

Research Article

Analyzing Household Vehicle Ownership in the Japanese Local City: Case Study in Toyota City

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This study aims to understand the crucial factors affecting vehicle ownership in the local city, Japan. 14,855 household sample data in Toyota City are used as the research sample. The sample data are extracted from the 5th Person Trip Survey data in the Chukyo region. First, the unknown annual income is complemented by using an ordered probit model. Then, a trivariate ordered probit model is utilized to analyze ownership of light motor vehicles, ordinary motor vehicles, and small trucks simultaneously. To estimate unknown parameters effectively and efficiently, one type of Markov Chain Monte Carlo methods called the Gibbs Sampler algorithm is applied in this study. The significant findings suggest the following: (1) the annual income only affects the ownership of ordinary motor vehicles; (2) a household with a 60-year-old or older householder is more likely to own small trucks, compared to that with a householder below the age of 60; (3) the population density negatively affects the number of light motor vehicles and that of small trucks; (4) there is a substitution effect of vehicle ownership between light motor vehicles and small trucks.

1. Introduction

The private car ownership has been increasing dramatically since the second half of the 20th century in developed countries due to the progress of motorization society. The penetration of private cars changes the lifestyle of residents and enlarges their activity areas, especially for those living in the local city where the public transportation system is not sufficient. Meanwhile, it also leads to many externalities to the environment of the metropolis, such as severe air pollution and heavy traffic congestion.

Japan has initiated the motorization society since the 1960s, and the ownership of private and commercial passenger cars increased approximately by 27 times from 2.29 million in 1966 to 61.77 million in 2019 [1]. Different vehicle types were designed and manufactured to supply the various transport demand. Generally, private cars at the household level can be divided into two types, ordinary motor vehicles and light motor ones. Compared to ordinary motor vehicles, the average price of light motor ones is 54.7% lower at 1.45

million JPY [2]. The classification method of household vehicle types used in the 5th Person Trip Survey (2011) in the Chukyo region, Japan, is shown in Table 1. This classification method of private cars is used in the Person Trip Survey in this region in 1971, 2001, and 2011. Meanwhile, the road traffic census data in 1999 and 2005 in Japan were also using this same classification method. Since light motor vehicles have some merits, such as lower price, lower taxation, and smaller size for parking space, compared to ordinary motor vehicles, the ownership of light motor vehicles increased more obviously from the beginning of the 1990s in Japan [3]. Figure 1 shows the number of registered vehicles (including motorbikes) in Japan, the ratio of light motor vehicles, and that of light motor trucks in the last 20 years [4]. It is found that the ratio of light motor vehicles increased dramatically from 3.5% in 1989 to 27.3% in 2018, which indicates the number of light motor vehicles increased more obviously, compared to other types of registered vehicles. Meanwhile, the ratio of light motor trucks decreased gradually from 21.1% in 1989 to 10.4% in 2018, which indicates that light

TABLE 1: Classification method of vehicle types used in the 5th Person Trip Survey.

Classification	Subclassification	Definition
Passenger cars	Light motor vehicles	Length ≤ 3.48 m, width ≤ 1.48 m, height ≤ 2.00 m, displacement ≤ 660 cc, capacity ≤ 4 seats
	Ordinary motor vehicles	Others
Trucks	Small trucks*	(1) Light motor trucks (length ≤ 3.48 m, width ≤ 1.48 m, height ≤ 2.00 m, displacement ≤ 660 cc, cargo capacity ≤ 350 kg) (2) Compact vans
	Ordinary trucks	Others

*Light motor trucks and compact vans are merged into small trucks from the 3rd Person Trip Survey (1991).

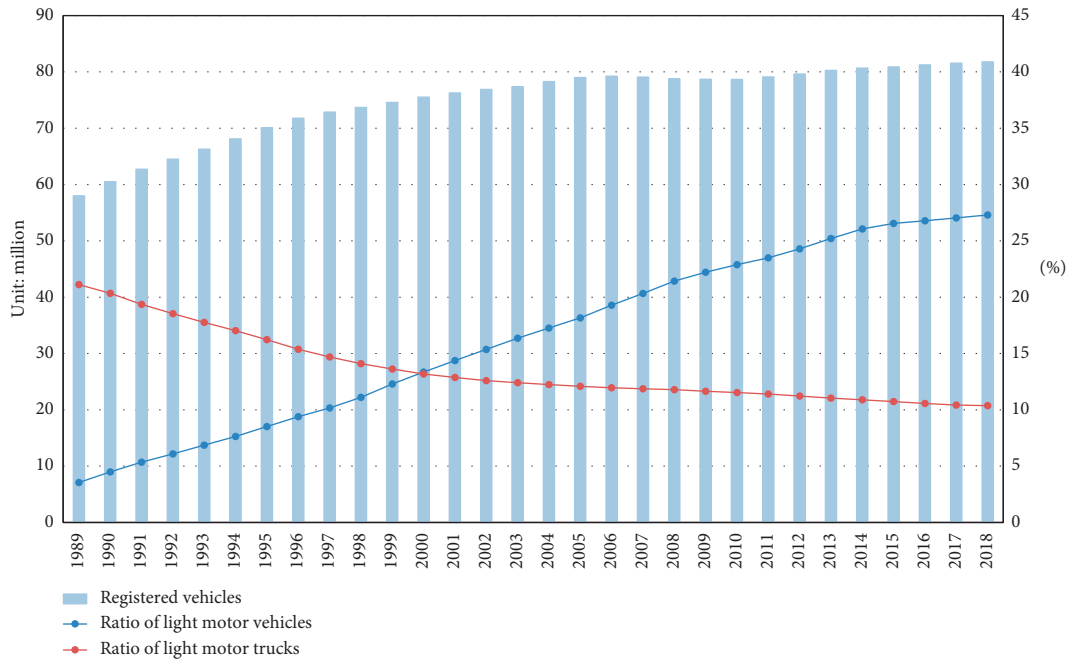


FIGURE 1: Registered vehicles and ratio of light motor vehicles and that of light motor trucks.

motor trucks might be necessary for some occasions, such as farm work and transportation.

