Development of Multivariate Ordered Probit Model to Understand Household Vehicle Ownership Behavior in Xiaoshan District of Hangzhou, China

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Abstract: With the rapid increase of motorization in China, transitions have taken place in regards to traditional private transportation modes. This paper aims to understand four types of vehicle ownership within a household, including automobile, motorcycle, electric bicycle and human-powered bicycle. This study presents a cross-sectional multivariate ordered probit model, with a composite marginal likelihood estimation approach that accommodates the effects of explanatory variables, and capturing the dependence among the propensity to household vehicle ownership. The sample data are obtained from the residents’ household travel survey of Xiaoshan District, Hangzhou, in 2015, which can analyze the significant effects of sociodemographic attributes and built environment attributes. Interestingly, the major findings suggest that: (1) The households with higher income tend to own more automobiles, yet the effect is not obvious with a small value of elasticity, which is similar to developed countries. (2) The household education level, which takes a positive effect on automobile ownership, is a more elastic factor than income. (3) The higher population density contributes to less ownership of automobiles and motorcycles, due to traffic congestions and parking challenges. (4) There is a large substitutive relation between automobile and electric bicycle/motorcycle, and the vehicle ownership of electric bicycle/motorcycle and bicycle are mutually promoted, while motorcycle and electric-bicycle are mutually substituted.

Keywords: household vehicle ownership; vehicle type; multivariate ordered probit model; composite marginal likelihood

1. Introduction

Since 2006, there has been an increasing demand for automobiles in China, with the private vehicle stock increasing from 43.39 million to 108.50 million [1]. The vehicle market of China has stood as the largest vehicle sales market worldwide since 2009 [2]. However, the automobile ownership in China now is approximately 100 automobiles per 1000 people, which is a figure much lower than developed countries [3], and it is estimated that the automobile ownership will continue to grow in China, reaching 500 per 1000 people by 2050 [4].

Accordingly, the environmental issue has drawn growing concern along with the rapid development of transport industry all over the world. Nowadays, the energy consumption and greenhouse gas emissions from the transport sector account for about one third, and one quarter, respectively [5]. The increased levels of motorization have partly contributed to many externalities to the environment, including air pollution and traffic congestion, which are not conducive to sustainable development. To alleviate the above problems, some measures are implemented for reducing motor
vehicle ownership and usage, and others are aimed at investment in the public transport and road infrastructure. Meanwhile, vehicle ownership-related topics have been extensively explored in the literature, especially in the aspects of vehicle ownership, vehicle type choice and vehicle usage [6].

In recent years, the transitions have taken place in traditional private transportation mode in China. Firstly, the city’s motorization level was improved, which means that households transition from relatively smaller or non-motorized vehicle (e.g., bicycle or electric bicycle) to heavier motorized vehicle (e.g., automobile) [7]. Secondly, the electric bicycle and automobile have been suitable substitutes for motorcycles, possibly due to the heavy motorcycle restrictions in more than 200 cities in China [8]; and the electric bicycle market has been larger than that of motorcycle since 2005 [9]. Therefore, the needs to study the transitions of private transport modes is urgent. It is necessary to analyze the factors that affect the private vehicle ownership of various types based on China’s conditions. Also, it is of great practical significance to study the relationships among different types of vehicles (mutually substitutive or promotive).

For the study of vehicle ownership of different types, the ordered probit (OP) model was found to be an appropriate modeling method compared with multinomial logit (MNL) model in such cases [10–12], because the non-ordered discrete choice model cannot properly account for the ordinal nature of the number of vehicles owned. Most previous literature in this field developed bivariate ordered probit (BOP) model that analyzes both household automobiles and motorcycles ownership, which need to take account of the interdependencies between them [13–17]. Furthermore, the multivariate ordered probit model can be developed by extending the dimensions of the study object. But related applications for the extension of the model are rare. The trivariate binary probit model that Yamamoto [18] developed is used to evaluate the vehicle ownership of different types, including car, motorcycle and bicycle. Fang [19] proposed the Bayesian multivariate ordered probit model to estimate household decisions on the number of vehicles in each category, which is a more flexible method to handle a large number of vehicles. In both studies, the population density was found to be the major factor for household vehicle ownership. On the other hand, the modeling methods are commonly applied to the field of travel activity [20–23] to analyze the trip frequency of non-work or commute activity episodes, as well as applied in the field of traffic safety [24–26], which aims to reduce the chance of accidents or congestion [27–29]. In addition to the above models, there are other modeling approaches related to the research topic. One of the examples is Zhao’s [30], which first applied a multivariate negative binomial model to the number of vehicles by type and provided a way to capture the underlying preference of vehicle type.

In light of the data sets of different countries and regions, the factors that affect vehicle ownership are different in various literature. In general, the factors can be divided into four aspects: Household demographics, individual attributes, built environment and transit attributes, while most literature only cover one or two aspects. Household demographics are the most common consideration [10,11,13,17–19,30,31], and the factors including household income, household size, number of worker, and number of driver were analyzed frequently. In terms of built environment, the factors of residential regions and population density were considered in Bhat et al., Senbil et al., etc. [11,13,18,19,32,33]. Besides, there are relatively few studies on individual attributes and transit attributes. For instance, Gómez-Gélvez [17] and Yamamoto [18] analyzed the transit attributes (e.g., access to public transportation), while West [34], and Matas [35], took account of factors, such as education and child(ren) to reflect the individual attributes. In addition, there are many studies on automobile ownership. In some of the literature, automobiles were subdivided into passenger car, SUV, pickup and minivan for automobile ownership analysis [30,33].

