Comparative Analysis of the Household Car Ownership between Toyota City and Nagoya City

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Abstract: This study investigates the household passenger car ownership in the local city and its difference from that in the metropolis in Japan. Large scale person trip survey data for Toyota City and Nagoya City are used for empirical analysis. A bivariate ordered probit model is developed to analyze the ownership of the light motor car and the ordinary motor one. The Gibbs Sampler algorithm is implemented to estimate the parameters. The major findings suggest: 1) that population density and density of railway stations have different effects on the ownership of two vehicle types between two cities; 2) that population density only significantly and negatively impacts the ownership of the light motor car, and density of railway stations does not impact ownership of two vehicle types in Toyota City; 3) that population density and density of railway stations significantly and negatively impact the ownership of two vehicle types in Nagoya City.

Keywords: Car Ownership, Vehicle Type, Person Trip Survey Data, Bivariate Ordered Probit Model

1. INTRODUCTION

Due to the development of motorization society, the private car ownership has been increasing dramatically since the second half of the 20th century in developed countries\textsuperscript{1}. The penetration of private cars can change the lifestyle of residents, especially in the local city where the public transportation system is not sufficient. Meanwhile, it also leads to many externalities to the environment of the metropolis, such as air pollution, traffic congestion and so on. The administrator of the metropolis has tried to control the ownership of private cars by implementing one urban planning strategy called the transit oriented city development (Curtis \textit{et al.}, 2009; Suzuki \textit{et al.}, 2013). As a result, the ownership of private cars in the local city and that in the metropolis are not identical.

Japan initiated the motorization society since 1960s, and the ownership of private and commercial passenger cars increased approximate 25 times from 2.29 million in 1966 to 59.36 million in 2013. It is reported that 17.7\% of CO2 emissions are from the transport sector in Japan by 2012. In order to reduce the CO2 emissions from the transport sector, the Japanese Government has implemented an action plan to promote alternative fuel vehicles by given some incentives, such as providing subsidy, deploying the fueling stations for alternative fuel vehicles and so on. The promotion of alternative fuel vehicles in the local city seems more promising than that in the metropolis. There are 3 reasons listed as follows. Firstly, the replacement of

\textsuperscript{1} The car is defined as a passenger car and does not include the truck in this study.
conventional cars by alternative fuel vehicles can contribute more reduction amount of CO2 emissions, since the vehicle ownership and usage in the local city are more than that in the metropolis. Secondly, the deployment of fueling stations for alternative fuel vehicles is easier than that in the metropolis, since there is more space available in the local city. Thirdly, since the household in the local city usually has his or her own parking space at home, some types of alternative fuel vehicles, like battery electric vehicles or plug-in hybrid electric vehicles can be charged at home by the normal charger.

Since some types of alternative fuel vehicles, like micro-cars or battery electric vehicles are usually with small size or low displacement similar to the light motor car, and households might choose the vehicle type similar to the former one, when they decide to replace the conventional car by the alternative fuel vehicle, it is necessary to understand the vehicle choice behavior for conventional vehicle types including the light motor car and the ordinary motor one, in order to promote the alternative fuel vehicles in the local city.

Most of existed studies mainly investigated the household car ownership in metropolitan areas. Sanko et al. (2009) investigated the household car ownership and motorcycle ownership behaviors in Nagoya metropolitan area of Japan. Yamamoto (2009) analyzed household car, motorcycle and bicycle ownership between Osaka metropolitan area, Japan and Kuala Lumpur, Malaysia. Meanwhile, the study investigating the household car ownership in the local city is relatively limited.

From this view point, the household car ownership in the local city is investigated in this study, and its difference from that in the metropolis is also observed. Large scale person trip survey data for Toyota City and Nagoya City are used for empirical analysis. The vehicle types are classified into the light motor car and the ordinary motor car. In order to reveal the preference of households on vehicle type choices as well as the relation of ownerships between two vehicle types, a bivariate ordered probit model is implemented. Based on the comparative analysis of the estimation results, we can understand the household car ownership in the local city and its difference from that in the metropolis in Japan.

The rest of this paper is organized as follows. Section 2 gives a brief literature review concerning the methodology related to the analysis of vehicle ownership and type. Section 3 describes the data sets used for empirical analysis. Section 4 discusses the proposed model in this study and the implemented Gibbs Sampler algorithm for parameter estimation. The results of parameter estimation and comparative analysis are reported in Section 5. Finally, this study is concluded in Section 6 along with a discussion about future research issues.