To reduce externalities caused by private cars, some plausible measures are implemented, such as more investment for the public transport system and regulations aimed at reducing vehicle ownership and usage. To ensure policy measures effectively, it is essential to understand vehicle ownership and usage at the household level. There are some previous studies related to this topic. As the proposed methodology in previous studies, either the discrete choice or the discrete-continuous choice model was implemented. The discrete choice model utilized a nested logit structure to represent the combination of vehicle types conditional on the fixed vehicle ownership [5, 6]. The discrete-continuous choice model used the discrete component to represent the vehicle ownership and the continuous component to portray the vehicle usage or mileage [7–10].

Since the classification methods of household vehicle types in Japan and other countries are different, previous studies concerning light motor vehicles are rather limited. The study proposed by Kobayashi et al. extended the Bayesian Multivariate Ordered and Probit Model proposed

by Fang to analyze the ownership and usage of the light motor vehicle and the ordinary motor one at the household level [10, 11]. The sample was the data of the nationwide road traffic census in 1999 and 2005 in Japan. That study observed the impact of the population density and the accessibility of the railway system on the vehicle's type and ownership. The population density or residential density was found to be a crucial factor for vehicle ownership and usage in the household [10, 11]. Yang et al. analyzed the difference of ownership between Nagoya and Toyota and found that the density of railway stations affects the ownership of these two types of vehicles in Nagoya [12].

Based on the literature review mentioned above, we found that there are three unclear problems in previous studies in Japan. Firstly, most previous studies in Japan are mainly focusing on the metropolitan area level. Therefore, vehicle ownership in the local city is not clear enough. Secondly, the ownership of small trucks is seldom considered in the model framework, and it might be unreasonable in the local city since many households might work on the farm, and small trucks are helpful for their work. Meanwhile, the ratio of small trucks, including light motor trucks and

compact vans, might be over the average level (10.4%) nationwide in Japan as shown in Figure 1, which should be not be neglected in the vehicle ownership analysis problem. Thirdly, the annual income, a crucial factor affecting vehicle ownership indicated by some previous studies, was seldom set as an explanatory variable in the model, which might result from the fact that annual income data was not investigated in the large-scale Person Trip Survey in Japan.

This study aims to reveal the household preference of owning three different types of vehicles, that is, light motor vehicles, ordinary motor vehicles, and small trucks, in the local city, Japan. We utilize a trivariate ordered probit model to model three types of vehicles at the household level simultaneously. The relationship of ownership among light motor vehicles, ordinary motor ones, and small trucks is measured by the correlation ratio of error items. The Gibbs Sampler algorithm is implemented in this study to estimate the parameters effectively and efficiently. 14,855 household sample data extracted from the Person Trip Survey data in Toyota in 2011 are utilized to estimate the unknown parameters. The discussion of estimation results is carried out to understand factors affecting the ownership of three different types of vehicles, especially that affecting the ownership of small trucks, which was seldom observed in previous studies.

The rest of this paper is organized as follows. Section 2 describes the fundamental statistics of the sample data and the proposed method for complementing the unknown annual household income data. Section 3 describes the trivariate ordered probit model proposed in this study, the explanatory variables, and the Gibbs Sampler algorithm used in this study. The estimation results of this proposed model are shown in Section 4, along with a discussion based on the results. Finally, this study is concluded in Section 5, along with a discussion about future issues.

2. Data

2.1. Introduction of Research Area. Toyota is located in the Chukyo metropolitan area, Japan. By December 2019, Toyota has a population of 425,677, which is the second biggest in the Chukyo metropolitan area following Nagoya. The total area is 918.32 km², which is the largest in the Chukyo metropolitan area. It is located about 35 minutes from Nagoya by Meitetsu-Toyota Line. The head office of Toyota Motor Co., Ltd. is located in Toyota, and many factories belonging to Toyota Motor Co., Ltd. are also located in or near to the city. So the automobile industry is taking a predominant status in Toyota. Meanwhile, approximately 68% of the city region is covered by forests as shown in Figure 2. Therefore, agriculture in Toyota is also famous for its products of rice and fruits such as peaches and pears, which might suggest that small trucks are necessary for farm work or transportation.

The geographic feature of Toyota is that the eastern part of the city is the intermediary area between plains and mountains with a higher altitude compared to the western part. Therefore, Toyota is characterized by a relatively low population density except for urban areas as shown in

Figure 3(a), which indicates that most residents are living in the southwest part of this city. Meanwhile, Toyota does not have a sufficient railway system as shown in Figure 3(b), compared to Nagoya, which might suggest that private cars might be a dispensable transportation alternative to fulfill activities including commuting and shopping for the residents living in the area far from railway stations, especially for the residents living in the eastern part of Toyota.

