A Discrete-Continuous Model for Analyzing the Ownership and Usage of Electric Vehicles Using Stated Preference Data

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Abstract: This paper develops a discrete-continuous model to examine the ownership and usage of electric vehicles in the household. The impact of the ownership and usage of ordinary vehicles is taken into consideration. 5766 stated preference data concerning purchasing electric vehicles in the Chukyo region in Japan are utilized as the research sample. The monthly mileages of ordinary and electric vehicles are measured by a Tobit model, respectively. The ordinary vehicle ownership is measured by an ordered probit model, while the electric vehicle ownership is measured by a binary probit model. Gibbs sampler algorithm is used to estimate four jointed equations. The result shows that there is a substitution effect between two types of vehicles in the ownership and usage. The price, capacity, range and charging rate in the gas station impact both the ownership and usage of electric vehicles. Meanwhile, charging time does not affect either the ownership or usage.

Keywords: Electric Vehicles, Vehicle Ownership, Vehicle Usage, Discrete-Continuous, Stated Preference Data

1. INTRODUCTION

The electric vehicle is considered to be one of the most sustainable transportation modes in next decades. For it does not emit any carbon dioxide or particle materials during the running stage, it can contribute to relieving the global warming phenomenon. In Japan, Cabinet meeting (2008) was making a great effort to promote electric vehicles to maintain the harmony of the metropolis environment.

The next-generation vehicles generally include electric, hybrid electric, plug-in hybrid electric, fuel cell, liquid natural gas vehicles and so on. For high dependency on the import of natural resources, the implement of the liquid natural gas vehicle is not emphasized in Japan. Meanwhile, the penetration of fuel cell vehicles seems difficult, for the production of hydrogen is very expensive. As a result, three kinds of eco-friendly vehicles have been diffusing in Japan. The penetration of the hybrid electric vehicle had been realized. Although it can recycle the energy during the running stage, it cannot use the electricity as the direct energy resource. As a result, the consumer did not treat it as a special kind of vehicles. For the plug-in hybrid electric vehicle is very expensive, the penetration of it is not promising. Compared with the plug-in hybrid electric vehicle, the electric vehicle is not very expensive. Although the penetration process is at initial stage, it is considered to be the most promising vehicle in future.

Due to the predominance of sale and usage of the ordinary vehicle, the penetration of next-generation vehicles seems not easy. Many countries implemented favorite policies to

promote their market shares. In Japan the government had introduced tax reduction and replacement subsidy to promote the next-generation vehicles. Previous research has found that the favorite policies can induce consumers to purchase the next-generation vehicles (Caulfield *et al.*, 2010).

Models for forecasting electric vehicles demand based on stated preference survey had been constructed (Bunch *et al*., 1993; Segal, 1995). In one recent study, Sakai *et al.* (2011) utilized a binary-probit model to examine factors which affected electric vehicles purchasing behavior in the Chukyo region in Japan. Yang *et al.* (2012) extended this model and developed a 3-level nested logit model to make a further research on electric vehicles purchasing behavior.

After reviewing the previous studies, the authors found that most of existing studies only predicted the probability of the household to purchase or hold electric vehicles. Only a few of studies were incorporating both purchasing and using behavior in the model, for the stated preference survey was always used to investigate vehicle purchasing behavior, while the using behavior of electric vehicles was seldom investigated.

Our study aims at revealing the holding and using behavior concerning the electric vehicle, and gives insight into factors which have significant effects on these two kinds of behavior. The impact of the ownership and usage of ordinary vehicles is taken into consideration in this study. The results of the stated preference survey concerning purchasing electric vehicles are utilized as the research sample. Each element of the sample is supposed to represent the vehicle ownership and usage information in one household. We utilize a Bayesian Multivariate Tobit, Ordered and Binary Probit (BMTOBP) model based on Bayesian Markov Chain Monte Carlo method to analyze the ownership and usage of these two kinds of vehicles. This model is the modified version of the Bayesian Multivariate Ordered Probit and Tobit (BMOPT) model proposed by Fang (2008). The difference between these two models will be discussed in Section 3.

The rest of the paper is organized as follows. Section 2 introduces the summary of the stated preference data collected in the Chukyo region in Japan and the method how we create the sample which represents the vehicle ownership and usage information in the household. Section 3 explains the reason why the modified version of the BMOPT model is utilized, and describes the BMTOBP model proposed in this study. Section 4 instructs the estimation method of our model, and then makes a discussion on the corresponding estimation results. Section 5 makes a sensitive analysis of the monthly mileage and holding share concerning the attributes of the electric vehicle to investigate the most crucial factors for households to hold and use electric vehicles. Finally, this study is concluded in Section 6 along with a discussion about future research issues.

2. DATA

To reveal the consumer preference of purchasing the electric vehicle, our laboratory carried on the Internet questionnaires in the Aichi prefecture in December, 2010 and in the Gifu and Mie prefecture in January, 2011, respectively. As the research object, the respondents were confined to the householder who owned the driver license and vehicles at that time.

The questionnaire included five parts listed as follows. In the first part, the vehicle ownership and usage in the household were observed. Characteristics and usage of each vehicle were recorded. We only investigated the four most frequently used vehicles in the household if the household owned more than four vehicles. The second part collected the information of the fuelling behavior concerning the most frequently used vehicle in the household. The stated preference survey examining purchasing, charging and using behavior concerning electric

vehicles was conducted in the third part. The fourth part made a survey concerning the subjected attitudes towards the current vehicle usage and penetration of the electric vehicle. The last part surveyed the household characteristics and the information of each family member. In this study, we only used the information subtracted from part one, part three and part five. For the stated preference data is a crucial component for us to examine the ownership and usage of electric vehicles, the detail of the survey method will be illustrated in Section 2.1.

2.1 Stated Preference Survey Design

The survey items included two aspects of factors relating to the electric vehicles. The first aspect was concerning attributes of the electric vehicle, and the other one contained the installation rates of public charging facilities.