2. LITERATURE REVIEW

There are many previous studies on vehicle ownership and type in the household. Either the discrete choice or the discrete-continuous choice model was implemented in previous research. The difference of these two methodologies was resulting from the sample data used for empirical study. Since some survey data did not include the monthly or annual mileage of the respondent, only the car ownership can be modeled by the discrete choice model.

There are mainly two types of discrete choice models implemented in the previous studies, the ordered response model and the unordered response model. The ordered response model utilizes the ordered probit or logit model to analyze the car ownership in the household level (Bhat and Puluguata, 1998; Chu, 2002; Kim and Kim, 2004; Matas and Raymond, 2008). The number of the threshold values in the ordered probit model was decided by the car ownership.

The unordered response model utilizes the alternatives in the nested logit structure to represent the car ownership and its type choice (Bhat and Puluguata, 1998; Feng et al., 2005;
West, 2004). The nested logit model usually contains two levels in the nested structure. The upper level of the nest is used to represent the possible number of vehicle ownership in the household. Meanwhile, the lower level is representing the possible combinations of vehicle types conditional on a fixed vehicle number. Two demerits of the unordered response model are existed. On one hand, the alternatives in the nested logit model are increasing dramatically with the increase of the car ownership or type. On the other hand, the complementary or substitution effect between different vehicle types cannot be observed by this method.

If the monthly or annual mileage is also investigated in the survey, the vehicle type and usage can be analyzed simultaneously in one unified framework by the discrete-continuous choice model. There are mainly three types of discrete-continuous choice models implemented in previous studies, the indirect utility function based discrete-continuous (IUFBDC) model, the multiple discrete-continuous extreme value (MDCEV) model and the Bayesian multivariate ordered probit and tobit (BMOPT) model.

The IUFBDC model is deriving from the random utility maximization following the methodology developed by Dubin and MacFadden (1984) and Hanemann (1984). This method utilizes the indirect function to represent the maximum utility for one choice considering the budget constraint. Two merits of utilizing the indirect utility function are listed as follows. On one hand, the indirect utility function can be used to calculate the maximum utility within the budget constraint for vehicle choice, and then the multinomial logit model can be used to model the vehicle type choice. On the other hand, the optimal vehicle usage in the form of the annual or monthly mileage can be derived by Roy’s identity based on the indirect utility function. Since the optimal mileage usually has some observed errors, one error item following the normal distribution can be added. And then, the joint likelihood function including the likelihood function of vehicle type choice (the discrete choice) and that of vehicle usage choice (the continuous choice) can be derived. Since the optimal vehicle usage derived from the indirect utility function using Roy’s identity is usually in a non-linear form, the approximation method is usually applied in this procedure (Dubin and MacFadden, 1984).

The second type of discrete-continuous choice models called the MDCEV model was firstly proposed by Bhat (2005). Bhat and Sen (2006) extended the MDCEV model to analyze the car ownership and usage in the household in San Francisco Bay Area in America. This model utilized the annual or monthly mileages by each type of vehicles as the continuous variables, and the total mileage was considered to be one constraint. The vehicle type choice was captured by a multinomial logit similar component in the object utility function. This model utilized the vehicle usage to represent the vehicle choice. For example if the household owns one light motor car, the mileage driven by it is more than zero. Since the closed-form of its likelihood function could be derived straightforward based on the model specification, it offers a practical methodology for modeling the multiple vehicle types choice effectively. Two demerits of this model are listed as follows. On one hand, the MDCEV model requires one constraint condition in order to estimate the parameters. Usually, the total vehicle mileage or expenditure of all vehicles in the household is chosen, which is doubted by some researchers. On the other hand, 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 inefficient.

