Empirical Studies on the Ownership and Usage of Eco-Friendly Vehicles

エコカーの保有及び利用に関する実証的研究

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Empirical Studies on the Ownership and Usage of Eco-Friendly Vehicles

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Abstract

In order to relieve the external diseconomy of private cars, Japanese Cabinet Meeting proposed the action plan to promote next-generation vehicles in the sales market through the policy of tax exemption. As one kind of next-generation vehicles, the electric vehicle is treated as one ideal vehicle type, since the price of this vehicle is not very expensive. Meanwhile, the electric vehicle can be charged at home, if the household has individual parking space. As one of the competitors to the electric vehicle, the light motor vehicle has its merits, such as cheap price, low displacement and excellent fuel consumption. So this thesis is focusing on the ownership and usage of these two types of eco-friendly vehicles in the Chukyo region in Japan.

Chapter 3 examines the preference of electric vehicles purchasing behavior and gives insight into factors which have significant effects on promoting electric vehicles. 5766 stated preference survey data collected in the Chukyo region is treated as the research sample. A 3-level nested logit model is proposed to properly represent the purchasing behavior including Addition, Exchange and Constant. Main conclusions in this chapter contain three aspects as follows. Firstly, it is found that the factors including price of the electric vehicle, installation rate of charging facilities at the gas station, charging vehicles near home, annual income of the household, owning the hybrid vehicle, the number of drivers in one household and no occupation may play important roles on purchasing behavior involving Addition and Exchange. Secondly, capacity and vehicle range of the electric vehicle are key factors on Addition and Exchange. While, charging time is a key factor only on Exchange. Thirdly, displacement, vehicle age and vehicle capacity are important factors of choosing the vehicle in use, when the respondent decides to treat the electric vehicle as Exchange.

Chapter 4 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. The 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.

Chapter 5 forecasts the demand of electric vehicles ownership and usage in the Chukyo region in Japan. The discrete-continuous model proposed in chapter 4 is applied in this chapter. The 4th person trip survey data (2001) in this region are used as the sample. The household annual income is estimated using an ordered probit model. The result shows that average ownership and monthly mileage of electric vehicles are 0.324 and 259.36 km per household, respectively. Meanwhile, it shows that the average ownership and monthly mileage of electric vehicles in suburban areas are more than that in urban areas.

Chapter 6 examines the variation of the household vehicles owning behavior in the Chukyo region in Japan. The vehicle type is classified into the light motor car and the ordinary motor one. The person trip survey data in 1971 and 2001 are used as the sample. A bivariate ordered probit model is proposed for analyzing the ownership of two types of private cars. The Gibbs sampler algorithm is implemented in this chapter. The conclusions of this chapter are listed as follows. Firstly, age of the householder, numbers of workers and number of members (>= 25 years old) were significant factors with same effects both in 1971 and 2001. Secondly, gender of the householder, district, population density and density of railway stations changed their effects from 1971 to 2001. The households with female householder were unwilling to own the light motor car only in 1971.The residents living in Nagoya would not like to own the ordinary motor car in 2001. Population density and density of railway stations affected ownership of the light motor car only in 2001. Lastly, there was a substitution effect on ownership between the light motor car and the ordinary motor one only in 2001.

Chapter 7 analyzes the ownership of the light motor vehicle considering the heterogeneity of family constitution. The 4th person trip survey data in the Chukyo region is used as the research sample. We divide 85047 sample data into 9 groups according to its family type. The bivariate binary probit is utilized to analyze the ownership of the light motor vehicle in the households with only one member. Meanwhile, the bivariate ordered probit model is utilized to examine

the ownership of the light motor vehicle in the family with multiple members. The bivariate binary probit model is estimated by the maximum likelihood estimation. Meanwhile, the bivariate ordered probit model is estimated by the Gibbs sampler algorithm. The annual income data is also complemented and included in the model. It is shown that the ownership of the light motor vehicle is impacted by family constitution significantly, since estimated parameters in different groups are not identical. The ownership of the light motor vehicle in many family types is affected by the district, number of workers, and population density. The female young single and childless middle-age female single are willing to own the light motor vehicle rather than the ordinary motor vehicle. The annual income only affects the ownership of the light motor vehicle in the childless middle-age single household. The accessibility to railway system only affects the ownership of the light motor vehicle in the young single and childless young couple household. The annual income and accessibility to the railway system impacts the ownership of ordinary motor vehicle significantly for many family types. It is also found that the substitution effect between the ownership of the light motor vehicle and the ordinary motor one is not existed in the childless elder single household.

The econometric models proposed in the thesis can be used by the local government to forecast vehicles demand in the region. Meanwhile, the manufacturers of private vehicles can also utilize the similar economic methods to analyze the market share of their vehicles based on the individual consumer oriented survey data.

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Chapter 1

Introduction

1.1 Background

Transportation (transport) has been taking an important role in the daily life of humanity including carrying persons or goods. It is always considered as a kind of derived demand of other activities. For example, we may take the urban rail transit or drive private cars to commute in weekday. During this process, the transportation demand is derived from the activity of working or studying. The choice of transportation mode is indispensable in the travel demand decision making procedure. For example, the household living near to an urban rail transit station can take a train or drive his or her vehicle to go to work. He or she had to make an optimal choice to decide which mode is more economical for him or her. As the classification of transportation modes in the urban areas, usually, we can classify them into two main divisions according to the length of trip distance shown in Figure 1.1.

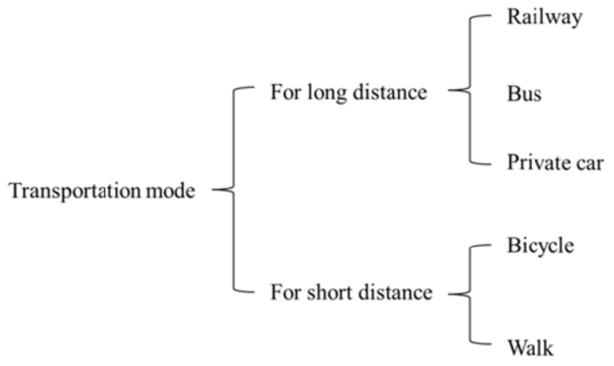

Figure 1.1 Classification of transportation modes by the trip distance

As one kind of the transportation modes for the long distance trip, the railway system including the subway and the light rail transit seems to be the most ideal mode in the urban district, since it can provide puncture and comfortable service for the passengers. Meanwhile, it is also characterized by the huge volume and high frequency. These merits are attractive during the peak hour. As a result, one planning strategy in urban areas called the transit oriented city development was implemented into the metropolitan area (Curtis *et al.*, 2009; Suzuki *et al.*, 2013). It can be concluded that the transit oriented development strategy was successfully implemented in Tokyo metropolitan area, since the railway can account for approximate 30% as the reprehensive transportation mode for all the trips according to the research report of person trip survey in Tokyo metropolitan in 2008. The huge structure of the railway network in the urban area of Tokyo is shown in Figure 1.2 (Toei Transportation Information, 2014).

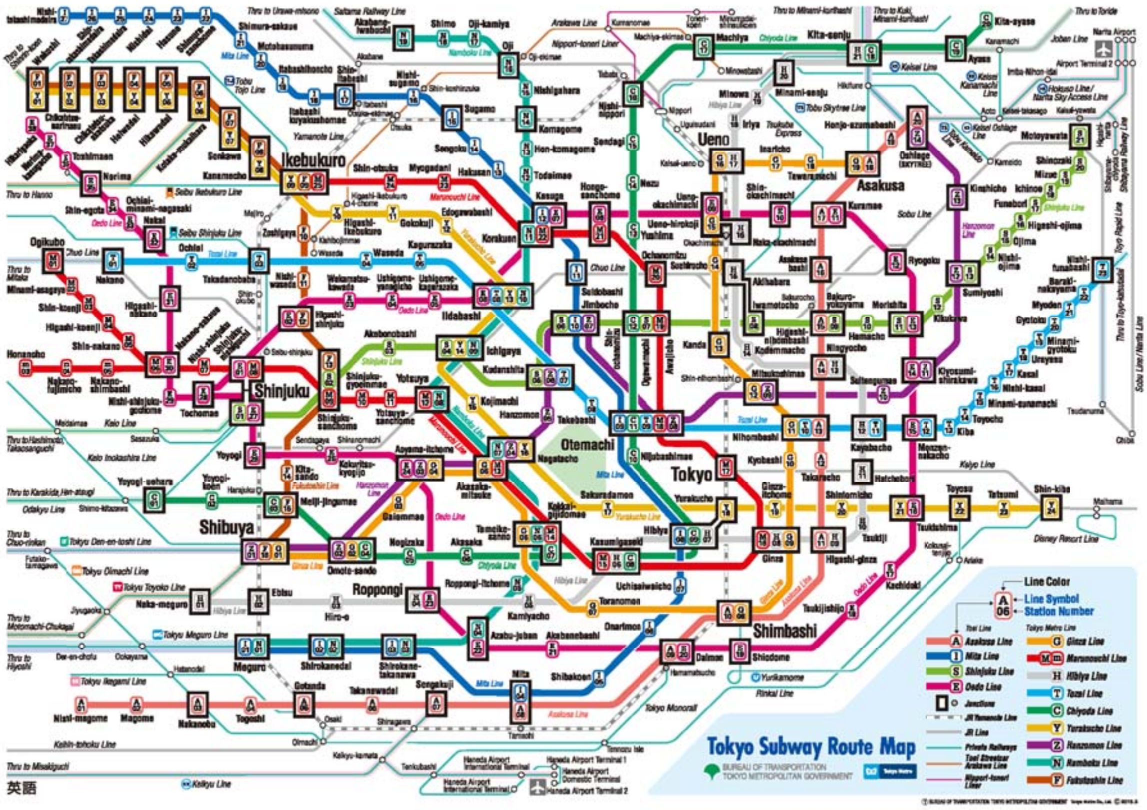

Figure 1.2 Railway network in the urban area of Tokyo

Because of the huge investment of the railway planning and construction, transit oriented development usually was only implemented in the metropolitan area. Unlike the railway, operation of the bus service system in the urban area is not very expensive. The bus can provide the puncture and comfortable service for the passengers. However, the limited number of bus routes and the long interval sometimes impede the popularity of bus service. As a result, the private cars have been playing an important role in the daily life, especially in the region where the public transportation system is not sufficient, such as the suburban areas far from the city center.

The process of the penetration of private cars was called as the motorization of the society. Japan has begun its motorization by 1960s (Kitamura, 2001). As the two characteristics of the motorization of the society, the mass production of private cars and the ownership in the household were increased drastically. As the number of private vehicles increased dramatically, the external diseconomy of private cars was turned up, such as the time delay due to the severe traffic congestion, the air pollution due to the emission gas from the pile, the huge demand of the crude oil resource for the refining the gasoline, and so on.

Considering the severe external diseconomy from the section of private cars, the Japanese Cabinet Meeting (2008) had decided to import next-generation vehicles to improve the energy efficiency of private cars as one part of action plans for achieving a low-carbon society. Although the share of next-generation vehicles only accounted for 2% in the car sales market in 2008, the Japanese government has an ambition to increase it to 50% by 2020. Compared to traditional vehicles, some types of next-generation vehicles with higher energy efficiency seem not easily to be penetrated, since some of them need the supply of the alternative fuel resource, such as the electricity, hydrogen, liquid natural gas and so on. Fueling stations for traditional vehicles are not suitable for supplying new fueling resources. So the planning of the new fueling stations is crucial for promoting the next-generation vehicles. Meanwhile, the scare fueling resource such as hydrogen might impede the penetration of the fuel cell vehicle at this time.

1.2 Definition of the eco-friendly vehicle

The action plan in 2008 gave a concrete definition of next-generation vehicles which include hybrid vehicles, electric vehicles, plug-in hybrid electric vehicles, fuel cell vehicles, clean diesel vehicles, compressed natural gas vehicles, and so on. The fuels for next-generation vehicles are extended to the electricity, the hydrogen, the compressed natural gas, and so on. Since they might save the consumption of gasoline or reduce the emission of carbon dioxide, all of these kinds of vehicles can be treated as the eco-friendly vehicles.

The variety of the fuel resource seems to be prosperous, while the fuel resources themselves sometimes are not easily supplied in public fueling stations. For example, the mass production of hydrogen seems to be difficult, and the deployment of the hydrogen fueling station is far more difficult considering the high risk of the transportation service using traditional tank vehicles. Compared with other kinds of vehicles, the electric vehicle seems to be more prosperous, since the driver can charge his or her vehicle near to home or in public charging stations despite of the long charging time. Usually, the electric vehicle has two charging modes, the fast one and the slow one. There are two socket connectors in one vehicle corresponding to two different charging modes. In the fast model the vehicle can be charged into 80% of the battery volume in approximate 30 minutes. Meanwhile, the electric vehicle can be charged at home or near to the office building in the slow model, which takes the vehicle several hours to charge the battery into full state.

Actually, these are three kinds of next-generation vehicles related to the electricity including the hybrid electric vehicle, the electric vehicle, and the plug-in hybrid electric vehicle. The hybrid electric vehicle has an internal combustion engine and one electric motor. It cannot use the electricity as the direct fuel, and the electric motor just uses the electricity recycled during the running stage. Since the usage of this vehicle is similar to the traditional one, the fueling behavior of the driver nearly does not change.

Unlike the hybrid electric vehicle, the electric vehicle has only one electric motor. The primary fuel resource for it is the electricity. It is treated as one kind of the most prosperous vehicles in future, since the zero emission can be realized through the innovated technology in the process of electricity generation, such as the electricity generated from the photovoltaic cell panel or the wind power. Meanwhile, the electric vehicle might be cheaper than the plug-in hybrid electric vehicle. The fueling behavior for it changed obviously, since it can be charged either in public charging stations or near to home, and the charging time seem to be much longer than the fueling time of the traditional vehicle. Due to the volume of the battery, the vehicle range is shorter than that of the traditional vehicle. The newly innovated electric vehicle Leaf has a vehicle range at 228 km under the running test by JC08 mode (Nissan Motor Co., Ltd., 2014). Compared to the short vehicle range of the electric vehicle, the fact that the traditional vehicle can run 400-500 km at one time is not unusual.

The plug-in hybrid electric vehicle is better than the electric vehicle, since it can use both the gasoline and electricity as the fuel resource. It does not only have an internal combustion engine but also one electric motor just like the hybrid electric vehicle. The battery inside it can be charged as the electric vehicle. As a result, the fueling behavior for it seems to be more complicated than other types of vehicles. Meanwhile, the plug-in hybrid electric vehicles are more expensive than electric vehicles.

Before the introduction of next-generation vehicles, usually the classification of the traditional vehicles is divided by their displacement. Although these are several types of traditional vehicles in the market, the person trip survey only classified the traditional vehicles (excluding the trucks) into two types, the ordinary motor vehicle and the light motor vehicle. The criterion of the light motor car is listed as follows (Japanese Ministry of Land, Infrastructure, Transportation and Tourism, 2012).

1) The length is no more than 3.40 m.

2) The width is no more than 1.48 m.

3) The height is no more than 2.00 m.

4) The displacement is no more than 660 cc.

5) The capacity is no more than 4 seats.

6) The cargo capacity is no more than 350 kg.

Since the light motor vehicle has a lower displacement compared to other vehicles, it is considered as one type of the eco-friendly vehicles in Japan. This argument can be supported by the vehicle oriented tax-exemption policies implemented by the Japanese government. (Japanese Ministry of Land, Infrastructure, Transportation and Tourism, 2013)

1.3 Motivation of this thesis

Although the electric vehicle only has a relatively shorter vehicle range than other vehicles, the merit of nearly zero emission during the running stage is attractive. As a result, this thesis will treat the electric vehicle as one research object. The research contents concerning the electric vehicle are trying to answer the questions listed as follows.

1) Which factors affect the purchasing behavior of the electric vehicle in the household level?

2) Which factors affect the ownership and usage of the electric vehicle for the household?

3) How about the potential demand including ownership and usage in the Chukyo region in Japan?

Since the light motor vehicle has a cheap price and a low displacement, it is considered as the relatively powerful competitor for next-generation vehicles. So it is necessary to analyze the ownership of the light motor vehicle in the household level. As a result, this thesis will treat the light motor vehicle as the other research object. The research contents about the light motor vehicle are trying to answer the questions listed as follows.

1) How did the holding behavior of the light motor change during the development of the motorization in the Chukyo region in Japan?

2) How does the characteristic of household constitute affect the ownership of the light

motor vehicle in this region?

The thesis is mainly focus on the empirical study on the ownership and usage of the electric vehicle and the light motor one in the Chukyo region in Japan. Since the data concerning usage of the light motor vehicle is not included in the 4th person trip survey, the usage of the light motor vehicle is not examined in the thesis.

1.4 Outline of the thesis

This dissertation is composed of 8 chapters. The outline of this dissertation is presented in the following and for each chapter the author shows the reference to the publication on which it is based, if it has been published in the journal or conference proceedings.

Chapter 2 makes a review of the related literatures concerning the analysis of ownership and usage of vehicles in the household. The contents of literature review can be divided into 3 parts including the review of the methodology including discrete choice models and discrete-continuous choice models, that of the parameter estimation technology, and that of the data source used in previous studies.

Chapter 3 examines the preference of electric vehicles purchasing behavior and give insight into factors which have significant effects on promoting electric vehicles. The factors include attributes of the electric vehicle, current vehicle usage, characteristics of the household and the installation rates of charging facilities in public places. Here, the purchasing behavior is classified into Addition, Exchange and Constant. Moreover, the vehicle choice behavior for Exchange is also observed. 5766 stated preference data collected through the Internet questionnaires in the Chukyo region in Japan is used for a case study.

Yang, J., Miwa, T., Morikawa, T. and Yamamoto, T. (2012) Examining the preference of electric vehicles purchasing behavior using stated preference data. *Journal of International City Planning*, 213-223.

Chapter 4 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.

Yang, J., Miwa, T., Morikawa, T. and Yamamoto, T. (2013) A discrete-continuous model for analyzing the ownership and usage of electric vehicles using stated preference data. *Journal of the Eastern Asia Society for Transportation Studies*, 10, 499-514.

Chapter 5 forecasts the demand of electric vehicles ownership and usage in the Chukyo region in Japan. A discrete-continuous model called the Bayesian multivariate tobit, ordered and binary probit model is applied here. The 4th person trip survey data (2001) in this region are used as the sample.

Yang, J., Miwa, T., Morikawa, T. and Yamamoto, T. (2013) Forecasting the demand of electric vehicles ownership and usage in the Chukyo region in Japan. *Proceedings of the 4th International Conference on Transportation Engineering*, 245-251.

Chapter 6 examines the variation of the household vehicles owning behavior in the Chukyo region in Japan. The vehicle type is classified into the light motor car and the ordinary motor one. Meanwhile, the impact of the ownership of trucks is not taken into consideration. The person trip survey data in 1971 and 2001 are used as the sample.

Yang, J., Tian, M.M., Miwa, T. and Morikawa, T. (2014) Examining the variation of household vehicle holding behavior in the Chukyo region in Japan. *Procedia - Social and Behavioral Sciences*, 138, 174-184.

Chapter 7 examines the factors affecting the ownership of the light motor vehicle in the Chukyo region in Japan considering the difference of family constitute. Since the income data is not included in the 4th person trip survey data, this chapter firstly complements this explanatory variable by applying the estimated model proposed in chapter 5. The person trip survey data in 2001 is used as the research sample.

Chapter 8 provides the conclusions and future directions followed by this thesis.

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Chapter 2

Literature Review

Analyzing the problem concerning the ownership and usage of private cars in the household level is usually based on the microeconomic model.

Generally, there are two kinds of economic models applied for the economic problems, the macroeconomic model and the microeconomic one. The macroeconomic model forecasts the demand in the macro scope, such as the city or the national. In the field of transportation demand analysis, the classical 4 steps aggregation model is one kind of macroeconomic model based on the zone level (Hensher and Button, 2007). As it is known to us, the characteristics of the individual could not be observed in this model.

Unlike the macroeconomics model, the microeconomic model can analyze economic behavior in the individual level, and it can utilize the individual sample data to estimate the parameters and apply estimated parameters to forecast the potential demand in the future. For example, in the field of transportation demand analysis, the disaggregated model analyzing the transportation mode choice is the classical microeconomic analysis model. The choice probability for each mode of the individual is estimated and forecasted. Since the ownership and usage of private vehicles in the household level are examined in this thesis, the microeconomic model is applied in this thesis rather than the macroeconomic model.

Two types of the microeconomic model are utilized in this thesis, the discrete choice model and the discrete-continuous choice model. The reason for the different implementation of two models is coming from the sample data, since sometimes the usage of the vehicle is not observed in the survey. As a result, the vehicle usage in the household cannot be observed by the discrete-continuous choice model. The discrete-continuous choice model can be applied if and only if the vehicle usage in the household is investigated in the survey. The parameter estimation procedures for these two types of microeconomic models sometimes are different, since the maximum likelihood estimation as the traditional methodology might have a low efficiency.

The contents in chapter 2 include 5 sections listed as follows. Section 2.1 illustrates the related discrete choice models applied in the analysis of the vehicle ownership in the household sector. The review of related discrete-continuous choice models applied in the analysis of the ownership and usage in the family level is introduced in section 2.2. Section 2.3 introduces the estimation methodology for these two kinds of microeconomic model including the maximum likelihood method and the Markov Chain Monte Carlo method applied in the previous studies. We discuss the data sources used as the research sample in existed studies and compare the characteristics of data sources in section 2.4. The final section will summarize this chapter and point out the microeconomic models, estimation methods and data sources used in the thesis.

2.1 Discrete choice models

The discrete choice model is based on the random utility theory. The vocabulary of utility represents the willing to pay in the economic activity. The phrase of random means the utility could not be observed definitely and always with some unobserved errors. As the fundamental book concerning the theory, the reader can refer to the book named *Discrete Choice Analysis* (Ben-Akiva and Lerman, 1989). For the advanced level of this concept, the reader can refer to the book named *Discrete Choice Methods with Simulation* (Train, 2003). There are mainly two types of discrete choice models used in previous studies, the ordered response model and the nested logit model.