  Attributes of the electric vehicle included capacity (3 levels: 2, 4 and 7 seats), price (3 levels: 1.5, 2.5 and 4.0 million JPY), charging time by fast charger (3 levels: 30, 20, and 10 minutes) and vehicle range (3 levels: 100, 200, and 300 km). Additionally, if the capacity was 7 seats, the price in 3 levels would be 2, 3 and 4.5 million JPY, respectively. The installation rates of public charging facilities included that in the gas station (3 levels: 1/10, 1/3 and 1) and in the highway service area (2 levels: 1/3 and 1). The installation rate in the shopping center was also taken into consideration, which was designed to be randomly equal to the rate in the highway service area or zero.

  27 patterns were designed in the survey based on the experiment designing method. The five factors included price, vehicle range, charging time, the installation rate of charging facilities in the gas station and that in the highway service area.

  The scenario of the state preference survey was generated by one 3-step procedure as follows. Firstly, the capacity of the electric vehicle was randomly selected from the 3 levels. Secondly, only one pattern randomly chosen from the designed 27 patterns was selected. Lastly, the installation rate in the shopping center was randomly equal to that in the highway service area according to the pattern generated in step 2 or zero. The combination of variables generated from the 3 steps illustrated above could fabricate only one kind of electric vehicles and the installation rates in different public places to the respondent.

  Each respondent answered the survey for two times. The survey in the first time was designed to have a larger vehicle capacity than that in the second time, which confirmed that each time the survey was conducted indifferent scenario. Respondents were required to make a choice from three items which were defined as Addition, Exchange and Constant, which represent that the consumer could add one electric vehicle, replace one vehicle in use or have no plan to purchase it, respectively. The using and charging behavior concerning the supposed electric vehicle was also observed if the respondent decided to treat the electric vehicle as Addition or Exchange. Meanwhile, the usage of the holding vehicle after purchasing the electric one was also investigated, for we wanted to observe the vehicle usage variation in the household. It is supposed that the data collected in part three could represent the holding and using behavior concerning the electric vehicle in future. The detail of creating the sample will be illustrated in next section.

2.2 Method to Create the Sample

The original number of valid questionnaires was 2883. For each respondent answered the stated preference survey for two times, the stated preference data was 5766. We suppose that each stated preference data could represent one household in this study. Combining the current vehicle usage information in part one and the result of the stated preference survey in part three,

we create the sample according to the rules listed as follows.

If the household decided to treat the electric vehicle as Addition, the vehicle number would increase by one, and the usage of each vehicle after holding electric vehicle is used. If the household considered the electric vehicle as Exchange, the vehicle number would not change, and the usage of each vehicle after exchanging is recorded. If the household had no plan to buy one electric vehicle, the current vehicle ownership and usage of each vehicle is used.

We investigated the vehicle usage in the form of enquiring the frequency and vehicle mileage in the weekday and weekend, respectively. The monthly mileage of each vehicle was treated as the measurement for its usage in this study. Combining the vehicle holding and using information and the result of the stated preference survey, the sample used in this study could be clearly defined.

2.3 Data Description

Table 1 shows the descriptive statistics concerning the sample in this study. 92.8% of the householders are male, which results from the fact that most of householders in Japan are male. 56.1% of the households are able to install vehicle charging facilities near their houses, which may be a crucial factor of purchasing and using electric vehicles. The households from the Aichi prefecture (including Nagoya) take a ratio of 67.0% corresponding to its dominant status in the Chukyo region. 19.2% of the households have more than two drivers in their families. 75.9% of the households have annual income more than 3 and less than 10 million JPY, which indicates that samples may not be biased in this attribute. Only 13.7% of the householders do not have fixed occupation including items of homemaker, part-time, others and free.

Table 1 Descriptive statistics

Attribute	Percentage	Attribute	Percentage
Gender		Charging facilities near home	
Male	92.8%	Installable	56.1%
Female	7.2%	Uninstallable	43.9%
Districts		Drivers in the household	
Nagoya	34.1%	1	23.3%
Aichi (Excluding Nagoya)	32.9%	2	57.5%
Gifu	17.6%	3	11.9%
Mie	15.4%	>=4	7.3%
Household annual income		Occupation of householders	
<2 million JPY	5.0%	Public servant	7.9%
>=2 and <3 million JPY	7.6%	Manager	3.2%
>=3 and <4 million JPY	12.4%	Clerical officer	18.2%
>=4 and <5 million JPY	17.4%	Technical officer	29.0%
>=5 and <6 million JPY	14.1%	Other officer	17.5%
>=6 and <7 million JPY	10.9%	Self-employed	8.9%
>=7 and <8 million JPY	9.5%	Freelance professional	1.5%
>=8 and <10 million JPY	11.6%	Homemaker	0.8%
>=10 and <15 million JPY	8.8%	Part-time	3.3%
>=15 million JPY	2.7%	Others	8.2%
		Free	1.4%

Table 2 shows the cross aggregation result concerning the vehicle ownership. Since respondents were confined to the householders owning driver licenses and vehicles in the survey, the household in the sample at least holds one kind of vehicle. This may lead to the problem of underestimating total demand of electric vehicles. The cell with 1580 households holding the electric vehicle is corresponding to the result of the stated preference survey in part three. The cell with the largest number of observations has 2940 households owning one

ordinary vehicle and no electric vehicles, while the cell with the least observation has 158 households holding two or more ordinary vehicle and one electric vehicle. It is found that approximate 87.7% of households would like to hold one or more ordinary vehicles, which indicates the predominant status of the ordinary vehicle in the household.