Based on the existing literature, the research of vehicle ownership and vehicle type is not sufficient in China. Firstly, most studies in China mainly analyze the vehicle ownership of a single type [36–38], rather than discussing the correlation and transition of vehicle ownership between different types. Secondly, the ownership of electric bicycle is seldom considered in model framework [39,40]. It might be unreasonable in China, since electric bicycles have grown in popularity over the past decade.
and are now a substantial portion of the transportation system in most urban areas [41]. Thirdly, the explanatory variables involved in the study are not comprehensive enough. The influencing factors considered in some research are in only one category (e.g., built environment attributes) [36,39].

To supplement the insufficiency of the existing studies in China, this study attempts to investigate the interactions among different types of vehicle ownership by cross-sectional multivariate ordered probit model (CMOP) with composite marginal likelihood (CML) estimation approach at the household level. Meanwhile, the effects of both sociodemographic and built environment attributes on vehicle ownership can be analyzed by the estimation results. This paper aims to understand the vehicle ownership of four types at the level of household. In the developed model, the research dimensions and model complexity are increased, since four types of vehicles are taken into consideration—automobile, motorcycle, electric bicycle and human-powered bicycle. The data set for empirical analysis was extracted from residents’ household travel survey in Xiaoshan District, Hangzhou, Zhejiang. Since Zhejiang is the third province with the highest level of vehicle ownership [1], the study of the district casts light on the regions with high motorization level in China. This paper applied a CMOP model to fill the gap in vehicle ownership of four private vehicle types in China. The conclusions obtained by estimated results provide a reference for policy makers in similar cities. By discussing the influencing factors and the relations among vehicle ownership of different types, the study can help to promote the sustainable development of transportation.

The rest of this paper is structured as follows. The next section introduces the estimation method of the multivariate ordered probit model. Section 3 provides the basic statistics of sample data for empirical analysis and describes the explanatory variables used in the proposed model. And the estimation results of Xiaoshan District are discussed in Section 4. The final section concludes the paper by summarizing the findings along with future research directions.

2. Modeling Methodology

Since there are four types of private vehicles (i.e., automobile, motorcycle, electric bicycle, human-powered bicycle) being potentially chosen by each household, each household may choose zero, one, two or more vehicles in each type. Thus, a cross-sectional ordered probit modeling approach should be appropriate to model the owned vehicle number in each type, which takes an ordered value in nature. After a model is specified, parameter estimation is of great importance to obtain consistent coefficients and error correlations. It is appropriate to adopt composite marginal likelihood (CML) estimation approach to estimate error correlations among random utility functions for four types of vehicles. The data set used for modeling analysis is extracted from residents’ household travel survey in Xiaoshan District of Hangzhou City. The model is developed based on the random utility maximization (RUM) principle to examine the causal relationship between explanatory variables and vehicle ownership.

For better understanding influential factors of the vehicle number of different types, it is desirable to develop individual ordered model for each type of vehicles. One can set up the following latent propensity functions for household \( q \) owning vehicle type \( i \):

\[
y^*_q = \beta'_i x_q + \varepsilon_q, y^{m_{qi}}_q = m_{qi} \text{ if } \theta^{m_{qi} - 1}_i < y^*_q \leq \theta^{m_{qi}}_i,
\]

where \( q \) is an index for households \( (q = 1, 2, \ldots, Q) \), where \( Q \) denotes the total number of households in the data set), and \( i \) is an index \( (i = 1, 2, \ldots, I) \) for an ordered-response variable (i.e., vehicle number of each type). \( I = 4 \) in this study while \( i \) denotes automobile, motorcycle, electric bicycle, human-powered bicycle in sequence. Let the observed discrete and ordinal level \( y_q \) be \( m_{qi} \) and \( m_{qi} \in \{0, 1, 2 \text{ or more}\} \), reflecting three levels of ownership for each type of vehicle. \( x_q \) is an \((L \times 1)\) vector of exogenous variables (not including a constant), \( \beta_i \) is a corresponding \((L \times 1)\) vector of coefficients to be estimated, \( \varepsilon_q \) is a standard normal error term, and \( \theta^{m_{qi}}_i \) is the upper bound threshold for discrete level \( m_{qi} \) of
variable \( i (\theta_1^0 < \theta_2^1 < \theta_2^2 < \cdots < \theta_i^{K_i}; \theta_i^0 = -\infty, \theta_i^{K_i} = +\infty \) for each variable \( i \)). Since \( m_qi \) has three categories, only \( \theta_1^1 \) and \( \theta_1^2 \) exist in this study; and Equation (1) in this paper equals to:

\[
y_{qi}^* = \beta_i'x_{qi} + \varepsilon_{qi}, y_{qi} = \begin{cases} 
0, & \text{if } y_{qi}^* \leq \theta_1^1 \\
1, & \text{if } \theta_1^1 < y_{qi}^* \leq \theta_2^1 \\
2 \text{ or more}, & \text{if } y_{qi}^* > \theta_2^1 
\end{cases} \tag{2}
\]

