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 $i$,

$\beta_k$ : the vector of parameters in the $kth$ equation, and

$\varepsilon_{ki}$ : 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, $\alpha_{31}$ and $\alpha_{32}$ 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. $\alpha_{31}$ and $\alpha_{32}$ are set to be -0.431 ( $\Phi^{-1}(1/3)$ ) and 0.431 ( $-\Phi^{-1}(1/3)$ ), respectively ( $\Phi^{-1}$ 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 $\beta$ and $\sum$. Each iteration of the Gibbs sampler is conducted by the order of $y_i^*$, $\beta$ and $\sum$ 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,

$\pi$ : 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.

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

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

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

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

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 $\beta$ is multivariate normal distribution with the mean $\beta_0$ and the covariance matrix $V_0$, it is not difficult to derive the conditional posterior distribution of $\beta$ illustrated as follows.

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

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

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

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 $\beta_0$ to be a column vector of zeros, and $V_0$ to be diagonal matrix with $100$ on the diagonal.

If the prior distribution of $\Sigma$ is supposed to be an Inverse-Wishart distribution with the freedom $v$ and the scale matrix $\Psi$, 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 $\Sigma$ to be identified during the cycle of the Gibbs sampler. We set $v$ to be 10, and $\Psi$ 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.

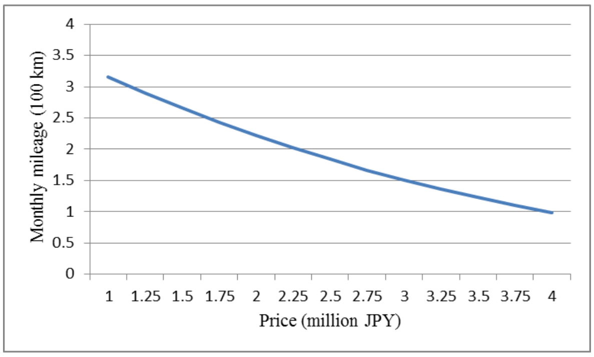


Figure 1 Monthly mileage variation (price)

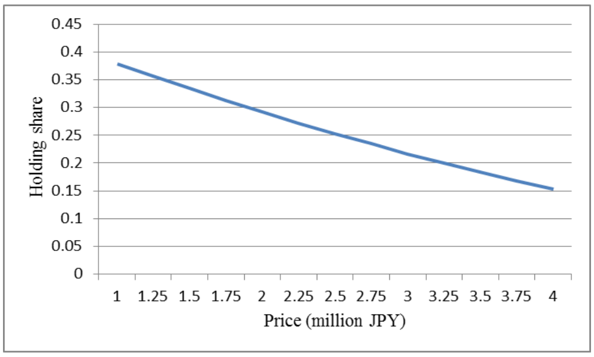


Figure 2 Holding share variation (price)

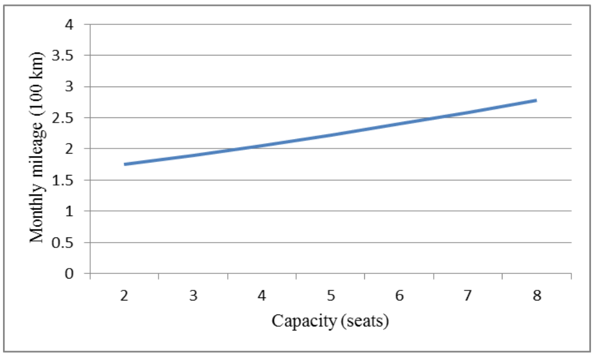


Figure 3 Monthly mileage variation (capacity)

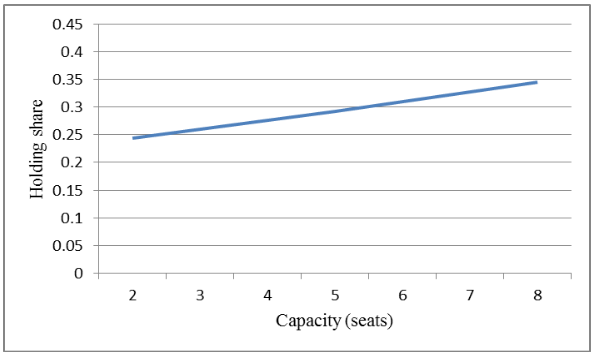


Figure 4 Holding share variation (capacity)

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%.

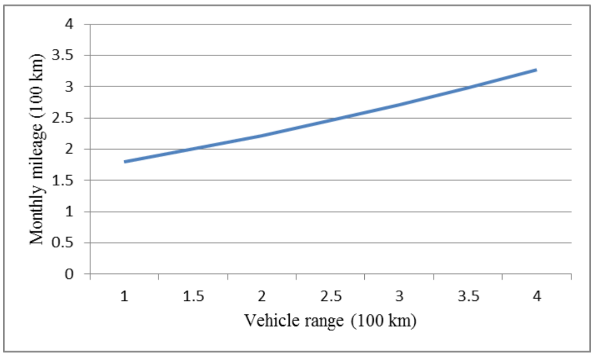


Figure 5 Monthly mileage variation (vehicle range)

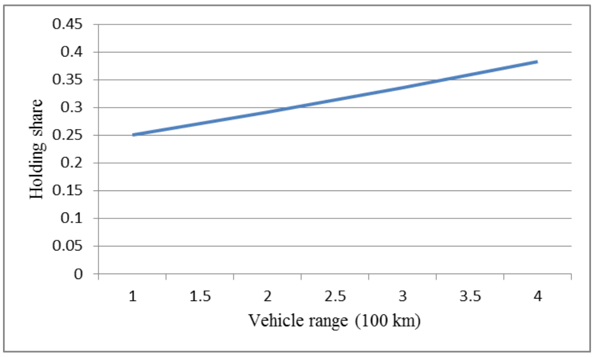


Figure 6 Holding share variation (vehicle range)

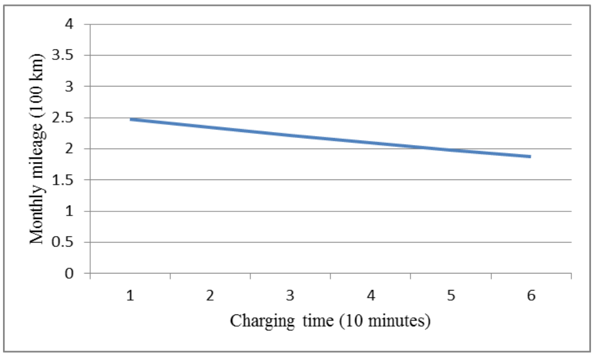


Figure 7 Monthly mileage variation (charging time)

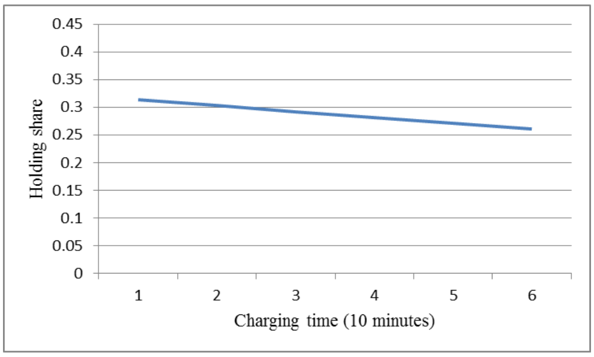


Figure 8 Holding share variation (charging time)

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

This research is supported by Environment Research & Technology Development Fund (2010) from Japanese Ministry of Environment. The authors would like to thank members in our research group who collected and aggregated results of the Internet questionnaires.

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