Table 2 Tabulation of vehicle ownership

	Number of ordinary vehicles			Total
	0	1	>=2	
Number of electric vehicles				
0	0	2940	1246	4186
1	708	714	158	1580
Total	708	3654	1404	5766

Description of the vehicle ownership and usage are reported in Table 3. The average number of the ordinary vehicle ownership is 1.167, and average number of electric vehicles is 0.274. The standard variance of ordinary vehicles number is high, with some households having a total of four and some none. The average of monthly mileage driven by ordinary vehicles is 6.058, much higher than 1.916 the average monthly mileage driven by the electric vehicle. For only 27.4% of the households are supposed to hold the electric vehicle, the standard variance in monthly mileage driven by electric vehicles is lower than that of ordinary vehicles. Here, the monthly mileage is the total mileage of all vehicles in the same type in one household.

Table 3 Description of the vehicle ownership and usage

Variable	Mean	SD	Min	Max
Number of ordinary vehicles	1.167	0.707	0	4
Number of electric vehicles	0.274	0.446	0	1
			25 quantile	75 quantile
Monthly mileage: ordinary vehicles (100 km)	6.058	7.399	1.350	8.000
Monthly mileage: electric vehicles (100 km)	1.916	4.901	0	1.350

3. MODEL SPECIFICATION

3.1 Selection of the Discrete-continuous Model

In this study, a modified version of BMOPT model is developed to analyze household`s vehicle holding and using behavior concerning the electric one. Meanwhile, the ownership and usage of ordinary vehicles are taken into consideration.

The multiple discrete-continuous extreme value (MDCEV) model proposed by Bhat (2005) was used to analyze the household vehicle holding and using behavior in previous research (Bhat and Sen, 2006). However, this model cannot be applied to the sample in this study. The reasons for it are illustrated as follows. In the first place, the MDCEV model requires a constraint condition in order to estimate the parameters. Usually, the total vehicle mileage or the expenditure of all vehicles in the household is chosen. While, the aggregation result of the mileage before and after purchasing the electric vehicle shows that households would increase their vehicle mileage, especially for the households treating the electric vehicle as Addition. Meanwhile, the aggregation result of expenditure in the household shows that if the household considered the electric vehicle as Exchange, the total money spent on vehicle usage would decrease obviously. As a result, the constraint condition could not be clearly defined. In the second place, the MDCEV model only considers the vehicle types and the usage of them. If the household owns two vehicles in one type, this model seems low efficient. In the sample

households holding two or more ordinary vehicles takes a ratio of approximate 24.3%.

The BMOPT model proposed by Fang (2008) utilized a multivariate ordered probit model describing vehicle ownership and a multivariate Tobit model analyzing vehicle usage considering multiple vehicle types held in the household. This model can complement the two weak points of the MDCEV model mentioned above. The BMOPT model was utilized by Fang (2008) to make an analysis of the household holding and using behavior concerning cars and trucks in California, USA. The number of cars or trucks was both classified into 0, 1 and 2 or more. The usage of them was measured by average annual vehicle mileage. Since in the research sample the households at most hold only one electric vehicle, the modified version called the BMTOBP model is proposed in this study.

3.2 BMTOBP Model Specification

Let two latent continuous variables y_{1i}^* and y_{2i}^* represent uncensored monthly mileage driven by ordinary vehicles and by electric vehicles. Let other two latent variables y_{3i}^* and y_{4i}^* represent the preference for holding ordinary vehicles and electric vehicles. The equations system for discrete-continuous ownership and usage of two types of vehicles is represented as follows.

$$y_{1i}^* = x_{1i}^T \beta_1 + \varepsilon_{1i} \tag{1}$$
$$y_{2i}^* = x_{2i}^T \beta_2 + \varepsilon_{2i} \tag{2}$$
$$y_{3i}^* = x_{3i}^T \beta_3 + \varepsilon_{3i} \tag{3}$$
$$y_{4i}^* = x_{4i}^T \beta_4 + \varepsilon_{4i} \tag{4}$$

where,
i : indexing the household in the sample $(i = 1, ..., N)$,
k : the list number of the equation $(k = 1, ..., 4)$,
x_{ki} : the vector of explanatory variables in the kth equation for the household i,
β_k : the vector of parameters in the kth equation, and
ε_{ki} : the error item in the kth equation for the household i.

The whole equations system concerning the latent variables can be written into a seemingly unrelated regression form (Koop, 2003).

$$y_i^* = x_i \beta + \varepsilon_i \tag{5}$$

where, the error vector has an independent and identical multivariate normal distribution with zero means and unrestricted covariance matrix represented as follows.

$$\varepsilon_i \sim^{i.i.d} MVN(0, \Sigma) \tag{6}$$

The number of ordinary vehicles y_{3i} and that of electric vehicles y_{4i} held by household i are determined by the values of corresponding latent utility y_{3i}^* and y_{4i}^*, respectively. The monthly mileage driven by ordinary vehicles y_{1i} is observed when the household holds at least one ordinary vehicle. The same logic can be applied to the monthly mileage driven by electric

vehicles y_{2i}. The relation between latent and observed variables is illustrated as follows.

$$y_{1i} = \begin{cases} y_{1i}^*, & if \; y_{1i}^* > 0 \\ 0, & if \; y_{1i}^* \leq 0 \; (y_{3i} = 0) \end{cases} \tag{7}$$

$$y_{2i} = \begin{cases} y_{2i}^*, & if \; y_{2i}^* > 0 \\ 0, & if \; y_{2i}^* \leq 0 \; (y_{4i} = 0) \end{cases} \tag{8}$$

$$y_{3i} = \begin{cases} 0, & if \; y_{3i}^* \leq \alpha_{31} \\ 1, & if \; \alpha_{31} < y_{3i}^* \leq \alpha_{32} \\ 2 \, or \, more, & if \; \alpha_{32} < y_{3i}^* \end{cases} \tag{9}$$

$$y_{4i} = \begin{cases} 1, & if \; y_{4i}^* \geq 0 \\ 0, & if \; y_{4i}^* < 0 \end{cases} \tag{10}$$

where, α_{31} and α_{32} are the threshold values of the ordered probit model which is used to measure the ownership of ordinary vehicles. For constraining the lowest and highest threshold values is equivalent to constraining one cut point and the variance for identification when the ordered probit model is estimated (Nandram and Chen, 1996). In this study we utilize the same setting method in Fang`s study. α_{31} and α_{32} are set to be -0.431 ($\Phi^{-1}(1/3)$) and 0.431 ($-\Phi^{-1}(1/3)$), respectively (Φ^{-1} indicates the inverse of normal cumulative density function). In equations system we use a binary probit model to measure the number of electric vehicles (one or zero) instead of the ordered probit model.

