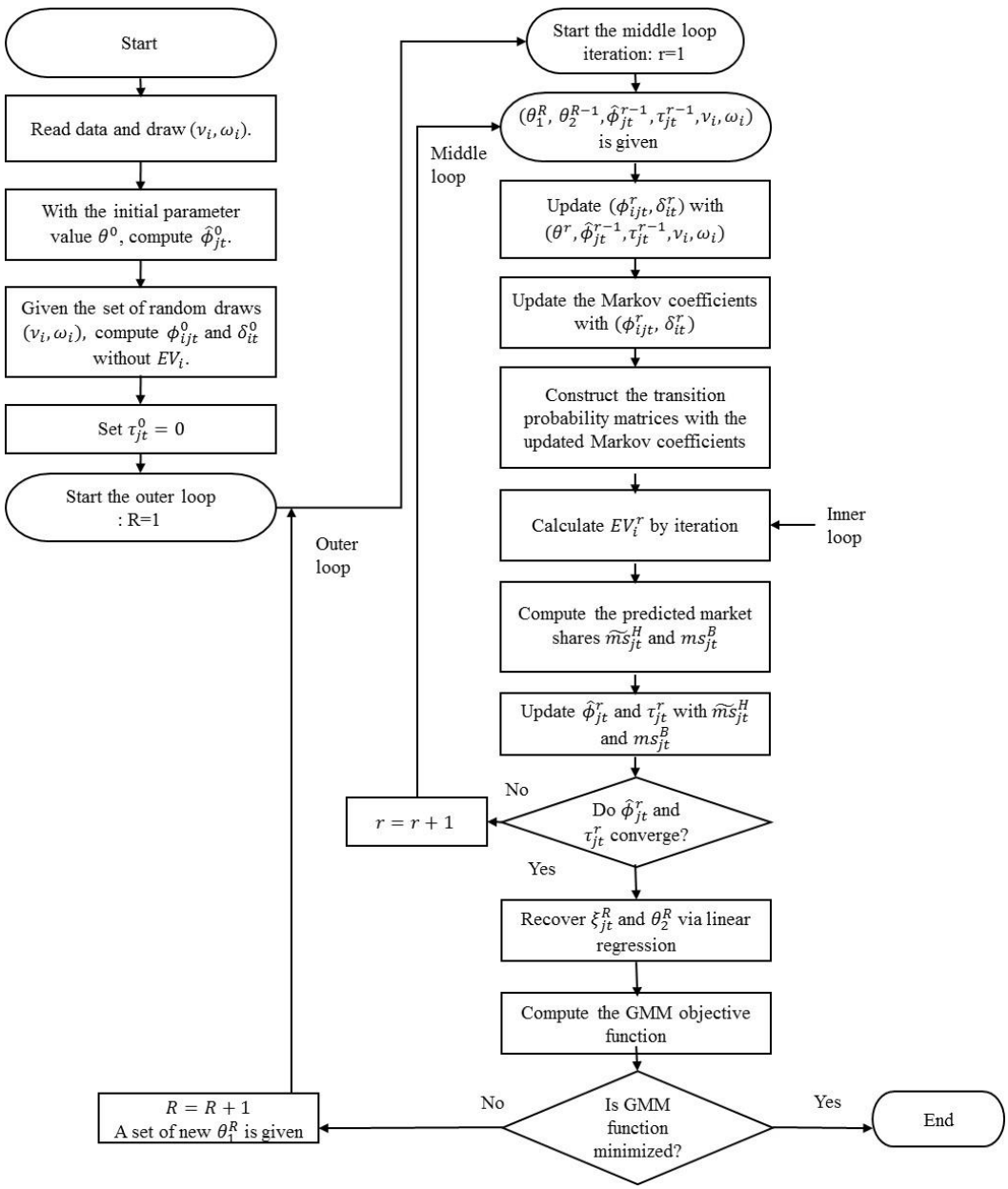


Figure 5. Estimation overview

The estimation procedure is as follows. Let the superscript R denote the outer loop iteration and r denote the middle loop iteration. At iteration r, given $(\theta_1^R, \theta_2^{R-1},\ \hat{\phi}_{jt}^{r-1}, \tau_{jt}^{r-1}, \nu_i, \omega_i, EV_i^{r-1})$,

1) Update $(\phi_{ijt}^r, \delta_{it}^r)$ with $(\theta_1^R, \theta_2^{R-1}, \hat{\phi}_{jt}^{r-1}, \tau_{jt}^{r-1}, \nu_i, \omega_i)$ using equation (6)' and (7).