In a traditional ordered probit model, the \( \varepsilon_{qi} \) terms are assumed independent and identical across individuals (for each and all \( i \)). For identification reasons, the variance of each \( \varepsilon_{qi} \) term is normalized to 1. However, in this study, the correlation in the \( \varepsilon_{qi} \) terms across variables \( i \) are specified to investigate whether two types of vehicles are mutually “substitutive” or “promotive”. If \( \varepsilon_q = (\varepsilon_q, \varepsilon_{q2}, \cdots, \varepsilon_{qi}) \), \( \varepsilon_q \) is assumed to be multivariate normal distributed with a mean vector of zeros and a correlation matrix as follows:

\[
\varepsilon_q \sim N \left( \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ \varepsilon_1^t \varepsilon_2^t \cdots \varepsilon_i^t \varepsilon_{q} 
\end{bmatrix} \right) \quad \text{or } \varepsilon_q \sim N[0, \Sigma]. \tag{3}
\]

The off-diagonal terms in \( \Sigma \) stand for the error covariances across the underlying latent continuous variables, capturing the effects of common unobserved factors influencing the underlying latent propensities. Note that the diagonal elements of \( \Sigma \) are normalized to one for identification purposes. All the error covariances can be stacked into a vertical vector \( \Omega \). If all the correlation parameters (i.e., off-diagonal elements of \( \Sigma \)) in vector \( \Omega \) are identically zero, the model system in Equation (1) collapses to independent ordered probit models.

The parameter vector (to be estimated) of the multivariate probit model is \( \delta = (\beta_1^1, \beta_2^1, \cdots, \beta_i^1, \theta_1^1, \theta_2^1, \cdots, \theta_i^1; \Omega) \) where \( \theta_i = (\theta_1^1, \theta_2^1, \cdots, \theta_i^{K_i-1}) \) for \( i = 1, 2, \cdots, I \). The likelihood function for household \( q \) can be written as follows:

\[
L(\delta) = \Pr(y_{q1} = m_{q1}, y_{q2} = m_{q2}, \cdots, y_{qI} = m_{qI}) \\
= \int_{v_1=q_1^{01}}^{q_1^{K_11}} \cdots \int_{v_I=q_I^{01}}^{q_I^{K_I1}} \prod_{i=1}^{I} \phi_{v_i}(v_i, v_2, \cdots, v_I; \Omega) dv_1 dv_2 \cdots dv_I, \tag{4}
\]

where \( \phi_{v_i} \) is the standard multivariate normal density function of dimension \( I \). The likelihood function above involves an \( I \)-dimensional integral for each individual \( q \). The objective is to obtain the parameter values in \( \delta \) under the maximum likelihood function.

In transportation literature, Maximum Simulated Likelihood (MSL) estimation methods have been widely applied for evaluating the multi-dimensional integral in a multivariate ordered response model system, using quasi-Monte Carlo simulation methods [21,42,43]. Conceptually, MSL methods can be extended to any number of correlated ordered-response outcomes, but numerical stability, convergence, and precision problems emerge when the number of dimensions increases. The composite marginal likelihood (CML) estimation approach is a relatively simple approach that can be used when the full likelihood function is near impossible or plain infeasible to evaluate, due to the underlying complex dependencies [44]. The key contribution of CML method is to provide consistent estimators for both coefficients of explanatory variables and correlations in the error covariance matrix. The pairwise marginal likelihood function for individual \( q \) may be written for the cross-sectional multivariate ordered probit model (CMOP) as follows:
1. Model specification: The threshold value $\delta$ with asymptotic mean $\Phi$ for AE variable (i.e., household size). The formulae for sustainability 2018

2. Model estimation: Developing cross-sectional multivariate ordered probit model (CMOP) with small interval provides sufficiently accurate estimates for "households own more than 2 vehicles, the vehicle frequency at the "2+" level is approximately owned 0, 1 or 2+ (i.e., 2 or more) vehicles given by the ordered probit model. Since few explanatory variables and aggregate semi-elasticities (AE) based on model coefficients, aggregate elasticities (AE) are computed for key continuous explanatory variables and aggregate semi-elasticities (ASE) are computed for key ordinal discrete variable (i.e., household size). The formulae for AE and ASE are given as below:

$$AE = \frac{\Delta \sum_{q=1}^{Q} \Pi_{m=0}^{m+1} [m \times P_{qm}(x_q z + \Delta z_q)]}{\sum_{q=1}^{Q} \Pi_{m=0}^{m+1} [m \times P_{qm}(x_q z)]} \approx \frac{1}{\lambda} \left\{ \frac{\sum_{q=1}^{Q} \Pi_{m=0}^{m+1} [m \times P_{qm}(x_q z + \Delta z_q)]}{\sum_{q=1}^{Q} \Pi_{m=0}^{m+1} [m \times P_{qm}(x_q z)]} - 1 \right\},$$

$$ASE = \frac{\sum_{q=1}^{Q} \Pi_{m=0}^{m+1} [m \times P_{qm}(x_q z + \Delta z_q)]}{\sum_{q=1}^{Q} \Pi_{m=0}^{m+1} [m \times P_{qm}(x_q z)]} - 1.$$

In the above equation, $P_{qm}$ (i.e., “$P_{q0}$”, “$P_{q1}$”, “$P_{q2}$”) respectively represents the probability for owning 0, 1 or 2+ (i.e., 2 or more) vehicles given by the ordered probit model. Since few households own more than 2 vehicles, the vehicle frequency at the “2+” level is approximately counted as 2. “$x_q z$” represents a vector of explanatory variables except the one (i.e., $z_i$) whose elasticity or semi-elasticity is being computed. “$\Delta$” takes a value of 0.01 in this study as it is found that such a small interval provides sufficiently accurate estimates for “AE” and “ASE” in the model.