2.2. Basic Statistics of Sample Data. To understand vehicle ownership at the household level, we use the data from the 5th Person Trip Survey in the Chukyo region, Japan, a cross-sectional survey of about 140 thousand households in this region. The Person Trip Survey in the Chukyo metropolitan area was carried out every ten years from 1971 to 2011, and the data used in this study are selected from the survey data in 2011. 14,855 households in Toyota extracted from the Person Trip Survey data are used as the research sample. The description of the sample data is shown in Figure 4.

76.4% of householders are male, which might indicate that the householder of the family is usually a male (Figure 4(a)). The ratio of 60-year-old or older householders is more than 50%, which might indicate the trend of an aging society in Toyota (Figure 4(b)). The ratio of households having less than four members is 71.0%, which might indicate that the small size of the household takes a predominant status in Toyota (Figure 4(c)). The ratio of householders with a fixed occupation (employed status) is 57.7%, and the ratio of householders without a fixed occupation including children, students, homemakers, and unemployed status is 42.3% (Figure 4(d)).

The ownership of three different vehicle types, light motor vehicles, ordinary motor vehicles, and small trucks, is shown in Figure 5. The categories of three vehicle types are set to be 0, 1, and more than 1 in this study following the classification method in our previous studies [12]. Figure 4 indicates that the number of ordinary motor vehicles is more than that of light motor vehicles and that of small trucks since only 19.3% of households do not own any ordinary motor vehicles. In contrast, the number of small trucks is the smallest among the three types of vehicles, since 91.7% of households do not own any small trucks, which might result from the fact that small trucks might be used for some particular purposes, such as farming or transport working.

Meanwhile, the ownership of ordinary trucks is not considered in this study for two reasons listed as follows. Firstly, subjects of the Person Trip Survey in the Chukyo region are households randomly sampled from the residence record, and companies are not included. Therefore, only 2.4% of households had ordinary trucks at the household, which might indicate the householder is self-employed for transportation work. Secondly, compared to small trucks, ordinary trucks are designed and manufactured mainly for professional transportation works, which might be totally different from the usage of passenger cars, including light motor vehicles and ordinary motor ones. Therefore, we will not consider the impact of the ownership of ordinary trucks at the household in this study.

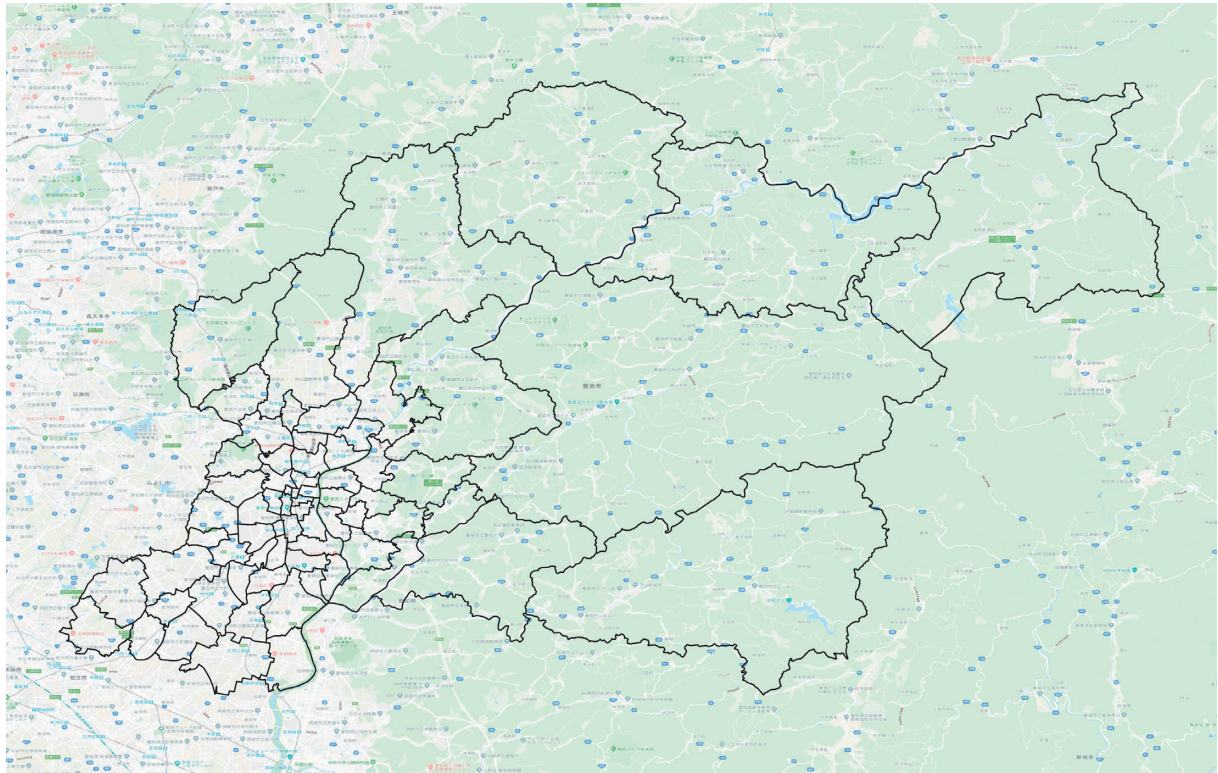


FIGURE 2: Google map of Toyota with the small zone division in the 5th Person Trip Survey.