2) Update the Markov coefficients $(\gamma^r, \rho^r, \sigma_\delta, \sigma_\phi)$ with $(\phi_{ijt}^r,\ \delta_{it}^r)$ using (9) and (10).

3) Construct the transition probability matrices with the updated Markov coefficients.

4) Calculate EV_i^r by iteration using (8).

5) Compute the predicted market shares $\widetilde{ms}_{jt}^H$ and ms_{jt}^B using (11), (12), (13), and (14).

6) Calculate $\hat{\phi}_{jt}^r$ and τ_{jt}^r using the following equations:

$$\hat{\phi}_{jt}^r = \hat{\phi}_{jt}^{r-1} + \psi_1\left(\ln(\check{s}_{jt}^H) - \ln(\widetilde{ms}_{jt}^H(\hat{\phi}_{jt}^{r-1}, \tau_{jt}^{r-1}, \theta^r)\right), \tag{16}$$

$$\begin{aligned}(\hat{\phi}_{jt}^r - \tau_{jt}^r) = (\hat{\phi}_{jt}^{r-1} - \tau_{jt}^{r-1} + \psi_2\big(\ln(\check{s}_{jt}^B)\\ - \ln(ms_{jt}^B(\hat{\phi}_{jt}^{r-1}, \tau_{jt}^{r-1}, \theta^r)).\end{aligned} \tag{17}$$

where $\check{s}_{jt}^H$ and $\check{s}_{jt}^B$ are the observed data counterparts of $\widetilde{ms}_{jt}^H$ and ms_{jt}^B, and $\psi_1 = 1-\beta,\ \psi_2 = (1-\beta)^2$ are the tuning parameters that increase the convergence rate.

7) If $\hat{\phi}_{jt}^r$ and τ_{jt}^r converge, then recover ξ_{jt}^R and the linear parameter θ_2^R via linear regression.

8) Given ξ_{jt}^{R}, compute the GMM objective function with the instruments. If the function is not minimized, go back to (1) with the new set of θ_1^{R+1}.

I use the estimates of a static model without transaction costs as initial parameters.

5.4. Identification

The intuition for identification, as discussed in the previous sections, is that the presence of transaction costs is the source of infrequent replacement. Without frictions, under the assumption that cars depreciate constantly every year, consumers will maximize their utility by replacing their holdings each year to the preferred qualities. In the real world, since the transaction costs make replacement costly, consumers have incentive to keep their ownerships until the utility from purchasing a product net of transaction costs becomes higher than the utility from holding their endowments

Like in Schiraldi (2011) and in other BLP literature, consumer preferences on product characteristics are identified as α, and the variations on the preferences are captured as σ. To separately identify the product-specific time-varying unobservable transaction costs τ_{jt} from the unobservable product characteristics ξ_{jt}, I conduct two different BLP contraction mappings simultaneously on two different market shares: shares of consumers who hold a product and shares of those who buy the same product as a replacement. Since the transaction costs τ_{jt} are incurred only in purchase, the purchase share reflects both τ_{jt} and ξ_{jt} while the holding share reflects only ξ_{jt}. Therefore, via two BLP contraction mappings on the two different shares, both unobservable components can be identified.

One limitation of this model is that the transaction costs for new products cannot be identified, since there is no 'holding share' for newly purchased vehicles. Therefore, I set $\hat{\phi}_{jt}$ to account for both mean net augmented utility and transaction costs when j is a new product.

6. Results

6.1. Utility parameters

Table 7 reports the parameter estimates of product characteristics that enter the utility function. Most estimates are highly significant, and the signs of the coefficients are mostly consistent with the expectation. The coefficient for the Design dummy (which is equal to 1 if the vehicle is not a sedan) is negative, which reflects higher market shares of sedans. In Column 2 to 4, the sign of Age^2 coefficient becomes negative when the transaction costs are included in the model. This indicates that the utility diminishes in a quadratic rate as the car age goes up, implying greater decrease in utility for older vehicles. Negative coefficients for the brand dummies reflect great popularity of Hyundai in Korea, in which Hyundai products take up almost 50% of the entire market transactions. The positive Engine coefficient reflects that consumers prefer cars with larger engines, and the negative Diesel coefficient is consistent with the fact that diesel vehicles are less traded than gasoline vehicles. The Price coefficient is reported to be negative in all four models, although its magnitude varies across the models. In the dynamic model, the coefficient of the Foreign brand dummy becomes smaller in absolute value, and the nonlinear coefficient $\sigma_{foreign}$ becomes significant, indicating that tastes for foreign brands vary across individuals.