3.3 Explanatory Variables

Besides attributes of the electric vehicle and installation rates in three different public places designed in the stated preference survey, variables concerning characteristics of neighborhood and household are also selected as explanatory variables in the model. The explanation of these variables is listed in Table 4.

Table 4 Part of explanatory variables in the model

Variable	Description
Home vehicle charging (dummy)	1 if charging facilities can be installable near home; 0 otherwise
Annual income (10 million JPY)	This variable is investigated in the form of group data concerning annual income in the household, which are corresponding to the items listed in Table 1. The middle point of the income threshold bounds is used. While, If the annual income is less than 2 million JPY, we use 1.7 million JPY. If it is more than 15 million JPY, we use 18 million JPY.
Number of drivers	The number of family members who owns the driver license
No occupation (dummy)	1 if the occupation of householders is homemaker, part-time, free, or others; 0 otherwise
Prefecture (dummy)	1 if the household is living in the Gifu or Mie prefecture; 0 otherwise
Number of adults	The number of members who are more than 18 years old
ChildL4 (dummy)	1 if the household has a baby equal to or less than 4 years old; 0 otherwise

4. MODEL ESTIMATION AND PERFORMANCE

4.1 Model Estimation Method

Considering the similarity between BMTOBP model developed in this study and the BMOPT model proposed by Fang (2008), we utilize the Bayesian Markov Chain Monte Carlo method to estimate parameters. Compared to the simulated based algorithm such as the GHK algorithm, the Bayesian approach can void computational cost of direct evaluating the multiple integrals and has a higher efficiency (Fang, 2008). We implement the Gibbs sampler algorithm to draw random numerical value or matrix from the conditional distribution for latent variables y_i^* and unknown parameters β and Σ. Each iteration of the Gibbs sampler is conducted by the order of y_i^*, β and Σ listed as follows.

$$draw \quad y_i^* \mid \beta, \Sigma, y_i \quad from \quad \pi(y_i^* \mid \beta^{(k-1)}, \Sigma^{(k-1)}, y_i) \tag{11}$$

$$draw \quad \beta \mid \Sigma, y_i^* \quad from \quad \pi(\beta \mid \Sigma^{(k-1)}, y_i^{*(k)}) \tag{12}$$

$$draw \quad \Sigma \mid y_i^*, \beta \quad from \quad \pi(\Sigma \mid y_i^{*(k)}, \beta^{(k)}) \tag{13}$$

where,
   π : the conditional posterior distribution, and
   k : the order of the iteration in the Gibbs sampler.

Sampling the latent variables y_i^* from the truncated multivariate normal distribution can be realized through drawing from a series of full conditional distribution of each element of y_i^* given all the others variables (Geweke, 1991). It is not difficult to prove that equations 14-17 can draw a sample from the full conditional distribution for y_{ki}^* $(k = 1,...,4)$, respectively.

$$y_{1i}^* = \begin{cases} y_{1i}, & if \ y_{1i} > 0 \\ \mu_{1|\neg1} + \sigma_{1|\neg1}\Phi^{-1}(U\Phi((-\mu_{1|\neg1})/\sigma_{1|\neg1})), & if \ y_{1i} = 0 \end{cases} \tag{14}$$

$$y_{2i}^* = \begin{cases} y_{2i}, & if \ y_{2i} > 0 \\ \mu_{2|\neg2} + \sigma_{2|\neg2}\Phi^{-1}(U\Phi((-\mu_{2|\neg2})/\sigma_{2|\neg2})), & if \ y_{2i} = 0 \end{cases} \tag{15}$$

$$y_{3i}^* = \begin{cases} \mu_{3|\neg3} + \sigma_{3|\neg3}\Phi^{-1}(U(1-\Phi((0.431-\mu_{3|\neg3})/\sigma_{3|\neg3})) + \Phi((0.431-\mu_{3|\neg3})/\sigma_{3|\neg3})), & if \ y_{3i} \geq 2 \\ \mu_{3|\neg3} + \sigma_{3|\neg3}\Phi^{-1}(U(\Phi((0.431-\mu_{3|\neg3})/\sigma_{3|\neg3}) - \Phi((-0.431-\mu_{3|\neg3})/\sigma_{3|\neg3})) \\ \qquad\qquad\qquad\qquad\qquad + \Phi((-0.431-\mu_{3|\neg3})/\sigma_{3|\neg3})), & if \ y_{3i} = 1 \\ \mu_{3|\neg3} + \sigma_{3|\neg3}\Phi^{-1}(U\Phi((-0.431-\mu_{3|\neg3})/\sigma_{3|\neg3})), & if \ y_{3i} = 0 \end{cases} \tag{16}$$

$$y_{4i}^* = \begin{cases} \mu_{4|\neg4} + \sigma_{4|\neg4}\Phi^{-1}(1-(1-U)\Phi(\mu_{4|\neg4}/\sigma_{4|\neg4})), & if \ y_{4i} = 1 \\ \mu_{4|\neg4} + \sigma_{4|\neg4}\Phi^{-1}(U\Phi((-\mu_{4|\neg4})/\sigma_{4|\neg4})), & if \ y_{4i} = 0 \end{cases} \tag{17}$$

where,
   U : a random variable following the uniform distribution between 0 and 1,
   $\mu_{j|\neg j}$: the mean of equation j fully conditional on other equations, and
   $\sigma_{j|\neg j}$: the standard variance of equation j fully conditional on other equations.