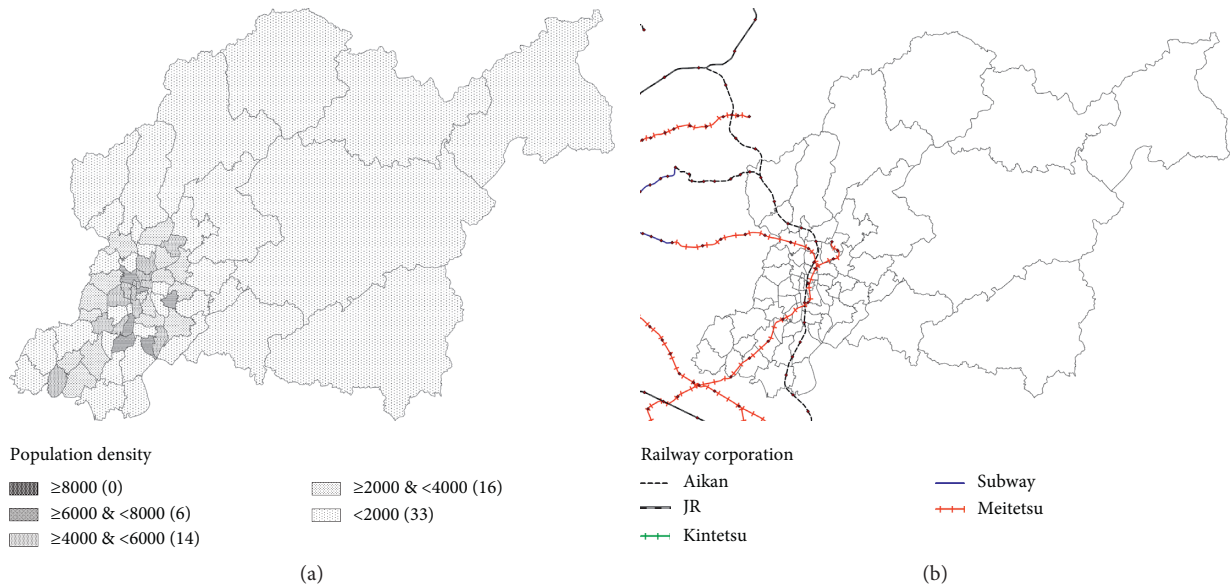


FIGURE 3: Population density and the railway system of Toyota. (a) Population density. (b) The railway system.

2.3. *Complement of the Annual Income Data.* The income data were found to be a significant explanatory variable in the econometric model for modeling vehicle ownership concluded in many previous studies. In order to protect the privacy of the respondent, this item is usually investigated in the form of the group data, and the income level is reported instead of monetary value. Many previous studies

have used the mathematics model to convert such discrete variables into continuous variables. The ordered probit model was utilized to solve this problem [13, 14]. Sometimes these data are, however, unreported because of the respondents' privacy, and the method to solve the unreported income data was proposed in some previous studies [13, 15, 16].

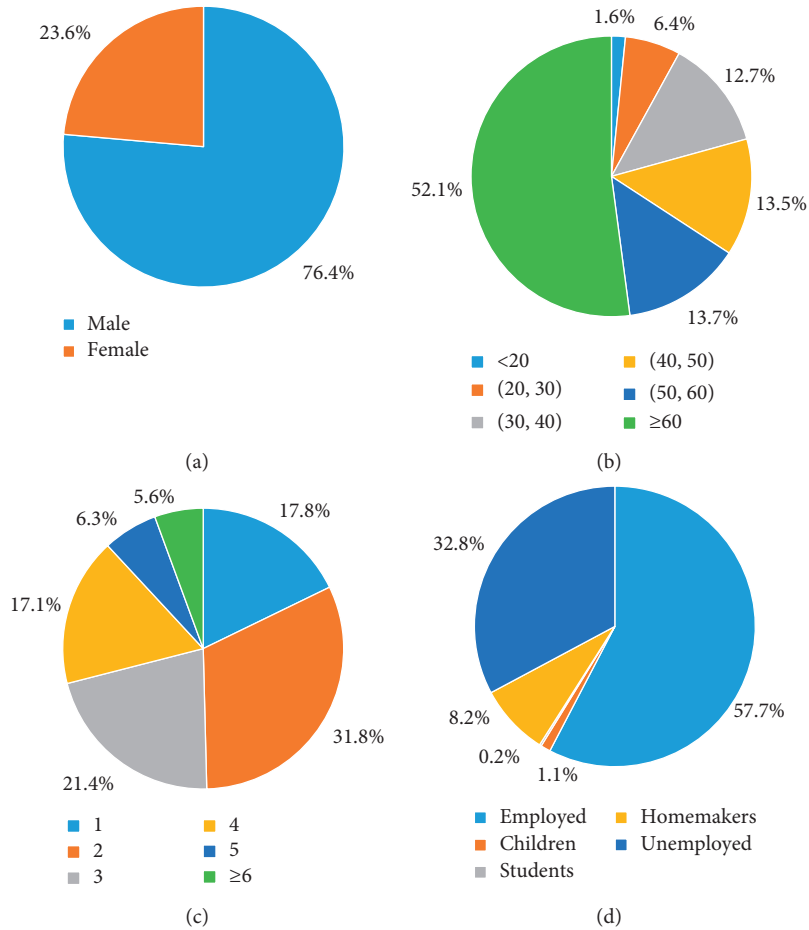


FIGURE 4: Data description of the sample data ($N=14,855$). (a) Gender of the householder. (b) Age category of the householder. (c) Household member. (d) Occupation of the householder.