Table 7. Estimation results – Utility parameters

	Homogeneous model without transaction costs	Homogeneous model with transaction costs	Heterogeneous model with transaction costs	Heterogeneous dynamic model with transaction costs
Constant	-10.118*** (0.11)	-7.647*** (0.13)	-9.518*** (0.12)	-8.210*** (0.13)
Design (non-sedan)	-0.324*** (0.02)	-0.439*** (0.02)	-0.492*** (0.03)	-0.471*** (0.02)
Diesel	-0.197*** (0.02)	-0.426*** (0.02)	-0.412*** (0.03)	-0.401*** (0.03)
Engine(cc)	0.0002*** (6e-5)	0.0005*** (7e-5)	0.0003*** (1e-5)	0.0004*** (4e-5)
Age	-0.482*** (0.01)	0.768*** (0.01)	0.680*** (0.02)	0.580*** (0.01)
Age^2	0.048*** (0.001)	-0.072***(0.001)	-0.256*** (0.001)	-0.312*** (0.003)
Log(price)	-0.044*** (0.01)	-0.038*** (0.02)	-1.459*** (0.02)	-2.013*** (0.02)
Brands				
Foreign	-0.523*** (0.03)	-0.821*** (0.03)	-1.063*** (0.04)	-0.428*** (0.102)
Domestic (other than Hyundai)	0.088*** (0.02)	-0.207*** (0.02)	-0.240*** (0.03)	-0.197*** (0.02)
Nonlinear Parameters				
σ_p			8.146 (16)	1.016 (3.12)
$\sigma_{foreign}$			0.899 (4.49)	0.801** (0.49)

Standard errors in parenthesis. ***: p-value<0.01, **: p-value<0.05

6.2. Transaction costs

Table 8 shows the parameter estimates of the retrieved transaction costs regressed on the observed product characteristics. Here, transaction costs refer to all the costs related to the purchase of vehicles, such as search costs and information asymmetry. The coefficient for initial stock variable is negative and large in absolute value, which means that the more products available in the market, the smaller transaction costs incurred in purchase, perhaps due to the lower search costs. The coefficient for the Design (non-sedan) dummy is negative, which is consistent with the recent market report that the stock of sports utility vehicles (SUV) is greater than that of mid-size or large sedans in the used car market.[7] The Price coefficient becomes insignificant in the heterogeneous models, which implies that the price level itself does not affect the magnitude of transaction costs. The positive coefficient of Age variable indicates that the transaction cost increases with the car age, perhaps because of greater variation in quality. The positive effect of Foreign*Engine variable offsets or even dominates the negative effect of the Foreign brand dummy and thus suggests higher transaction costs for foreign vehicle purchase. The negative coefficient of the Year dummy and the Foreign*Time variable reflects the expansion of the used car market in Korea and rapid growth of foreign vehicle trades in the market.

[7] "SUV, the most popular vehicle in the used car market," *Joongang Daily*, Dec.24, 2014. http://article.joins.com/news/article/article.asp?total_id=16772322&cloc=olink|article|default