In order to overcome two demerits of the MDCEV model mentioned above, the third type of discrete-continuous choice models, the BMOPT model was proposed by Fang (2008). The BMOPT model utilizes a multivariate ordered probit model to portrait the ownership of multiple vehicle types and a multivariate tobit model to analyze vehicle usage corresponding to vehicle types owned by the household. The relationship of vehicle ownership and usage inside the same vehicle type and between the different vehicle types could be observed by the correlation matrix of the error items in the equation system.
It should be noticed that this model can be extended easily, since the multivariate ordered probit model can be used for analyzing the ownership of multiple vehicle types in the household, when the vehicle usage is not investigated. Meanwhile, if the vehicle type is further analyzed, this model can be easily modified to fulfill this requirement, and Fang (2008) has proved the merit of this model in his or her study. Furthermore, if the ownership is extended to more alternatives, for example from 3 alternatives (0, 1, >=2) to 4 alternatives (0, 1, 2, >=3), this model can be modified to solve this problem easily, and Kobayashi et al. (2009) extended the BMOPT model to analyze the ownership and usage of the ordinary motor car and that of the light motor one in the national wide in Japan.

Since the monthly or annual vehicle mileage is not investigated in the person trip survey in the Chukyo region in Japan, the discrete-continuous choice model cannot be implemented in this study. Meanwhile, the private cars are classified into the ordinary motor car and the light motor one in the person trip survey. So in this study the simplified version of the BMOPT model is used to model the vehicle type choice of the light motor car and the ordinary motor one. The Gibbs Sampler algorithm is implemented to estimate the parameters based on the data sets for Toyota City and Nagoya City, respectively. Meanwhile, this study is an empirical study on the household car ownership in the local city and its difference from that in the metropolis in Japan.

3. DATA

3.1 Basic Statistics

We use the data from the 5th person trip survey in the Chukyo region in Japan, a cross-section survey of about 140 thousand households in this region. As the 3rd major metropolitan area in Japan, the Chukyo region is centered on Nagoya City, Toyota City is also located in the Chukyo metropolitan area. The person trip survey in the Chukyo metropolitan area is carried out every 10 years, and the data used in this study is from the survey data in 2011. As a local city, Toyota City is characterized by the relatively low population density and highly dependent on private cars. Compared to Toyota City, the metropolis Nagoya city is characterized by high population density and with the sufficient railway or subway system. The different characteristics of these two cities will be discussed in Section 3.2.

14855 households in Toyota City and 36243 households in Nagoya City from the person trip survey data are used as the research sample, respectively. The description of the sample data for two cities are shown in Table 1, respectively. Compared to the gender of the householders in Toyota City, the householders in Nagoya City have a lower ratio of male, at around 66.1%. For the age of the householders, two cities do not have the significant difference, and the ratios of the householders equal to or more than 60 years old are both more than 50%. It might indicate the trend of aging society in Japan. The ratio of households having less than 4 members in Nagoya City is 80.1% and more than that in Toyota City at 71.1%. It might indicate the fact that in the city with high population density, room sizes of the apartment in these places are relatively small and cannot capacity big family. The ratio of unemployed householders in Nagoya City at 44.8% is a little more than that in Toyota City at 42.3%.

Table 2 shows the cross aggregation result concerning the car ownership for two cities, respectively. As the car ownership in Toyota City, only 11.73% of the households do not own the light motor car or the ordinary motor one. Around 36.59 % of households own the light motor car. Meanwhile, the ratio of households owning the ordinary motor car at around 80.70% is much higher than that of households owning the light motor car. These results might indicate that private cars seem to be necessary in Toyota City, and the ordinary motor car is more popular.
than the light motor one.