2.1.1 Ordered response model

Many previous studies utilized the ordered response model to analyze the ownership in the household (Bhat and Puluguata, 1998; Chu, 2002; Kim and Kim, 2004; Matas and Raymond, 2008). The ordered response model is based on the hypothesis that one single latent continuous variable represents preference of holding vehicles in the household. This latent variable is called the utility for this household, and it cannot be observed directly. We can only observe the vehicle ownership in the household. The equation for this unobserved utility is represented as follows.

$$U_i = \beta x_i^T + \varepsilon_i \tag{2.1}$$

In this equation, x_i is a column vector of household i `s characteristics (whose first element is fixed to be 1), β term is the estimated parameters, and ε_i terms corresponds to random error items following identical and independent distribution (I.I.D). In this ordered response model there are some unknown parameters called threshold values, which is decided by the number of categories (ownership). For example, if there are three possible levels of car ownership (0, 1 or >=2), only one threshold value should be estimated, and the other one is set to be 0. This ordered response model can be represented in the equation system as follows.

$$k = \begin{cases} 0, \; if\, \beta x_i^T + \varepsilon_i \le 0 \\ 1, \; if\, 0 < \beta x_i^T + \varepsilon_i \le \lambda \\ 2\; or\; more, \; if\, \lambda < \beta x_i^T + \varepsilon_i \end{cases} \tag{2.2}$$

where, k is the ownership of private cars, and λ is the threshold value estimated in the model. This proposed ordered response model is in the univariate form, and it cannot consider the vehicle types in the household. If the vehicle type is also included in the observation, the multivariate ordered response model (Greene and Hensher, 2010) can be utilized. The distribution of the error item in the equation 2.1 decides the type of the ordered response model. If it follows the standard normal distribution, we call it the ordered probit model. If it follows the standard Gumbel distribution, it is named as the ordered logit model. Usually, the univariate ordered response model could be estimated by the maximum likelihood method. The detail of the estimation methodology will be discussed in section 2.3.

2.1.2 Nested logit model

The nested logit model used in the analysis of ownership of private vehicles is usually called the unordered-response mechanism. Unlike the ordered response model, this model utilizes the alternatives in the nested logit structure to represent the vehicle ownership and its type choice. Previous studies had utilized this model to analyze the ownership of private vehicles in the household (Bhat and Puluguata, 1998; Feng, *et al.*, 2005; West, 2004).

The nested logit model usually contains two levels in the structure. In order to illustrate it clearly, we will show a simple example. Let us suppose there are only two types of vehicles A and B in the market. The households can own 3 vehicles at most. So the nested logit structure here is represented as Figure 2.1.

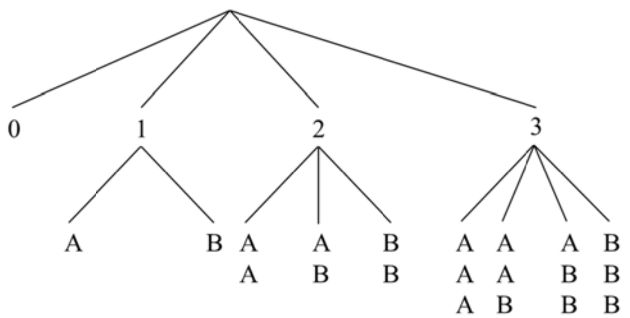

Figure 2.1 The nested logit structure for this simple example

As it is shown in Figure 2.1, the upper level of the nest is used to represent the possible number of vehicles (0, 1, 2 or 3) in the household. As a result, the nested structure in this case has 4 alternatives in the first level. Meanwhile, the lower level is representing the possible combinations of vehicle types (A and B) conditional on a fixed vehicle number (0, 1, 2 or 3), respectively. This structure is very convenient to model the ownership of the multiple types in the household. At the same time the demerits of this structure are existed obviously.

On one hand, when the vehicle type or ownership increases, the actual alternatives in the nested logit model are increasing dramatically. So it is not easy to set explanatory variables in the proposed model. Just in this example, the maximal number of vehicle ownership is confined to be 3, and the number of vehicle type is set to 2. So the number of actual alternatives is 10, and setting explanatory variables in the model is not an easy task. Usually, this kind of the nested logit model concentrates on one-vehicle and two-vehicle households, when the vehicle type is rather limited. On the other hand, the substitution effect between different vehicle types cannot be examined. In this example, we can only observe the combination of A and B, while the relation between them is not observed. Usually, the estimation method of the nested logit model is the full information likelihood estimation, which will be discussed in section 2.3.1.

2.2 Discrete-continuous choice models

Discrete choice models illustrated above including the ordered response model and the nested logit model are utilized only to analyze the vehicle ownership in the household. The usage of the vehicles cannot be observed within these models. The reason is that sometimes the annual or monthly mileage of vehicles is not included in the research sample. As a result, some previous studies only examine the ownership of vehicles. If the ownership and usage of different vehicle types could be investigated simultaneously, the discrete-continuous choice model can be applied to analyze the vehicle ownership and usage in one unified framework. According to characteristics of the modeling technology, there are mainly three kinds of discrete-continuous choice models, namely the indirect utility function based discrete continuous model, the multiple discrete continuous extreme value model and the Bayesian multivariate ordered probit and tobit model.

2.2.1 Indirect utility function based discrete continuous model

The indirect utility function based discrete continuous model is deriving from the random utility maximization following the methodology developed by Dubin and MacFadden (1984) and Hanemann (1984).

This method utilizes an indirect function to represent the maximum utility for one choice considering the budget constraint. The two reasons 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 choice i. 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 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 imported. Here, the joint likelihood function including the likelihood function of vehicle type choice (the discrete choice) and that of vehicle usage (the continuous choice) can be derived. Meanwhile, Since the optimal vehicle usage derived from the indirect utility function using Roy`s identity is often in a non-linear form, the approximation method is usually applied in this procedure (Dubin and MacFadden, 1984).

2.2.2 Multiple discrete continuous extreme value model

The multiple discrete-continuous extreme value (MDCEV) model was firstly proposed by Bhat (2005). Bhat and Sen (2006) extended the MDCEV model to analyze the vehicle 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 drawbacks of this model are listed as follows. On one hand, 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, 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 low efficient.

2.2.3 Bayesian multivariate ordered probit and tobit model

In order to overcome the two drawbacks of the MDCEV model, the third type of discrete-continuous model, a Bayesian multivariate ordered probit and tobit (BMOPT) model was proposed by Fang (2008). This BMOPT model utilized a multivariate ordered probit model to portrait the ownership of multiple vehicle types and a multivariate tobit model to analyzing vehicle usage corresponding to vehicle types held in the household. The relationship of vehicle usage and ownership 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 is suitable 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 classified, this model can be extended to model this problem, and Fang (2008) has proved the merit of this model in his or her study. Furthermore, if the ownership is extended to more alternatives, such as from 3 alternatives (0, 1, >=2) to 4 alternatives (0, 1, 2, >=3), this model can be modified to solve this problem, and Kobayashi (2009) extended the BMOPT model to analyze the ownership and usage of ordinary motor vehicles and light motor ones in the national wide in Japan.

Compared to the traditional estimation method, this model can estimate the parameters with a higher efficiency, since the estimation procedure employs the data augmentation (Albert and Chib, 1993; Chib and Greenberg, 1998) and Gibbs sampler algorithm (Koop, 2003; Koop *et al.*, 2007). The detail of this estimation method is discussed in Section 2.3.2.

2.3 Estimation method

There are mainly two kinds of parameter estimation methodology applied in the previous studies concerning analysis of the ownership and usage of vehicles in the household, i.e. the maximum likelihood estimation and the Markov Chain Monte Carlo method. As the traditional parameter estimation method, the maximum likelihood estimation can be used to estimate many types of discrete choice models, such as the univariate ordered response model, the nested logit model and so on. The Markov Chain Monte Carlo method is a kind of simulation-based estimation method, and usually it is used to estimate the proposed models, when the maximum likelihood estimation is in a low efficiency or failed.

2.3.1 Maximum likelihood estimation

The maximum likelihood estimation is the traditional parameter estimation method applied in the econometric models. The concept of this estimation method is that parameters are estimated to have the highest joint probability of having the sample data already observed. In the field of the discrete choice model, the principle of maximum likelihood estimation can be illustrated by equation 2.3 and 2.4 as follows.

$$\max_{\beta} L = \prod_{n=1}^{N}\prod_{i=1}^{J} P_n(i)^{d_{in}} \tag{2.3}$$

$$d_{in} = \begin{cases} 1, \textit{if person n chooses the alternative i} \\ 0, \textit{does not choose it} \end{cases} \tag{2.4}$$

In this occasion, the multiple choices are not allowed, since the principle of utility maximization has decided that the decision maker choose the best alternative which has the highest utility for him or her. So the equation 2.3 represents the multiply of N functions, and each function stands for the optimal choice of one person in the sample. Since equation 2.3 is the multiply of a series of probability numbers, it is supposed to be near to zero. So the natural logarithm function is used here, to make sure the maximum value of equation 2.3 can be solved. If the probability functions of discrete choice models such as the multinomial logit model or the nested logit model have a closed-form function represented by the mathematic equation, this method can be utilized to estimate parameters very straightforward. The estimation of the ordered logit model can also utilized this traditional method as illustrated by Greene in the textbook of modeling the order response (2010). We can also change the form of probability function to estimate various types of discrete choice models.

The function of this estimation method has been included in many types of statistical software, such as GAUSS, R, MATLAB and so on. The maximum likelihood function in the package provides the configuration of this method, just like the tools. The only task that we will do is to define the corresponding form of the likelihood function, and we do not need to care about the calculation procedure. So it can make sure that the researchers pay more attention to the model specification rather than the solution method. The proposed econometric models in this thesis are solved by the platform of GAUSS 3.2, and the solution methods will be introduced in corresponding chapters.

The procedure of using the maximum likelihood estimation is listed as follows. At First, define the form of the likelihood function in the problem. Next, take the natural logarithm function of the likelihood function. Lastly, use the partial derivative function to estimate the parameters, when the likelihood function will reach its maximum value. Just as the contents illustrated above, the GAUSS and R program can provide a convenient configuration for this method, which makes it easily to be coped with.

2.3.2 Markov Chain Monte Carlo method

Unlike the maximum likelihood estimation method, the Markov Chain Monte Carlo method is a simulated based methodology. The simulated based methodology means that the method is the sampling method from the probability distributions in various types, such as the normal distribution, the truncated normal distribution and so on. The Markov Chain has a property that given to the present state, the future state is independent of the past states in a stochastic process. Meanwhile, Monte Carlo means that the Monte Carlo integration, which utilizes the simulation technic to find integrals rather than doing it analytically. In Bayesian statistics, there are mainly two kinds of Markov Chain Monte Carlo methods, the Gibbs sampler algorithem and the Metropolis-Hastings algorithm.

In the Bayesian statistics, the Bayesian estimation usually can be illustrated as follows. Suppose the unknown parameter set θ following the hypothetical distribution $f(\theta)$ called the prior probability distribution. It represents the belief of the people for the knowledge of the unknown parameters. After observing the sample X, the knowledge of the people will change based on the observation. They will update the prior probability distribution $f(\theta)$ to the posterior probability distribution $f(\theta | X)$. The relation between the prior probability distribution and the posterior probability distribution can be illustrated as follows in equation 2.5 and 2.6.

$$f(\theta | X) = \frac{L(X | \theta) f(\theta)}{f(X)} \tag{2.5}$$

$$f(X) = \int_{\theta} L(X | \theta) f(\theta) d\theta = C \tag{2.6}$$

This relation can be explained as the “being proportional to”, and it makes it conveniently to find the posterior probability distribution for the unknown parameters. The steps to calculate the conditional posterior probability distribution are as follows.

1) Write the likelihood function multiplying the prior probability normal distribution.

2) Pick up all the blocks of parameters $\theta_1, (\theta_1 \subseteq \theta)$ and neglect any blocks which do not depend on θ_1.

3) Use the fundamental knowledge to figure out the conditional probability distribution of θ_1.

4) Repeat the step 2 and 3 for other parameters in the unknown parameter set θ.

The similarity of the Gibbs sampler algorithm and the Metropolis-Hastings algorithm is that they both try to find out the fully conditional posterior distribution for each unknown parameters in the unknown parameter set θ. Meanwhile, the difference is that if we can confirm the fully conditional posterior probability distributions for all the unknown parameters, the Gibbs sampler will be used to estimate the parameters. Otherwise, when part of the unknown parameters is difficult to be represented by the traditional distribution, the Metropolis-Hastings algorithm will be applied instead of the Gibbs sampler algorithm. In this chapter, the Metropolis-Hastings algorithm will not be intensively introduced, since we only use the Gibbs sample method to estimate the discrete choice model or the discrete-continuous choice model in this thesis.

As it is illustrated above, the Gibbs sampler algorithm is a simulation-based estimation method for the estimating the unknown parameters. Compared to the traditional estimation method, the maximum likelihood estimation, this method is very straightforward in the parameter estimation for the multivariate discrete and continuous choice model, since it can avoid integrals of multivariate normal distributions, unlike the GHK algorithm (Train, 2003). This algorithm will be illustrated in the following chapter intensively. Previous studies have implemented this method to estimate the unknown parameters in the designed models.

2.4 Data source

As the important part in the studies concerning the vehicle ownership and usage in the household, the data source is indispensable. The data used in previous studies generally can be classified into three kinds including the person trip survey data, vehicle-oriented survey data and the stated preference survey data.

The person trip survey and vehicle-oriented survey are called as the reveled preference survey. The revealed preference survey is investigating the consumer behavior in reality. In the field of the vehicle ownership analysis, it contains the question such as “How many vehicles do you own in the household?” Meanwhile, the stated preference survey might investigate the consumer behavior in the hypothetical scenario, such as the question such as “Would you like to buy one electric vehicle in the future?” This kind of survey is aiming to know the intention of the consumer to do some economic behaviors in the market. In this section, we will make a brief introduction about three different kinds of data in previous studies.

2.4.1 Person trip survey

The person trip survey is aiming to provide the sample data for the comprehensive urban travel demand analysis in the metropolitan area. In the Chukyo region in Japan, the person trip survey was conducted every 10 years. The latest person trip survey was conducted in 2011. The person trip survey collected the data including the household information, the individual information, and the trip information for each individual in the household. The household information included in the survey contains the geological information, the number of household members, vehicle ownership and type and so on. Meanwhile, the individual information contains the sex, age, occupation, driver license and so on. Here, these two kinds of information can be combined to know the household information more exactly, such as the number of adults, that of people who has the driver license, that of members who have a fixed occupation and so on. As it is known to us, these factors might have a significant effect on the ownership of vehicles.

It should be noticed that the household income data is not investigated in the person trip survey in the Chukyo region, since it might be treated as the privacy. The person trip survey in the United States of America actually investigates the household income data, and it can be included in the discrete choice model. Meanwhile, the usage of vehicles in the household is not included in the person trip survey in the Chukyo region. The person trip survey in the United States of America also includes this item, which is convenient for the researchers to analyze the ownership and usage in the household based on the discrete-continuous choice model illustrated in the Section 2.2.

Here, the trip information for each individual in the household is not utilized in the analysis of the ownership and usage of vehicles in the household, since the research unit is not the trip. While, the information contained in the person trip survey has a merit of high reliability, since the sample ratio is near to 3%. This kind of survey data is usually used in the analysis the ownership of vehicles in the household level in previous studies. However, the vehicle type is fixed to the existed type in the market, and if the researchers want to investigate the vehicle manufacturer-type-model, they have to fabricate the choice set based on vehicle types in the market and use the historical data. Since the choice set is difficult to be confined, many studies did not observe the vehicle manufacturer-model. Usually the vehicle type included in the person trip survey is observed in many previous studies.

Since the purpose of person trip survey is to make a comprehensive urban travel demand analysis, the households without any vehicles are also included in the survey data. Unlike the other two types of discrete-continuous choice models, the BMOPT model proposed by Fang (2008) can examine these households in the model structure, and if these households are not included in the model, the estimation bias might occur inevitably.

2.4.2 Vehicle-oriented survey

The vehicle-oriented survey is aiming at investigating the origin-destination of the vehicles in the road network system. In Japan, the vehicle-oriented survey is conducted every 5 years in the national wide, which is called road traffic census data. This kind of survey includes many contents, including the survey of traffic volume in the road link and the number of vehicle trips for one origin-destination pair. The survey of owner interview is included in this survey, and it aims to investigate the ownership and usage of vehicles in the household, and the household information and geological characteristics are also included in the survey, such as the number of family members, the number of children in the family, the location of the residence and so on. As it is known to us that the discrete choice model examining the consumer behaviors in the household, and it requires the sample data including the household information.

This kind of survey has a merit that is the short interval and huge number of sample data, and the demerit of it is that the survey does not include the household not owning any vehicles and these households are very important for us to analyze the ownership of vehicles in the household. Kobayashi *et al.* (2009) had utilized the road traffic census to analyze the ownership and usage of the ordinary motor vehicle and the light motor one in Japan. Since the research object of the road traffic censes is the vehicle in the road network system, it is more convenient for the research on the traffic volume in the national wide. Compared to the person trip survey usually conducted in the metropolitan areas, the road traffic census data has a larger research areas and it is very important for us to study the road status, such as traffic congestion, traffic speed in the road network. The introduction of the road transportation census in Japan can be found in the website of Ministry of Land, Infrastructure, Transport and Tourism.

2.4.3 Stated preference survey

The original of the stated preference survey comes from the research area of experimental economics and it relies on the assumption of rational choosing behaviors and utility maximization. Compared to the reveal preference survey, the stated preference survey can fabricate the new alternative in the choice set. In the research field of vehicle type and ownership, the alternative of next-generation vehicles such as the electric vehicle can be included in the designed choice set.

This survey technic is very suitable for the analysis of the vehicle type which has a potential to be penetrated into the market. The experiment designing method is usually employed in the survey to set the attributes of vehicles such as the price, the displacement, the fuel economy and so on as factors. This survey can collect the several samples from the same respondent by change the scenario of the stated preference survey. It is considered to be the most effective way to examine the preference of consumer to the newly alternative fuel vehicles in the market, since many researchers applied this survey to collect the sample data in previous studies. For example, Caulfield *et al.* (2010) examined a new car tax and vehicle registration tax scheme introduced by the Irish government in 2008, and the sample data in this study was collected through the stated preference survey.

The stated preference survey is collected through the hypothetical scenario and sometimes seems to be unreliable, while considering the fact that there is not a better method to collect the research sample for analyzing the vehicle ownership and usage for newly alternative vehicles, the author believes that it is the one of the most practical and effective methods nowadays. Since the stated preference survey can examine the vehicle ownership and usage in the household, the specification of the model structure in the proposed study is flexible. Either the discrete choice model or the discrete-continuous choice model can be implemented according to different research tasks.

Considering the merit of the stated preference survey, our laboratory collected the stated preference survey concerning the purchasing behavior of electric vehicles in the Chukyo region in Japan. The research sample in the chapter 3 and 4 is coming from this survey data. As the other research object in this thesis, the light motor vehicle related studies are based on the person trip survey data in 1971 and 2001, respectively.

2.5 Summary

This chapter reviews the previous studies concerning the ownership and usage of vehicles in the household sector. The model methodology, parameter estimation method, and research sample data are classified and introduced, respectively.

The model methodology contains discrete choice models and discrete-continuous choice models. The discrete choice models include the ordered response model and the nested logit model. The discrete-continuous choice models refer to the indirect utility function based model, the multiple discrete continuous extreme value model and the Bayesian multivariate ordered probit and tobit model. The merit and demerit of models are illustrated and compared.

The maximum likelihood estimation and the Markov Chain Monte Carlo method are usually implemented in previous studies. Compared to the maximum likelihood estimation, the Markov Chain Monte Carlo method seems to be more appropriate for multivariate discrete choice models or multivariate discrete-continuous choice models, since it can avoid the integrals of multivariate normal distribution through the data argument technic.

Some previous studies utilize the person trip survey data to analyze the ownership and usage in the household. Meanwhile, the vehicle-oriented survey is also suitable for analyzing this problem. Both of these two kinds of data sources are called as the revealed preference survey, and the revealed preference survey is not suitable for analyzing the new type of vehicles which has not been penetrating into the market. The stated preference survey is more practical and effective to collect the research sample data for the newly innovated vehicle.

Compared to previous studies, this thesis is aiming at modeling the ownership and usage of eco-friendly vehicles (the electric vehicle and the light motor vehicle) in the Chukyo region in Japan. As far as I know, the methodology in this thesis is similar to some of the previous studies, while research topics here are origin and seldom observed by other researchers in this field. The characteristic of this thesis is the empirical study, and we are more interested in observing the consumer behavior using the proposed econometric models.

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Chapter 3

Examining the Preference of Electric Vehicles Purchasing Behavior Using Stated Preference Data

As one kind of next-generation vehicles, the electrical vehicle is considered to be a sustainable transportation mode in the next decades. It contributes to reducing the emission of CO_2 which is considered as one of main reasons for global warming. Japanese Cabinet Meeting (2008) has been making a great effort to promote electric vehicles to maintain environment of the metropolis.

The next-generation vehicles include electric, hybrid electric, fuel cell, liquid natural gas vehicles and so on. Many countries had implemented favorite policies to increase their market share. The consumer preference of choosing vehicles under the impact of favorite policies had been observed in previous studies (Diamond, 2009; Caulfield *et al.*, 2010; Gallagher and Muehlegger, 2011). For example, Caulfield *et al.* (2010) examined a new car tax and vehicle registration tax scheme introduced by the Irish government in 2008, and found that consumers did not rate greenhouse gas emissions or vehicle registration tax as crucial attributes when they purchased a new vehicle.

Compared with hybrid electric and plug-in hybrid vehicles, electric vehicles have relatively shorter vehicle range. The study carried out by Bunch *et al.* (1993) found that the range between refueling was a crucial attribute, particularly if the range for an alternative fuel was substantially less than that for gasoline. It can be concluded that the availability of charging facilities was a key factor for the diffusion of the electric vehicle. This problem is controversial topics nowadays, since we do not know the investment of the public charging facilities are enough to supply the demand of electric vehicles at the beginning stage, and the demand of electric vehicles are unknown at this time.

Models for forecasting electric vehicles demand based on stated preference survey had been proposed (Beggs and Cardell, 1981; Bunch *et al.*, 1993; Segal, 1995; Brownstone *et al.*, 1996). In one recent study, Sakai *et al.* (2011) utilized a binary-probit model to examine factors which impacted electric vehicles purchasing behavior. In the stated preference survey designed in their study, consumer behavior was classified into adding one electric vehicle (Addition) or exchanging one vehicle in use (Exchange) if he or she decided to purchase it. However, they did not differentiate these two situations in their binary-probit model.

This study aims at revealing the consumer preference of electric vehicles purchasing behavior, and gives insight into factors which have significant effects on promoting electric vehicles. In our model, behaviors of Addition and Exchange will be differentiated. Moreover, this model considers over that which vehicle in use will be replaced if the consumer decides to exchange one vehicle in use.

The rest of the chapter is organized as follows. Section 3.1 introduces the summary of the data collected in the Chukyo region and results of the stated preference experiment. Section 3.2 describes the structure of the 3-level nested logit model in this study, and illustrates explanatory variables in the model. Section 3.3 illustrates the method to estimate this proposed model based on the maximum likelihood estimation. Section 3.4 makes a discussion on the corresponding estimation results. Section 3.5 makes a sensitivity analysis of this proposed model by changing the attribute of the electric vehicle and forecasts the diffusion rate of electric vehicles in the Chukyo region in Japan. Finally, the chapter is concluded in Section 3.6 along with the future directions.