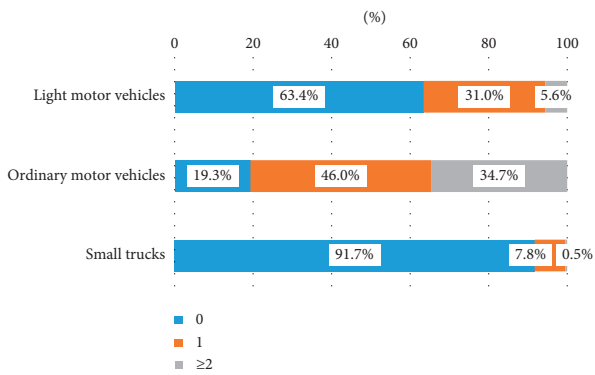


FIGURE 5: The ownership of three vehicle types ($N=14,855$).

The 5th Person Trip Survey data in the Chukyo region did not contain the annual income item, which is different from the missing or unreported income data. It can be treated as an unknown explanatory variable. Yang et al. proposed an ordered probit model to estimate the annual income in the household and applied it to forecast the electric vehicle demand in the Chukyo region [17]. This ordered probit model is used here to complement the annual income data for the sample data in this study. The parameters of this proposed model are illustrated in Table 2.

Nine threshold values in the ordered probit model shown in Table 2 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 to the estimation result for complementing the uninvestigated annual income of one household. The estimation method is illustrated as follows. Combining the explanatory variables in the sample data and the estimated parameters in Table 2, we can complement the uninvestigated annual income data in the 5th Person Trip Survey in this study:

$$A_i = \exp(\alpha^T x_i + U\sigma), \quad (1)$$

where A_i is annual income of the household i (unit: 10 thousand JPY), α is the vector of estimated parameters shown in Table 2, x_i is the vector of related explanatory variables of the household i , U is a random variable sampled from the standard normal distribution, and σ is the standard deviation of error item in the ordered probit model shown in Table 2.

3. Model Specification and Estimation

3.1. Model Specification. Let three latent variables y_{1i}^* , y_{2i}^* , and y_{3i}^* represent the preference of households for owning the light motor vehicle, the ordinary motor one, and the

TABLE 2: Estimation model for complementing annual income.

Explanatory variable	Parameter	Standard deviation	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 deviation of the error item	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	

Threshold values indicate the maximum or minimum value of income categories. The threshold values log (200) and log (300) are used for the annual income category from 200 to 300 (unit: 10 thousand million JPY) [17].

small truck, respectively. The three-equation system for discrete choice of three types of vehicles is represented as follows:

$$\begin{aligned} y_{1i}^* &= x_{1i}^T \beta_1 + \varepsilon_{1i}, \\ y_{2i}^* &= x_{2i}^T \beta_2 + \varepsilon_{2i}, \\ y_{3i}^* &= x_{3i}^T \beta_3 + \varepsilon_{3i}, \end{aligned} \quad (2)$$

where i is indexing the household in the sample ($i = 1, \dots, N$), k is the list number of the equation ($k = 1, 2, 3$), x_{ki} is the vector of explanatory variables in the k th equation for the household i , β_k is the vector of parameters in the k th equation, and ε_{ki} is the error item in the k th equation for the household i .

The whole equation system concerning three latent variables can be written into a seemingly unrelated regression form [18]:

$$y_i^* = x_i \beta + \varepsilon_i, \quad (3)$$

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

$$\varepsilon_i \sim \text{i.i.d. TVN}(0, \Sigma). \quad (4)$$

The relation between latent variables y_{ki}^* ($k = 1, 2, 3$) and observed ones y_{ki} ($k = 1, 2, 3$), that is, vehicle ownership, is illustrated as follows:

$$y_{1i} = \begin{cases} 0, & \text{if } y_{1i}^* \leq \alpha_{11}, \\ 1, & \text{if } \alpha_{11} < y_{1i}^* \leq \alpha_{12}, \\ 2 \text{ or more,} & \text{if } \alpha_{12} < y_{1i}^*, \end{cases} \quad (5)$$

$$y_{2i} = \begin{cases} 0, & \text{if } y_{2i}^* \leq \alpha_{21}, \\ 1, & \text{if } \alpha_{21} < y_{2i}^* \leq \alpha_{22}, \\ 2 \text{ or more,} & \text{if } \alpha_{22} < y_{2i}^*, \end{cases} \quad (6)$$

$$y_{3i} = \begin{cases} 0, & \text{if } y_{3i}^* \leq \alpha_{31}, \\ 1, & \text{if } \alpha_{31} < y_{3i}^* \leq \alpha_{32}, \\ 2 \text{ or more,} & \text{if } \alpha_{32} < y_{3i}^*, \end{cases} \quad (7)$$

where α_{11} and α_{12} are the two threshold values of the ordered probit model used to measure the ownership of light motor vehicles. It was indicated that 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 [19]. In this study, we utilize the same setting method in previous studies [10, 12]. Two threshold values 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 method can be used for setting two threshold values in the equation for measuring the ownership of ordinary motor vehicles denoted by α_{21} and α_{22} and two threshold values in the equation for measuring the ownership of small trucks denoted by α_{31} and α_{32} .

Here, the categories of ownership for three types of vehicles are identical and set as 0, 1, and more than 1 as shown in equations (5)–(7). The reasons for this method are listed as follows. Firstly, we will investigate the impact of annual income data by comparing the estimation results of this study with that in our previous study without income data. So we use the same categories for the ownership of light motor vehicles and ordinary motor ones [12]. Secondly, we compare the standard deviation of the error item of the equation for small trucks with that of light motor vehicles and that of ordinary motor ones to know the difference in the distribution of error items for three different vehicle types.