The full conditional mean and variance can be calculated according to Poirier (1995). For y_i^* is following the multivariate normal distribution before we know y_i, we could change the order of dependent variables and that of mean of the four equations 1-4 at the same time, and modify the covariance matrix to represent the joint distribution of the element in y_i^* in

different forms. As a result, the calculation of the full conditional mean and variance is equally straightforward.

If the prior distribution of β is multivariate normal distribution with the mean β_0 and the covariance matrix V_0, it is not difficult to derive the conditional posterior distribution of β illustrated as follows.

$$\beta \mid y_i^*, \Sigma \sim N(\bar{\beta}, \bar{V}) \tag{18}$$

$$\bar{V} = (V_0^{-1} + \sum_{i=1}^{N} x_i^T \Sigma^{-1} x_i)^{-1} \tag{19}$$

$$\bar{\beta} = \bar{V}(V_0^{-1} \beta_0 + \sum_{i=1}^{N} x_i^T \Sigma^{-1} y_i^*) \tag{20}$$

where, N is the number of households in the sample. Sampling from a multivariate normal distribution can be implemented referring to the method mentioned by Greene (2011). We set β_0 to be a column vector of zeros, and V_0 to be diagonal matrix with 100 on the diagonal.

If the prior distribution of Σ is supposed to be an Inverse-Wishart distribution with the freedom v and the scale matrix Ψ, the conditional posterior distribution can be derived as follows.

$$\Sigma \mid y_i^*, \beta \sim W^{-1}(v+N, \sum_{i=1}^{N} \left(y_i^* - x_i \beta\right)\left(y_i^* - x_i \beta\right)^T + \Psi) \tag{21}$$

where, W^{-1} represents the Inverse-Wishart distribution. In our model, the binary probit model is included. For the identification of its variance is necessary, we utilize the method proposed by Nobile (2000) to sample the random matrix following the same distribution shown in the equation 21 conditional on the diagnose element $\sigma_{44} = 1$. By fixing the standard variance of the binary probit model to be 1, we confirm each element of the covariance matrix Σ to be identified during the cycle of the Gibbs sampler. We set v to be 10, and Ψ to be an identical matrix.

4.2 Model Performance

We use GAUSS 3.2 to implement the program of the estimation method illustrated above. In the Gibbs sampler, we take 11000 times of iterations and burn the first 1000 iterations, for the first 1000 iterations are highly dependent on the initial value of the parameters. The remaining 10000 draws are used to estimate parameters of the posterior inference. The Geweke diagnostic test indicates a high degree of convergence and accuracy with the number of iterations. The authors draw the time series plot diagram for each parameter, and they are all displaying the stationary states. The result of model estimation is reported in Table 5. All of the parameters are estimated with expected sigh, and the analysis of significant explanatory variables is illustrated as follows.

Concerning the usage of ordinary vehicles, the positive parameter of annual income at the 1% significance level indicates that households have more demand of using ordinary vehicles if they have a higher income. The positive parameter of number of drivers at the 1% significance level indicates that the households with more drivers would use the ordinary vehicle more frequently. The parameter of prefecture at the 1% significance level shows that residents living in the Gifu or Mie prefecture have a higher demand of using ordinary vehicles, for there is no sufficient subway or railway system in these areas compared with the Aichi prefecture. The insignificant parameter of the childL4 with minus sign indicates that this kind of household

does not have a preference of driving ordinary vehicles frequently. The family may have a strong desire to own ordinary or electric vehicles. While, they might usually use them to make a short distance travel, since the purpose of the trip is very limited.

Table 5 Model estimation result

Explanatory variable	Parameter	Standard variance	T-statistic
(1) Monthly mileage of ordinary vehicles (100 km)			
Annual income (10 million JPY)	1.053	0.363	2.90
Number of drivers	0.979	0.233	4.20
No occupation (dummy)	-0.174	0.348	-0.50
Prefecture (dummy)	1.485	0.246	6.04
Number of adults	0.338	0.191	1.77
ChildL4 (dummy)	-0.481	0.320	-1.50
Constant	1.331	0.360	3.70
(2) Monthly mileage of electric vehicles (100 km)			
Electric vehicle price (million JPY)	-2.850	0.213	-13.35
Electric vehicle capacity (seats)	0.595	0.097	6.13
Electric vehicle range (100 km)	1.587	0.228	6.95
Vehicle charging time (10 minutes)	-0.433	0.237	-1.82
Facility installation rate (gas station)	1.309	0.491	2.66
Home vehicle charging (dummy)	3.709	0.427	8.70
Annual income (10 million JPY)	1.850	0.645	2.87
Number of drivers	0.875	0.318	2.75
No occupation (dummy)	-1.920	0.684	-2.81
Prefecture (dummy)	0.667	0.459	1.45
Number of adults	0.086	0.201	0.43
ChildL4 (dummy)	1.102	0.515	2.14
Constant	-11.642	1.146	-10.16
(3) Number of ordinary vehicles			
Annual income (10 million JPY)	0.087	0.021	4.04
Number of drivers	0.180	0.009	20.35
No occupation (dummy)	-0.013	0.021	-0.64
Prefecture (dummy)	0.133	0.015	9.10
ChildL4 (dummy)	0.067	0.019	3.50
Constant	-0.359	0.022	-16.32
(4) Number of electric vehicles			
Electric vehicle price (million JPY)	-0.243	0.018	-13.87
Electric vehicle capacity (seats)	0.050	0.008	5.98
Electric vehicle range (100 km)	0.127	0.020	6.42
Vehicle charging time (10 minutes)	-0.032	0.022	-1.47
Facility installation rate (gas station)	0.092	0.043	2.17
Home vehicle charging (dummy)	0.308	0.036	8.55
Annual income (10 million JPY)	0.154	0.058	2.66
Number of drivers	0.080	0.022	3.68
No occupation (dummy)	-0.179	0.059	-3.06
Prefecture (dummy)	0.038	0.042	0.89
ChildL4 (dummy)	0.127	0.047	2.72
Constant	-0.937	0.101	-9.28