Table 8. Estimation results – Transaction costs

	Homogeneous model	Heterogeneous model	Heterogeneous dynamic model
Constant	2.776*** (0.16)	2.404*** (0.15)	2.108*** (0.15)
Design (non-sedan)	-0.140*** (0.02)	-0.140*** (0.02)	-0.108*** (0.01)
Diesel	-0.158*** (0.02)	-0.168*** (0.02)	-0.169*** (0.02)
Engine(cc)	0.0005*** (1e-6)	0.0004*** (9e-5)	0.0003*** (9e-5)
Age	1.244*** (0.02)	1.266*** (0.02)	1.268*** (0.03)
Age^2	-0.121*** (0.002)	-0.121*** (0.001)	-0.013*** (0.001)
Log(price)	-0.09*** (0.02)	-0.011 (0.02)	-0.05 (0.09)
Year (Year dummy = 1 for 2013 and after)	-0.425*** (0.03)	-0.425*** (0.03)	-0.425*** (0.03)
Initial stock of car *j*	-12.211*** (4.92)	-12.759***(4.92)	-13.871*** (4.97)
Brands			
Foreign	-2.196*** (0.03)	-1.977*** (0.12)	-1.278*** (0.13)
Foreign*Engine	0.0008*** (5-e5)	0.0009*** (4e-5)	0.0011*** (4e-5)
Foreign*Time	-0.022 (0.05)	-0.022 (0.04)	-0.032* (0.024)
Domestic (other than Hyundai)	-1.00*** (0.08)	-0.922*** (0.06)	-0.901*** (0.06)
Domestic*Engine	0.0003*** (4e-5)	0.0004***(4e-5)	0.0005*** (4e-5)

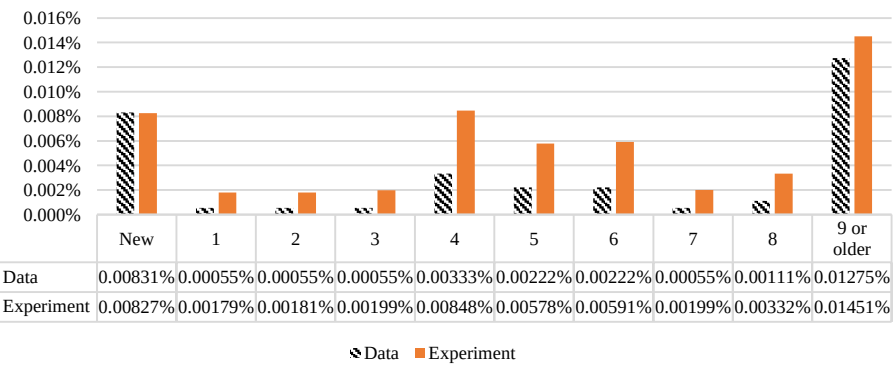
Standard errors in parenthesis. ***: p-value<0.01, **: p-value<0.05, *: p-value<0.1

6.3. Counterfactual experiments

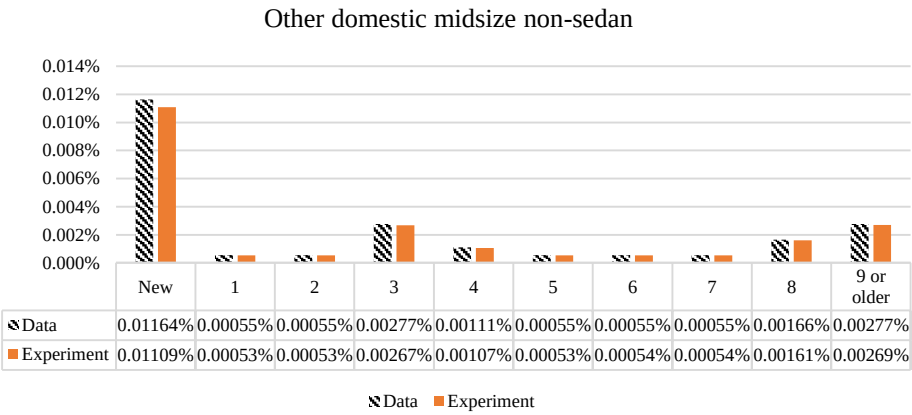
Taking advantage of the structural demand model, I conduct two counterfactual experiments to see the potential impact of transaction cots on sales. With the estimated parameters and arbitrary transaction costs as an input, I recalculate the market shares using the static model with consumer heterogeneity and compare them with the actual data to see how changes in transaction costs might affect the purchase shares of different products.