Table 1. Description of the sample data for Toyota and Nagoya

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Percentage [Toyota]</th>
<th>Percentage [Nagoya]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender of the householder</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>76.4%</td>
<td>66.1%</td>
</tr>
<tr>
<td>Female</td>
<td>23.6%</td>
<td>33.9%</td>
</tr>
<tr>
<td>Age of the householder</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;= 19 years old</td>
<td>1.6%</td>
<td>1.2%</td>
</tr>
<tr>
<td>&gt;= 20 &amp; &lt; 30 years old</td>
<td>6.4%</td>
<td>4.4%</td>
</tr>
<tr>
<td>&gt;= 30 &amp; &lt; 40 years old</td>
<td>12.7%</td>
<td>13.2%</td>
</tr>
<tr>
<td>&gt;= 40 &amp; &lt; 50 years old</td>
<td>13.5%</td>
<td>16.1%</td>
</tr>
<tr>
<td>&gt;= 50 &amp; &lt; 60 years old</td>
<td>13.7%</td>
<td>15.0%</td>
</tr>
<tr>
<td>&gt;= 60 years old</td>
<td>52.1%</td>
<td>50.1%</td>
</tr>
<tr>
<td>Household member</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>17.8%</td>
<td>26.4%</td>
</tr>
<tr>
<td>2</td>
<td>31.8%</td>
<td>33.5%</td>
</tr>
<tr>
<td>3</td>
<td>21.4%</td>
<td>19.2%</td>
</tr>
<tr>
<td>4</td>
<td>17.1%</td>
<td>14.9%</td>
</tr>
<tr>
<td>5</td>
<td>6.3%</td>
<td>4.4%</td>
</tr>
<tr>
<td>&gt;=6</td>
<td>5.5%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Occupation of householder</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manager</td>
<td>7.1%</td>
<td>10.4%</td>
</tr>
<tr>
<td>Engineer</td>
<td>17.5%</td>
<td>14.6%</td>
</tr>
<tr>
<td>Clerical officer</td>
<td>5.8%</td>
<td>9.0%</td>
</tr>
<tr>
<td>Salesman</td>
<td>2.1%</td>
<td>5.1%</td>
</tr>
<tr>
<td>Servicer</td>
<td>4.5%</td>
<td>6.8%</td>
</tr>
<tr>
<td>Security worker</td>
<td>0.9%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Farmer</td>
<td>2.7%</td>
<td>0.1%</td>
</tr>
<tr>
<td>Production worker</td>
<td>11.1%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Communication worker</td>
<td>1.2%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Construction worker</td>
<td>1.5%</td>
<td>1.3%</td>
</tr>
<tr>
<td>Transport worker</td>
<td>1.3%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Other worker</td>
<td>2.0%</td>
<td>2.5%</td>
</tr>
<tr>
<td>No occupation</td>
<td>42.3%</td>
<td>44.8%</td>
</tr>
</tbody>
</table>

Table 2. Tabulation of car ownership for Toyota and Nagoya

<table>
<thead>
<tr>
<th>Sample for Toyota [N=14855]</th>
<th>Number of ordinary motor cars</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of light motor cars</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0.1173</td>
<td>0.2602</td>
</tr>
<tr>
<td>1</td>
<td>0.0616</td>
<td>0.1724</td>
</tr>
<tr>
<td>&gt;=2</td>
<td>0.0141</td>
<td>0.0274</td>
</tr>
<tr>
<td>Total</td>
<td>0.1930</td>
<td>0.4600</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample for Nagoya [N=36243]</th>
<th>Number of ordinary motor cars</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of light motor cars</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0.3126</td>
<td>0.4052</td>
</tr>
<tr>
<td>1</td>
<td>0.0710</td>
<td>0.0643</td>
</tr>
<tr>
<td>&gt;=2</td>
<td>0.0053</td>
<td>0.0038</td>
</tr>
<tr>
<td>Total</td>
<td>0.3888</td>
<td>0.4733</td>
</tr>
</tbody>
</table>

Compared to the tabulation result of car ownership in Toyota City, the ownership of two types of private cars are different in Nagoya City. About 31.26% of households investigated in Nagoya City do not owning any type of private cars. Around 15.92% of households own the light motor car. Meanwhile, the ratio of households owning the ordinary motor car at 61.12%
is much higher than that of households owning the light motor car. These results might indicate that the dependency on private cars in Nagoya City is not as strong as that in Toyota City, since the sufficient railway system might be able to control the ownership and use of private cars.

3.2 Data Aggregation

In order to compare geological characteristics and the ownership of private cars between Toyota City and Nagoya City, we draw the figures concerning some attributes for these two cities, respectively. The results shown in this section are aggregated results based on all the households living in the city, not just based on the sample data.

Figure 1 shows the population density in Toyota City and Nagoya City, respectively. The population density in Toyota City is lower than that in Nagoya City. As a local city, Toyota City is characterized by low population density in most areas and high population density only in the city center. Compared to Toyota City, the metropolis Nagoya City is characterized by high population density in most areas and low population density in suburban areas.

The accessibility to the railway or subway system in two cities are shown in Figure 2, respectively. The number of railway or subway stations in Nagoya City seems to be very large. Compared to that in Nagoya City, the number of the railway or subway stations in Toyota City is much smaller. Meanwhile, all of the stations are in the west part of the city, since the east part of Toyota City is the intermediary area between plains and mountains. It might decide that private cars are indispensable in the east part of Toyota City.