Based on the above methodology, the overall framework can be established to describe the work of this study. The modeling procedures are given as follows:

1. Model specification: The threshold value $\theta^{m+1}_{q}$ was introduced for ordered probit model and the basic likelihood functions of household $q$ can be formulated, which were shown in Equations (1) and (4) respectively.

2. Model estimation: Developing cross-sectional multivariate ordered probit model (CMOP) with the form of pairwise marginal likelihood function as shown in Equation (5). The estimation approach is composite marginal likelihood (CML) to adapt the underlying complex dependencies.
By this method, both coefficients of explanatory variables and correlations in the error covariance matrix can be obtained.

3. Elasticity calculation: In the case of estimated results, AE and ASE can be calculated for continuous variables and key explanatory variables respectively, as Equation (8) displayed.

3. Data Collection and Descriptive Analysis

3.1. Introduction to the Research Area

Xiaoshan, located on the southeast coast of China, is one of the biggest districts of Hangzhou with an area of 1420 km², which is the provincial capital of Zhejiang province. The district divisions of Hangzhou and Xiaoshan are depicted in Figure 1. By 2017, Xiaoshan District is the most populous region in Hangzhou as a representative study object, the paper would provide some evidence for household vehicle ownership issue in rapidly developed areas of China. During the process of industrialization, an expanding economy has been improved, and there are two metro lines and 160 bus lines in operation so far. Taking Xiaoshan as a representative study object, the paper would provide some evidence for household vehicle ownership issue in rapidly developed areas of China.

![Figure 1. Cont.](image-url)
100,000~300,000 Yuan. To calculate the average annual household income, the discrete variable $X_i$ acquired average value is 169 thousand Yuan, which is higher than the average income in Zhejiang province.

The household proportions of owning their home and driving licenses are considerable with the percentage of 91% and 88.2% respectively. Besides, the families with pre-school children account for a significant proportion in the sample. According to the survey, more than 90% of households have no motorcycles, which might be related to the regional policies of environmental protection and traffic safety [47]. In addition, approximately 30% of households own human-powered bicycles, which are more than motorcycles, but far less than automobiles.

According to the survey, nearly 60% of households have an annual income ranging from 100,000–300,000 Yuan. To calculate the average annual household income, the discrete variable of household income should be changed into continuous variable based on the Gaussian distribution. The acquired average value is 169 thousand Yuan, which is higher than the average income in Zhejiang Province. Most households have 3~5 members and about a quarter of households have children under the age of 6, which indicates that the families with pre-school children account for a significant proportion in the sample. Besides, the household proportions of owning their home and driving licenses are considerable with the percentage of 91% and 88.2% respectively.
### Table 1. Description of the sample data (N = 2558).

| Description of Discrete Variable | Attribute | Percent | Description of Discrete Variable | Attribute | Percent |
|----------------------------------|-----------|---------|----------------------------------|-----------|---------|
| Annual household income [Yuan]   | Mean      | $1.69 \times 10^5$ | Automobile ownership            | Mean      | 1.13    |
|       ≤100,000                   | 30.5%     | 0       |                                  | 15.9%     |
|       100,000–300,000            | 58.1%     | 1       |                                  | 57.4%     |
|       300,000–500,000            | 9.9%      | 2+      |                                  | 26.7%     |
|       500,000–1000,000           | 1.3%      |         |                                  |           |
| Household size                   | Mean      | 3.99    |                                   | 0         | 93.5%   |
|                                   | 1         | 0.1%    |                                   | 1         | 6.1%    |
|                                   | 2         | 7.2%    |                                   | 2+        | 0.4%    |
|                                   | 3         | 32.7%   |                                   | 0         | 93.5%   |
|                                   | 4         | 26.0%   |                                   | 1         | 6.1%    |
|                                   | 5         | 23.6%   |                                   | 2+        | 0.4%    |
|                                   | 6         | 8.2%    |                                   | 3         | 45.5%   |
|                                   | 7+        | 2.2%    |                                   | 2+        | 39.4%   |
| The population under the age of 6| Mean      | 0.29    | Human-powered bicycle ownership   | Mean      | 0.32    |
|                                   | 0         | 73.6%   |                                   | 0         | 72.6%   |
|                                   | 1         | 24.1%   |                                   | 1         | 23.6%   |
|                                   | 2+        | 2.3%    |                                   | 2+        | 3.8%    |
| Home ownership                    | Self-owned house | 91.0% |                                   | Beigan Street | 14.7%   |
|                                   | Non-self-owned house | 9.0% |                                   | Chengxiang Street | 24.9%   |
| Licensed household members 2      | Have a license | 88.2% |                                   | Ningwei Town | 9.7%    |
|                                   | Not have a license | 11.8% |                                   | Puyang Town | 0.4%    |
|                                   |            |         |                                   | Shushan Street | 13.5%   |
| Real estate price [Yuan/m²]       | Mean      | 9855    |                                   | Suoqian Street | 3.0%    |
|                                   | <10,000   | 49.3%   |                                   | Wenyan Street | 5.9%    |
|                                   | 10,000–15,000 | 46.8% |                                   | ETD Zone 3   | 4.7%    |
|                                   | 15,000–20,000 | 3.2%  |                                   | Xinjie Town 3 | 7.2%    |
|                                   | 20,000–30,000 | 0.5%  |                                   | Xintang Street | 15.8%   |
|                                   | >30,000   | 0.2%    |                                   | Yanqian Town | 0.4%    |
|                                   |           |         |                                   | Beigan Street | 14.7%   |