3.1 Data

3.1.1 Basic characteristic of the data

The data were collected through the Internet questionnaires which were carried out in the Aichi prefecture in December, 2010 and the Gifu and Mie prefecture in January, 2011, respectively. The total number of the valid samples was 2883. In the survey, the respondents were confined to the householders who owned the driver license and vehicles currently. 92.8% of respondents were male. 54.4% of the households could be able to take advantage of charging facilities near their houses, which was a crucial factor for the decision of purchasing electric vehicles. The households from the Aichi prefecture (including Nagoya) took a ratio of 67.0% corresponding to its dominant status in the Chukyo region. 95.3% of the respondents had one or two vehicles. 75.8% of the households had annual income more than 3 and less than 10 million JPY, which indicated that samples are not biased in this attribute. Only 13.7% of the respondents did not have fixed occupation including items of homemaker, part-time, others and free. 14.7% of the households had more than four family members. 19.2% of the households had more than two drivers in their families.

Table 3.1 Summary of data characteristics

Attribute	Percentage	Attribute	Percentage
Gender		Charging facilities near home	
Male	92.8%	Installable	54.4%
Female	7.2%	Uninstallable	45.6%
Districts		Number of vehicle ownership	
Nagoya	34.1%	1	67.3%
Aichi (Excluding Nagoya)	32.9%	2	28.0%
Gifu	17.6%	3	3.3%
Mie	15.4%	4	1.4%
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%
Number of family members		Drivers in the household	
1	14.9%	1	23.3%
2	22.6%	2	57.5%
3	20.8%	3	11.9%
4	27.0%	4	6.4%
>=5	14.7%	>=5	0.9%

3.1.2 Stated preference survey design

There were two aspects in the items of the survey. One contained attributes of the electric vehicle, and the other included 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 in the fast mode (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 increased by 0.5 million JPY, respectively.

The installation rates of public charging facilities included that at 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 factors included price, vehicle range, charging time, the installation rate of charging facilities at the gas station and that in the highway service area. Each respondent answered the survey for two times. So the number of the stated preference samples was up to 5766. At each time, only one electric vehicle with the supposed attributes selected from designed 27 patterns was offered to respondents. Meanwhile, electric vehicle capacity was also randomly selected from 3 levels at each time. The installation rate of charging facilities at the shopping center was randomly equal to that in the highway service area or zero at each time.

Respondents were required to make a choice from three items which were defined as Addition, Exchange and Constant. Addition meant that he or she would purchase one as an additional vehicle. The behavior that he or she would exchange one vehicle in use was defined as Exchange. At the same time, the vehicle which would be exchanged was also recorded. Constant meant that he or she had no plan to purchase electric vehicles.

In Japan, three kinds of eco-friendly vehicles including electric, hybrid electric and plug-in hybrid electric vehicles have been diffusing. The diffusion of the hybrid electric vehicle had been realized, while consumers did not treat it as a kind of special vehicles for its similarity compared with ordinary vehicles. For the high price of the plug-in hybrid electric vehicle, we did not set it as a choice in this survey. Compared with the plug-in hybrid electric vehicle, the electric vehicle is not so expensive, and the diffusion process is at the beginning stage. In this study, the factors which have significant effects on promoting electric vehicles were examined.

3.1.3 Results of the stated preference survey

Figure 3.1 showed that nearly 27% of the respondents would purchase the electric vehicle either as Addition (5%) or as Exchange (22%). The survey also investigated vehicle usage behavior after electric vehicles were purchased. According to the current vehicle ownership, respondents were classified into three groups (one, two, and three or four vehicles). Figure 3.2 showed that mean value of monthly vehicle mileage of Addition for households increased more drastically than that of Exchange in three groups. This result indicated that households would like to take advantage of vehicles more frequently after adding an electric vehicle. However, it should be noticed that in this study we did not take adding or exchanging an ordinary vehicle into consideration. It is likely that adding an ordinary vehicle would also increase vehicle mileage because of the increased vehicle ownership. It also indicted that due to lower fuel cost of electric vehicles, households for Exchange also increased their vehicle mileage insignificantly.

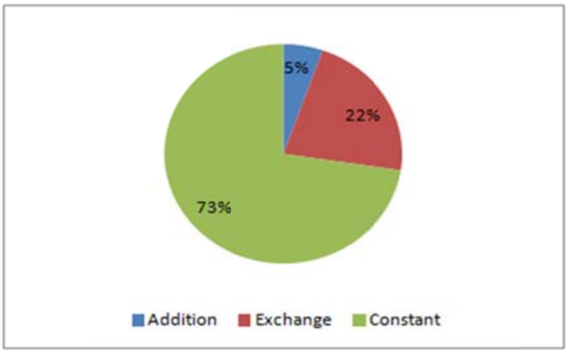

Figure 3.1 Ratio of answers

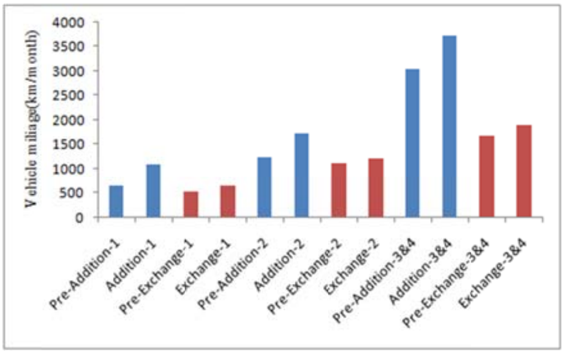

Figure 3.2 Mean of vehicle mileage for households

In order to examine factors which had significant effects, samples were divided into groups according to important characteristics of households and current vehicle usage. Part of the results in different groups was shown in Figure 3.3, 3.4, 3.5, 3.6, 3.7 and 3.8, respectively.

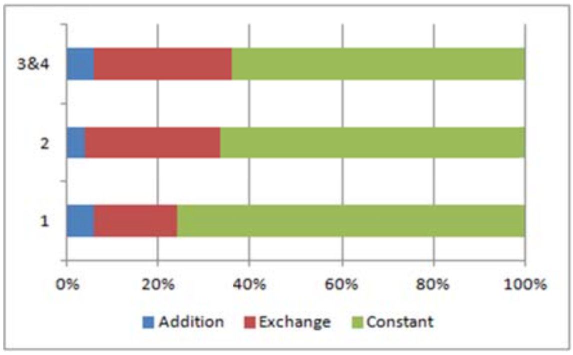

Figure 3.3 Vehicle ownership

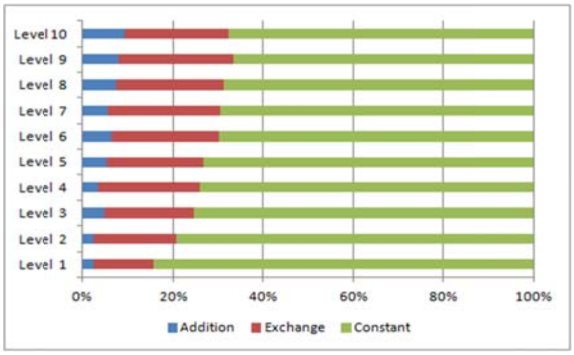

Figure 3.4 Annual income

Figure 3.3 showed that with the increasing number of vehicle ownership, ratios of Addition and Exchange did not always increase. Respondents who had two vehicles would not like to add one electric vehicle, while respondents owning more than one vehicle seem to having a preference of exchanging one vehicle in use.

The annual income was classified into level 1 to 10 from less than 2 million JPY to more than 15 million JPY in Table 3.1. The higher level corresponded to the more annual income, which means that level1 indicated the item of less than 2 million JPY. Figure 3.4 showed that with the increase of annual income, ratios of Addition and Exchange increased, respectively. The trend of Addition was more obvious than that of Exchange.

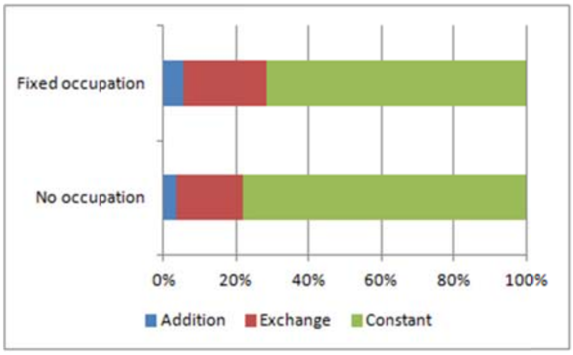

Figure 3.5 Occupation

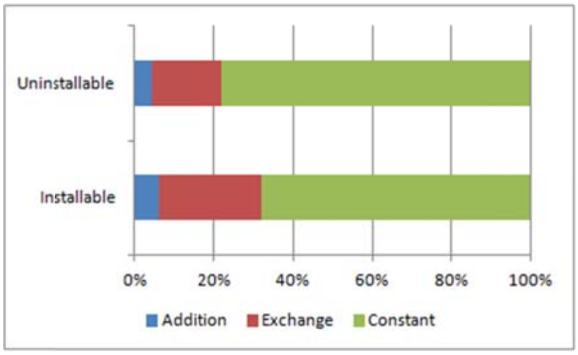

Figure 3.6 Charging facilities near home

The occupation was classified into fixed occupation and no occupation. No occupation included items of homemaker, part-time, others and free. It was shown that respondents having fixed occupation would like to purchase the electric vehicle as Addition or Exchange (Figure 3.5).

Figure 3.6 showed that if the charging facility could be installable near the vehicle owners' house, the ratios of both Addition and Exchange would be increasing dramatically. We may conclude that the convenient charging facility would encourage the respondents to purchase electric vehicles.

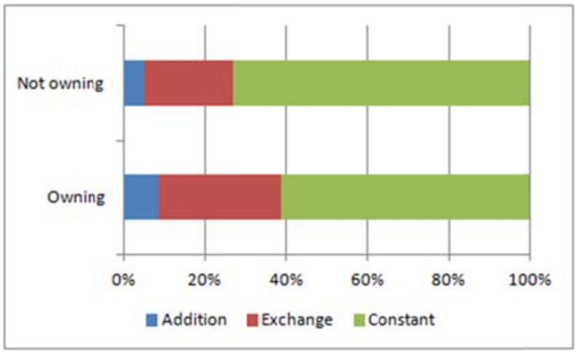

Figure 3.7 Hybrid vehicle ownership

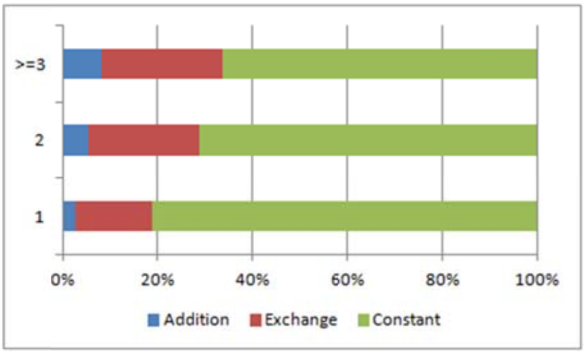

Figure 3.8 Drivers in the household

Figure 3.7 showed that compared with the respondents who did not own hybrid vehicles, the respondents owning hybrid vehicles took more ratios of Addition and Exchange. This result indicated that the hybrid vehicle owners preferred eco-friendly vehicles with higher fuel efficiency.

Meanwhile, with the increase number of drivers in one household, the ratios of Addition and Exchange would be increased (Figure 3.8). Moreover, the trend of Addition was more drastically than that of Exchange. It inferred that with more drivers in one household, the vehicle usage would be increased more significantly.

3.2 Model specification

3.2.1 Model structure

Based on the classification of the choosing behavior, a 3-level nested logit model was constructed to represent electric vehicles purchasing behavior (Figure 3.9). In the questionnaire, top four of the most frequently used vehicles were investigated if there were five or more vehicles in one household. There were four alternatives in the lowest level, named ex1, ex2, ex3 and ex4, which correspond to the four vehicles investigated if he or she decides to treat the electric vehicle as Exchange. The order of the four choice items was based on vehicle mileage in a month. For example, ex1 indicated the most frequently used vehicle. There were two alternatives in the middle level, which represented that if the respondent decides to buy one electric vehicle, he or she would have a choice of treating it as Addition (bad) or Exchange (bex) conditional on the decision that he or she would like to buy one electric vehicle. There were two alternatives in the highest level, which mean the respondent would like to buy an electric vehicle (buy) or not to buy it (ntb).

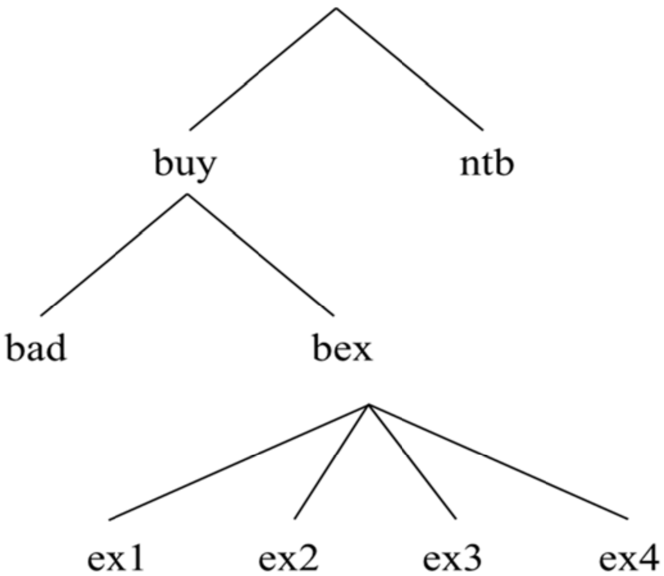

Figure 3.9 The structure of the nested logit model

3.2.2 Explanatory variables

Referring to the aggregation results of stated preference survey, some explanatory variables were chosen to construct the nested logit model. In this study, besides attributes of the electric vehicle, current vehicle usage and household and individual information, some special dummy variables were utilized in the model. The descriptions of these dummy variables were shown in Table 3.2.

Table 3.2 Explanatory dummy variables

Variable name	Description
Home vehicle charging	1 if charging facilities could be installable near home; 0 otherwise
Owning hybrid vehicle	1 if the household was holding hybrid vehicles; 0 otherwise
No occupation	1 if the occupation of householders was homemaker, part-time, free, or others; 0 otherwise
Prefecture	1 if the respondent was living in Gifu or Mie prefecture; 0 otherwise
Vehicle capacity	1 if capacity of the electric vehicle was 7 seats and vehicle capacity was more than 5 seats, or if capacity of the electric vehicle was 4 seats and vehicle capacity was 3, 4 or 5 seats, or if capacity of the electric vehicle was 2 and vehicle capacity was less than 4 seats; 0 otherwise
Using purpose	1 if the vehicle was used for commuting in a weekday; 0 otherwise
Vehicle mileage	1 if vehicle mileage in a weekday was less than the supposed electric vehicle range; 0 otherwise

3.3 Model estimation

In this study, the full information maximum likelihood estimation method (Ben-Akiva and Lerman, 1989) was used to estimate the unknown parameters. According to the structure of the model shown in Figure 3.9, the derive procedure of joint probability function for each actual alternative in the choice set (Addition, Exchange1, Exchange2, Exchange3, Exchange4 and Constant) are listed as follows.

$$P(exi \mid (buy, bex)) = \frac{\exp(V_{exi})}{\sum_{j=1}^{k} \exp(V_{exj})} \tag{3.1}$$

$$logsum1 = \ln\left(\sum_{j=1}^{k} \exp(V_{exj})\right) \tag{3.2}$$

$$P(bex \mid buy) = \frac{\exp(\mu_1 (V_{bex} + logsum1))}{\exp(\mu_1 (V_{bex} + logsum1)) + \exp(\mu_1 V_{add})} \tag{3.3}$$

$$P(bad \mid buy) = \frac{\exp(\mu_1 V_{add})}{\exp(\mu_1 (V_{bex} + logsum1)) + \exp(\mu_1 V_{add})} \tag{3.4}$$

$$logsum2 = \frac{1}{\mu_1}\ln(\exp(\mu_1 V_{bad}) + \exp(\mu_1(V_{bex} + logsum1))) \tag{3.5}$$

$$P(buy) = \frac{\exp(\mu_2(V_{buy} + logsum2))}{\exp(\mu_2(V_{buy} + logsum2)) + \exp(\mu_2 V_{ntb})} \tag{3.6}$$

$$P(ntb) = \frac{\exp(\mu_2 V_{ntb})}{\exp(\mu_2(V_{buy} + logsum2)) + \exp(\mu_2 V_{ntb})} \tag{3.7}$$

$$P(Addition) = P(buy, add) = P(add \mid buy)P(buy) \tag{3.8}$$

$$P(Exchangei) = P(buy, bex, exi) = P(exi \mid (buy, bex))P(bex \mid buy)P(buy) \tag{3.9}$$

$$P(Contant) = P(ntb) \tag{3.10}$$

where,

i : indexing the list number of the vehicle in the household $(i <= 4)$,

k : number of the vehicles in the household currently $(k <= 4)$,

V_{exi} : deterministic utility specific to virtual alternative exi $(i <= 4)$,

V_{buy} : deterministic utility specific to virtual alternative buy,

V_{bad} : deterministic utility specific to virtual alternative bad,

V_{bex} : deterministic utility specific to virtual alternative bex,

V_{ntb} : deterministic utility specific to virtual alternative ntb,

μ_1 : the scale parameter in the middle level of the nested structure and,

μ_2 : the scale parameter in the top level of the nested structure $(0 < \mu_2 < \mu_1 < 1)$.

It should be noticed that the vehicle ownership in the household is not fixed to 4 for all the households, and the number of choices for each household might be different. So the availability of the alternative in the nested logit structure should be taken into consideration. Based on the form of joint probability functions illustrated above, the maximum likelihood estimation implemented in the platform of GAUSS 3.2 was very straightforward.

3.4 Results and discussion

The estimation result was shown in Table 3.3. This study aims at examining various factors which might impact electric vehicles purchasing behavior. So we preserved some necessary insignificant explanatory variables to understand the effects of these factors clearly.

Table 3.3 Model estimation result

Explanatory variable	Parameter	T-statistic
Alternative specific constant		
buy	-6.027	-2.98
bad	-0.082	-0.11
ex2	-0.205	-2.24
ex3	-0.440	-1.72
ex4	-1.173	-1.88
buy		
Electric vehicle price (million JPY)	-2.404	-2.81
Facility installation rate (gas station)	1.037	2.28
Facility installation rate (highway service area)	0.072	0.19
Facility installation rate (shopping center)	0.102	0.38
Home vehicle charging (dummy)	1.618	2.53
Annual income (million JPY)	0.816	1.85
Owning hybrid vehicle (dummy)	2.110	2.58
Drivers in one household	0.515	1.97
No occupation (dummy)	-1.121	-2.07
Prefecture (dummy)	0.182	0.71
bex		
Electric vehicle capacity (seats)	0.555	2.76
Electric vehicle range (100 km)	1.322	2.78
Vehicle charging time (minutes)	-0.033	-1.93
bad		
Electric vehicle capacity (seats)	0.479	2.41
Electric vehicle range (100 km)	1.081	2.31
Vehicle charging time (minutes)	-0.010	-0.53
ex1, ex2, ex3 and ex4		
Displacement (100 cc)	-0.183	-2.35
Fuel consumption (100 km/l)	-2.018	-1.40
Vehicle age (years)	0.085	4.27
Vehicle capacity (dummy)	0.435	3.77
Using purpose (dummy)	0.049	0.50
Vehicle mileage (dummy)	0.644	1.11
Scale parameter of the middle level	0.898	4.85
Scale parameter of the highest level	0.286	2.84
Log-likelihood at Zero	-6952.00	
Log-likelihood at Convergence	-4153.59	
McFadden's Rho-squared	0.403	
Adjusted McFadden's Rho-squared	0.398	
Number of cases	5766	

It was obvious that this model can well capture electric vehicles purchasing behavior in terms of goodness-of-fit indicator (adjusted McFadden's Rho-squared: 0.398). Two scale parameters were correctly estimated between 0 and 1, and both of them were at the 5% significance level. Magnitudes of both parameters were decreasing with increasing level of the nesting structure as expected. According to the structure of the model (Figure 3.9), the effects of parameters were illustrated below.

For the alternatives buy and ntb in the highest level, all the parameters were estimated with expected signs. The minus parameter of electric vehicle price at the 5% significance level indicated that, with the increase of price, the preference of purchasing vehicles would decrease. For the installation rates of public charging facilities, only the installation rate at the gas station at the 5% significance level had a significant effect on purchasing behavior. While, installation rate in the highway service area and that in the shopping center could not affect the purchasing behavior. The positive parameter of home vehicle charging at the 5% significance level indicated that if charging facilities could be installed near the vehicle owners' house, the preference of purchasing vehicles would increase. The effect of annual income indicated that rich households might have a preference of purchasing electric vehicles. The positive parameter of owning hybrid vehicles at the 5% significance level indicated that the household owning hybrid vehicles would like to purchase electric vehicles. The positive parameter of drivers in one household at the 5% significance level suggests that if there were more drivers in the household, the preference of purchasing electric vehicles would increase. The minus parameter of no occupation indicates that if the householder did not have fixed occupation, he or she would not like to purchase electric vehicles. In addition, the respondents living in Gifu or Mie prefecture did not have a preference of purchasing electric vehicles. For the alternative ntb did not contain any explanatory variables, its utility was supposed to be zero.

In the middle level, the parameter of electric vehicle capacity for bad and that for bex were at the 5% significance level. Through the statistical test of mean values of capacity for bad and bex, it was found that the difference was not significant. We could conclude that the capacity had indifferent marginal utility for Addition and Exchange. Meantime， electric vehicle range had the same effect on both bad and bex. Charging time of electric vehicles had a significant effect on bex. With the increase of charging time, the utility of bex was decreased.

In the lowest level, around half of parameters were at the 5% significance level. Vehicle displacement had an obvious effect on vehicles choosing behavior. The respondents would like to exchange the vehicle with lower displacement. Vehicle age also affected vehicles choosing behavior significantly, and the older vehicle would be replaced. The effect of vehicle capacity (dummy) indicated that the vehicle with similar capacity to that of the electric vehicle would be exchanged. Fuel consumption and using purpose of commuting in a weekday did not have significant effects on choosing vehicles. The effect of vehicle mileage (dummy) did not have significant effect, which indicated that the respondents did not have a preference of choosing the vehicle whose mileage in a week day was shorter than supposed range of the electric vehicle for Exchange.