Figure 3 shows the ownership of ordinary motor cars in Toyota City and Nagoya City,
respectively. It can be known that the ownership of ordinary motor cars in the west part of Toyota City is more than that in the east part. Compared to that in Toyota City, the ownership of ordinary motor cars in Nagoya City is relatively small, and the difference of the ownership among small zones is not obvious.

**Figure 3.** Ownership of ordinary motor cars (unit: cars/household)

Figure 4 shows the ownership of light motor cars in Toyota City and Nagoya City, respectively. It can be known that the ownership of light motor cars in the east part of Toyota City is more than that in the west part. Compared to that in Toyota City, the ownership of ordinary motor cars in Nagoya City is relatively small, and the ownership in suburban areas is more than that in urban areas.

**Figure 4.** Ownership of light motor cars (unit: cars/household)

### 4. MODEL INSTRUCTION

#### 4.1 Model Specification

Let two latent variables $y^*_1$ and $y^*_2$ represent the preference of households for owning the light motor car and the ordinary motor one, respectively. The two equations system for discrete choice of these two types of cars is represented as follows.

$$
y^*_1 = x^*_1 \beta_1 + \varepsilon^*_1 \tag{1}
$$

$$
y^*_2 = x^*_2 \beta_2 + \varepsilon^*_2 \tag{2}
$$
where,
\( i \): indexing the household in the sample \( i = 1, \ldots, N \),
\( k \): the list number of the equation \( k = 1, 2 \),
\( x_{ki} \): 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 two latent variables can be written into a seemingly unrelated regression form (Koop, 2003).

\[
y^*_i = x_i \beta + \varepsilon_i
\]  

(3)

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

\[
\varepsilon_i \sim \text{i.i.d. } BVN(0, \Sigma)
\]  

(4)

The relation between latent and observed variables is illustrated as follows.

\[
y_{1i} = \begin{cases} 
0, & \text{if } y^*_{1i} \leq \alpha_{11} \\
1, & \text{if } \alpha_{11} < y^*_{1i} \leq \alpha_{12} \\
2 \text{ or more}, & \text{if } \alpha_{12} < y^*_{1i}
\end{cases}
\]  

(5)

\[
y_{2i} = \begin{cases} 
0, & \text{if } y^*_{2i} \leq \alpha_{21} \\
1, & \text{if } \alpha_{21} < y^*_{2i} \leq \alpha_{22} \\
2 \text{ or more}, & \text{if } \alpha_{22} < y^*_{2i}
\end{cases}
\]  

(6)

where, \( \alpha_{11} \) and \( \alpha_{12} \) are the threshold values of the ordered probit model used to measure the ownership of light motor cars. 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 the previous study of Fang (2008). Two threshold values \( \alpha_{11} \) and \( \alpha_{12} \) 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). The same method can be used for setting two threshold values \( \alpha_{21} \) and \( \alpha_{22} \) of the equation measuring the ownership of ordinary motor cars.

### 4.2 Model Estimation

In order to estimate the parameters in the proposed model, the Gibbs Sampler algorithm is implemented in this study. The Gibbs Sampler algorithm is one type of the Bayesian Markov Chain Monte Carlo methods implemented to estimate the 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). Unlike the maximum likelihood estimation method, the Gibbs Sampler algorithm can estimate the parameters effectively and efficiently, when some sample share is very small. Just
in the sample for Nagoya City, the sample share of the households owning more than one light motor car is very small about 0.01.

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 \( \Sigma \). Each iteration of the Gibbs Sampler is conducted by the order of \( y_i^* \), \( \beta \) and \( \Sigma \) listed as follows.

\[
\begin{align*}
\text{draw} & \quad y_i^* | \beta, \Sigma, y_i \quad \text{from} \quad \pi(y_i^* | \beta^{(k-1)}, \Sigma^{(k-1)}, y_i) \\
\text{draw} & \quad \beta | \Sigma, y_i^* \quad \text{from} \quad \pi(\beta | \Sigma^{(k-1)}, y_i^{(k)}) \\
\text{draw} & \quad \Sigma | y_i^*, \beta \quad \text{from} \quad \pi(\Sigma | y_i^{(k)}, \beta^{(k)})
\end{align*}
\]

where, \( \pi \) : the conditional posterior distribution, and

\( k \) : the order of the iteration in the Gibbs Sampler algorithm.