**Description of continuous variable**

| Attribute | Mean | Standard Deviation |
|-----------|------|--------------------|
| Population density [thousand people] 4 | 9.45 | 14.690 |
| Average age of household members      | 37.05 | 7.697 |
| Average education years of household members | 12.10 | 2.357 |
| Male proportion of household members | 0.48 | 0.193 |
| Employed proportion of household members | 0.89 | 0.219 |
| Average number of trips per person    | 2.94 | 0.810 |
| Average commute travel time [min]     | 22.23 | 13.290 |

1 Yuan: Unit of RMB, currency in China; 1 Yuan = approx. US$0.1465. 2 The italics in the table indicate that the attribute is derived from the datasets of personal attribute survey or personal travel survey by aggregate method. 3 ETD Zone is the abbreviation of Economic-Technological Development Zone. 4 Population density is measured by the communities, in which the household is located.

In the description of the continuous variable, the population density is obtained by the traffic analysis zones (communities), in which the household is located. The samples are randomly distributed in 150 communities among 11 zones in Xiaoshan District, and each community corresponds to different population density. By aggregating the personal survey data to household attributes or aggregating the travel survey data to household attributes (the latter needs to convert to personal attributes firstly), some important variables can be added to provide more choices for explanatory variables, which are displayed in the form of italics in Table 1. Based on the table, it is shown that the average education
level of household members is around high school (education for 12 years) and the male proportion in household is slightly lower than 50%. The proportion of employed members in household is nearly 90%, which might indicate that the employment rate is high, and the large group of household members are at working age. Travel time is an important attribute that can be used to analyze travel distribution and pathfinding [48,49]. It can be estimated that the average number of trips per person is about three, and the average commute travel time is 22–23 min through the personal travel data.

3.3. Explanatory Variables

By multivariate ordered probit modeling approach, the significant explanatory variables were selected. Table 2 shows the explanatory variables used in the proposed model, which is classified as the sociodemographic (household or individual) attributes or built environment attributes. To understand explanatory variables explicitly, the types and descriptions of the variables are displayed as follows.

| Table 2. Explanatory variables. |
|---------------------------------|
| **Name** | **Type** | **Description** | **Mean** | **S.D.** |
| **Household sociodemographic attributes** | | | | |
| Household income [10 thousand Yuan] | Continuous | Annual household income converted from discrete variable in household survey data. | 16.89 | 11.016 |
| Household size | Ordinal | Number of family members in the household. | 3.99 | 1.193 |
| Home ownership | Dummy | 1 if the house is self-owned; 0 otherwise. | 0.91 | 0.286 |
| Real estate price [10 thousand Yuan/m²] | Continuous | House price of the residence place converted from discrete variable in household survey data (similar to household income variable). | 0.99 | 0.340 |
| **Individual sociodemographic attributes** | | | | |
| Age of household members | Continuous | Average age of household members based on personal survey data. | 37.05 | 7.697 |
| Education level of household members | Continuous | Average education years of household members based on personal survey data. | 12.10 | 2.357 |
| Licensed household members | Dummy | 1 if at least one person has a license in household; 0 otherwise. | 0.88 | 0.322 |
| **Built environment attributes** | | | | |
| Population density [thousand people] | Continuous | The population density is obtained based on the small zone level (communities) where the household is located. | 9.45 | 14.690 |
| Zone: Street/Town | Categorical | The area (11 streets/towns) where the household is located in Xiaoshan District. | — | — |

4. Empirical Results

4.1. Estimated Results and Elasticity Analysis

The estimation results of developed multivariate ordered probit model of automobile, motorcycle, electric bicycle and human-powered bicycle ownerships in Xiaoshan District are shown in Table 3. The explanatory variables, which have been described in Table 2, have statistically significant coefficient estimates in Table 3. The effect (positive or negative) of each variable on private vehicle ownership of different vehicle type can be analyzed from the table.
Table 3. Estimated result of the proposed model (N = 2558).