The minus parameters of alternative specific constant of ex2, ex3 and ex4 were all at the 10% significance level, and were decreasing with the ascending order, which illustrated that respondents would tend to choose the most frequently used vehicle if they decided to treat the electric vehicle as Exchange. Here, alternative specific constant of ex1 was supposed to be zero.

3.5 Simulation analysis

Combining model estimation results in Section 3.4 and the 4th personal trip survey data (2001) in the Chukyo region, the sensitive analysis and the demand of electric vehicles could be analyzed. The probabilities of Addition, Exchange and Constant for one household were predicted by functions of conditional probability.

Table 3.4 Hypothetical values for simulation

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 (minutes)	10	20	***30***	40	50	60							
Vehicle range (km)	100	150	***200***	250	300	350	400						

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

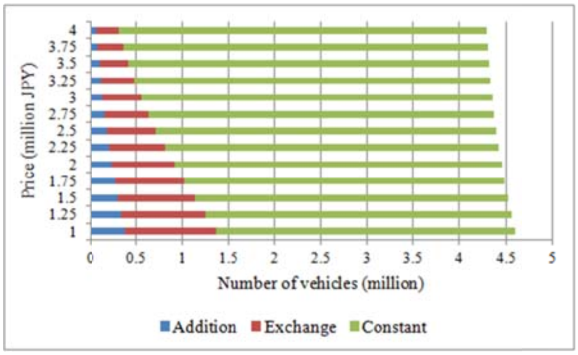

Figure 3.10 Change of price

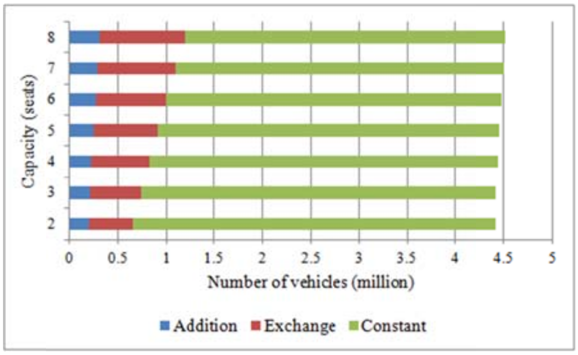

Figure 3.11 Change of capacity

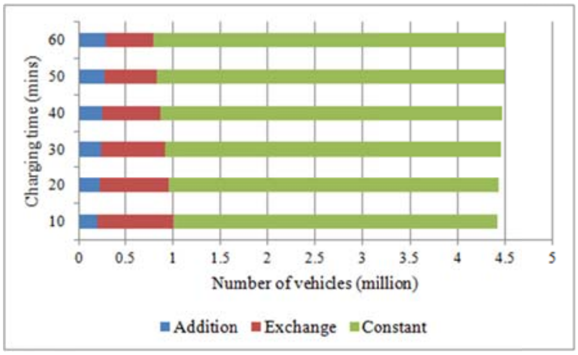

Figure 3.12 Change of charging time

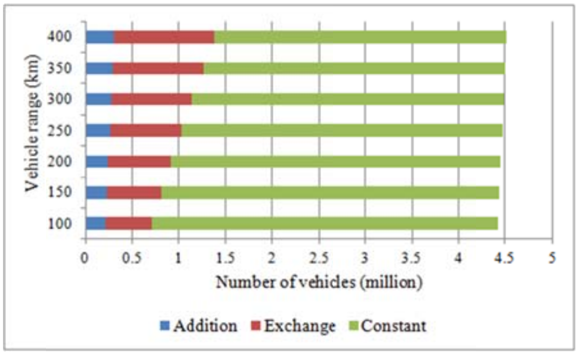

Figure 3.13 Change of vehicle range

From the 4th personal trip survey data, we could get values including number of drivers in households, the occupation of householders, and the living zones. When we calculated annual income of the household and other attributes, four groups including Nagoya, Aichi (excluding Nagoya), Gifu and Mie were divided. Samples of stated preference survey were used to make a linear regression analysis. We used these four regression models to estimate annual income of households in different areas. According to the naive method, other variables including dummy variables in the model were based on the mean value of samples which had the same vehicle ownership in these four areas in the stated preference survey. Since this study does not emphasize the precision of forecasting result, the insignificant explanatory variables in the model (Table 3.4) were used here.

In order to simulate the demand of electric vehicles, hypothetical values concerning attributes of electric vehicles were designed and shown in Table 3.4. The bold and italic characters in Table 3.4 were the standard parameters. Each time we only changed one attribute and compared the ratio variation of electric vehicles during this process. The installation rates of charging facilities in three places were supposed to be 20%.

The simulating results were shown in Figure 3.10, 3.11, 3.12 and 3.13, respectively. The price and vehicle range of electric vehicles seemed to be crucial factors of promoting electric vehicles. It was found that if the price was reduced by 1 million JPY, the share of electric vehicles would increase by around 7%. If the vehicle range was increased by 100 km, the share of electric vehicles would increase by about 5%.

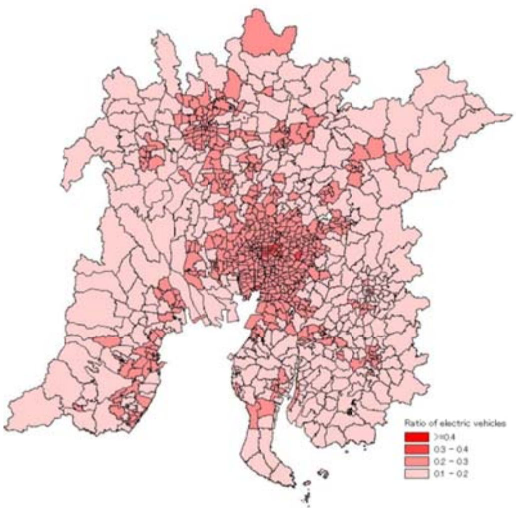

Figure 3.14 Ratio of electric vehicles

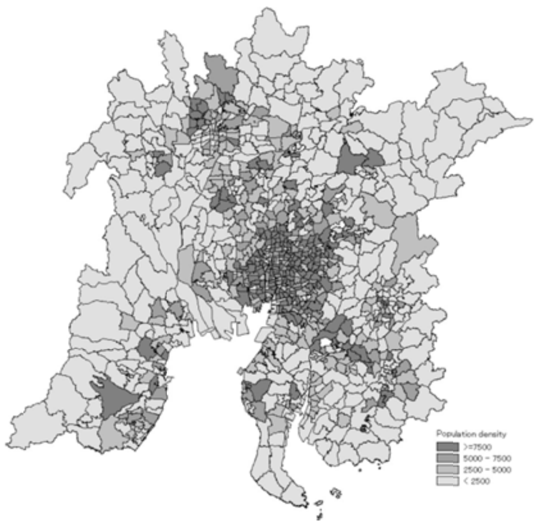

Figure 3.15 Population density

Figure 3.14 showed the ratio of electric vehicles in different areas in the Chukyo region estimated by using standard parameters. The total demand of electric vehicles could reach to 0.92 million which took 20.5% of all vehicles (4.46 million). Referring to the figure of population density (unit: people per km^2) in this region (Figure 3.15), it could be inferred that the ratio in the urban areas was higher (more than 20%) than that in other suburban areas. It was more than 30% in some urban places. It was also found that the electric vehicle demand in suburban was more than that in urban. However, compared to their huge vehicle ownership currently, the diffusion ratio of electric vehicles in suburban was lower than that in the urban area.

3.6 Summary

This study examined the factors which might have significant effects on the electric vehicle purchasing behavior through stated preference survey. The data were collected from 2883 respondents in the Chukyo region in Japan. Estimation based on a 3-level nested logit model identified the importance of attributes of electric vehicle, current vehicle usage, individual and household characteristics, as well as the installation rates of charging facilities in public places.

It was shown that individuals considered the price of electric vehicles, charging vehicle near home, annual income, hybrid vehicle ownership, number of drivers, occupation of the householder and the installation rate of charging facilities in the gas station as crucial factors when they purchased electric vehicles. Capacity and range of the electric vehicle had nearly the same marginal utility on the choices of Addition and Exchange. Charging time was only a crucial factor for Exchange. In addition, when individuals were treating electric vehicles as Exchange, displacement, age and capacity of current vehicles would play important roles. Forecasting on the demand of electric vehicles in the Chukyo region showed us that the ratio in the urban areas was higher (over 20%) compared with other suburban areas.

There are some research issues remaining as future tasks. The vehicle usage behavior after respondents purchased the electric vehicle was also investigated in the Internet questionnaire. In this study, we only did some basic analysis of it. Next, we will make a further research on variation of vehicle mileage to examine the factors which have significant effect on vehicle usage. Moreover, in order to evaluate the impact of the government policy toward electric vehicles, the quantitative evaluation method is a further research area.

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Chapter 4

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

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. We extended this model and developed a 3-level nested logit model to make a further research on electric vehicles purchasing behavior in chapter 3.

After reviewing the previous studies, the author 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 4.3.

The rest of the chapter is organized as follows. Section 4.1 reviews 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 4.2 explains the reason why the modified version of the BMOPT model is utilized, and describes the BMTOBP model proposed in this study. Section 4.3 instructs the estimation method of our model, and then makes a discussion on the corresponding estimation results. Section 4.4 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 4.5 along with a discussion about future research issues.

4.1 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 original data used in this chapter is the same with the data used in chapter 3. Since this study might use the stated preference survey data concerning other contents, the main constitutions of the questionnaire are illustrated as follows.

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 review of the survey method will be illustrated in Section 4.5

4.1.1 Review of 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.

4.1.2 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 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.

4.1.3 Data description

Table 4.1 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. 54.4% 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. 75.8% 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 4.1 Descriptive statistics

Attribute	Percentage	Attribute	Percentage
Gender		Charging facilities near home	
Male	92.8%	Installable	54.4%
Female	7.2%	Uninstallable	45.6%
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 4.2 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 4.2 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 4.3. 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 4.3 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

4.2 Model specification

4.2.1 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.

4.2.2 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.

$$y_{1i}^* = x_{1i}^T \beta_1 + \varepsilon_{1i} \tag{4.1}$$
$$y_{2i}^* = x_{2i}^T \beta_2 + \varepsilon_{2i} \tag{4.2}$$
$$y_{3i}^* = x_{3i}^T \beta_3 + \varepsilon_{3i} \tag{4.3}$$
$$y_{4i}^* = x_{4i}^T \beta_4 + \varepsilon_{4i} \tag{4.4}$$

where,

i : indexing the household in the sample $(i = 1, \ldots, N)$,

k : the list number of the equation $(k = 1, \ldots, 4)$,

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 rewritten into a seemingly unrelated regression form (Koop, 2003).

$$y_i^* = x_i \beta + \varepsilon_i \tag{4.5}$$

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

$$\varepsilon_i \sim^{i.i.d} MVN(0, \Sigma) \tag{4.6}$$

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.

$$y_{1i} = \begin{cases} y_{1i}^*, & if\ y_{1i}^* > 0 \\ 0, & if\ y_{1i}^* \le 0\ (y_{3i} = 0) \end{cases} \tag{4.7}$$

$$y_{2i} = \begin{cases} y_{2i}^*, & if\ y_{2i}^* > 0 \\ 0, & if\ y_{2i}^* \le 0\ (y_{4i} = 0) \end{cases} \tag{4.8}$$

$$y_{3i} = \begin{cases} 0, & if\ y_{3i}^* \le \alpha_{31} \\ 1, & if\ \alpha_{31} < y_{3i}^* \le \alpha_{32} \\ 2\, or\ more, & if\ \alpha_{32} < y_{3i}^* \end{cases} \tag{4.9}$$

$$y_{4i} = \begin{cases} 1, & if\ y_{4i}^* \ge 0 \\ 0, & if\ y_{4i}^* < 0 \end{cases} \tag{4.10}$$

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 two cut points called as threshold values is equivalent to constraining one cut point and the variance of the equation, 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 four equations system we use a binary probit model to measure the number of electric vehicles (one or zero) instead of the ordered probit model.

4.2.3 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 4.4.

Table 4.4 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 4.1. 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

4.3 Model estimation

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 (Train, 2003), 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.

$$draw \quad y_i^* \mid \beta, \Sigma, y_i \quad from \quad \pi(y_i^* \mid \beta^{(k-1)}, \Sigma^{(k-1)}, y_i) \tag{4.11}$$

$$draw \quad \beta \mid \Sigma, y_i^* \quad from \quad \pi(\beta \mid \Sigma^{(k-1)}, y_i^{*(k)}) \tag{4.12}$$

$$draw \quad \Sigma \mid y_i^*, \beta \quad from \quad \pi(\Sigma \mid y_i^{*(k)}, \beta^{(k)}) \tag{4.13}$$

where,

π : 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 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 4.14, 4.15, 4.16, and 4.17 can draw a sample from the full conditional distribution for y_{ki}^* $(k = 1, \ldots, 4)$, respectively.

$$y_{1i}^* = \begin{cases} y_{1i}, & if \ \ y_{1i} > 0 \\ \mu_{1|\neg 1} + \sigma_{1|\neg 1}\Phi^{-1}(U\Phi((-\mu_{1|\neg 1})/\sigma_{1|\neg 1})), & if \ \ y_{1i} = 0 \end{cases} \tag{4.14}$$

$$y_{2i}^* = \begin{cases} y_{2i}, & if \ \ y_{2i} > 0 \\ \mu_{2|\neg 2} + \sigma_{2|\neg 2}\Phi^{-1}(U\Phi((-\mu_{2|\neg 2})/\sigma_{2|\neg 2})), & if \ \ y_{2i} = 0 \end{cases} \tag{4.15}$$

$$y_{3i}^* = \begin{cases} \mu_{3|\neg 3} + \sigma_{3|\neg 3}\Phi^{-1}(U(1-\Phi((0.431-\mu_{3|\neg 3})/\sigma_{3|\neg 3})) + \Phi((0.431-\mu_{3|\neg 3})/\sigma_{3|\neg 3})), & if \ \ y_{3i} \geq 2 \\ \mu_{3|\neg 3} + \sigma_{3|\neg 3}\Phi^{-1}(U(\Phi((0.431-\mu_{3|\neg 3})/\sigma_{3|\neg 3}) - \Phi((-0.431-\mu_{3|\neg 3})/\sigma_{3|\neg 3})) & \\ \qquad + \Phi((-0.431-\mu_{3|\neg 3})/\sigma_{3|\neg 3})), & if \ \ y_{3i} = 1 \\ \mu_{3|\neg 3} + \sigma_{3|\neg 3}\Phi^{-1}(U\Phi((-0.431-\mu_{3|\neg 3})/\sigma_{3|\neg 3})), & if \ \ y_{3i} = 0 \end{cases} \tag{4.16}$$

$$y_{4i}^* = \begin{cases} \mu_{4|\neg 4} + \sigma_{4|\neg 4}\Phi^{-1}(1-(1-U)\Phi(\mu_{4|\neg 4}/\sigma_{4|\neg 4})), & if\ \ y_{4i} = 1 \\ \mu_{4|\neg 4} + \sigma_{4|\neg 4}\Phi^{-1}(U\Phi((-\mu_{4|\neg 4})/\sigma_{4|\neg 4})), & if\ \ y_{4i} = 0 \end{cases} \tag{4.17}$$

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 3.1, 3.2, 3.3 and 3.4 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.

$$\beta \mid y_i^*, \Sigma \sim N(\overline{\beta}, \overline{V}) \tag{4.18}$$

$$\overline{V} = (V_0^{-1} + \sum_{i=1}^{N} x_i^T \Sigma^{-1} x_i)^{-1} \tag{4.19}$$

$$\overline{\beta} = \overline{V}(V_0^{-1}\beta_0 + \sum_{i=1}^{N} x_i^T \Sigma^{-1} y_i^*) \tag{4.20}$$

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.

$$\Sigma \mid y_i^*, \beta \sim W^{-1}\left(v+N, \sum_{i=1}^{N}\left(y_i^* - x_i\beta\right)\left(y_i^* - x_i\beta\right)^T + \Psi\right) \tag{4.21}$$

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.

4.4 Results and discussion

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 author 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 4.5. All of the parameters are estimated with expected sigh, and the analysis of significant explanatory variables is illustrated as follows.

Table 4.5 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 4.6 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 4.6. 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 4.7 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 4.7 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.

4.4 Sensitive 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 4.8. 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 4.8 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 (minutes)	10	20	***30***	40	50	60							
Vehicle range (km)	100	150	***200***	250	300	350	400						

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

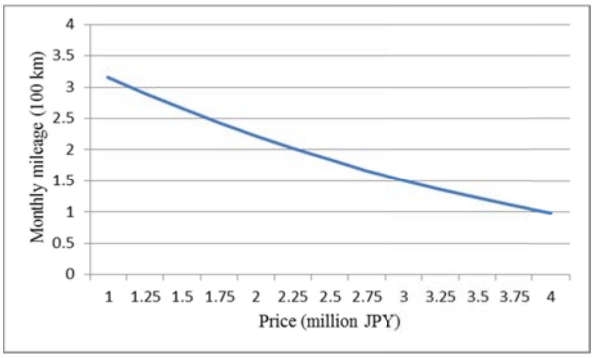

Figure 4.1 Monthly mileage variation (price)

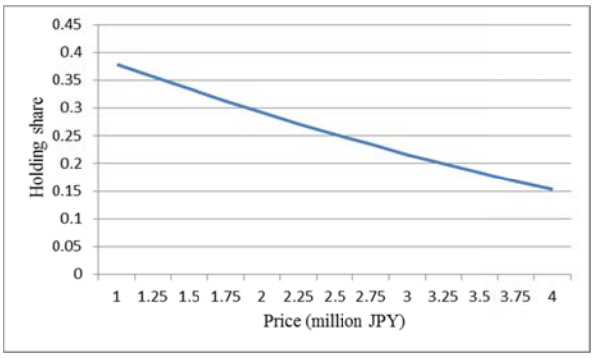

Figure 4.2 Holding share variation (price)

Figure 4.1 and Figure 4.2 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%.

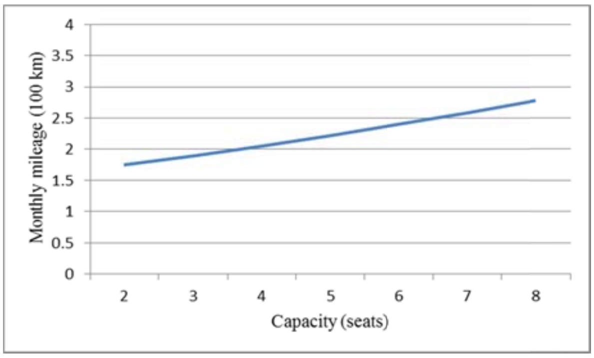

Figure 4.3 Monthly mileage variation (capacity)

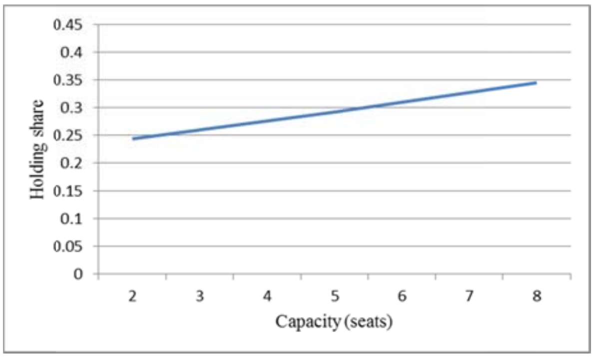

Figure 4.4 Holding share variation (capacity)

The variation of monthly mileage and that of holding share with the change of the vehicle capacity are shown in Figure 4.3 and Figure 4.4, 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%.

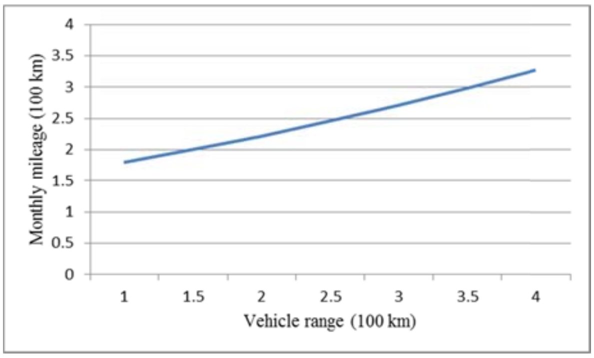

Figure 4.5 Monthly mileage variation (vehicle range)

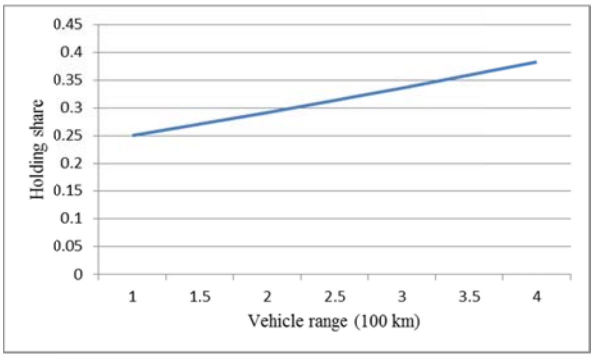

Figure 4.6 Holding share variation (vehicle range)

The variation of monthly mileage and that of holding share with the change of the vehicle range are shown in Figure 4.5 and Figure 4.6, 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 4.7 and Figure 4.8, 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%.

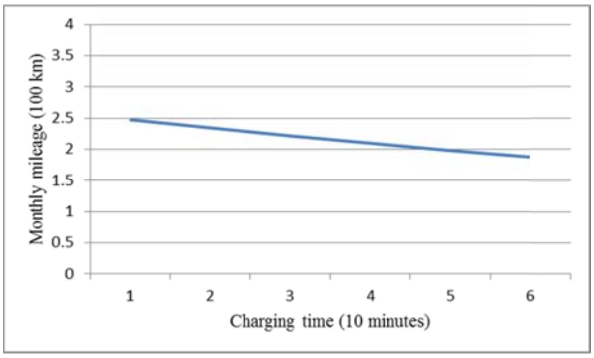

Figure 4.7 Monthly mileage variation (charging time)

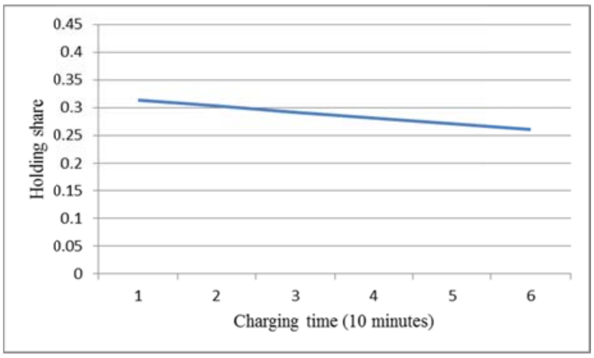

Figure 4.8 Holding share variation (charging time)

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.

4.5 Summary

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.