Sampling the latent variables \( y_i^* \) from the truncated multivariate normal distribution can be implemented through drawing from a series of full conditional distribution of each element of \( y_i^* \) given other variables (Geweke, 1991). It is not difficult to prove that equations 10-11 can draw a sample from the full conditional distribution for \( y_{bi}^* (k = 1,2) \), respectively.

\[
\begin{align*}
y_{bi}^* &= \begin{cases} 
\mu_{i-1} + \sigma_{i-1}\Phi^{-1}(U(1-\Phi((0.431-\mu_{i-1})/\sigma_{i-1}))+\Phi((0.431-\mu_{i-1})/\sigma_{i-1})), & \text{if } y_{bi} \geq 2 \\
\mu_{i-1} + \sigma_{i-1}\Phi^{-1}(U\Phi(0.431-\mu_{i-1})/\sigma_{i-1})-\Phi((-0.431-\mu_{i-1})/\sigma_{i-1})), & \text{if } y_{bi} = 1 \\
\mu_{i-1} + \sigma_{i-1}\Phi^{-1}(U\Phi((-0.431-\mu_{i-1})/\sigma_{i-1})), & \text{if } y_{bi} = 0
\end{cases} \\
y_{2i}^* &= \begin{cases} 
\mu_{2-1} + \sigma_{2-1}\Phi^{-1}(U(1-\Phi((0.431-\mu_{2-1})/\sigma_{2-1}))+\Phi((0.431-\mu_{2-1})/\sigma_{2-1})), & \text{if } y_{2i} \geq 2 \\
\mu_{2-1} + \sigma_{2-1}\Phi^{-1}(U(0.431-\mu_{2-1})/\sigma_{2-1})-\Phi((-0.431-\mu_{2-1})/\sigma_{2-1})), & \text{if } y_{2i} = 1 \\
\mu_{2-1} + \sigma_{2-1}\Phi^{-1}(U\Phi((-0.431-\mu_{2-1})/\sigma_{2-1})), & \text{if } y_{2i} = 0
\end{cases}
\end{align*}
\]

where,

\( U \) : a random variable following the uniform distribution between 0 and 1,

\( \mu_{j-1} \) : the mean of equation \( j \) fully conditional on other equations, and

\( \sigma_{j-1} \) : the standard variance of equation \( j \) fully conditional on other equations.

The calculation of the full conditional mean and variance is equally straightforward according to the textbook by Poirier (1995). Meanwhile, if the prior distribution of \( \beta \) is a 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.

\[
\begin{align*}
\beta | y_i^*, \Sigma & \sim N(\overline{\beta}, \overline{V}) \\
\overline{V} &= (V_0^{-1} + \sum_{i=1}^N y_i^T \Sigma^{-1} y_i)^{-1} \\
\overline{\beta} &= \overline{V}(V_0^{-1} \beta_0 + \sum_{i=1}^N y_i^T \Sigma^{-1} y_i)
\end{align*}
\]
where, \( N \) is the number of households in the sample. Sampling from a multivariate normal
distribution can be implemented referring to the method proposed 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. Meanwhile, 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 of \( \Sigma \) can be derived as follows.

\[
\Sigma | y_i^*, \beta \sim W^{-1}(v + N, \sum_{i=1}^{N} (y_i^* - x_i \beta)(y_i^* - x_i \beta)^T + \Psi)
\]

where, \( W^{-1} \) represents the Inverse-Wishart distribution. We set \( v \) to be 10, and \( \Psi \) to be an identical matrix. The generation of random matrix following the Inverse-Wishart distribution is implemented by using the Bartlett decomposition (Smith and Hocking, 1972).

Since we utilize the similar bivariate ordered probit model proposed in our previous study (Yang et al., 2014), the instruction of the implemented Gibbs Sampler algorithm can be also found in that study. We use GAUSS 3.2 to implement the Gibbs Sampler algorithm illustrated above. We take 11000 times of iterations and burn the first 1000 times. The remaining 10000 draws are used to estimate parameters of the posterior inference.