| Explanatory Variable                                      | Estimate | S.E.  | T-Statistic |
|-----------------------------------------------------------|----------|-------|-------------|
| **Automobile ownership (0, 1 or >= 2)**                  |          |       |             |
| Household income                                         | 0.0368   | 0.0006| 58.343      |
| Household size                                           | 0.2749   | 0.0074| 37.284      |
| Home ownership                                           | 0.7340   | 0.0300| 24.469      |
| Population density                                       | -0.0032  | 0.0006| -5.451      |
| Age of household members                                 | 0.0119   | 0.0012| 9.737       |
| Education level of household members                     | 0.1160   | 0.0041| 27.975      |
| Licensed household members                               | 1.9041   | 0.0342| 55.670      |
| Zone: ETD Zone (dummy)                                   | 0.5712   | 0.0447| 12.773      |
| Zone: Xinjie Town (dummy)                                | -0.2601  | 0.0348| -7.465      |
| $\theta_1^1$                                             | 4.4965   | 0.0880| 51.087      |
| $\theta_1^2$                                             | 6.8033   | 0.0927| 73.375      |
| **Motorcycle ownership (0, 1 or >= 2)**                  |          |       |             |
| Household size                                           | 0.1301   | 0.0116| 11.201      |
| Population density                                       | -0.0147  | 0.0014| -10.758     |
| Age of household members                                 | -0.0186  | 0.0022| -8.473      |
| Education level of household members                     | -0.0901  | 0.0075| -11.995     |
| Licensed household members                               | -0.2224  | 0.0390| -5.700      |
| Zone: Suoqian Town (dummy)                               | -0.6533  | 0.1083| -6.033      |
| Zone: ETD Zone (dummy)                                   | -0.5296  | 0.0824| -6.427      |
| $\theta_2^1$                                             | -0.0314  | 0.1462| -0.215      |
| $\theta_2^2$                                             | 1.1692   | 0.1589| 7.357       |
| **Electric bicycle ownership (0, 1 or >= 2)**             |          |       |             |
| Household income                                         | -0.0088  | 0.0008| -10.893     |
| Household size                                           | 0.2632   | 0.0064| 41.178      |
| Real estate price                                        | -0.3143  | 0.0225| -13.999     |
| Age of household members                                 | -0.0116  | 0.0011| -10.582     |
| Education level of household members                     | -0.0462  | 0.0038| -12.059     |
| Licensed household members                               | -0.5357  | 0.0261| -20.487     |
| Zone: Beigan Street (dummy)                              | -0.1914  | 0.0223| -8.599      |
| Zone: Shushan Street (dummy)                             | -0.1786  | 0.0220| -8.113      |
| Zone: Wenyuan Town (dummy)                               | 0.1973   | 0.0359| 5.493       |
| $\theta_3^3$                                             | 1.6235   | 0.0806| 20.217      |
| $\theta_3^2$                                             | -0.6211  | 0.0793| -7.829      |
| **Human-powered bicycle ownership (0, 1 or >= 2)**        |          |       |             |
| Household size                                           | 0.1138   | 0.0076| 14.957      |
| Age of household members                                 | -0.0117  | 0.0012| -9.398      |
| Education level of household members                     | -0.0391  | 0.0048| -8.146      |
| Licensed household members                               | -0.0977  | 0.0141| -6.915      |
| Zone: Wenyuan Town (dummy)                               | 0.2979   | 0.0380| 7.835       |
| Zone: Xinjie Town (dummy)                                | 0.4210   | 0.0331| 12.718      |
| Zone: Xintang Street (dummy)                             | -0.2493  | 0.0264| -9.451      |
| $\theta_4^4$                                             | 0.0398   | 0.0916| 0.435       |
| $\theta_4^2$                                             | 1.2558   | 0.0930| 13.509      |

Note: The above explanatory variables are significant at 1% level; $\theta_i^{m_q}$ is the upper bound threshold for discrete level $m_q$ of ordered-response variable $i$, which is shown in Equation (1). $^1 LL_{CM}(\beta)$ represents the composite marginal log-likelihood value of the model at convergence; $^2 LL_{CM}(c)$ represents the composite marginal log-likelihood value of the model with threshold constants only; $^3 \rho_{CM}^2(c)$ is computed as $[1 - LL_{CM}(\beta)/LL_{CM}(c)]$, which is analogous to the likelihood ratio index in the standard MLE (Maximum Likelihood Estimate) procedure to measure the improvement in goodness-of-fit contributed from all the explanatory variables and correlations.

Table 4 selected several key explanatory variables for elasticity analysis, including household income, education level of household members, age of household members and household size.
The elasticities obtained by the Equation (8) is the measurement of how explanatory variables respond to a change in vehicle ownership. In the study, aggregate elasticities (AE) are computed for continuous variables and aggregate semi-elasticities (ASE) are computed for ordinal discrete variables.

Table 4. Elasticities of selected key explanatory variables.

| Variable                        | Automobile | Motorcycle | E-Bicycle | Bicycle |
|---------------------------------|------------|------------|-----------|---------|
| Household Income                | 0.216      | 0.000      | −0.069    | 0.000   |
| Education Level of Household Members | 0.501      | −1.946     | −0.858    | −0.599  |
| Age of Household Members        | 0.156      | −1.288     | −0.197    | −0.555  |
| Household Size *                | 0.097      | 0.011      | 0.117     | 0.153   |

* Aggregate semi-elasticities are provided.

Through the analysis of coefficients and elasticities, it can be known that the influence of changes of the factors on the four types of vehicle ownership in Xiaoshan. The detailed discussions are made below.

- **Household Income**

  Household income is a key explanatory variable in the joint vehicle ownership model. One of the main objectives in this study is to quantify the elasticity of household income on various types of vehicle ownership. As per the estimation results, the household income plays a significant role in automobile and electric bicycle ownership. Households with higher income tend to own more automobiles, but less electric bicycles, as evidenced by the signs of coefficients in respective utility functions. The elasticity is estimated at only 0.216 and −0.069 for automobile and electric bicycle. In this area, income has become an inelastic factor in private automobile ownership, possibly due to the low price of automobiles and high-income level in Xiaoshan District, Hangzhou, China. Similar to the situation in developed countries, household income gradually becomes less important in determining household automobile ownership in the area of China with rapid economic development.