6.3.1. Experiment 1: Lower transaction costs for Hyundai vehicles

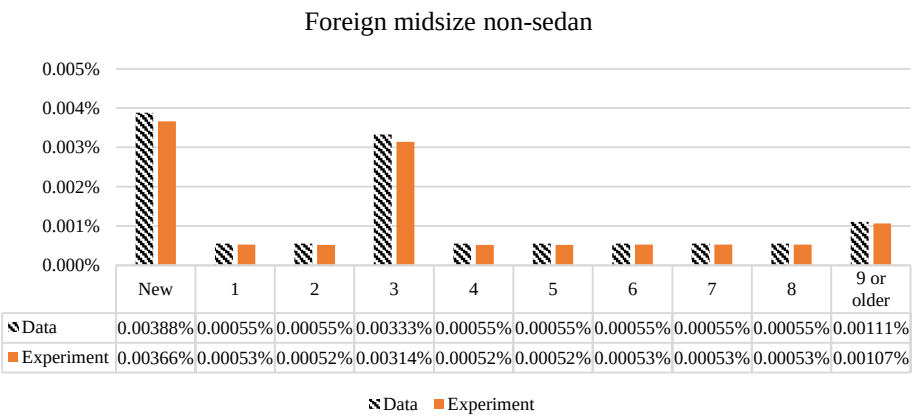
In Experiment 1, I lower the transaction costs for Hyundai vehicles to be 80% of the estimated costs and set the costs for other products to be equal. Figure 6 illustrates the result. As expected, unconditional purchase shares for Hyundai products increase dramatically, while other brands experience minor decrease in purchase shares.



	New	1	2	3	4	5	6	7	8	9 or older
Data	0.00831%	0.00055%	0.00055%	0.00055%	0.00333%	0.00222%	0.00222%	0.00055%	0.00111%	0.01275%
Experiment	0.00827%	0.00179%	0.00181%	0.00199%	0.00848%	0.00578%	0.00591%	0.00199%	0.00332%	0.01451%



	New	1	2	3	4	5	6	7	8	9 or older
Data	0.01164%	0.00055%	0.00055%	0.00277%	0.00111%	0.00055%	0.00055%	0.00055%	0.00166%	0.00277%
Experiment	0.01109%	0.00053%	0.00053%	0.00267%	0.00107%	0.00053%	0.00054%	0.00054%	0.00161%	0.00269%



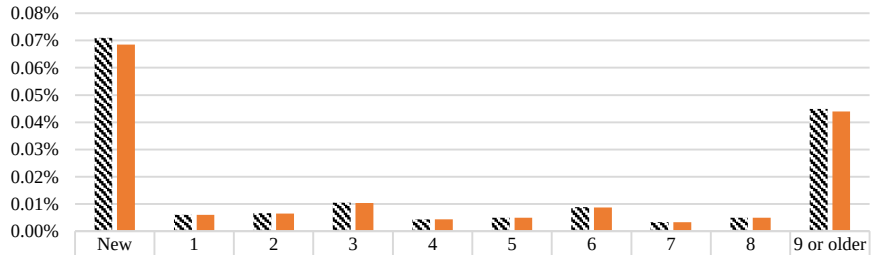
	New	1	2	3	4	5	6	7	8	9 or older
Data	0.00388%	0.00055%	0.00055%	0.00333%	0.00055%	0.00055%	0.00055%	0.00055%	0.00055%	0.00111%
Experiment	0.00366%	0.00053%	0.00052%	0.00314%	0.00052%	0.00052%	0.00053%	0.00053%	0.00053%	0.00107%

Figure 6. Experiment 1 – Changes in purchase share

6.3.2. Experiment 2: Lower transaction costs for imported vehicles

In Experiment 2, I lower the transaction costs for imported vehicles to be 80% of the estimated costs and set the costs for other products to be equal. Figure 7 illustrates the result. Consistent with the result in Experiment 1, unconditional purchase shares for imported vehicles go up, while domestic products experience minor decrease in purchase shares.

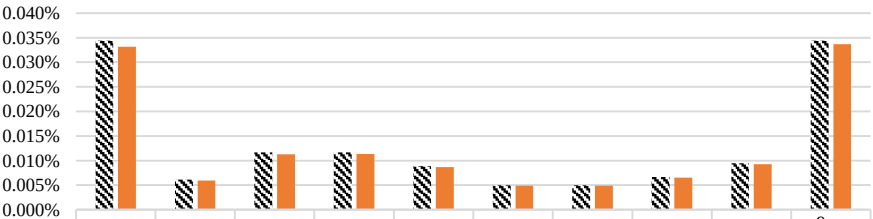
Hyundai midsize sedan



	New	1	2	3	4	5	6	7	8	9 or older
Data	0.07094%	0.00610%	0.00665%	0.01053%	0.00443%	0.00499%	0.00887%	0.00333%	0.00499%	0.04489%
Experiment	0.06847%	0.00601%	0.00656%	0.01041%	0.00441%	0.00495%	0.00880%	0.00332%	0.00497%	0.04400%