### 4.3 Explanatory Variables

The explanatory variables concerning household attributes and geological characteristics are included in the model. The explanatory variables concerning household attributes are derived from individual attributes for each household in the person trip survey. The explanatory variables concerning geological characteristics are calculated based on the unit of the small zone. The explanation of explanatory variables in the proposed model is listed in Table 3.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (dummy)</td>
<td>1 if age of the householder is 60 years older or above; 0 otherwise.</td>
</tr>
<tr>
<td>Workers</td>
<td>Number of workers in the household</td>
</tr>
<tr>
<td>Member25</td>
<td>Number of family members in the household (( \geq 25 ) years old)</td>
</tr>
<tr>
<td>Female (dummy)</td>
<td>1 if the householder is female; 0 otherwise.</td>
</tr>
<tr>
<td>Log(population density)</td>
<td>Population density is estimated based on the small zone by using the person trip survey data (persons/km(^2)).</td>
</tr>
<tr>
<td>Density of railway stations</td>
<td>The number of railway stations divided by area of the small zone (stations/km(^2)).</td>
</tr>
</tbody>
</table>

### 5. ESTIMATION RESULTS

In order to investigate the household car ownership in Toyota City and its difference from that in Nagoya City, we estimated the parameters using the data sets for two cities, respectively. Then we compared the similar and different effects of the estimated parameters. Estimation results of the samples data for two cities are shown in Table 4 and Table 5, respectively. In this study, it is supposed that one explanatory variable has a significant effect, if its significance level is equal to or less than 5%.
Table 4. Model estimation result [Toyota]

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Light motor car</th>
<th></th>
<th>Ordinary motor car</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parameter</td>
<td>T-statistic</td>
<td>Parameter</td>
<td>T-statistic</td>
</tr>
<tr>
<td>Age (dummy)</td>
<td>-0.083**</td>
<td>-5.53</td>
<td>-0.246**</td>
<td>-18.66</td>
</tr>
<tr>
<td>Female (dummy)</td>
<td>0.113**</td>
<td>6.65</td>
<td>-0.069**</td>
<td>-4.67</td>
</tr>
<tr>
<td>Member25</td>
<td>0.109**</td>
<td>12.06</td>
<td>0.094**</td>
<td>11.20</td>
</tr>
<tr>
<td>Workers</td>
<td>0.050**</td>
<td>3.96</td>
<td>0.193**</td>
<td>16.56</td>
</tr>
<tr>
<td>Log (population density)</td>
<td>-0.061**</td>
<td>-11.79</td>
<td>0.006</td>
<td>1.22</td>
</tr>
<tr>
<td>Density of railway stations</td>
<td>-0.041</td>
<td>-1.77</td>
<td>-0.015</td>
<td>-0.78</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.528**</td>
<td>-12.27</td>
<td>-0.306**</td>
<td>-7.76</td>
</tr>
</tbody>
</table>

Parameter | T-statistic

Variance of the light motor car | 0.435** | 37.04
Covariance | -0.126** | -24.56
Variance of the ordinary motor car | 0.385** | 49.82

Number of samples | 14855

** Significant at 1% level; * Significant at 5% level.

Table 5. Model estimation result [Nagoya]

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Light motor car</th>
<th></th>
<th>Ordinary motor car</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parameter</td>
<td>T-statistic</td>
<td>Parameter</td>
<td>T-statistic</td>
</tr>
<tr>
<td>Age (dummy)</td>
<td>-0.157**</td>
<td>-14.29</td>
<td>-0.268**</td>
<td>-36.28</td>
</tr>
<tr>
<td>Female (dummy)</td>
<td>0.023*</td>
<td>2.00</td>
<td>-0.137**</td>
<td>-17.16</td>
</tr>
<tr>
<td>Member25</td>
<td>0.071**</td>
<td>9.86</td>
<td>0.134**</td>
<td>25.67</td>
</tr>
<tr>
<td>Workers</td>
<td>0.057**</td>
<td>5.60</td>
<td>0.123**</td>
<td>16.52</td>
</tr>
<tr>
<td>Log (population density)</td>
<td>-0.181**</td>
<td>-16.06</td>
<td>-0.090**</td>
<td>-11.38</td>
</tr>
<tr>
<td>Density of railway stations</td>
<td>-0.072**</td>
<td>-10.19</td>
<td>-0.041**</td>
<td>-8.88</td>
</tr>
<tr>
<td>Constant</td>
<td>0.462**</td>
<td>4.51</td>
<td>0.323**</td>
<td>4.41</td>
</tr>
</tbody>
</table>