- **Education Level of Household Members**

  Mean education level of household members appears significant in all the utility functions for four types of vehicles. It takes a positive coefficient in automobile utility, but negative coefficients in motorcycle, e-bicycle and bicycle utilities. This factor is highly elastic for motorcycle ownership (elasticity is −1.946) while the elasticity for e-bicycle and bicycle are −0.858 and −0.599. It is reasonable to see that people with better educational background are not favor of using motorcycle. Between e-bicycle and bicycle, well-educated people dislike e-bicycle, presumably due to their more concerns on safety. As a result, households at a higher education level are fond of owning and using private automobiles. The elasticity of mean education years takes the value of 0.501 for automobile ownership, which is as 2.3 times as that of household income. Thus, the education level is found to be a more elastic factor for automobile ownership than household income in this area.

- **Household Size**

  It is reasonable to see that household size plays a positive role in household vehicle ownership. A large household tends to own more private vehicles, which become more necessary when a new family is formed, or a new baby comes into a family. However, the semi-elasticities take modest values of 0.097, 0.117, 0.153 for automobile, electric bicycle and bicycle, and only 0.011 for motorcycle.

- **Real Estate Price**

  Real estate price takes a negative coefficient in the electric bicycle utility function, indicating that households living in homes with higher price are less likely to own electric bicycles. The homes with higher price may have a better condition for using automobiles and people living there are less likely to use electric bicycle.
- **Home Ownership**
  
The dummy variable indicating households owning their homes takes a positive coefficient in automobile utility function. It is understandable that people will have more propensity to purchase private automobiles after owning their homes and settle down.

- **Population Density**
  
  Population density of the traffic analysis zone where the household is located takes negative coefficients in automobile and motorcycle utilities, indicating that higher population density leads to less ownership of automobiles or motorcycles. Intuitively, the area with higher population density suffers from more serious traffic congestions and parking challenges. Thus, people living there show less tendency to own automobiles or motorcycles.

- **Age of Household Members**
  
  Mean age of household members appears significant in all the four utility functions. The elasticity of $-1.288$ shows that the age is an elastic factor for motorcycle ownership. Between e-bicycle and bicycle, the ownership of bicycle is more elastic to age than that of e-bicycle. The elasticity of age is $0.156$ for automobile ownership. It is quite intuitive that elderly people probably cannot ride motorcycles and dislike to use bicycles or e-bicycles. As a result, automobiles become almost the only favorite alternative for their private vehicles. Elderly people dislike e-bicycles less than bicycle, probably because e-bicycles are powered by electricity and help to save manpower for travel.

- **Licensed Household Members**
  
  It is intuitive to see that households with licensed drivers are more likely to own automobiles, but less likely to own motorcycles, e-bicycles and bicycles, as shown by respective coefficients in four utility functions in Table 3.

- **Residential Zones of Household**
  
  For capturing spatial heterogeneities in the modeling area, multiple dummy variables indicating districts where households are located are specified into the joint model. The effect of residential zones on vehicle ownership may be determined by multiple factors, such as population density, geographical environment and socio-economic level. For instance, the factor of ETD Zone takes a positive effect on automobile, but negative effect on motorcycle, possibly because the ETD Zone is newly designed to better accommodate automobiles than motorcycles. Xinjie Town’s households prefer to own bicycles rather than automobiles, indicating that the residents in this area tend to make short-distance travel. We can also learn that the households in Wenyan Town are more inclined to own e-bicycles and bicycles. On the contrary, households of Beigan Street and Shushan Street dislike owning e-bicycle presumably due to their built environment.

In the empirical results, we analyzed the factors affecting vehicle ownership of three aspects: Household demographics, individual attributes and built environment. The study involved nine explanatory variables, which is comprehensive compared with the existing literature. Household income and population density, which have been emphasized in the past research, were also mainly analyzed in the above results. And home ownership and real estate price are the variables that rarely appeared in the previous literature, which also have high level of significance in vehicle ownership of different types, as shown in the results. Similarly, other conventional variables, such as household size, age and education, can be explained reasonably with common sense. Although the specified explanatory variables in the model are comprehensive, there are still some aspects that are not involved, due to data limitation. For instance, transit attribute is one of the important aspects affecting vehicle ownership, which is not considered in this study.

As the estimated results indicated, household income has a positive impact on automobile ownership (with positive coefficient). This finding coincides with that in Yamamoto [18],
Senbil et al. [13] and Gómez-Gélvez et al. [17], and the data set are from Kuala Lumpur, Jabotabek and Bogota respectively. It can be found that the household with high education level tend to own more automobiles, which is consistent with Fang’s conclusion from National Household Travel Survey (NHTS) [19]. Age of household members plays a positive role in automobile ownership, but a negative role in motorcycle ownership, which coincide with Senbil’s research that the data derived from Kuala Lumpur and Jabotabek [13]. Besides, similar to this model, Yamamoto reached the same conclusion from Osaka that lower population density leads to more ownership and usage of automobiles or motorcycles [18]. From the above, many conclusions of this study can be corroborated from the previous literature, which indicates that the estimation results are reasonable.

4.2. Discussions on Error Correlation Matrix

Figure 2 provides the error correlation matrix of the multivariate ordered probit model for household vehicle ownership. In the figure, the depth of color indicates the magnitude of correlation. The deeper the color, the greater the correlation between the vehicle ownership of different types. A negative correlation (in red) indicates that two types of vehicles are mutually substitutive while a positive correlation (in blue) indicates that two of them are mutually promotive at the household level.