3.2. Model Estimation. Since the sample share of households owning more than one small truck is very small at only 0.5%, the maximum likelihood estimator might have low efficiency. To estimate the unknown parameters effectively and efficiently, the Gibbs Sampler algorithm is implemented in this study [20, 21]. As one type of the Markov Chain Monte Carlo methods, it can be used to estimate the unknown parameters, when the maximum likelihood estimator does not perform efficiently, due to the small ratio of some sample share. This algorithm can estimate the unknown parameters of the multivariate ordered probit model efficiently, which was applied in our previous study [12].

The Gibbs Sampler algorithm is implemented by drawing random numerical value or vector from the conditional distribution for the latent variable y_i^* , the unknown parameter β , and Σ . Each iteration of the Gibbs Sampler is conducted by order of y_i^* , β , and Σ listed as follows:

$$\begin{aligned} & \text{draw } y_i^* \mid \beta, \Sigma, y_i \text{ from } \pi\left(y_i^* \mid \beta^{(t-1)}, \Sigma^{(t-1)}, y_i\right) \\ & \text{draw } \beta \mid \Sigma, y_i^* \text{ from } \pi\left(\beta \mid \Sigma^{(t-1)}, y_i^*\right) \\ & \text{draw } \Sigma \mid y_i^*, \beta \text{ from } \pi(\Sigma \mid y_i^*, \beta) \end{aligned} \quad (8)$$

where π is the conditional posterior distribution and t is the order of the iteration in the Gibbs Sampler algorithm.

Here, y_{ki} ($k = 1, 2, 3$) is informative about y_{ki}^* ($k = 1, 2, 3$) which follows a normal distribution in this proposed model, which indicates that conditional on β , Σ , and y_i^* , y_{ki}^* ($k = 1, 2, 3$) has a truncated normal distribution shown in equations (9)–(11). Here, $I(\text{statement})$ takes the value of 1

when the *statement* in brackets is true and 0 when the statement is false:

$$y_{1i}^* \mid y_{1i}, y_{2i}^*, y_{3i}^*, \beta, \Sigma \sim N(\mu_{1|1}, \sigma_{1|1}^2) I(\alpha_{y_{1i}} < y_{1i}^* \leq \alpha_{y_{1i+1}}), \quad (9)$$

$$y_{2i}^* \mid y_{2i}, y_{3i}^*, y_{1i}^*, \beta, \Sigma \sim N(\mu_{2|2}, \sigma_{2|2}^2) I(\alpha_{y_{2i}} < y_{2i}^* \leq \alpha_{y_{2i+1}}), \quad (10)$$

$$y_{3i}^* \mid y_{3i}, y_{1i}^*, y_{2i}^*, \beta, \Sigma \sim N(\mu_{3|3}, \sigma_{3|3}^2) I(\alpha_{y_{3i}} < y_{3i}^* \leq \alpha_{y_{3i+1}}), \quad (11)$$

where μ_{jlj} is the mean of equation j fully conditional on other equations and σ_{jlj} is the standard deviation of equation j fully conditional on other equations.

In this study, the prior distribution of β is supposed to be normal or noninformative as a multivariate normal distribution with the mean β_0 and covariance matrix V_0 ; the conditional posterior distribution of β is illustrated in the following equations:

$$\bar{\beta} = \bar{V} \left(V_0^{-1} \beta_0 + \sum_{i=1}^N x_i^T \sum_{j=1}^{-1} y_i^* \right), \quad (12)$$

$$\bar{V} = \left(V_0^{-1} + \sum_{i=1}^N x_i^T \sum_{j=1}^{-1} x_i \right)^{-1}, \quad (13)$$

$$\beta \mid y_i^*, \Sigma \sim \text{MVN}(\bar{\beta}, \bar{V}), \quad (14)$$

where N is the number of households in the sample. The prior distribution of Σ is supposed to be an Inverse-Wishart distribution with the freedom ν and the scale matrix Ψ ; the conditional posterior distribution of Σ can be derived as follows:

$$\Sigma \mid y_i^*, \beta \sim W^{-1} \left(\nu + N, \sum_{i=1}^N (y_i^* - x_i \beta) (y_i^* - x_i \beta)^T + \Psi \right). \quad (15)$$

The procedure of the Gibbs Sampler algorithm for this proposed model is listed as follows:

- (1) Set the initial values of parameters in the Gibbs Sampler algorithm shown in Table 3.
- (2) Sample latent variables y_{ki}^* ($k = 1, 2, 3$) in the order shown in equations (9)–(11), in which a truncated multivariate normal distribution is implemented through drawing from a series of the full conditional distribution of each element of y_i^* given other variables [21].
- (3) Sample parameters vector β from multivariate normal distribution shown in equations (12)–(14) using the proposed method by Greene [22].
- (4) Sample covariance matrix Σ from Inverse-Wishart distribution shown in equation (15), where the Inverse-Wishart distribution is generated by the Bartlett decomposition [23].

TABLE 3: Setting values of parameters in the proposed Gibbs Sampler algorithm.