For the usage of electric vehicles, the minus parameter of electric vehicle price at the 1% significance level indicates that households would not like to use the electric vehicle with higher price. For if households are unwilling to purchase the expensive vehicles, the usage of electric vehicles seems very limited or not existed. The positive parameter of electric vehicle capacity at the 1% significance level indicates that households would like to use electric vehicles more frequently if they have larger capacity, for the bigger vehicle can satisfy various activity purposes. The positive parameter of vehicle range at the 1% significance level indicates

that households will use the vehicle more frequently, if the vehicle range is longer. This may result from the fact that driving the vehicle with longer range, the drive will not worry about the depletion of the battery and enjoys its lower fuel consumption. The positive parameter of facility installation rate in the gas station at the 1% significant level indicates that households would like to use the electric vehicle more frequently if the charging rate in the gas station is higher, for they can charge vehicles without changing fuelling behavior. The positive parameter of home vehicle charging at the 1% significance level indicates that households would use the electric vehicle if it can be charged near their houses, for they can charge it at night and use it in the day. The positive parameter of annual income at the 1% significance level indicates that wealthier households would like to use the electric vehicle more frequently, for the electric vehicle sometimes can satisfy the travel demand as ordinary vehicles do. The positive parameter of number of drivers at the 1% significance level indicates that more drivers in the households would result in more demand on the usage of electric vehicles. It should be noticed that the households with more drivers have a huge demand of vehicle usage, and it does not have a relation with the vehicle type. The minus parameter of no occupation at the 1% significance level indicates that if the householder does not have a fixed occupation, the household would not like to use electric vehicle more frequently, for the demand may be satisfied by the ordinary vehicles already if it is not necessary to commute in weekday. The positive parameter of childL4 at the 5% significance level indicates that households with babies would like to use electric vehicles more frequently, since their short distance trips could be satisfied by the electric vehicle. Meanwhile the electric vehicle can save the fuel consumption.

As the factor impacting the ownership of ordinary vehicles, annual income at the 1% significance level indicates that the richer households could spent more money on holding ordinary vehicles, for only one vehicle would not satisfy their huge demand of activities. The positive parameter of number of drivers at the 1% level indicates that households with more drivers would like to hold more ordinary vehicles, for they can use different vehicles without impacting other family members. The positive parameter of prefecture at the 1% significance level indicates that ownership of ordinary vehicles in the Gifu or Mie prefecture seems more than that in the Aichi prefecture. This may result from the fact that ordinary vehicles are very necessary for the households when the public transportation system is insufficient. The positive parameter of childL4 at the 1% significance level indicates that households with the babies have a higher desire to hold ordinary vehicles. For the parents of the baby are usually less than 40 years old, the ordinary vehicle can be a welcomed transportation mode for them.

As the factor impacting ownership of the electric vehicle, the minus parameter of electric vehicle price at the 1% significance level indicates that households are unwilling to hold expensive vehicle, for they may care about the price of the electric vehicle so much, when they plan to purchase it. The positive parameter of electric vehicle capacity in the 1% significance level indicates that households would like to hold the electric vehicle with large capacity, for this kind of vehicle are highly welcomed for the household with more members. The positive parameter of electric vehicle range at the 1% significance level indicates that household would like to hold the electric vehicle with longer range. If the electric vehicle has a longer range, the depletion of the battery will not upset them seriously, when they plan to purchase the vehicle. The positive parameter of facility installation rate in the gas station at the 5% significant level indicates that households have a higher desire of holding the electric vehicle if the charging rate in the gas station is higher, for the vehicle can be charged conveniently in the gas station. The positive parameter of home vehicle charging at the 1% significance level indicates that households consider the vehicle charging near home as a crucial factor when they plan to hold electric vehicles, for it is not convenient to charge vehicles in public places every time. The positive parameter of annual income at the 1% significance level indicates that the richer

households would like to hold the electric vehicle, for they can spare more money on purchasing vehicles if it is necessary. The positive parameter of numbers of drivers at the 1% significance level indicates that households with more drivers would prefer to hold electric vehicles, for the demand of using vehicles is very strong, which is unrelated to the vehicle type. The minus parameter of no occupation at the 1% significance level indicates that the household would not like to hold electric vehicles, if the householder does not have a fixed job, for ordinary vehicles may have already satisfied the travel demand in the household. The positive parameter of childL4 at the 1% significance level indicates that households with babies also would like to hold the electric vehicle, for this kind of households have a higher desire of holding vehicles, which is unrelated to the vehicle type.

Table 6 Matrix of the error covariance

	Monthly mileage of ordinary vehicles	Monthly mileage of electric vehicles	Number of ordinary vehicles	Number of electric vehicles
Monthly mileage of ordinary vehicles	72.657 (8.524)			
Monthly mileage of electric vehicles	-30.258	145.647 (12.068)		
Number of ordinary vehicles	2.469	-3.068	0.198 (0.445)	
Number of electric vehicles	-2.998	11.985	-0.272	1.000

Note: The standard variance of four equations is reported in parentheses.

The matrix of the error covariance is shown in Table 6. The standard variance of the error of ordinary vehicles usage is 8.524, while that of electric vehicles is found to be 12.068. The standard variance of the latter is more than the former, which indicates that the usage of the electric vehicle is more difficult to be predicted. This might result from the fact that only 27.4% of the households are supposed to hold and use the electric vehicle in the sample. So the estimation result of the Tobit model might lead to the larger variance. The standard variance of the error of ordinary vehicles ownership (0.445) is determined by the threshold values in the ordered probit model, which seems to be reasonable. The standard variance of the binary probit model is fixed to be 1.000 as mentioned in Section 4.1.