![Error Correlation Matrix](image)

Figure 2. Estimated error correlation matrix.

It is found that the error correlation between automobile and e-bicycle is \(-0.3558\), indicating a considerable substitutive relation between automobile and electric bicycle. Similarly, there is also a substitutive relation between automobile and motorcycle, as shown by the error correlation of \(-0.2020\). As for the bicycle, its correlation with automobile is only \(-0.0732\), indicating a little substitutive relation with the automobile.

The relations of motorcycle with e-bicycle and bicycle are interestingly opposite. A negative correlation of \(-0.0946\) shows the mutually substitutive relation while a positive correlation of 0.1295 shows the mutually promotive relation. Since e-bicycle is powered by electricity, instead of manpower, and can be used to travel longer than bicycle, it can be a substitute for a motorcycle. On the other hand, both motorcycle and bicycle require travelers to be strong enough to ride a two-wheel vehicle and expose their bodies to the environment. The similarities between motorcycle and bicycle may cause a little promotive relation between them. Finally, it is interesting to see that e-bicycle and bicycle are also mutually promotive, as shown by the positive correlation (0.0273), although the correlation is very small, possibly due to the similarity between e-bicycle and bicycle on the aspect of flexibility and sustainability [50].
5. Conclusions and Discussions

This paper focuses on the factors affecting household vehicle ownership of multiple types of private vehicles. The data set used for empirical analysis is extracted from the residents' household travel survey in Xiaoshan District. The vehicle type investigated in this study is classified into automobile, motorcycle, electric bicycle and human-powered bicycle. To analyze the vehicle ownership and type, the study used cross-sectional multivariate ordered probit model (CMOP) with composite marginal likelihood (CML) estimation approach to estimate both coefficients of explanatory variables and correlations in the error covariance matrix, which can respectively evaluate the effect of variables on vehicle ownership and relations among different types of vehicles. Based on the estimation results of the model, the elasticities (AE or ASE) of selected key explanatory variables can be calculated to measure the sensitivity of vehicle ownership to a change in influential factors.

According to the empirical results, some interesting findings for selected key explanatory variables are listed as follows. In the estimated results, the coefficients for the following explanatory variables of household size, mean education level and mean age of household members are significant in all types of vehicle ownership.

- As an important explanatory variable, household income plays a positive role in automobile ownership, but a negative role in bicycle ownership. This factor is less important to affect automobile ownership with a small value of elasticity, which is similar to the situation in developed countries.
- The households with high education level incline to own more automobiles and dislike to use vehicles of the other types, especially of motorcycles. And the education level is a more elastic factor for automobile ownership than household income.
- Household size appears positive in all the four utility functions as generally we speculate. Motorcycles have less elasticity than the other three types of vehicle.
- The households with more elderly members prefer to own more automobiles as expected. Based on the elasticities, the degree of intolerance of elderly people for vehicle types can be ranked (from high to low): Motorcycle, bicycle, and e-bicycle.

Except above such conclusions can also be drawn as follows. The households with higher real estate price prices are less likely to own e-bicycles, while the households owning their homes are more willing to own automobiles. And higher population density leads to less ownership of automobiles and motorcycles, due to traffic congestions and parking challenges. Intuitively, the households with a license are more likely to own automobiles, but less likely to own other vehicles. Meanwhile, the residential zone of household is a necessary influencing factor for private vehicle ownership.

Furthermore, the interactions among vehicle ownership of four vehicle types can be examined through the error correlation matrix. There is a large substitutive relation between automobile and e-bicycle/motorcycle. It implies that the policy encouraging the ownership or use of e-bicycles can reduce the dependence on automobiles. It is also interesting to note that the vehicle ownership of e-bicycle/motorcycle and bicycle are mutually promoted, while motorcycle and e-bicycle are mutually substituted.

The analysis in this study provide exploratory methodological and empirical evidence that could lead to an approach to predicting the change in household vehicle ownership as a result of changes in future socioeconomic conditions and build environment. The empirical results provide a reference for related decision makers and policy makers to estimate potential changes in household vehicle ownership in Xiaoshan. Based on the results, some policy recommendations can be provided. (1) Encouraging education development to increase the household education level can reduce motorcycle ownership; (2) developing policies to avoid aging of population, which can slow down the increase of automobile ownership; (3) avoiding blindly expanding the urban area, automobile and motorcycle ownership tend to be restricted in high density areas; and (4) encouraging
the ownership and usage of e-bicycles and bicycles, which can reduce the dependence on automobiles and motorcycles.

The findings revealed the household preference of owning four types of vehicles, especially of electric bicycles, which was seldom discussed in previous literature. The influencing factors, particularly built environment variables, are regarded as the factors to encourage people to environmentally sustainable travel behaviors. The empirical results show a considerable substitution between automobile and electric bicycle, which implies that the promotion of electric bicycles may effectively reduce the dependence on high-energy consumption automobiles and therefore contributes to sustainable development of green transportation system.

The conclusions of this study can only be applied to the developed regions in developing countries like Xiaoshan District, which are not universal. The empirical results can be compared with the estimated results from other cities of different countries if possible in the future work. Due to the lack of survey data, the discussion of transit attributes is insufficient, and more variables need to be added with data support. In future studies, since public transit accessibility and land-use type might be crucial factors impacting vehicle ownership and type [37], the factors can be taken into consideration to improve the model.

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