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Chapter 5

Forecasting the Demand of Electric Vehicles Ownership and Usage in the Chukyo Region in Japan

In order to relieve the high dependency on the gasoline in the motorization society, the implement of next-generation vehicles is necessary. As one kind of next-generation vehicles, the electric vehicle is considered as the most sustainable vehicle in next decades, since it does not emit any carbon dioxide or particle materials during the running stage. In Japan, Cabinet Meeting (2008) was making a great effort to promote electric vehicles to maintain the harmony of the metropolis environment.

There are mainly three kinds of electric vehicles including hybrid electric, plug-in hybrid electric and electric vehicles. The hybrid electric vehicle can recycle the energy and transform it into electricity during the running state. Since it cannot use the electricity as the direct energy resource, it is not treated as a special kind of vehicles. The plug-in hybrid electric vehicle seems an ideal transportation model, since it can use both the gasoline and electricity as the power. Meanwhile, the price is very expensive compared with ordinary vehicles. Compared with the plug-in hybrid electric vehicle, the electric vehicle is not very expensive. Although the diffusion process is at the initial stage, it is considered to be the most promising vehicle in future.

Compared with other types of next-generation vehicles, the diffusion of electric vehicles seems more difficult, since the charging facilities in public places may be insufficient during the initial stage. Meanwhile, the rate of public charging facilities is determined by the ownership and usage of electric vehicles. This relation is just like the relation of chicken and eggs.

Many previous studies have proposed some location models for optimal deployment of the public charging facilities, such as the p-median model (Hakimi, 1964; Revelle and Swain, 1970), the flow-intercepting location model (Berman *et al.*, 1992), the flow-refueling location model (Kuby and Lim, 2005) and so on. These proposed location models for charging stations are based on the ownership or usage of electric vehicles. As a result, forecasting the demand of the ownership and usage of electric vehicles seems very crucial for us to implement and promote electric vehicles.

Models for forecasting electric vehicles demand based on stated preference survey had been proposed (Beggs and Cardell, 1981; Bunch *et al.*, 1993; Segal, 1995; Brownstone *et al.*, 1996; Sakai *et al.*, 2011). Chapter 3 proposed a forecasting method based on the 3-level nested logit model to estimate the demand of the electric vehicle ownership in the Chukyo region in Japan. Since this nested logit model also illustrated only investigated the purchasing behavior, it cannot forecast the usage of electric vehicles.

Chapter 4 proposed a Bayesian Multivariate Tobit, Ordered and Binary Probit (BMTOBP) model. The BMTOBP model was utilized to analyze the ownership and usage of electric vehicles in the household. In this study, we will apply this model to forecast the demand of ownership and usage of electric vehicles in the Chukyo region in Japan.

The rest of the chapter is organized as follows. Section 5.1 reviews the stated preference survey data concerning the purchasing behavior of the electric vehicles in the Chukyo region in Japan. Section 5.2 illustrates the BMTOBP model used in this study and shows the flowchart of the forecasting method for the demand of electric vehicle. Section 5.3 introduces the data used in this forecasting model. Section 5.4 shows the estimation result and makes a discussion concerning the estimated results. Lastly, this study is concluded in Section 5.5 along with a discussion about future issues.

5.1 Review of the stated preference survey

To reveal the consumer preference of purchasing the electric vehicle, our laboratory carried out 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 stated preference survey concerning purchasing and using electric vehicles was included in the questionnaire.

The items of the stated preference survey included two aspects of factors related to the electric vehicle. The first aspect was concerning attributes of the electric vehicle including capacity, price, charging time and range. The other one contained the installation rates of public charging facilities including that in the gasoline station, in the highway service area, and in the shopping center. The detail of the survey method can be found in section 4.1.1.

Through the Internet questionnaires, we collected 5766 valid stated preference data. We supposed that each stated preference data could represent one household. Based on this sample, the BMTOBP model was proposed to analyze the ownership and usage of electric vehicles in the household (Chapter 4). The specification of the BMTOBP model is introduced in the following section.

5.2 Introduction of the BMTOBP model

The BMTOBP model is the modified version of the Bayesian Multivariate Ordered Probit and Tobit (BMOPT) model proposed by Fang (2008). The BMTOBP model was used to analyze the ownership and usage of electric vehicles in the household. The impact of the ownership and usage of ordinary vehicles was taken into consideration. Meanwhile, the monthly mileages of ordinary and electric vehicles were described by one tobit model, respectively. The ordinary vehicle ownership was measured by an ordered probit model, meanwhile the electric vehicle ownership was measured by a binary probit model. Error items of four equations were supposed to follow the multivariate normal distribution with zero means and unconstraint covariance matrix. The Gibbs sampler algorithm was utilized to estimate four joint equations. It was found that this model nearly had an ideal and efficient estimation result as we expected.

The estimation results of the parameters and the error covariance matrix are shown in Table 5.1 and Table 5.2, respectively.

Table 5.1 Estimation result of BMTOBP model (N=5766)

Explanatory variable	Parameter	Standard variance	T-statistic
(1) Monthly mileage of ordinary vehicles (100 km): Tobit Model			
Household annual income (10 million JPY)	1.053	0.363	2.90
Number of drivers in one household	0.979	0.233	4.20
Householder with no occupation (dummy)	-0.174	0.348	-0.50
Household in the Mie or Gifu prefecture (dummy)	1.485	0.246	6.04
Number of adults [>=18 years old] in the household	0.338	0.191	1.77
Household with babies [<=4 years old] (dummy)	-0.481	0.320	-1.50
Constant	1.331	0.360	3.70
(2) Monthly mileage of electric vehicles (100 km): Tobit Model			
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
Household annual income (10 million JPY)	1.850	0.645	2.87
Number of drivers in one household	0.875	0.318	2.75
Householder with no occupation (dummy)	-1.920	0.684	-2.81
Household in the Mie or Gifu prefecture (dummy)	0.667	0.459	1.45
Number of adults [>=18 years old] in the household	0.086	0.201	0.43
Household with babies [<=4 years old] (dummy)	1.102	0.515	2.14
Constant	-11.642	1.146	-10.16
(3) Number of ordinary vehicles (0, 1 or >=2) [threshold values: -0.431 and 0.431]: Ordered Probit Model			
Household annual income (10 million JPY)	0.087	0.021	4.04
Number of drivers in one household	0.180	0.009	20.35
Householder with no occupation (dummy)	-0.013	0.021	-0.64
Household in the Mie or Gifu prefecture (dummy)	0.133	0.015	9.10
Household with babies [<=4 years old] (dummy)	0.067	0.019	3.50
Constant	-0.359	0.022	-16.32
(4) Number of electric vehicles (0 or 1): Binary Probit Model			
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
Household annual income (10 million JPY)	0.154	0.058	2.66
Number of drivers in one household	0.080	0.022	3.68
Householder with no occupation (dummy)	-0.179	0.059	-3.06
Household in the Mie or Gifu prefecture (dummy)	0.038	0.042	0.89
Household with babies [<=4 years old] (dummy)	0.127	0.047	2.72
Constant	-0.937	0.101	-9.28

Since the household annual income (unit: million JPY) was investigated in the form of grouped data including less than 2, [2, 3), [3, 4), [4, 5), [5, 6), [6, 7), [7, 8), [8, 10), [10, 15) and equal to or more than 15. The middle point of the income threshold bounds was used in the model. Meanwhile, if the annual income was less than 2, we used 1.7. If it was equal to or more than 15, we used 18.

Since only 27.4% of the households in the stated preference data were supposed to hold electric vehicles, the variance of monthly mileage of electric vehicles was larger than that of ordinary vehicles.

Table 5.2 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 (1.000)

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

5.3 The data used in the forecasting model

We have proposed one forecasting model to estimate the ownership of electric vehicles in the Chukyo region in Japan in chapter 3, and the flowchart of this forecasting method is illustrated as follows in Figure 5.1.

This proposed forecasting model in chapter 3 had some demerits. At first, this model only can forecast the ownership of the electric vehicle, and the usage cannot be included in the framework. Moreover, since the annual income data in the household was not included in the person trip survey, we utilized the linear regression analysis to estimate it based on the stated preference survey data, and the pho square ratio was not very high. At last, since the vehicle characteristic data is unknown in the person trip survey, we used the naive method to define many variables, and then applied these variables into the forecasting model. So the definition of so many unknown variables seems to be questionable.

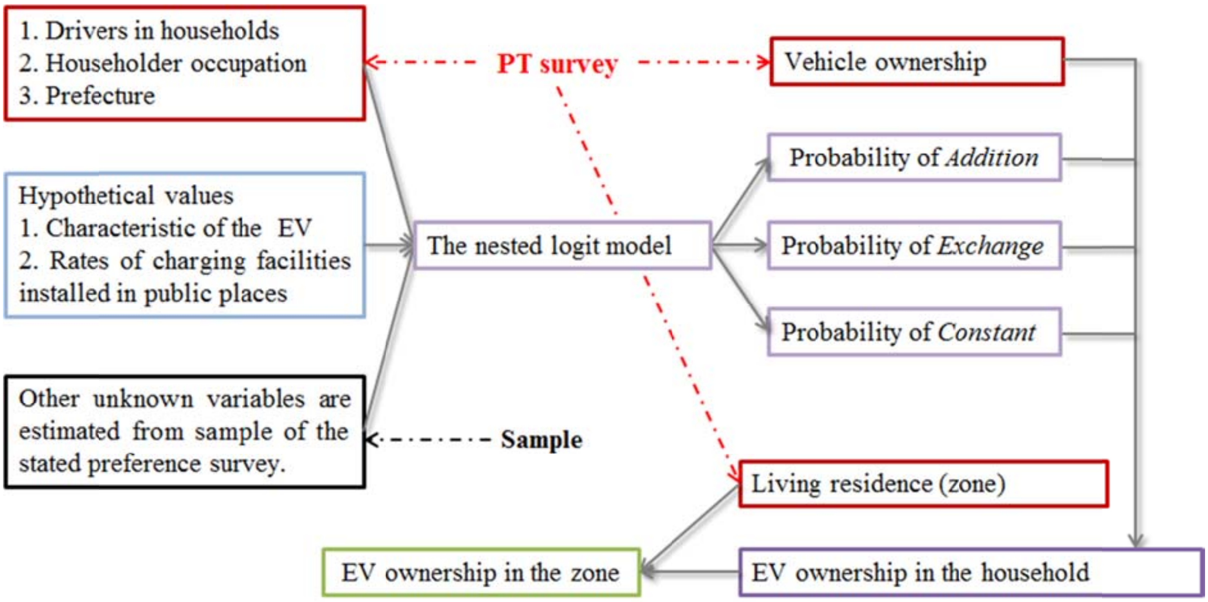

Figure 5.1 The flowchart of the forecasting model in chapter 3

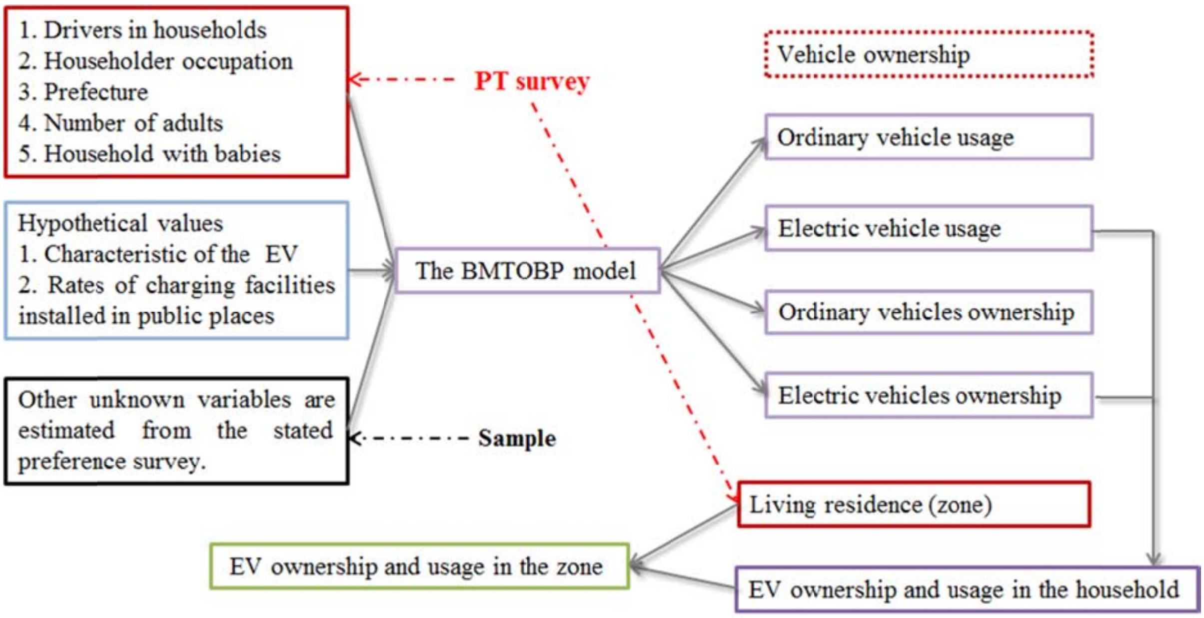

Figure 5.2 The flowchart of the proposed forecasting model in this study

Figure 5.2 shows the flowchart of the proposed forecasting method in this study. The input of the forecasting model constitute from three parts, the variables from person trip survey, the hypothetical values, and the unknown parameters. Compared to the forecasting method illustrated in Chapter 3, this method can complement the demerits of this proposed method. Especially, the unknown variables only include the charging vehicle at home (dummy) and the household annual income data.

In this forecasting model the 4th person trip survey data (2001) in the Chukyo region in Japan is used to estimate the demand of electric vehicles` ownership and usage. Except variables in the stated preference survey, most of variables in the BMTOBP model are acquired from the person trip survey data. Meanwhile, two unknown variables are estimated based on the sample.

Table 5.3 Parameters of annual income estimation model (N=5766)

Explanatory variable	Parameter	Standard variance	T-statistic
Householder: female (dummy)	-0.241	0.026	-9.43
Number of members in one household	0.022	0.007	3.25
Householder: >= 25 & <=34 years old (dummy)	0.131	0.083	1.59
Householder: >= 35 & <=44 years old (dummy)	0.273	0.082	3.34
Householder: >= 45 & <=54 years old (dummy)	0.398	0.082	4.87
Householder: >= 55 & <=64 years old (dummy)	0.299	0.084	3.57
Householder: >= 65 years old (dummy)	0.489	0.089	5.47
District: Mie prefecture (dummy)	0.014	0.021	0.65
District: Aichi prefecture [excluding Nagoya] (dummy)	0.026	0.018	1.45
District: Nagoya (dummy)	0.096	0.019	5.21
Householder: government employee (dummy)	0.637	0.028	22.60
Householder: company employee (dummy)	0.457	0.023	19.86
Householder: self-employed business (dummy)	0.190	0.028	6.68
Household: stand-alone building (dummy)	0.025	0.015	1.75
Number of family members [>=25 years old]	0.086	0.013	6.83
Number of workers in the household	0.088	0.009	9.45
Constant	5.189	0.085	61.34
Standard variance	0.454	0.005	98.01
Log-likelihood at Zero	-13276.706		
Log-likelihood at Convergence	-11883.870		
McFadden`s Rho-squared	0.105		
Adjusted McFadden`s Rho-squared	0.104		

The home charging vehicle (dummy) is determined by the naive method inside four different districts including Aichi (excluding Nagoya), Mie, Gifu and Nagoya. The household annual income is estimated based on the method proposed by Stewart (1983). This method assumes that the annual income follows log-normal distribution. The estimated parameters of the ordered probit model are shown in Table 5.3.

Nine threshold values in this model are *log(200)*, *log(300)*, *log(400)*, *log(500)*, *log(600)*, *log(700)*, *log(800)*, *log(1000)* and *log(1500)*, respectively. One random variable sampled from $N(0, 0.454^2)$ is added into the estimation result for simulating the annual income of one household. The equation of the annual income estimation is illustrated as follows.

$$A_i = exp(\beta^T x_i + U\sigma) \tag{5.1}$$

where,

A_i : annual income of the household i (unit: 10 thousand JPY),

β : the vector of estimated parameters shown in Table 5.3,

x_i : the vector of corresponding variables of the household i,

U : a random variable sampled from the standard normal distribution and

σ : the standard variance of the ordered probit model shown in Table 5.3.

5.4 Results and discussion

The explanatory variables related to attributes of the electric vehicle are supposed to be 2 million JPY (price), 5 seats (capacity), 300 km (range), 20 minutes (charging time by fast charger), and 0.2 (charging rate in the gas station).

The average electric ownership in this region could reach to 0.324 per household. Meanwhile, the average monthly mileage is 259.36 km per household. In order to compare the difference of electric vehicles ownership and usage in urban and suburban areas, we aggregate the results in the zone level. The average ownership and usage of electric vehicles in different zones are shown in Figure 5.3 and Figure 5.4, respectively.

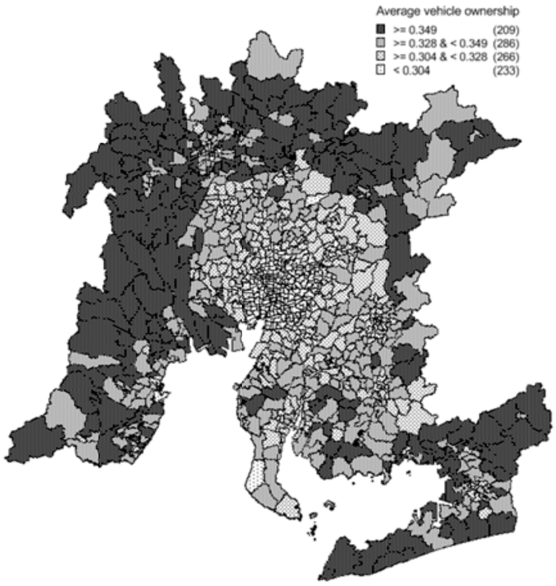

Figure 5.3 Average electric vehicles ownership

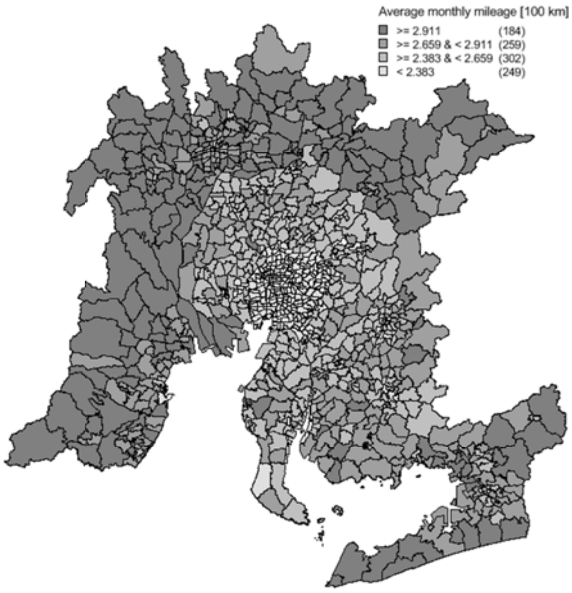

Figure 5.4 Average electric vehicles usage

Figure 5.3 shows that the average electric vehicles ownership in suburban areas is higher than that in urban areas. Most of suburban areas have a ratio of more than 0.328 per household. The monthly mileage of electric vehicles in suburban areas is more than that in urban areas. The monthly usage of electric vehicles in suburban areas could reach to more than 265.90 km per household.

The reasons for these results are lists as follows. Firstly, households in suburban area have a higher ratio of holding a stand-alone building. It confirms that they can charge vehicles at home. Secondly, the families in big size are usually living in suburban areas. They might have more drivers compared with families in small size. Lastly, the insufficient public transportation system might lead to a high dependency on private vehicles in suburban areas.

5.5 Summary

This study forecasts the demand of electric vehicles ownership and usage in the Chukyo region in Japan. The BMTOBP model proposed in Chapter 4 is utilized here. The 4th person trip survey data in 2001 are used as the sample. Since two variables cannot be acquired from the person trip survey data directly, we use the naive method to determine the variable named charging vehicle at home. We use an ordered probit model to estimate the household annual income in the person trip survey data.

The results show that the average ownership of electric vehicles could reach to 0.324, and the monthly mileage of electric vehicles is 259.36 km per household. Meanwhile, it is found that both the ownership and monthly mileage of electric vehicles in suburban areas are more than that in urban areas.

As the future issue, we will consider the topic about optimal deployment of public charging facilities in the Chukyo region based on the forecasting results in this study.

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Chapter 6

Examining the Variation of Household Vehicle Holding Behavior in the Chukyo Region in Japan

With the development of motorization society, the life of human has been highly dependent on the usage of private cars. Meanwhile, it may lead to many externalities to the environment of metropolitan, such as air pollution, traffic congestion and so on. The motorization may affect the vehicle utilization in the household in two aspects. On one hand, the number of vehicles has been increased obviously during the motorization process. On the other hand, the various types of vehicles has been designed and manufactured to satisfy the multiple purposes of usage.

Japanese car manufacturers have been improving their technology since 1955. As a result, the vehicle production increased drastically in the domestic market from 1965. The global economy was impacted by the first world oil crisis in 1973. Since Japan was highly dependent on the crude oil import from the Middle East at a ratio of 80% at that time, the impact on Japan was especially serious. As a result, the automobile industry slowed down from that year. The production of the private cars and that of trucks were obviously less than that in the previous year. Japan overcame the oil crisis by implementing strict cost reduction measures, energy and resource conservation initiatives, and unflagging export promotion efforts. Between 1987 and 1991 Japanese economy experienced a period of unprecedented prosperity called bubble economy. As a result, the vehicle production reached its peak at 13.5 million units in 1990. Since the bubble economy collapsed in 1991, the production declined yearly from 1991 to reach a pre-1980 level of 10.5 million units in 1994 (Japan Automobile Manufacturers Association, 2013). For Japanese car manufacturers were manufacturing affordable, reliable, and popular cars in the 1990s, Japan became the largest car manufacturing country in 2000.

In Japan the classification of vehicles are different from that used in America. The vehicles are mainly classified into the car and the truck. Moreover, the car is classified into the light motor car and the ordinary motor one. Meanwhile, the truck is classified into the light motor truck and the ordinary motor one. The household usually did not own a truck at home, since most of the activity demands could be satisfied by the light motor car or the ordinary motor one.

Compared to the ordinary motor car, the light motor one seems to be compact and eco-friendly. In the metropolitan area with an advanced subway or railway network, the merit of the light motor car seems obvious. The household could take the railway to commute or make a long-distance travel. Meanwhile, the short distance trip could be satisfied by the light motor car. The low displacement of it can help to relieve the problem of global warming. The Japanese government had carried out the policy on vehicle tax exemption (Japanese Ministry of Land, Infrastructure, Transportation and Tourism, 2013) to promote the purchase and usage of the light motor vehicle. Before prevailing of the next generation vehicles including plug-in hybrid electric vehicles, fuel cell ones and so on, the light motor car is treated as an ideal transportation mode for its eco-friendly merit and excellent fuel consumption. As a result, it is necessary to reveal the preference of holding the light motor car in the household.