Table 7 Matrix of the error correlation

	Monthly mileage of ordinary vehicles	Monthly mileage of electric vehicles	Number of ordinary vehicles	Number of electric vehicles
Monthly mileage of ordinary vehicles	1.000			
Monthly mileage of electric vehicles	-0.294	1.000		
Number of ordinary vehicles	0.652	-0.572	1.000	
Number of electric vehicles	-0.352	0.993	-0.611	1.000

Table 7 presents the error correlation matrix of four equations. These correlation ratios can illustrate the association between the errors of each two equations. The errors from monthly mileage of ordinary vehicles and monthly mileage of electric vehicles are found to be a negative correlation of -0.294. The correlation ratio between the number of ordinary vehicles and the number of electric vehicle is at -0.611. This indicates a substitution effect between ordinary vehicles and electric vehicles not only in the ownership but also in usage. Considering vehicles ownership and usage, we find that the error of number of ordinary vehicles is positively

correlated with utilization of them and negatively correlated with utilization of electric vehicles. The number of electric vehicles is also having the similar conclusion. Here, we find that the number of electric vehicles is highly correlated with their usage at a ratio of 0.993. This might result from the two reasons listed as follows. On one hand, the usage of electric vehicle does exit if and only if the household is supposed to hold it. On the other hand, the state preference survey maybe could not collect usage information of electric vehicles exactly, for the respondents answered the survey just under the hypothetical scenario. It is concluded that the BMTOBP model nearly has an ideal and efficient estimation result as we expected.

5. SENSITITIVE ANALYSIS

For the BMTOBP model proposed in this study can be used to analyze the ownership and usage of the electric vehicle in one household, the sensitive analysis is utilized to examine the effects of some parameters in the model. We use the variables concerning neighborhood and household characteristics in the sample, and design hypothetical values concerning attributes of the electric vehicle, which are shown in Table 8. Each time we only change one attribute, and compare the variation of monthly mileage in average and that of holding share, respectively. The installation rate of charging facilities in the gas station is supposed to be 0.2.

Table 8 Hypothetical values concerning attributes of the electric vehicle

Item	Value												
Price (million JPY)	1	1.25	1.5	1.75	*2*	2.25	2.5	2.75	3	3.25	3.5	3.75	4
Capacity (seats)	2	3	4	*5*	6	7	8						
Charging time (10 minutes)	1	2	*3*	4	5	6							
Vehicle range (100 km)	1	1.5	*2*	2.5	3	3.5	4						

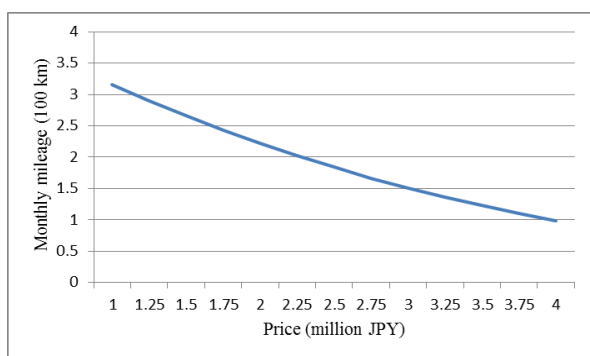Note: The bold and italic characters are the standard parameters.

Figure 1 Monthly mileage variation (price)
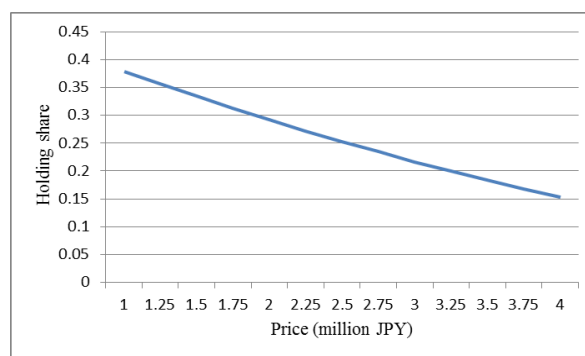

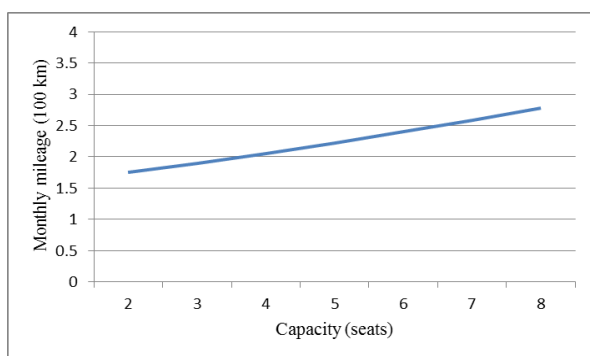Figure 2 Holding share variation (price)
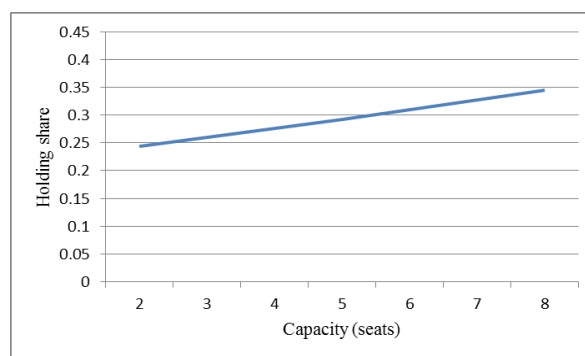

Figure 3 Monthly mileage variation (capacity)

Figure 4 Holding share variation (capacity)

Figure 1 and Figure 2 show the variation of monthly mileage and that of holding share with the change of the vehicle price, respectively. The variation of monthly mileage and that of holding share are both obvious. If the price increases by 1 million JPY, the monthly mileage will reduce by approximate 95 km, and the holding share would decrease by 8.2%.