Name	Type	Values
$\beta^{(0)}$	Initial item	One column vector of zeros
$\Sigma^{(0)}$	Initial item	One identity matrix
β_0	Fixed item	One column vector of zeros
V_0	Fixed item	One diagonal matrix with 100 on the diagonal
ν	Fixed item	10
Ψ	Fixed item	One identity matrix

The iteration cycles between steps 2 and 4, and it is repeated several thousand times, discarding the burn-in draws. The Gibbs Sampler algorithm implemented in this study takes 11000 times of the iterations and burns the first 1000 times. The remaining 10000 draws are used to estimate the parameters of posterior inference. Here, the convergence of the posterior mean for each unknown parameter of this proposed model is confirmed by the Bayesian output analysis (BOA) program. Meanwhile, we applied three independent ordered probit models for three vehicle types, respectively, and compared estimation results of three independent ordered probit models with estimation results in this study. It was found that the estimation results between these two methods are nearly identical for the estimated value for each unknown parameter.

3.3. Explanatory Variables. Table 4 shows the household-specific variables and neighborhood variables used in this proposed model. The household-specific variables are derived from the individual attributes for each household in the 5th Person Trip Survey data. The neighborhood variables are calculated by the unit of the small zone. Therefore, explanatory variables related to the household information and the geographical characteristic are included in the proposed model. The mean of each explanatory variable is reported in Table 4. It should be noticed that we set explanatory variables for each vehicle type referring results of data aggregation analysis for three vehicle types and our previous research work related to this study [12].

4. Results and Discussion

The estimation result of the proposed trivariate ordered probit model is shown in Table 5, and all the parameters applied to the number of light motor vehicles, that of ordinary motor vehicles, and that of small trucks are with the expected sign. Here, the parameters significant with a 95% Bayesian credible interval (95% BCI) are discussed in this study.

The Bayesian credible level of these parameters is identical to our previous study, in which annual income data and ownership of small trucks were not considered in this modeling framework [12]. In this study, it is found that the negative parameter of annual income for the number of light motor vehicles is not at a 95% Bayesian credible interval, which indicates that annual income might not affect the number of light motor vehicles. This might result from the

fact that the price of light motor vehicles is lower compared to ordinary motor vehicles, and households with high or low income can afford to own it. In contrast, the positive parameter of annual income for the number of ordinary motor vehicles at a 95% Bayesian credible interval indicates that the annual income might positively affect the number of ordinary motor vehicles. It might result from the fact that, with the increase of annual income, households are more likely to own ordinary motor vehicles.

In this study, we give insights into factors affecting the number of small trucks, which is seldom observed in most previous studies. The positive parameter of Age 60 at a 95% Bayesian credible interval indicates that households with the 60-year-old or older householder are willing to own small trucks, compared to those with the householder below 60 years of age. In contrast, the household with the householder below 60 years of age is willing to own either light motor vehicles or ordinary motor vehicles indicated in Table 5. The positive parameter of workers at a 95% Bayesian credible interval indicates that an increased number of members with a fixed occupation, that is, employed status (excluding children, students, homemakers, and unemployed status), will lead to the increasing number of small trucks as we expected. The positive parameter of farmer at a 95% Bayesian credible interval indicates that the household is more likely to own small trucks when the householder is farmer, compared to other occupations. It might result from the fact that small trucks are very convenient for farming or transport working. The negative parameter of the logarithm of the population density at a 95% Bayesian credible interval indicates that households living in the lower population density region, such as the eastern part of Toyota, are willing to own small trucks since small trucks might help them to do farm work. The sex of the householder, the number of 25-year-old or older members, and annual income are not affecting the ownership of small trucks indicated in this estimation result.

The matrix of the error covariance is shown in Table 6. The standard deviation of the error of the number of light motor vehicles is larger than that of ordinary motor vehicles and that of small trucks, which indicates that the ownership of light motor vehicles is a little difficult to be estimated. Meanwhile, the covariance between light motor vehicles and ordinary motor vehicles and that between light motor vehicles and small trucks are at a 95% Bayesian credible interval, indicating that there are substitution effects between these two combinations of two types of vehicles. The substitution effect between light motor vehicles and ordinary motor vehicles can be explained by the fact that these two types of vehicles nearly have the same function as a passenger car. In addition, the substitution effect between light motor vehicles and small trucks can be explained by the fact that they are having some similar characteristics, such as low price and taxation and small size for parking. However, the correlation ratio of the former is larger than the latter, which indicates that the substitution effect between light motor vehicles and small trucks is not as strong as that between light motor vehicles and ordinary motor ones.

TABLE 4: Explanatory variables.

Name	Description	Mean
Age (dummy)	1 if the age of the householder is 60 years or older; 0 otherwise	0.521
Female (dummy)	1 if the sex of the householder is female; 0 otherwise	0.236
Workers	Number of family members in the employed status	2.286
Member 25	Number of 25-year-old or older family members	1.877
Farmer (dummy)	1 if the occupation of the householder is a farmer; 0 otherwise	0.027
Log (population density)	The population density is calculated based on the small zone used in the 5th Person Trip Survey data shown in Figure 3(a)	7.505
The density of railway stations	The number of railway stations shown in Figure 3(b) divides area (unit: km ²) based on the small zone used in the 5th Person Trip Survey. The area of the small zone is extracted from the GIS polygon map	0.147
Annual income (10 million JPY)	The annual household income is complemented based on the ordered probit model shown in Table 2	0.566

TABLE 5: Estimation result of the proposed model ($N = 14,855$).