There are many previous studies on the choice of vehicle types in the household. Either the discrete choice or the discrete-continuous choice model was implemented in previous research. The discrete choice model usually utilized a nested logit structure to represent the combination of vehicle types conditional on the fixed vehicle ownership (Feng *et al.*, 2005; West, 2004). The discrete-continuous choice model usually used the discrete component to represent the vehicle ownership and the continuous component to portrait the vehicle usage or mileage (Dubin and McFadden, 1984; Hanemann, 1984; Bhat and Sen, 2006; Fang, 2008). Since the vehicle usage usually did not be investigated in the personal trip survey in Japan, the implement of the discrete-continuous choice model is not suitable in this study.

For the different classification of household vehicle types in Japan and other countries, previous studies concerning the light motor car are very limited. The study proposed by

Kobayashi *et al.* (2009) extended the BMOPT model proposed by Fang (2008) to analyze the ownership and usage of the light motor car and the ordinary motor one in the household. The sample was the data of national wide road traffic census in 1999 and 2005 in Japan. Their study observed impact of the population density and the accessibility of the railway system on the vehicles type and ownership. The population density or residential density was found to be an important factor for the vehicle ownership and usage in the household (Kobayashi *et al.,* 2009; Fang, 2008). Meanwhile, the railway accessibility was seldom investigated as the explanatory variable in the proposed choice model on vehicle types in previous studies.

This study aims to reveal the household preference of owning the light motor car and the ordinary motor one in the household in the Chukyo region in Japan. Meanwhile, it also examines the variation of vehicle holding behavior in the household form 1971 to 2001. In order to examine the impact of accessibility to the railway system on vehicle ownership, we prefer to use the density of railway stations as the explanatory variable rather than the number of the railway stations (Kobayashi *et al.*, 2009). Since the truck is seldom owned by the household, the ownership of it is not considered in this study.

We utilize a bivariate ordered probit model (Greene, 2011) to model two types of vehicles in the household. The relationship between the light motor car and the ordinary motor one is measured by the correlation ratio of the error items. The Gibbs sampler algorithm is implemented in this study to estimate the parameters effectively and efficiently. The person trip survey data in this region in 1971 and 2001 are utilized to estimate the parameters in the model, respectively. The discussion of estimation results is carried out to understand the variation of vehicle holding behavior in the household.

The rest of this paper is organized as follows. Section 6.1 describes the basic statistic of sample data, and compares the aggregation results to analyze the variation of vehicle ownership in the household from 1971 to 2001. Section 6.2 compares the aggregation results to analyze the variation of vehicle ownership in the household from 1971 to 2001.Section 6.3

describes the bivariate ordered probit model proposed in this study, the explanatory variables and the Gibbs sampler algorithm in this study. The estimation results of this model using the sample in 1971 and 2001 are shown in Section 6.4, along with a discussion based on the results. Finally, this study is concluded in Section 6.5 along with a discussion about future issues.

6.1 Data statistics

The person trip survey data in 1971 and 2001 are used in this study. The data in 1971 is corresponding to the initial stage of the motorization society in Japan. Meanwhile, the data in 2001 is corresponding to the advanced stage of the motorization society. The Chukyo region is the third metropolitan region in Japan. It is supposed that it can represent the motorization process of motorization society in this study. There are four times of the person trip survey carried out in the Chukyo region. Since only the surveys in 1971 and 2001 classified the private car into the light motor car and the ordinary motor one, the survey data in 1981 and 1991 cannot be utilized in this study. The survey data in 2001 contained more areas than that in 1971, the research area is confined to the survey area in 1971. We use the criterion of city, district, town and village to divide the research area into 111 zone units, since the original small zones in 1971 and 2001 could not be matched exactly. The basic statistic of attributes of household characteristics in 1971 and 2001 are shown in Table 6.1.

Compared to the gender of householders in 1971, the ratio of male householders nearly does not change in 2001. Around 83% of the householders are male. For the age of householders, the householders over 60 years old take a ratio of about 36.3% in 2001. The ratio of them is only about 15.2% in 1971. It might indicate the aging problem in Japan. The sample distribution of different districts nearly keeps unchanged. The households with more than 3 members at a ratio of nearly 32% decreased, compared to that in 1971 around 53%. It might indicate that constitute of the household became smaller than before. This might be a crucial factor for the vehicle choice, since the more members in the household can induce more travel demand. The ratio of unemployed householders increased dramatically compared to that in 1971, since the aged householders take a ratio of 36.3%.

Table 6.1 Basic statistic of the sample data in 1971 and 2001

Attribute	Percentage [1971]	Percentage [2001]
Gender of the householder		
Male	82.8%	82.5%
Female	17.2%	17.5%
Age of the householder		
<= 19 years old	4.8%	0.4%
>= 20 & <= 29 years old	18.3%	7.6%
>= 30 & <= 39 years old	26.9%	15.9%
>= 40 & <= 49 years old	20.6%	16.4%
>= 50 & <= 59 years old	14.2%	23.4%
>= 60 years old	15.2%	36.3%
District		
Nagoya	34.3%	32.1%
Aichi (Excluding Nagoya)	44.7%	45.9%
Mie	5.9%	7.2%
Gifu	15.1%	14.8%
Household member		
1	17.1%	19.1%
2	11.5%	29.9%
3	19.0%	19.4%
4	27.8%	18.6%
5	13.4%	8.0%
>=6	11.3%	5.0%
Occupation of the householder		
Farmer	5.2%	1.8%
Production worker	32.3%	17.3%
Salesman	5.4%	6.2%
Servicer	8.1%	6.8%
Communication worker	10.5%	4.2%
Security worker	9.5%	1.2%
Clerical officer	0.2%	7.0%
Engineer	6.3%	14.0%
Manager	8.8%	9.6%
Other officers	1.3%	5.1%
No occupation	12.4%	26.8%

Table 6.2 shows the cross aggregation result concerning the vehicle ownership. As the initial stage of motorization in 1971, the private car was not prevailing in that time. About 77.18 % of the investigated households did not own the light motor car or the ordinary motor one. Only 1.01% of the household would like to own these two types of cars at home. Around

6.41% of households owned the light motor car in the household. Meanwhile, the ratio of households owning the ordinary motor car was higher than that of the light motor car at a ratio of around 17.41%.

Compared to the tabulation result in 1971, the ownership of these two kinds of private cars changed dramatically. Only 19.15% of households investigated in 2001 did not owning any private cars. Meanwhile, households owning these two kinds of private cars increased obviously from 1.01% to 19.08%. Compared to the ratio of households owning the light motor car in1971, this ratio increased around 3 times from 6.41% to 24.05%. The ratio of households owning the ordinary motor car increased from 17.41% in 1971 to 75.89% in 2001.

Table 6.2 Tabulation of vehicle ownership

Sample in 1971 [N=64416]	Number of ordinary motor cars			Total
	0	1	>=2	
Number of light motor vehicle				
0	0.7718	0.1514	0.0126	0.9358
1	0.0525	0.0077	0.0012	0.0613
>=2	0.0017	0.0006	0.0006	0.0029
Total	0.8259	0.1597	0.0144	1.0000
Sample in 2001 [N=85047]	Number of ordinary motor cars			Total
	0	1	>=2	
Number of light motor vehicle				
0	0.1915	0.3593	0.2087	0.7595
1	0.0429	0.1260	0.0467	0.2157
>=2	0.0067	0.0112	0.0069	0.0248
Total	0.2411	0.4965	0.2624	1.0000

6.2 Data aggregation

In order to examine the variation of social economic attributes and the ownership of these two kinds of private cars, we draw the figures concerning these factors in 1971 and 2001, respectively. The figures of these variables are shown in Figure 6.1, 6.2, 6.3, 6.4, and 6.5, respectively. These variables include the population density, accessibility to railway network, the ownership of the light or the ordinary motor car, and the share of the light motor car. The results shown in this section are aggregated based on all the households in this region, not just based on the sample data.

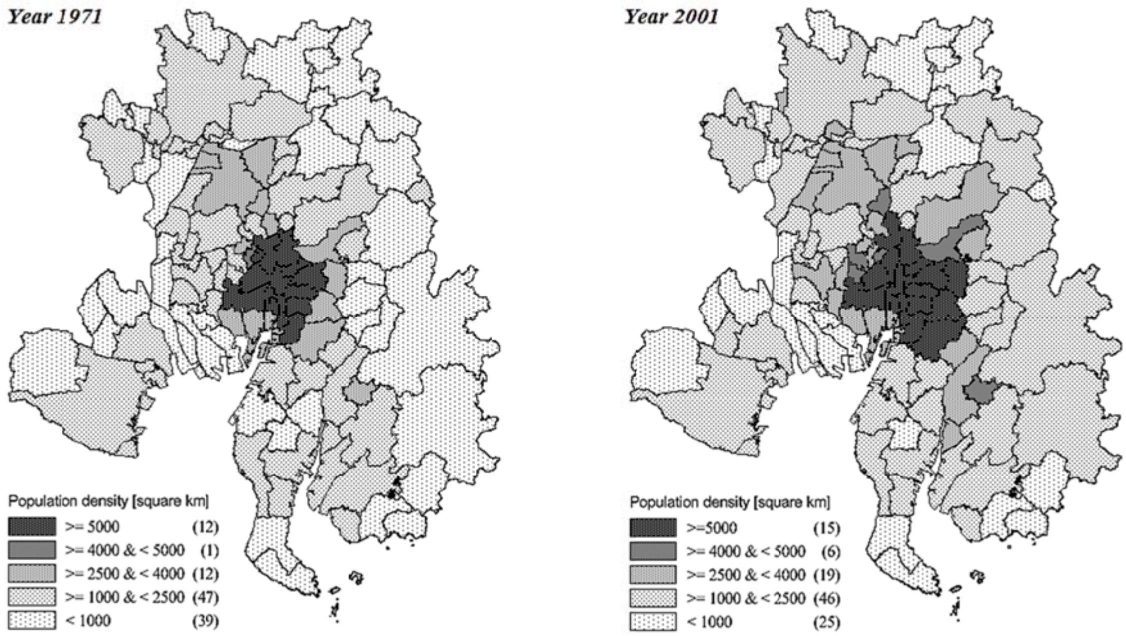

Figure 6.1 Population density in 1971 and 2001

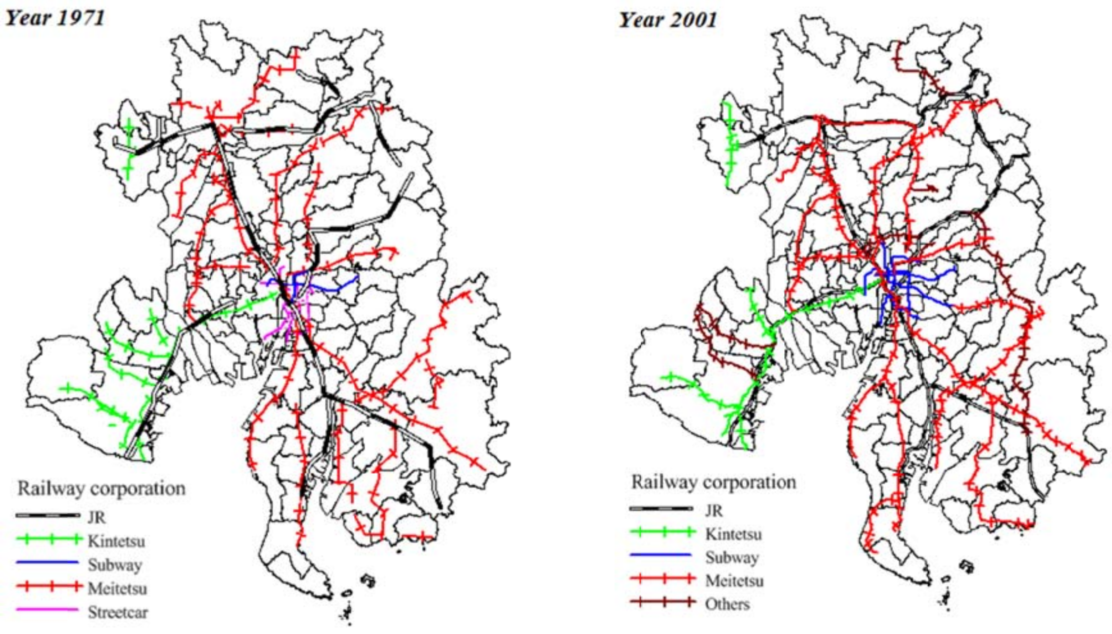

Figure 6.2 Accessibility to railway system in 1971 and 2001

Figure 6.1 shows the population density in this region both in 1971 and 2001. The area with the highest population density is corresponding to the metropolitan of Nagoya. The area of the highest population density expands a little, compared to that in 1971. It might indicate that some parts of suburban areas have merged into the urban areas in 30 years period. The population in this region is calculated from the person trip survey data. The number of family members and magnification factor corresponding to the household are included in the survey.

Figure 6.2 shows the railway accessibility in this region in 1971 and 2001. Compared to the railway network in 1971, the railway network had reached an advanced level in 2001. The streetcar system in Nagoya had been replaced with the subway system by 2001. The railway lines in suburban areas have also been extended to improve the accessible ability for passengers in 2001.

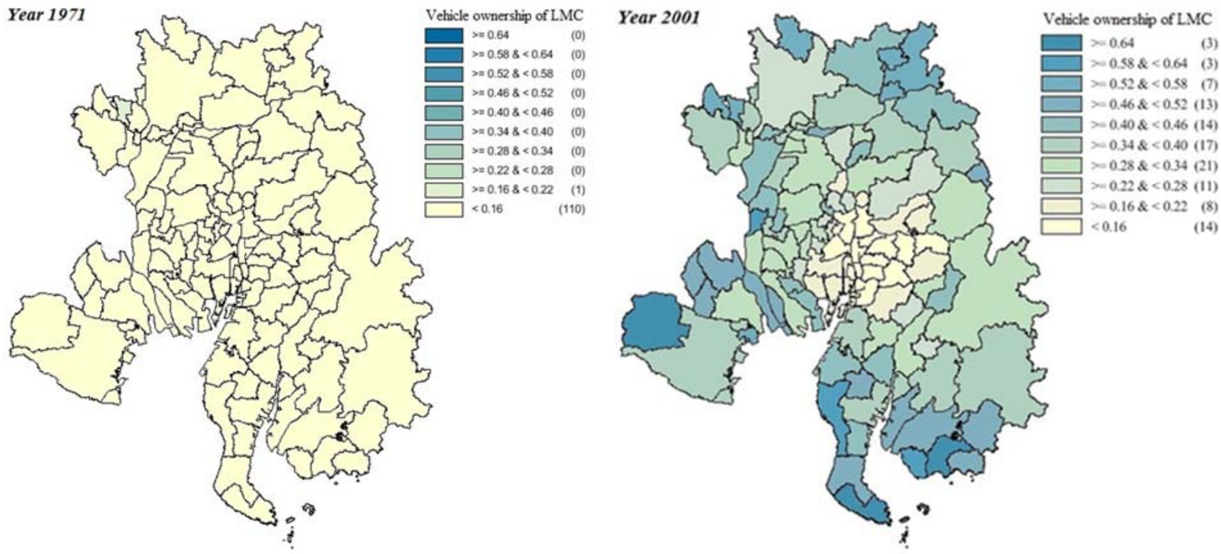

Figure 6.3 Ownership of the light motor car in 1971 and 2001

Figure 6.3 shows that ownership of the light motor car (LMC) in most areas increased obviously, compared to that in 1971. Meanwhile, household ownership in the metropolitan area of Nagoya nearly had no change and was still less than 0.16. The ownership of the light motor car in suburban areas is more than that in urban areas in 2001.

Figure 6.4 shows that ownership of the ordinary motor car (OMC) increased obviously both in urban and suburban areas, compared to that in 1971. The ownership of the ordinary motor car in suburban areas was more than that in urban areas, both in 2001 and 1971. It might indicate that there is huger demand and usage of the private car in suburban areas compared to urban areas.

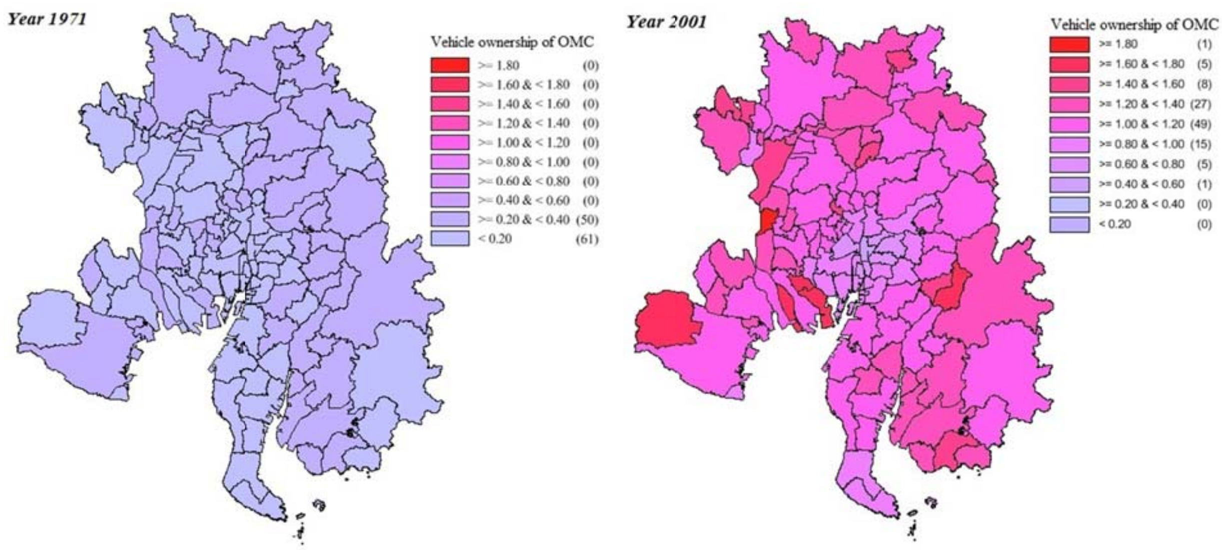

Figure 6.4 Ownership of the ordinary motor car in 1971 and 2001

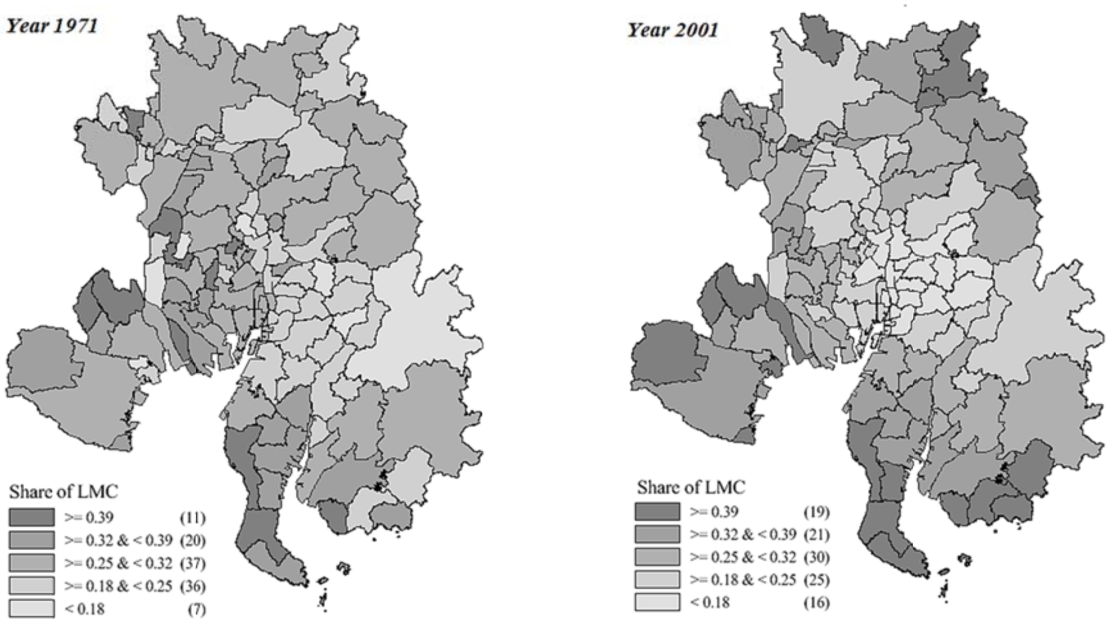

Figure 6.5 Share of the light motor car in 1971 and 2001

Figure 6.5 shows the share of the light motor car accounting for private cars in this region in 1971 and 2001. The share of the light motor vehicle in urban areas decreased in 2001, compared to that in 1971. It might indicate that the increase of the ordinary motor car is more than that of the light motor car in urban areas.

6.3 Model instruction

6.3.1 Model specification

Let two latent continuous variables y_{1i}^* and y_{2i}^* represent the preference for holding the light motor car and the ordinary motor one, respectively. The equation system for discrete choice of these two types of cars is represented as follows.

$$y_{1i}^* = x_{1i}^T \beta_1 + \varepsilon_{1i} \qquad (6.1)$$

$$y_{2i}^* = x_{2i}^T \beta_2 + \varepsilon_{2i} \qquad (6.2)$$

where,

i : indexing the household in the sample $(i = 1, \dots, N)$,

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,

β_k : the vector of parameters in the kth equation, and

ε_{ki} : the error item in the kth equation for the household i.

These two equations system concerning the latent variables can be written into a seemingly unrelated regression form (Koop, 2003) as follows.

$$y_i^* = x_i \beta + \varepsilon_i \qquad (6.3)$$

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

$$\varepsilon_i \sim^{i.i.d} MVN(0,\Sigma) \tag{6.4}$$

The relationship between latent variables and observed ones is illustrated as follows.

$$y_{1i} = \begin{cases} 0, & if\ y_{1i}^* \le \alpha_{11} \\ 1, & if\ \alpha_{11} < y_{1i}^* \le \alpha_{12} \\ 2\,or\ more, & if\ \alpha_{12} < y_{1i}^* \end{cases} \tag{6.5}$$

$$y_{2i} = \begin{cases} 0, & if\ y_{2i}^* \le \alpha_{21} \\ 1, & if\ \alpha_{21} < y_{2i}^* \le \alpha_{22} \\ 2\,or\ more, & if\ \alpha_{22} < y_{2i}^* \end{cases} \tag{6.6}$$

where, α_{11} and α_{12} are the threshold values of the ordered probit model which is 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 Fang`s study. α_{11} and α_{12} 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). The same setting method can be applied to the threshold values α_{21} and α_{22} in the ordered probit model measuring the ownership of ordinary motor cars.