The variation of monthly mileage and that of holding share with the change of the vehicle capacity are shown in Figure 3 and Figure 4, respectively. The variation of monthly mileage and that of holding share are both not obvious. If the capacity increases by one seat, the monthly mileage will rise by approximate 15 km, and the holding share will increase by 1.5%.
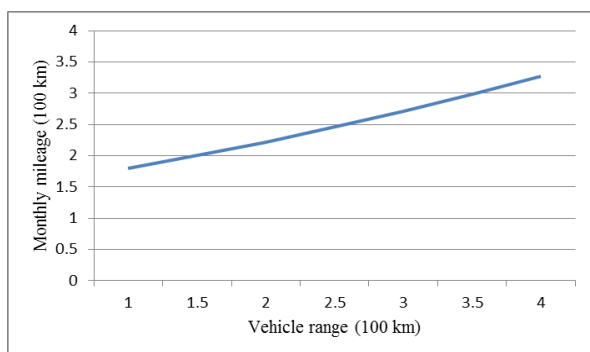
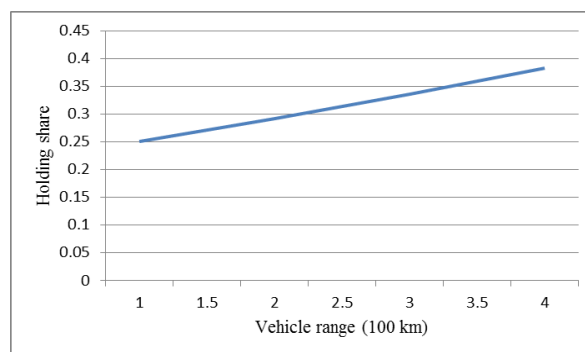Figure 5 Monthly mileage variation (vehicle range)
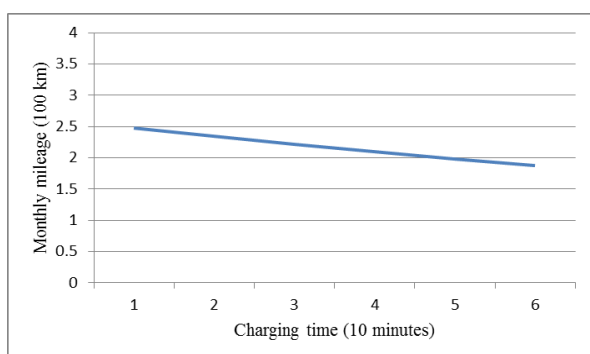
Figure 6 Holding share variation (vehicle range)

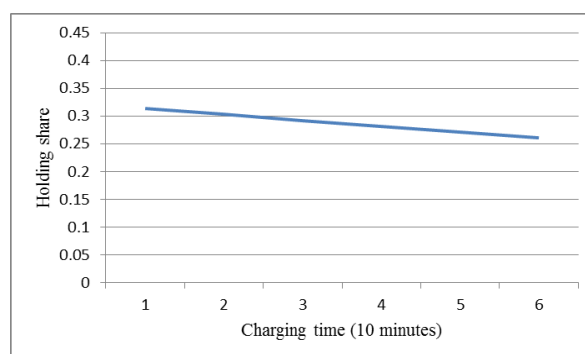Figure 7 Monthly mileage variation (charging time)

Figure 8 Holding share variation (charging time)

The variation of monthly mileage and that of holding share with the change of the vehicle range are shown in Figure 5 and Figure 6, respectively. The variation of monthly mileage and that of holding share are obvious. If the vehicle range increases by 100 km, the monthly mileage will rise by approximate 42 km, and the holding share will increase by 4.1%.

The variation of monthly mileage and that of holding share with the change of the vehicle charging time are shown in Figure 7 and Figure 8, respectively. The variation of monthly mileage and that of holding share are not obvious. If the charging time increases by 10 minutes, the monthly mileage would reduce by approximate 14 km, and the holding share would decrease by 1.1%.

According to the results of the sensitive analysis, the price and vehicle range seem to be the most crucial factors not only on the ownership but also on the usage of the electric vehicle. It should be noticed that the impact of the electric vehicle price on the usage of it may be an indirect effect, for the number of the electric vehicle has a high correlated ratio of 0.993 with the usage of it, and the price is also found to be a very crucial factor impacting the holding behavior. As it is known to us, these two factors seem to be the most controversial topics concerning electric vehicles nowadays.

6. CONCLUTIONS

This study analyzes the ownership and usage of electric vehicles in the household. Meanwhile, the impact of the ownership and usage of ordinary vehicles is taken into consideration. 5766 stated preference survey data in the Chukyo region in Japan are utilized as the research sample representing households` vehicle holding and using information. The estimation result based on a Bayesian Multivariate Tobit, Ordered and Binary Probit (BMTOBP) model suggests the importance of attributes of the electric vehicle, neighborhood and the household characteristics as well as the installation rates of charging facilities in public places. This model reveals the relation between the ownership and usage for each kind of vehicles (ordinary or electric ones). Meanwhile, it examines the relation of the ownership and usage between two types of vehicles.

It is shown that the annual income and the number of drivers in a household are crucial factors on the ownership and usage of both ordinary and electric vehicles. The householder without fixed occupation is unwilling to hold or use the electric vehicle. Households in the Gifu or Mie prefecture have a preference of holding and using ordinary vehicles. Households with babies would like to hold ordinary or electric vehicles, and they have a higher preference of using electric vehicles. Households who can charge vehicles at home have a higher preference of holding and using electric vehicles. The price, capacity, range and installation rates of charging facility in the gas station are crucial factors impacting the ownership and usage of the electric vehicle. Meanwhile, the charging time does not affect either the ownership or usage of the electric vehicle. It is also found that there is a substitution effect between ordinary vehicles and electric ones not only in the ownership but also in the usage.

There are some research issues remaining as future tasks. In this model, we utilize the stated preference data as the research sample to represent the vehicle ownership and usage in the household. As a result, it does not consider vehicle replacing behavior if the household treated the electric vehicle as Exchange. Next, we will make a further research concerning this behavior. Moreover, based on the estimation result in this study, we will use the 4th personal trip survey data (2001) to forecast the holding and using demand of the electric vehicle in the Chukyo region in Japan, and make a comparison with the result concluded from our previous research.

ACKNOWNLEGEMENTS

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