Data Experiment

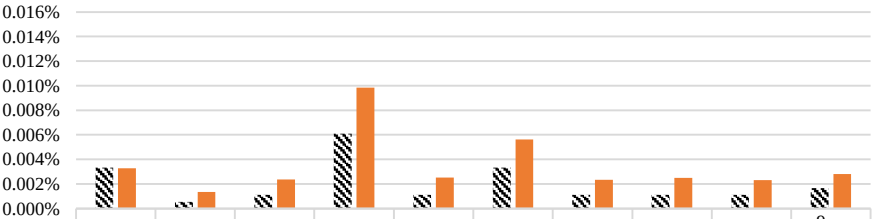
Other domestic midsize sedan



	New	1	2	3	4	5	6	7	8	9 or older
Data	0.03436%	0.00610%	0.01164%	0.01164%	0.00887%	0.00499%	0.00499%	0.00665%	0.00942%	0.03436%
Experiment	0.03315%	0.00592%	0.01131%	0.01137%	0.00865%	0.00487%	0.00488%	0.00654%	0.00923%	0.03366%

Data Experiment

Foreign midsize sedan



	New	1	2	3	4	5	6	7	8	9 or older
Data	0.00333%	0.00055%	0.00111%	0.00610%	0.00111%	0.00333%	0.00111%	0.00111%	0.00111%	0.00166%
Experiment	0.00329%	0.00135%	0.00238%	0.00984%	0.00252%	0.00561%	0.00234%	0.00250%	0.00231%	0.00282%

Data Experiment

Figure 7. Experiment 2 – Changes in purchase share

Both experiments suggest that, as expected, lowering transaction costs would be a significant demand booster in the used car market. If the supply-side

dynamics are included in the counterfactual experiment, it is likely that smaller transaction costs of certain brand would also increase the demand for new cars of the same brand since a consumer shopping for a new car would interpret smaller transaction costs as greater future resale chances and higher future resale values of the products. I leave this question for future research.

7. Conclusion

This study investigates the effect of transaction costs on automobile replacement when the second-hand market is present. Applying a dynamic structural demand model proposed by Schiraldi (2011) and adjusting it to the market data from Korea, I compare the utility parameter estimates of static and dynamic model, and explain the variations of transaction costs with a set of product features. Regression analysis shows that the transaction costs are highly correlated with product features including brand, design, car age; signs of the coefficients are consistent with recent market reports, supporting validity of the result. Policy evaluation implies that decreasing transaction costs might result in rather significant changes in market shares as well as in the market size. Therefore, rich managerial implications would be driven from the product-specific analysis of consumer-perceived transaction costs.

Future research will include more discussion on price endogeneity for consistent estimation of the parameters. Also, identification of transaction costs for new cars and the supply-side dynamics in the used car market will allow for deeper analysis of the automobile market. Using rich survey data about vehicle ownership will improve the estimation as well.

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Appendix

A.1. Static model with no consumer heterogeneity

As Berry (1994) shows, the mean utility value $\hat{\phi}_{jt}$ can be analytically obtained by inverting the market share data if the market is assumed to be homogeneous. Let s_{jt}^{p} be the unconditional market share of consumers who purchase product *j* at time *t*, and s_{jt}^{h} be the unconditional market share of consumers who hold the same product *j* from time *t-1* to *t*. Since the mean utility for consuming the outside good is normalized to 0, the market shares of purchases and holdings can be expressed as the following choice probabilities:

$$s_{jt}^{p} = \frac{\exp\left(\phi_{jt} - \tau_{jt}\right)}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{jt} - \tau_{jt}\right) + \exp(\phi_{kt})}, \tag{A1}$$

$$s_{jt}^{h} = \frac{\exp(\phi_{kt})}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{jt} - \tau_{jt}\right) + \exp(\phi_{kt})}, \tag{A2}$$

$$s_{0t} = \frac{1}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{jt} - \tau_{jt}\right) + \exp(\phi_{kt})}. \tag{A3}$$