Explanatory variable	Posterior mean	Posterior standard deviation	95% BCI
<i>Number of light motor vehicles (0, 1, or ≥ 2) [threshold values: -0.431 and 0.431]: ordered probit model</i>			
Age 60 (dummy)	<i>-0.085</i>	<i>0.015</i>	<i>(-0.11, -0.06)</i>
Female (dummy)	<i>0.109</i>	<i>0.017</i>	<i>(0.08, 0.14)</i>
Member 25	<i>0.111</i>	<i>0.009</i>	<i>(0.09, 0.13)</i>
Workers	<i>0.052</i>	<i>0.013</i>	<i>(0.03, 0.08)</i>
Log (population density)	<i>-0.061</i>	<i>0.005</i>	<i>(-0.07, -0.05)</i>
Density of railway stations	-0.039	0.024	(-0.09, 0.01)
Annual income (10 million JPY)	-0.026	0.021	(-0.07, 0.02)
Constant	<i>-0.517</i>	<i>0.044</i>	<i>(-0.60, -0.43)</i>
<i>Number of ordinary motor vehicles (0, 1, or ≥ 2) [threshold values: -0.431 and 0.431]: ordered probit model</i>			
Age 60 (dummy)	<i>-0.242</i>	<i>0.013</i>	<i>(-0.27, -0.22)</i>
Female (dummy)	<i>-0.060</i>	<i>0.015</i>	<i>(-0.09, -0.03)</i>
Member 25	<i>0.089</i>	<i>0.009</i>	<i>(0.07, 0.11)</i>
Workers	<i>0.189</i>	<i>0.012</i>	<i>(0.17, 0.21)</i>
Log (population density)	0.006	0.005	(0.00, 0.02)
Density of railway stations	-0.016	0.020	(-0.06, 0.02)
Annual income (10 million JPY)	<i>0.060</i>	<i>0.019</i>	<i>(0.02, 0.10)</i>
Constant	<i>-0.327</i>	<i>0.040</i>	<i>(-0.41, -0.25)</i>
<i>Number of small trucks (0, 1, or ≥ 2) [threshold values: -0.431 and 0.431]: ordered probit model</i>			
Age 60 (dummy)	<i>0.251</i>	<i>0.023</i>	<i>(0.21, 0.30)</i>
Female (dummy)	-0.040	0.027	(-0.09, 0.01)
Member 25	-0.026	0.014	(-0.05, 0.00)
Workers	<i>0.137</i>	<i>0.019</i>	<i>(0.10, 0.18)</i>
Farmer (dummy)	<i>0.610</i>	<i>0.039</i>	<i>(0.53, 0.69)</i>
Log (population density)	<i>-0.119</i>	<i>0.007</i>	<i>(-0.13, -0.11)</i>
Annual income (10 million JPY)	0.035	0.027	(-0.02, 0.09)
Constant	-0.817	0.055	(-0.92, -0.71)

Contents in bold and italic indicate that variables are significant with a 95% Bayesian credible interval.

TABLE 6: Matrix of the error covariance.

	Number of light motor vehicles	Number of ordinary motor vehicles	Number of small trucks
Number of light motor vehicles	<i>0.435 (0.660)</i>		
Number of ordinary motor vehicles	<i>-0.126</i>	<i>0.385 (0.620)</i>	
Number of small trucks	<i>-0.027</i>	0.005	<i>0.333 (0.577)</i>

Contents in bold and italic indicate that these variables are significant with a 95% Bayesian credible interval. The posterior standard deviation of three equations is reported in parentheses.

5. Conclusions and Future Tasks

This study analyzes the vehicle ownership and type in the local city, Japan. Large-scale Person Trip Survey data for Toyota are used for empirical analysis. The vehicle type is

classified into light motor vehicles, ordinary motor vehicles, and small trucks. One ordered probit model proposed by our previous study is applied to complement unknown annual income [12]. One trivariate ordered probit model is used to model ownership of three types of vehicles in one unified

framework simultaneously. The Gibbs Sampler algorithm is implemented to estimate the unknown parameters instead of the maximum likelihood estimator. Based on the estimation result, we can give insights into key factors affecting ownership of three different types of vehicles.

Some interesting findings are listed as follows. First, the annual income only affects the ownership of ordinary motor vehicles, since light motor vehicles and small trucks are cheap and affordable for the ordinary household. Second, compared to that with the householder below the age of 60 years, households with the 60-year-old or older householder are more likely to own small trucks, since the 60-year-old householder might work as an unprofessional farmer after retirement from the working corporation. Third, the population density negatively affects the ownership of the light motor vehicle and that of small trucks. This might result from the fact that light motor vehicles might be owned for saving running and maintaining costs, and small trucks might be used for farm or transport work in the low population density area such as the eastern part of Toyota. Lastly, there is a substitution effect of vehicle ownership between light motor vehicles and small trucks since they are having similar characteristics, such as low price, low taxation, and small size.

There is one research issue remaining as a future task. In this study, we do not consider the household structure as a factor impacting the ownership of three vehicle types [24]. For instance, compared to the household with many members, the single young household would like to own light motor vehicles with small size and relatively low price, which indicates the unobserved heterogeneity of the household structure in the vehicle ownership analysis problem. Since this factor was reported as a crucial factor impacting vehicle ownership and type, the empirical study to incorporate this factor into an analysis of vehicle ownership and type would be a further direction.

Data Availability

The Person Trip Survey data used in this study are provided by the Ministry of Land, Infrastructure, Transport, and Tourism, Japan.

Disclosure

An earlier version of this study has been presented at the inaugural World Transport Convention 2018 in Beijing, China. Some research contents are based on the previous study implemented by the first author during the Doctor Course in NUTREND (Nagoya University TRansport and ENvironment Dynamics) under the supervision of Associated Professor Tomio Miwa and Professor Takayuki Morikawa.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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