6.3.2 Model estimation

Since the sample share of households owned more than one light motor car were very small shown in Table 6.2, the maximum likelihood estimation method seems low efficient. In this study we utilize the Bayesian Markov Chain Monte Carlo method (Brooks *et al.*, 2011) to estimate parameters. 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.

$$draw \quad y_i^* \mid \beta, \Sigma, y_i \quad from \quad \pi(y_i^* \mid \beta^{(k-1)}, \Sigma^{(k-1)}, y_i) \tag{6.7}$$

$$draw \quad \beta \mid \Sigma, y_i^* \quad from \quad \pi(\beta \mid \Sigma^{(k-1)}, y_i^{*(k)}) \tag{6.8}$$

$$draw \quad \Sigma \mid y_i^*, \beta \quad from \quad \pi(\Sigma \mid y_i^{*(k)}, \beta^{(k)}) \tag{6.9}$$

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 other variables. It is not difficult to prove that equations 6.10 and 6.11 can draw a sample from the full conditional distribution for $y_{ki}^* \ (k=1,2)$, respectively.

$$y_{1i}^* = \begin{cases} \mu_{1|\neg 1} + \sigma_{1|\neg 1}\Phi^{-1}(U(1-\Phi((0.431-\mu_{1|\neg 1})/\sigma_{1|\neg 1})) + \Phi((0.431-\mu_{1|\neg 1})/\sigma_{1|\neg 1})), & if \ y_{1i} \geq 2 \\ \mu_{1|\neg 1} + \sigma_{1|\neg 1}\Phi^{-1}(U(\Phi((0.431-\mu_{1|\neg 1})/\sigma_{1|\neg 1}) - \Phi((-0.431-\mu_{1|\neg 1})/\sigma_{1|\neg 1})) + \Phi((-0.431-\mu_{1|\neg 1})/\sigma_{1|\neg 1})), & if \ y_{1i} = 1 \\ \mu_{1|\neg 1} + \sigma_{1|\neg 1}\Phi^{-1}(U\Phi((-0.431-\mu_{1|\neg 1})/\sigma_{1|\neg 1})), & if \ y_{1i} = 0 \end{cases} \tag{6.10}$$

$$y_{2i}^* = \begin{cases} \mu_{2|\neg 2} + \sigma_{2|\neg 2}\Phi^{-1}(U(1-\Phi((0.431-\mu_{2|\neg 2})/\sigma_{2|\neg 2})) + \Phi((0.431-\mu_{2|\neg 2})/\sigma_{2|\neg 2})), & if \ y_{2i} \geq 2 \\ \mu_{2|\neg 2} + \sigma_{2|\neg 2}\Phi^{-1}(U(\Phi((0.431-\mu_{2|\neg 2})/\sigma_{2|\neg 2}) - \Phi((-0.431-\mu_{2|\neg 2})/\sigma_{2|\neg 2})) + \Phi((-0.431-\mu_{2|\neg 2})/\sigma_{2|\neg 2})), & if \ y_{2i} = 1 \\ \mu_{2|\neg 2} + \sigma_{2|\neg 2}\Phi^{-1}(U\Phi((-0.431-\mu_{2|\neg 2})/\sigma_{2|\neg 2})), & if \ y_{2i} = 0 \end{cases} \tag{6.11}$$

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 the other equation, and

$\sigma_{j|\neg j}$: the standard variance of equation j fully conditional on the other equation.

The calculation of the full conditional mean and variance is equally straightforward according to Poirier (1995). 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.

$$\beta \mid y_i^*, \Sigma \sim N(\overline{\beta}, \overline{V}) \tag{6.12}$$

$$\overline{V} = (V_0^{-1} + \sum_{i=1}^{N} x_i^T \Sigma^{-1} x_i)^{-1} \tag{6.13}$$

$$\overline{\beta} = \overline{V}(V_0^{-1}\beta_0 + \sum_{i=1}^{N} x_i^T \Sigma^{-1} y_i^*) \tag{6.14}$$

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 1000 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.

$$\Sigma \mid y_i^*, \beta \sim W^{-1}(v + N, \sum_{i=1}^{N} \left(y_i^* - x_i\beta\right)\left(y_i^* - x_i\beta\right)^T + \Psi) \tag{6.15}$$

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

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. Meanwhile, the Geweke diagnostic test indicates a high degree of convergence and accuracy within the number of iterations. Compared to the maximum likelihood estimation method, the Gibbs sampler algorithm implemented in this study is found to more effective and efficient.

6.3.3 Explanatory variables

The household specific variables and neighborhood variables are included in the model. The household specific variables are derived from the individual attributes for each household in the person trip survey data. The neighborhood variables are calculated by the unit of the divided zone. The explanation of these explanatory variables is listed in Table 6.3.

Table 6.3 Explanatory variables

Name	Description
Nagoya (dummy)	1 if the household is in Nagoya; 0 otherwise.
Age (dummy)	1 if age of the householder is 60 years older or above; 0 otherwise.
Workers	Number of workers in the household
Member25	Number of family members in the household (>= 25 years old)
Female (dummy)	1 if the householder is female; 0 otherwise.
Log (population density)	The population density is calculated based on the zone level using the person trip survey data.
Density of railway stations	The number of railway stations divides area (unit: km^2) based on the zone level. The area of the zones in this study is coming from the digital map.

6.4 Results and discussion

In order to examine the variation of the vehicle holding behavior, we estimated the model using the data in 1971 and 2001, respectively. Then we compared the difference of the estimated parameters to observe explanatory variables which had changed its effect. The estimation results of these two samples are shown in Table 6.4 and Table 6.5, respectively.

For the ownership of the light motor car, district, age of the householder, number of workers, number of members (>= 25 years old) were important factors both in 1971 and 2001 and had the same sign. The gender of householder was found to be a significant factor only in 1971. It might indicate that the female householders changed holding behavior on owning light motor cars, because of the impact of motorization society. The population density and density of railway station were found to be significant factors only in 2001. It was shown that these two factors did not affect the ownership of the light motor car in 1971. It might indicate two facts mentioned as follows. Firstly, the differential in income between urbanized area and rural area widened from 1971 to 2001 and the households in urbanized area preferred ordinary motor car to light motor car. Secondary, along with the development of public transportation network in the urbanized area, it became unnecessary for households in such area to save money for operating vehicles. The alternative specified constant of the light motor car in 2001 was found to be minus sign with the 1% significance level indicated that in general the households did not have a preference to own or not to own light motor cars in 2001, due to the impact of the motorization society.

Table 6.4 Model estimation result [1971]

Explanatory variable	Light motor car		Ordinary motor car	
	Parameter	T-statistic	Parameter	T-statistic
Nagoya (dummy)	-0.059	-2.90	0.022	1.46
Age (dummy)	-0.083	-5.12	-0.061	-5.08
Workers	0.016	2.64	0.027	6.12
Member25	0.059	8.78	0.053	10.86
Female (dummy)	-0.090	-5.55	-0.089	-7.36
Log (population density)	-0.010	-0.93	-0.021	-2.58
Density of railway stations	-0.035	-1.02	-0.081	-3.26
Constant	-1.488	-18.55	-1.020	-17.45
	Parameter		T-statistic	
Variance of the light motor car	0.475		28.58	
Covariance	-0.007		-1.31	
Variance of the ordinary motor car	0.470		49.68	
Number of samples	64416			

For the ownership of the ordinary motor car, age of the householder, number of workers, number of member (>= 25 years old), gender of the householder, population density, and density of railway stations were significant factors both in 1971 and 2001 and had the same sigh. The explanatory variable Nagoya (dummy) was significant only in 2001. It indicated that there was an obvious difference of ownership of the ordinary motor car between the areas inside and outside Nagoya, due to the realization of motorization society. The residents living in Nagoya were unwilling to own the ordinary motor car in 2001, since the subway system in Nagoya was efficient and effective in 2001.

Table 6.5 Model estimation result [2001]

Explanatory variable	Light motor car		Ordinary motor car	
	Parameter	T-statistic	Parameter	T-statistic
Nagoya (dummy)	-0.145	-11.29	-0.057	-6.75
Age (dummy)	-0.178	-25.02	-0.258	-53.91
Workers	0.090	23.85	0.163	58.91
Member25	0.126	30.12	0.226	73.54
Female (dummy)	-0.010	-1.04	-0.206	-34.64
Log (population density)	-0.149	-22.61	-0.019	-3.94
Density of railway stations	-0.093	-3.15	-0.301	-16.79
Constant	0.016	0.33	-0.313	-8.61
	Parameter		T-statistic	
Variance of the light motor car	0.370		68.70	
Covariance	-0.114		-60.91	
Variance of the ordinary motor car	0.240		120.64	
Number of samples	85047			

According to the estimation results of the samples in 1971 and 2001, it was found that the substitution effect on ownership between the light motor car and the ordinary motor one only existed in 2001.

6.5 Summary

This study analyzed the variation of vehicle holding behavior in the Chukyo region in Japan from 1971 to 2001. The vehicle type was classified into the light motor car and the ordinary motor one. The impact of the truck in the household was not taken into consideration. The 1st and 4th person trip survey data in this region were used in this study, which were collected in 1971 and 2001, respectively. A bivariate ordered probit model was applied to estimate the parameters of the proposed model using the data in 1971 and 2001, respectively. In order to estimate the model efficiently, the Gibbs sampler algorithm was implemented using GAUSS 3.2. The estimation results suggested the importance of household and neighborhood characteristic factors in 1971 and 2001, as well as the variation of vehicle holding behavior in this region.

It was shown that age of the householder, number of workers, number of members (>= 25 years old) were the important factors for owning the light and ordinary motor car both in 1971 and 2001. The residence in Nagoya affected ownership of the light motor car in 1971 and 2001. Meanwhile, it affected ownership of the ordinary motor car only in 2001. The gender of the household impacted the ownership of ordinary motor cars in 1971 and 2001. Meanwhile, it only impacted the ownership of light motor cars in 1971. The population density and density of railway stations were significant factors for ownership of the ordinary motor car in 1971 and 2001. They affected the ownership of the light motor car only in 2001. It was found that there was a substitution effect on the ownership between the light motor car and the ordinary motor one only in 2001.

As the future task, we will analyze impact of life stage or life style on the ownership of the light motor car in the household level. The proposed ordered probit model in this study will also be utilized in the next research work.

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Chapter 7

Examining the Preference of the Light Motor Vehicle Holding Behavior Considering the Heterogeneity of Family Constitution

The light motor vehicle is treated as the environmental friendly vehicle, since the low displacement of it can reduce the burden to the environment of the metropolitan area. From the beginning stage of the motorization society, the light motor vehicles have been penetrating in the marker. Conclusion of chapter 6 has shown that the households have more desire to own the light motor vehicle compared to the behavior in the 30 years ago. It could be concluded that the light motor vehicle had been becoming more and more popular for the residents living in the Chukyo region in Japan.

As it is known to us, the light motor vehicle is characteristic of its compact design, low price, and excellent fuel consumption. Compared to the ordinary motor vehicle, this compact design is very suitable for the family in the small size, especially for the single household. While, this compact characteristic might be not suitable for the family in big size. As a result, the preference of holding behavior in the households with different family constitution might be not identical. For its compact design, this vehicle is much cheaper than the traditional vehicle. As a result, the households with high annual income might not purchase the light motor vehicle, since they may concern more about the performance, such as capacity or power rather than the vehicle price.

Previous studies have observed the ownership of vehicles considering the heterogeneity of family constitution (Kobayashi *et al.*, 2009; Ishida *et al.*, 2003; Ishida *et al.*, 2004). The family constitution is an important factor for the households to own the private cars. As a result, it is necessary to analyze the ownership of vehicles based on the family constitutions.

The proposed study in chapter 6 did not classify the households into different types to analyze the ownership. The reason for it is listed as follows. On one hand, chapter 6 aims at examining the variation of holding behavior of vehicle types including the ordinary motor vehicle and the light motor one form 1971 to 2001 in general. On the other hand, the classification of the family constitution in 1971 has one problem, since the number of sample data in some group is very small. So the bias of the estimation result might occur.

There is another problem concerning the proposed model in chapter 6, lack of the household annual income data. Since the annual income data is not included in the 4th person trip survey (2001), we did not incorporate this explanatory variable in the model. As far as we know, the income data was usually not included in the person trip survey in the Chukyo region. So the complement method to fulfill the income data is necessary and crucial for us to make an analysis on the ownership of the light motor vehicle using the person trip survey data in the region.

In this study the heterogeneity of family constitution and the annual income will be taken into consideration. The households were divided into different groups classified by family constitution. Meanwhile, the annual income data is complemented by the ordered probit model following Swart (1983) proposed in chapter 5. The classification of vehicles is confined to the ordinary motor vehicle and the light motor one. Only the 4th person trip survey data collected in the Chukyo region will be used as the research sample. The effects of the same explanatory variables in different groups are examined to understand the heterogeneity of family constitution impacting the ownership of the light motor vehicle in the household.

The rest of this chapter is organized as follows. Section 7.1 introduces the person trip data used in this study and the criteria to classify the sample into 9 groups considering family constitution. The estimation method of the annual income data is reviewed in section 7.2. Section 7.3 shows two econometric models used in this study, their explanatory variables and corresponding estimation methods. The estimation results of two proposed models for difference family groups are shown in section 7.4, and discussions about the estimation results will be illustrated. Section 7.5 gives a conclusion for this chapter along with the future direction.

7.1 Data

The 4th person trip survey in the Chukyo region (2001) is used in the study. Since we incorporate the household annual income data into the proposed model, the research sample is set to be the same sample in chapter 6. So we can examine the effect of the income data in the proposed model. The number of sample is 85047, and the research areas are confined to areas where the 1st person trip survey data (1971) was collected. The detail information of the division of the zones can be found in section 6.1 in this thesis.

Since the person trip survey included the information of the family members, we can know the constitution of the household by aggregating the information of individual members into the household level. For example, we can understand the age of the householder, the number of the children or youths and so on. Since we cannot know the relationship between the husband and wife in the household, we use the criterions listed as follows to judge the relation of couple.

1) There are at least two persons in the household constituted by one male and one female.

2) The difference of age between these two persons is less than 10 years old.

3) Both of them are equal to or more than 18 years old.

If the household fulfills the criterion listed above, the relation of couple in the household is supposed to be existed. Here, the first criterion confines the necessity for the couple relation, where there are at least two persons in different sex type. The second criterion confines the age gap of two persons and eliminates the relations such as father and daughter, mother and son, grandfather and grandson, grandmother and granddaughter and so on. The third criterion eliminates the relation of brother and sister in the household.

In this study we use the criterion of classifying the households listed as follows in Table 7.1. The criterion is based by the number of family members, relation of couple, and age of the oldest person or the youngest person in the household. The criterion is similar to the classification of households based on division of the life stage (Sun, 2009).

Table 7.1 Criterion of classifying the households considering the family constitution

Name	Explanation of family constitute
Young single	1 person, age: 30- and 17+
Childless couple	2 person, age of couple: 65- and 17+
Couple with young children	2+ persons, age of couple: 65- and 17+, age of the youngest child :18-
Couple with all adult children	2+ persons, age of couple: 65-,17+, age of the youngest child: 17+
Childless middle-age single	1 person, age: 65- and 30+
Middle-age single with children	1+ persons, no couple, age of the oldest person: 65- and 30+
Childless older couple	2 persons, age of couple: 65+
Childless older single	1 person, age of the person: 65+
Big family	Other types of family constitute

Here, we propose the classification criterion for the division of the family, and it aims at combining the factor of life stage and one obvious social phenomenon in Japan. Some of the singles are unwilling to get married when they are more than 30 years old, and the statistical data from Ministry of Heath, Labor and Welfare in 2012 showed that rates of the unmarried male and female were found to be 20.1% and 10.6%, respectively. So we included this kind of household into the groups.

Based on the classification criterion illustrated in Table 7.1, the sample data can be classified into 9 groups. The distribution of the data in different groups is listed in the Table 7.2 as follows.

Table 7.2 Distribution of the households in 9 defined groups

List number of group	Name	Number of sample	Percentage
Group 1	Young single	4029	4.7%
Group 2	Childless couple	13280	15.6%
Group 3	Couple with young children	11387	13.4%
Group 4	Couple with all adult children	7574	8.9%
Group 5	Childless middle-age single	8612	10.1%
Group 6	Middle-age single with children	5700	6.7%
Group 7	Childless older couple	5612	6.6%
Group 8	Childless older single	6308	7.4%
Group 9	Big family	22545	26.5%

It is shown that the young single families take the smallest ratio at 4.7%, and the big families take the largest ratio at 26.5%. The young single family usually indicates the family constituted by one young worker or one student. Meanwhile, the big family usually indicates the relatively complex family constitution. This kind of families usually has large family size, and the householder of the family is an elderly person, who is equal to or more than 65 years old. The sum of childless older couple families and older single ones takes a ratio at 14%, and these two kinds of families are expected to be different concerning the usage of vehicles in the household.

7.2 Complement of the annual income data

The income data is treated as an important variable in the econometric model. In order to protect privacy of the respondent, this variable is usually investigated in the form of the group data, and the income level is reported instead of the monetary value. Many previous studies have used the mathematics model to change this discrete variable into the continuous variables. The ordered probit model was utilized to solve this problem (Stern, 1991; Stewart, 1983). Sometimes the income data is unreported because of the privacy of the respondents, and the method to solve the unreported income data was proposed by in previous studies (Stern, 1991; Bhat, 1994; Tong and Lee, 2009).

The 4th person trip survey data in the Chukyo region in Japan did not contain the income items, and this is different from the missing or unreported income data. It can be treated as the unknown variable. Chapter 5 has proposed an ordered probit model to estimate the annual income in the household to forecast the electric vehicle demand in the Chukyo region. Here, this model is applied to complement the annual income data for the person trip survey. The parameters of this model are illustrated in Table 7.3, and the detail introduction of this proposed model can be found in the Section 5.3. Combining the explanatory variables in the person trip survey and the estimation parameters in Table 7.3, we can complement the annual income data in the 4th person trip survey.

Table 7.3 Estimation results of the applied ordered logit model

Explanatory variable	Parameter	Standard variance	T-statistic
Householder: female (dummy)	-0.241	0.026	-9.43
Number of members in one household	0.022	0.007	3.25
Householder: >= 25 & <=34 years old (dummy)	0.131	0.083	1.59
Householder: >= 35 & <=44 years old (dummy)	0.273	0.082	3.34
Householder: >= 45 & <=54 years old (dummy)	0.398	0.082	4.87
Householder: >= 55 & <=64 years old (dummy)	0.299	0.084	3.57
Householder: >= 65 years old (dummy)	0.489	0.089	5.47
District: Mie prefecture (dummy)	0.014	0.021	0.65
District: Aichi prefecture [excluding Nagoya] (dummy)	0.026	0.018	1.45
District: Nagoya (dummy)	0.096	0.019	5.21
Householder: government employee (dummy)	0.637	0.028	22.60
Householder: company employee (dummy)	0.457	0.023	19.86
Householder: self-employed business (dummy)	0.190	0.028	6.68
Household: stand-alone building (dummy)	0.025	0.015	1.75
Number of family members [>=25 years old]	0.086	0.013	6.83
Number of workers in the household	0.088	0.009	9.45
Constant	5.189	0.085	61.34
Standard variance	0.454	0.005	98.01
Threshold value 1	log (200)		
Threshold value 2	log (300)		
Threshold value 3	log (400)		
Threshold value 4	log (500)		
Threshold value 5	log (600)		
Threshold value 6	log (700)		
Threshold value 7	log (800)		
Threshold value 8	log (1000)		
Threshold value 9	log (1500)		
Log-likelihood at Zero	-13276.706		
Log-likelihood at Convergence	-11883.870		
McFadden`s Rho-squared	0.105		
Adjusted McFadden`s Rho-squared	0.104		

Note: The income data is investigated in the form of 10 levels in the stated preference survey.

7.3 Model instruction and estimation

The 4th person trip survey data are classified into 9 groups according to the family constitution. There are three types of families which only have one member, young single, childless middle-age single and childless elder single. Since we suppose the consumer is rational, one people would not like to buy two vehicles for him or her in the household. So estimation models for single should be different from other types. Here, the classification of vehicles is confined to the light motor vehicle and the ordinary motor vehicle, and this is unrelated to the family constitution.

7.3.1 Estimated model for households with the single member

In order to examine the ownership of the light motor vehicle for households with the single member, the bivariate binary probit model was used in this study. The ownership of these two types of vehicles is classified into 0 and 1. The ownership of each type of vehicles is measured by one binary probit model, respectively. The error items of these two equations are correlated by ρ. Tian (2013) proposed this model to analyze the vehicle ownership of the light motor vehicle in the Chukyo region in Japan. This study is different from his or her study from two aspects. Firstly, the multiple ownership of the same type vehicle was observed in this study. Secondly, the proposed models will include the household annual income as the explanatory variable. This proposed bivariate binary probit model is illustrated in Figure 7.1.

This bivariate binary probit model is estimated by the maximum likelihood estimation. Since the GAUSS 3.2 has a function to calculate the probability accumulative function conveniently, the parameter estimation of this model is very straightforward.

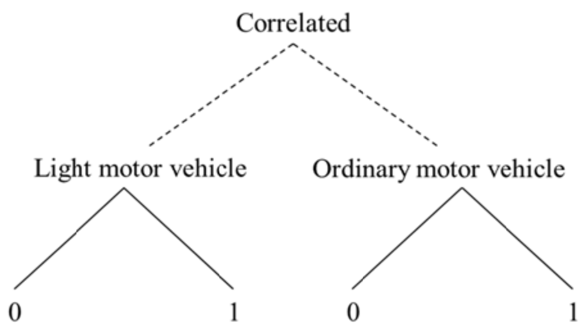

Figure 7.1 Model structure of the proposed bivariate binary probit model

7.3.2 Estimated model for households with multiple members

In order to examine the ownership of the light motor for households with multiple members, the bivariate ordered probit model is used in this study. The ownership of these two types of vehicles is classified into 0, 1 and more than 1. The ownership of each type of vehicles is measured by an ordered probit model, respectively. The relation between ownership of these two types of vehicles is measured by the covariance matrix in the seemingly unrelated regression model. This model structure is same as the model proposed in chapter 6, and the introduction of this model can be found in Section 6.3.1. This proposed bivariate ordered probit model is illustrated in Figure 7.2.