Therefore, I can compute the mean utility net of transaction costs and the mean utility respectively by dividing the two observed market shares with s_{0t}.

$$\frac{s_{jt}^{p}}{s_{0t}} = \exp\left(\phi_{jt} - \tau_{jt}\right), \tag{A4}$$

$$\ln\left(s_{jt}^{p}\right) - \ln(s_{0t}) = \phi_{jt} - \tau_{jt},$$

$$\frac{s_{jt}^{h}}{s_{0t}} = \exp\left(\phi_{jt}\right), \tag{A5}$$

$$\ln\left(s_{jt}^{h}\right) - \ln(s_{0t}) = \phi_{jt}.$$

The linear parameters α^{x} and the error term ξ_{jt} are obtained by regressing ϕ_{jt} on the control variables. Since there is no heterogeneity, only the linear parameters are identified and there is no search over nonlinear parameters σ_p or σ_f.

A.2. Static model with consumer heterogeneity

When there is consumer heterogeneity, the mean utility ϕ_{jt} and transaction costs τ_{jt} can no longer be analytically solved. Predicted market shares are computed via integration over the individual preferences with R simulated draws:

$$\begin{aligned}\hat{s}_{jt}^{p} &= \int_{\nu_i} \frac{\exp\left(\phi_{ijt} - \tau_{jt}\right)}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{ijt} - \tau_{jt}\right) + \exp(\phi_{ikt})} dP_{\nu} \\ &\approx \frac{1}{R} \Sigma_{\mathrm{i}=1}^{\mathrm{R}} \frac{\exp\left(\phi_{ijt} - \tau_{jt}\right)}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{ijt} - \tau_{jt}\right) + \exp(\phi_{ikt})},\end{aligned} \tag{A6}$$

$$\begin{aligned}\hat{s}_{jt}^{h} &= \int_{\nu_i} \frac{\exp\left(\phi_{ijt}\right)}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{ijt} - \tau_{jt}\right) + \exp(\phi_{ikt})} dP_{\nu} \\ &\approx \frac{1}{R} \Sigma_{\mathrm{i}=1}^{\mathrm{R}} \frac{\exp\left(\phi_{ijt}\right)}{1 + \Sigma_{j \in J_t \setminus \{k\}} \exp\left(\phi_{ijt} - \tau_{jt}\right) + \exp(\phi_{ikt})}.\end{aligned} \tag{A7}$$

Given the predicted market shares, I compute $\hat{\phi}_{jt}$ and τ_{jt} via two different contraction mappings:

$$\hat{\phi}'_{jt} = \hat{\phi}_{jt} + \ln\left(s_{jt}^{h}\right) - \ln\left(\hat{s}_{jt}^{h}\right),$$

$$\left(\hat{\phi}_{jt} - \tau_{jt}\right)' = \left(\hat{\phi}_{jt} - \tau_{jt}\right) + \ln\left(s_{jt}^{p}\right) - \ln\left(\hat{s}_{jt}^{p}\right).$$

국문 초록

거래 비용이 자동차 교체에 미치는 영향

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본 연구는 Schiraldi(2011)가 제안한 구조적 동적 수요 모형 (structural dynamic demand model)을 확장하여 소비자들의 전략적 소비와 소비자 간의 이질성을 반영한 임의계수 이산선택모형 (random coefficients discrete choice model)을 구축하였다. 이 모형을 신차와 중고차 구매 내역이 모두 기록된 서울시 자동차 등록 데이터에 적용하여 자동차 구매 시 발생하는 시기별 상품별 거래비용을 분석하였다. Berry et al.(1995)이 소개한 수축매핑기법 (contraction mapping technique)과 Rust(1987)가 제안한 고정점 알고리즘 (nested fixed point algorithm)을 결합하여 관측되지 않는 상품 특성과 거래비용을 분리하여 추정하였다. 실제로 추정된 모수들과 임의의 거래비용을 입력하여 시장점유율을 예측하는 실험을 통해 거래비용의 변화가 수요에 유의한 영향을 미칠 수 있음을 확인하였다.

……

주요어 : 내구재 소비, 수요 전망, 이산선택모형, 중고 시장, 동적 프로그래밍, 거래 비용
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