Parameter | T-statistic

Variance of the light motor car | 0.381** | 36.71
Covariance | -0.090** | -27.27
Variance of the ordinary motor car | 0.291** | 77.27

Number of samples | 36243

** Significant at 1% level; * Significant at 5% level.

After the comparison of the estimation results shown in Table 4 and Table 5, we can conclude that as the explanatory variables concerning attributes of the household, the age and gender of the householder, number of workers, and number of members (>= 25 years old) have nearly the same effects on the car ownership in two cities, since all of these parameters are in the same sign at least with a 5% significance level. As the factors impacting the vehicle type in either of two cities, except the gender of the householder other parameters have the same sigh for two types of vehicles as we expected. It can be concluded that if the householder is equal to or more than 60 years old, the household would not like to own the light motor car or the ordinary motor one. It might indicate that the private cars are more popular in the young household compared to the aged household. It is also found that with the increase number of workers or that of members (>= 25 year old), the household would like to own more private cars, since the demand of using private cars is huge in this type of family. As the factor impacting the vehicle type with different effects, the households with the female householder would like to own the light motor car, and would not like to own the ordinary motor car. It might indicate that the light motor car is very popular for female, since its compact design and cheap price are attractive.

As the explanatory variables concerning the geological characteristics, population density and density of railway stations have different effects between two cities. It can be concluded
that population density in Toyota City only impacts the ownership of the light motor car. It might indicate that households living in the place with lower population density are willing to own the light motor car, since the light motor car has a cheap price and excellent fuel consumption. Meanwhile, population density does not impact the ordinary motor car in Toyota City. It can be also found that density of railway stations does not impact either type of cars in Toyota City, since the explanatory variables for two vehicle types are both not at a 5% significance level. It might indicate that the railway system cannot limit the number of private cars in Toyota City, since the residents living in Toyota City are highly dependent on private cars. Compared to the estimation result in Toyota City, the estimated parameters of population density and density of railway stations in Nagoya City indicate two facts as we expected. Firstly, the residents living in the place with higher population density are unwilling to own private cars, since the parking fee in this residences is very expensive and the parking lots are very limited. Secondly, the residents living in the place with more railway stations are unwilling to own private cars, since the railway or subway system might be convenient and sufficient for them to use in Nagoya City.

Lastly, since the covariance of the two equations measuring two types of cars is significant both for Toyota City and Nagoya City, it is found that there is a substitution effect between the light motor car and the ordinary motor one in both of cities. It might indicate that if residents are willing to own one type of cars either in the light motor one or the ordinary motor one, they would not like to own the other type of cars.

6. CONCLUSIONS

This study analyzes the household car ownership in the local city and its difference from that in the metropolis in Japan. Large scale person trip survey data for Toyota City and Nagoya City are used for empirical analysis. The type of passenger cars is classified into the light motor car and the ordinary motor one. The bivariate ordered probit model is used to model the ownership of two vehicle types in the disaggregated level. The Gibbs Sampler algorithm is implemented to estimate the results in Toyota City and Nagoya City, respectively. The comparison of the estimation results suggest the similar and the different characteristics of the car ownership between Toyota City and Nagoya City.

It is shown that as the explanatory variables concerning household attributes, the age and gender of the householder, number of workers and that of member (≥ 25 years old) are found to be significant factors and nearly having the same effects on vehicle type between Toyota City and Nagoya City. As the explanatory variables concerning geological characteristics, population density and density of railway stations have different effects on vehicle ownership between two cities. Population density only impacts the ownership of the light motor car in Toyota City. Meanwhile, it impacts on the ownership of both the light motor car and the ordinary motor one in Nagoya City. Density of railway stations does not impact the ownership of these two types of cars in Toyota City. Meanwhile, it impacts the ownership of both two types of cars in Nagoya City.

There is one research issue remaining as the future task. In this study we do not consider the life stage or life style as a factor impacting vehicle ownership. Since this factor might be a crucial factor impacting the ownership of private cars, the empirical study to incorporate this factor into the analysis of vehicle ownership and type would be a further direction.

REFERENCES