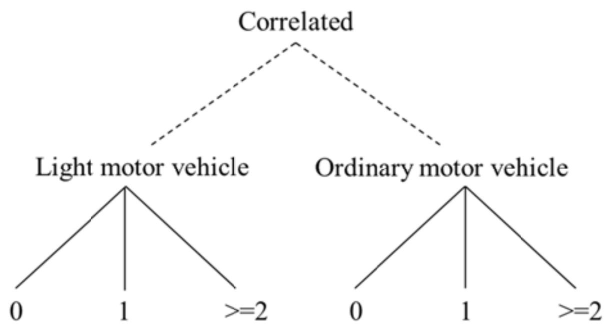

Figure 7.2 Model structure of the proposed bivariate ordered probit model

The Gibbs sampler algorithm is used in this study to estimate the parameters in the model, and the estimation method for this proposed model can be found in section 6.3.2. For the different groups expect for the single family, we can run this estimation program independently and get the estimation results for corresponding different groups.

7.3.3 Explanatory variables for the proposed models in this study

As the explanatory variables in the model, the geological characteristic, the household information, population density, the accessibility to the railway system, and household annual income are included. Since sample data in some groups share the same value of explanatory variables, these variables are not included in the corresponding model. For example, in the youth single group the householders are less than 30 years old, and the age (dummy) should be eliminated from the model used for this group. The instruction of the explanatory variables is listed as follows in Table 7.4. It should be noticed that although the structures of these two proposed models are different, the explanatory variables are same.

Table 7.4 Explanatory variables

Name	Description
Nagoya (dummy)	1 if the household is in Nagoya; 0 otherwise.
Age (dummy)	1 if age of the householder is 60 years older or above; 0 otherwise.
Workers	Number of workers in the household
Member25	Number of family members in the household (>= 25 years old)
Female (dummy)	1 if the householder is female; 0 otherwise.
Annual income (10 million JPY)	The household annual income is calculated based on the ordered probit model in section 5.3.
Log (population density)	The population density is calculated based on the zone level using the person trip survey data.
Density of railway stations	The number of railway stations divides area (unit: km^2) based on the zone level. The area of the zones in this study is coming from the digital map.

Note: Age (dummy) and member25 are only used in the model for sample data in the group 9.

7.4 Results and discussion

The estimated results of the proposed bivariate binary probit model for the households with multiple members are illustrated in Table 7.5, and the results of the proposed bivariate binary probit model for families with one member are shown in Table 7.6, respectively. Since we propose two different models to analyze the light motor vehicle according to family constitution, it is difficult to compare the values of the same parameters in different groups. So we only examine the significance of the estimated parameters in this study.

The estimation result of all of sample data is also shown in Table 7.6, since we want to examine effect of household annual income impacting the vehicle ownership in the household level. It is found that parameters of annual income data in these two equations are insignificant. It indicates that the annual income does not impact the decision of the households to increase or decrease the ownership of these two types of vehicles. Compared to the estimation results without income data shown in Table 7.7, we can find that the parameters do not change obviously, which also indicates that the impact of the annual income data is not significant.

In order to examine ownership of the ordinary motor vehicle and the light motor one considering the heterogeneity of the family constitution, we would like to compare the different effects of the same explanatory variables among different groups.

Table 7.5 Estimation results of households with multiple members

	Group 2	Group 3	Group 4	Group 6	Group 7	Group 9	All
Ownership of the light motor vehicle: Ordered probit model [threshold values: -0.431 and 0.431]							
Nagoya (dummy)	-0.071**	-0.131**	-0.153**	-0.109**	-0.205**	-0.172**	-0.145**
Age (dummy)						-0.094**	-0.179**
Workers	0.041**	0.056**	0.116**	0.096**	0.095**	0.099**	0.091**
Member25						0.101**	0.127**
Female (dummy)	-0.096*	-0.108	-0.102	-0.040*	-0.439	-0.043	-0.011
Log (population density)	-0.142**	-0.143**	-0.230**	-0.159**	-0.132**	-0.171**	-0.150**
Density of rail stations	-0.210**	-0.018	0.032	-0.123	0.232	-0.054	-0.094**
Annual income [10 million JPY]	-0.007	-0.001	-0.030	-0.050	-0.044	-0.002	-0.011
Constant	0.323**	0.428**	0.820**	0.487**	-0.146	0.154	0.021
Ownership of the ordinary motor vehicle: Ordered probit model [threshold values: -0.431 and 0.431]							
Nagoya (dummy)	-0.057**	-0.024	-0.150**	-0.042	-0.066*	-0.059**	-0.057**
Age (dummy)						-0.146**	-0.258**
Workers	0.114**	0.033**	0.139**	0.140**	0.165**	0.147**	0.162**
Member25						0.203**	0.225**
Female (dummy)	-0.070*	0.125	-0.140	-0.148**	-0.406**	-0.174**	-0.205**
Log (population density)	-0.034**	-0.044**	-0.069**	-0.044*	0.038	-0.001	-0.019**
Density of rail stations	-0.128**	-0.111**	-0.366**	-0.277**	-0.443**	-0.424**	-0.301**
Annual income [10 million JPY]	0.031*	0.020	0.052*	0.031	0.082**	0.014	0.005
Constant	0.218**	0.468**	0.886**	0.312*	-0.731**	-0.385**	-0.315**
Estimation results of the Covariance matrix of the seemingly unrelated regression model							
Variance (equation 1)	0.270**	0.218**	0.510**	0.288**	0.385**	0.466**	0.371**
Covariance	-0.106**	-0.111**	-0.200**	-0.142**	-0.090**	-0.133**	-0.114**
Variance (equation 2)	0.188**	0.160**	0.407**	0.251**	0.240**	0.333**	0.240**
Correlated ratio	-0.471	-0.595	-0.439	-0.527	-0.297	-0.337	-0.337
Number of sample	13280	11387	7574	5700	5612	22545	85047

** At the 1% significance level. * At the 5% significance level.

Note: 1) The division of the groups is followed by the definition in Table 7.2.

2) Variance (equation 1) means the variance of the ordered probit model for measuring the ownership of the light motor vehicle.

3) Variance (equation 2) means the variance of the ordered probit model for measuring the ownership of the ordinary motor vehicle.

4) The significance level of the parameter is calculated by the posterior mean and posterior standard deviation.

5) The correlated ratio is calculated by covariance, variance of equation 1 and variance of equation 2.

Table 7.6 Estimation results of households with single member

Single type of families	Group 1	Group 5	Group 8
Ownership of the light motor vehicle: Binary probit model			
Nagoya (dummy)	-0.273*	-0.310**	-0.149
Age (dummy)			
Workers	-0.016	0.128*	0.503**
Member25			
Female (dummy)	0.853**	0.297**	-0.587**
Log (population density)	0.048	-0.108**	-0.072
Density of rail stations	-0.873**	-0.107	-0.495
Annual income [10 million JPY]	0.292	0.182*	-0.053
Constant	-1.961**	-0.577*	-0.800
Ownership of the ordinary motor vehicle: Binary probit model			
Nagoya (dummy)	-0.216**	-0.042	0.023
Age (dummy)			
Workers	0.659**	0.505**	0.677**
Member25			
Female (dummy)	-0.686**	-0.540**	-0.962**
Log (population density)	-0.123**	-0.068*	-0.011
Density of rail stations	-0.245	-0.830**	-0.537**
Annual income [10 million JPY]	0.358**	-0.031	0.020
Constant	0.909**	0.790**	-0.332
Correlated ratio	-0.571**	-0.412**	-0.038
Log-likelihood at Zero	-5585.380	-11938.767	-8744.745
Log-likelihood at Convergence	-3351.679	-8007.648	-3215.610
McFadden’s Rho-squared	0.400	0.329	0.632
Adjusted McFadden’s Rho-squared	0.397	0.328	0.631
Number of cases	4029	8612	6308

** At the 1% significance level. * At the 5% significance level.

Note: The division of the groups is followed by the definition in Table 7.2.

Table 7.7 Model estimation result without annual income data

Explanatory variable	Light motor car		Ordinary motor car	
	Parameter	T-statistic	Parameter	T-statistic
Nagoya (dummy)	-0.145	-11.29	-0.057	-6.75
Age (dummy)	-0.178	-25.02	-0.258	-53.91
Workers	0.090	23.85	0.163	58.91
Member25	0.126	30.12	0.226	73.54
Female (dummy)	-0.010	-1.04	-0.206	-34.64
Log (population density)	-0.149	-22.61	-0.019	-3.94
Density of railway stations	-0.093	-3.15	-0.301	-16.79
Constant	0.016	0.33	-0.313	-8.61
	Parameter		T-statistic	
Variance of the light motor car	0.370		68.70	
Covariance	-0.114		-60.91	
Variance of the ordinary motor car	0.240		120.64	
Number of samples	85047			

Note: This estimation result is the same as the result shown in Table 6.5 in section 6.4.

For the ownership of the light motor vehicle, the parameters of Nagoya (dummy) are significant with a minus sign except for that of childless elder single household. It indicates that unlike other types of households, the childless elder single household living in the Nagoya city is not reluctant to own the light motor vehicle. The parameter of age (dummy) for the big family type is significant with a minus sign. It indicates that in the big family household the household is unlikely to own the light motor vehicle, if the householder is over 60 years old. The parameters of workers are significant with a positive sign expect for that of the young single household. It indicates that the ownership of the light motor vehicle is not affected by the employ status of the householder. The positive parameter of member25 at a 1% significance level for the big family household indicates that with the increase of the members who are equal to or more than 25 years old, the household would like to own the light motor vehicle. The parameters of female (dummy) for young single household and the childless middle-age family are significant with a positive sign. It indicates that the light motor vehicle is popular for them, since the compact design is just suitable for the family size. The parameters of female (dummy) for the childless couple, middle-age single with children, and the childless elder single family are significant with a minus sign. It indicates that if the householder is a female, the household would not like to own the light motor vehicle. The parameters of population density are significant with a minus sign expect for that of the young single and childless elder single household. It indicates that most of households living in the high population density area are reluctant to own the light motor vehicle. The accessibility to the railway system is only significant for the young single and childless couple household with a minus sign. It indicates that the ownership of light motor vehicle is impacted by the density of the railway stations significantly, and with the increase of the station density, they are unlike to own the light motor vehicle. The positive parameter of the annual income for the childless middle-age single household at a 5% significance level indicates that the household with a high income would like to own the light motor vehicle, since it is convenient and suitable for them to use. The minus parameters of constant for the young single and childless middle-age single household are significant. It indicates that these two types of families are reluctant to own the light motor vehicles in general. The childless couple, couple with young children, couple with adult children and middle-age single with children are likely to own the light motor vehicle, since the parameters of constant for them are positive significantly.

For the ownership of the ordinary motor vehicle, the parameters of Nagoya (dummy) are significant with a minus sigh for young single, couple with no children, couple with adult children, and childless elder couple. It indicates that these kinds of household living in the Nagoya city are reluctant to own ordinary vehicles. The parameter of age (dummy) is significant with a minus sign for the big family type. It indicated that the household would not like to own the ordinary motor vehicle, if the householder is equal to or more than 65 years old. The parameters of workers for all family types are significant with a positive sign. It indicates that the number of worker in the household might decide the demand of the vehicle usage. The parameter of member25 for big family type is significant with a positive sign. It indicates that with increase of the members who are equal to or more than 25 years old, the probability owning the ordinary motor vehicle for the big family type is increased. The parameters of female (dummy) are significant with a minus sign expect for the couple with young children and couple with adult children. It indicates that most types of the households are unwilling to own the ordinary motor vehicle, if the householders are female. The parameters of population density are significant with a minus sign expect for the childless elder couple, childless elder single, and the big family type. It indicates that the population density cannot affect the ownership of ordinary vehicles in other groups. The parameters of density of railway stations are significant with a minus sigh expect for the young single household. It indicates that the accessibility to the railway system can affect the ownership of the ordinary vehicle for most of family types. The parameters of annual income are significant with a positive sign for young single, childless couple, couple with adult children, and childless elder couple. It indicates that the income level is affecting the ownership of the ordinary motor vehicle in these types of households. The parameters of constant are significant with a positive sign except for the childless elder couple, childless elder single, and big family type. Meanwhile, the parameters of constant are significant with a minus sign for the childless elder couple and big family type.

Referring to the explanation of the estimation results illustrated above, the ownership of the light motor vehicle is found to be not identical in different groups. It might show that the heterogeneity of family constitution affects the ownership of the light motor vehicle significantly. Observing the ownership of the light motor vehicle and that of ordinary motor vehicle inside one group or among different groups, we can find many interesting findings listed as follows.

1) For the young single and childless middle-age single household the female householder would like to own the light motor vehicle, rather than the ordinary motor one.

2) For the childless elder couple household the household are only unwilling to own the ordinary motor vehicle.

3) The ownership of the light motor vehicle only in childless middle-age single household is affected by the annual income significantly. Meanwhile, this factor can impact the ownership of the ordinary motor vehicle in other groups, such as the young single, childless young couple and so on.

4) The population density can affect the ownership of the light motor vehicle and that of the ordinary motor one for 6 types of the family constitution at the same time.

5) The accessibility to the railway system impacts the ownership of the ordinary motor vehicle much more significantly than that of the light motor one. It indicates that the extended structure of the railway network can control the increased number of ordinary motor vehicle effectively.

6) For the childless elderly single household the substitution effect between the ownership of the light motor vehicle and that of the ordinary motor vehicle is not existed, since the correlation ratio is not at a 5% significance level.

7.5 Summary

This study analyzed the ownership of the light motor vehicle considering the heterogeneity of family constitution. The vehicle type was classified into the light motor vehicle and the ordinary motor one. The 4th person trip survey data in the Chukyo region in Japan was used as the research sample. We divided 85047 sample data into 9 groups according to the family type. The classification of the household is based on the number of family members, the couple relation, the age of the householder, and the number and age of children. The bivariate binary probit was utilized to analyze the ownership of the light motor vehicle in the households with only one member. Meanwhile, the bivariate ordered probit model was utilized to examine the ownership of the light motor vehicle in the families with multiple members. The bivariate binary probit model is estimated by the maximum likelihood estimation, and the bivariate ordered probit model was estimated by the Gibbs sampler algorithm, respectively. The annual income data was complemented and included in the model based on an ordered probit model.

It was shown that the ownership of the light motor vehicle was impacted by the family constitution significantly. The parameters in the different groups were not identical or with the same sign. The ownership of the light motor vehicle in many family types was affected by the district, number of workers, and population density. The female young single and childless middle-age female single were willing to own the light motor vehicle rather than the ordinary motor vehicle. The annual income only affected the ownership of the light motor vehicle in the childless middle-age single household. The accessibility to railway system only affected the ownership of the light motor vehicle in the young single and childless couple household. The annual income and accessibility to the railway system impacted the ownership of ordinary motor vehicle significantly for many family types. It was also found that the substitution effect between the ownership of the light motor vehicle and the ordinary motor one was not existed in the childless elder single household.

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Chapter 8

Conclusions and Future Tasks

8.1 Conclusions

With the development of the motorization society, the private vehicles are very popular and convenient for people`s life. While, the rapidly increased number of private vehicles leads to environmental burden due to the external diseconomy. In order to solve this problem, Japanese Cabinet Meeting (2008) has begun to promote the sales of next-generation vehicles. Meanwhile, the tax-exemption policies were also proposed to subsidy consumers purchasing and using next-generation vehicles (Japanese Ministry of Land, Infrastructure, Transportation and Tourism, 2013).

As one kind of next-generation vehicles, the electric vehicle is treated as the most competitive vehicle in the market. It may result from three facts as follows. Firstly, the vehicle price is relatively cheap compared to the plug-in hybrid vehicles. Secondly, fueling electrical vehicles seems to be very convenient, since the charging facilities can be deployed near to home and in the public places. Thirdly, vehicle range of the electric vehicle is extended to more than 200 km, and it might satisfy the daily mileage of drivers living in the Chukyo region in Japan, where the railway system is sufficient enough.

Meanwhile, the light motor vehicle is one kind of traditional vehicles in the market. For its cheap price, low displacement, and excellent fuel consumption, the light motor vehicle has been penetrating in the market. The light motor vehicle is an excellent competitor for the electric vehicle. So it is necessary to observe the ownership of the light motor vehicle, and examine the variation of vehicle holding behavior in history.

This thesis analyzed the ownership and usage of eco-friendly vehicles including the electric vehicle and the light motor vehicle. These two kinds of vehicles are more competitive than other vehicle types. The conclusions of this thesis are listed as follows.

Chapter 3 examines the preference of electric vehicles purchasing behavior and gives insight into factors which have significant effects on promoting electric vehicles. The factors include attributes of the electric vehicle, current vehicle usage, characteristics of the household and the installation rates of charging facilities in public places. Here, the purchasing behavior is classified into Addition, Exchange and Constant. Moreover, the vehicle choice behavior for Exchange is also observed. 5766 stated preference data were collected through the Internet questionnaires in the Chukyo region in Japan. A 3-level nested logit model is applied to properly represent the purchasing behavior. According to the structure and estimation results of the model, main conclusion in this chapter contains three parts as follows. Firstly, it is found that the factors including price of the electric vehicle, installation rate of charging facilities at the gas station, charging vehicles near home, annual income of the household, owning the hybrid vehicle, the number of drivers in one household and no occupation may play important roles on purchasing behavior involving Addition and Exchange. Secondly, capacity and vehicle range of the electric vehicle are key factors on Addition and Exchange, and had nearly the same marginal utility for Addition and Exchange. While, charging time is a key factor only on Exchange. Thirdly, displacement, vehicle age and vehicle capacity are important factors of choosing the vehicle in use when the respondent decides to treat the electric vehicle as Exchange.

Chapter 4 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.

Chapter 5 forecasts the demand of electric vehicles ownership and usage in the Chukyo region in Japan. A discrete-continuous model called the Bayesian multivariate tobit, ordered and binary probit model is applied here. The 4th person trip survey data (2001) in this region are used as the sample. The household annual income is estimated using an ordered probit model. The result shows that average ownership and monthly mileage of electric vehicles are 0.324 and 259.36 km per household, respectively. Meanwhile, it shows that the average ownership and monthly mileage of electric vehicles in suburban areas are more than that in urban areas.

Chapter 6 examines the variation of the household vehicles owning behavior in the Chukyo region in Japan. The vehicle type is classified into the light motor car and the ordinary motor one. Meanwhile, the impact of the ownership of trucks is not taken into consideration. The person trip survey data in 1971 and 2001 are used as the sample. A bivariate ordered probit model is proposed for analyzing the ownership of two types of private cars. Since the maximal likelihood estimation method was found to be low efficient, the Gibbs sampler algorithm is implemented in this study. The conclusions of this study are listed as follows. Firstly, age of the householder, numbers of workers and number of members (>= 25 years old) were significant factors with same effects both in 1971 and 2001. Secondly, gender of the householder, district, population density and density of railway stations changed their effects from 1971 to 2001. The households with female householder were unwilling to own the light motor car only in 1971.The residents living in Nagoya would not like to own the ordinary motor car in 2001. Population density and density of railway stations affected ownership of the light motor car only in 2001. Lastly, there was a substitution effect on ownership between the light motor car and the ordinary motor one only in 2001.

Chapter 7 analyzes the ownership of the light motor vehicle considering the heterogeneity of family constitution. The 4th person trip survey data in the Chukyo region in Japan is used as the research sample. In order to observe the heterogeneity of family constitution, we divide 85047 sample data into 9 groups according to the family type. The bivariate binary probit is utilized to analyze the ownership of the light motor vehicle in the households with only one member. Meanwhile, the bivariate ordered probit model is utilized to examine the ownership of the light motor vehicle in the families with multiple members. The bivariate binary probit model is estimated by the maximum likelihood estimation. Meanwhile, the bivariate ordered probit model is estimated by the Gibbs sampler algorithm. The annual income data is also complemented and included in the model. It is shown that the ownership of the light motor vehicle is impacted by family constitution significantly. The parameters in the different groups are not identical. The ownership of the light motor vehicle in many family types is affected by the district, number of workers, and population density. The female young single and childless middle-age female single are willing to own the light motor vehicle rather than the ordinary motor vehicle. The annual income only affects the ownership of the light motor vehicle in the childless middle-age single household. The accessibility to railway system only affects the ownership of the light motor vehicle in the young single and childless young couple household. The annual income and accessibility to the railway system impact the ownership of ordinary motor vehicle significantly for many family types. It is also found that the substitution effect between the ownership of the light motor vehicle and the ordinary motor one is not existed in the childless elder single household.

8.2 Future tasks

This thesis only investigates the ownership and usage of electric vehicles and the ownership of the light motor vehicle, respectively. Based on the estimation results, there are some future tasks listed as follows.

Firstly, the ownership of the electric vehicle and that of the light motor vehicle are observed, respectively. The competition of these two kinds of environmental friendly vehicles cannot be measured in this study. If the household have already owned one light motor vehicle, it might be impossible for him or her to add one electric vehicle, since the light motor vehicle is economical for its excellent fuel consumption. So the ownership of the light motor vehicle can impact the penetration of the electric vehicle. Since the stated preference survey data collected in the Chukyo region did not include the information of the light motor vehicle, the extra stated preference survey is necessary.

Secondly, the discrete-continuous choice model is applied to analyze the ownership and usage of the electric vehicle in the household in chapter 4. The impact of the ordinary motor vehicle is taken into consideration. So we neglect impact of the hybrid vehicle to the ownership and usage of electric vehicles. As the next step, the classification of the vehicles is extended to three types including the ordinary motor vehicle, the hybrid one, and the electric one. The modification version of the proposed model in chapter 4 will be applied in next stage.

Thirdly, the demand of the electric vehicle in the Chukyo region was forecasted in the chapter 5. Based on estimation results of the vehicle demand, the deployment of the public charging facilities can be made a further discussion. The p-median location model (Hakimi, 1964; Revelle and Swain, 1970) or the flow-intercepting location model (Berman *et al.*, 1992) can be applied in next step. Compared to the p-median location model, the flow- intercepting location model is based on the traffic assignment of the electric vehicle flow in the road link. So the person trip survey data should also be used in the next step.

Fourthly, we compare the holding behavior of the light motor vehicle in 1971 and 2001 to observe behavior variation from the viewpoint of the time span in chapter 6. Meanwhile, the changed holding behaviors from viewpoint of space span is also deserved to be examined. For example, the ownership of the light motor vehicle in Nagoya city and that in Toyota city seem to be different, since this urban railway transit is much more sufficient in Nagoya city, compared to that in Toyota city. We are very interested in the different holding behaviors between these two cities.

Lastly, we observe the ownership of the light motor vehicle considering the heterogeneity of family constitution in chapter 7. It is shown that the heterogeneity of family constitution impacts the ownership of the light motor vehicle significantly. The heterogeneity is not included in the model structure as one explanatory variable. The method to incorporate the heterogeneity of family constitution is deserved as a future task.

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Curriculum Vitae

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List of Publications

1. Yang, J., Miwa, T., Morikawa, T., Yamamoto, T. (2012) Examining the preference of electric vehicles purchasing behavior using stated preference data. *Journal of International City Planning 2012*, 213-223.

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