CAR OWNERSHIP ANALYSIS IN MARYLAND: A LATENT CLASS MODEL APPROACH

Di Yang, Graduate Research Assistant
Department of Civil and Environmental Engineering
1173 Glenn Martin Hall
University of Maryland
College Park, MD 20742
Phone: 301-272-0690
E-mail: dyang114@umd.edu

Chenfeng Xiong, Graduate Research Assistant
Department of Civil and Environmental Engineering
1173 Glenn Martin Hall
University of Maryland
College Park, MD 20742
Phone: 301-661-9635
E-mail: cxiong@umd.edu

Rolf Moeckel, Faculty Research Associate
National Center for Smart Growth Research and Education
1226B Preinkert Field House
University of Maryland
College Park, MD 20741
Phone: 301-405-9424
E-mail: rolf.moeckel@udo.edu

Lei Zhang, Associate Professor
(Corresponding author)
Department of Civil and Environmental Engineering
1173 Glenn Martin Hall
University of Maryland
College Park, MD 20742
Phone: 301-405-2881
E-mail: lei@umd.edu

Submitted for Peer Review and for Publication at the Annual Meeting of the Transportation Research Board (TRB) in January 2016

Date Submitted:

Word Count: 4,528
Number of Figures: 1
Number of Tables: 3
Total Count: 4,528 + (4 × 250) = 5,528
ABSTRACT

As an important transportation research topic, car ownership is of great interest to a variety of audiences. Vehicle manufacturers, oil companies and government agencies at different levels have developed various car ownership models to assist their decision making processes. An extensive literature exists regarding different aspects of car ownership modeling, which makes it one of the most explored transportation domains.

However, the majority of studies assume that impacts of explanatory variables stay identical across the whole population, which results in potential preference heterogeneity in population being overlooked. In reality, there may exist distinct classes within the population whose preferences towards car ownership decisions are different. Therefore, this paper proposes a latent class version of the multinomial logit (MNL) model to better understand the preference heterogeneity phenomenon. Using the 2007/2008 household travel survey data from Washington and Maryland area, both the standard MNL model and the latent class model (LCM) are estimated and evaluated. Various measures are established to assess the performance of different models. Results confirm the existence of segmentation within the population and the LCM outperforms the MNL model in terms of the interpretation capability.

Key Words: car ownership, latent class model, preference heterogeneity, multinomial logit model, built environment
1. INTRODUCTION

Car ownership forecasting is crucial in the decision-making process of many disciplines. In the automobile industry, car ownership models are employed by vehicle manufacturers to estimate the market size. Oil companies develop models to predict demand for future products. Government agencies at different levels use car ownership models for various purposes from taxation related policy making to energy consumption, travel demand and emission forecasting (De Jong, 2004).

Car ownership modeling also plays an important role in the overall transportation and land use planning process. It is considered as a key determinant of the overall travel behavior of individuals and households (Scott and Axhausen, 2006). In the short run, owning a car/several cars, to some degree, determines travelers’ mode choice (Bhat, 1997), trip frequency (Meurs, 1990), duration, and destination choice for different trip purposes. In the long run, level of car ownership inevitably influences people’s residential location decisions, which potentially leads to changes in land use patterns (Eluru et al., 2010). Thus, it is critical for urban planners and decision makers to understand factors that affect people’s auto ownership decisions.

The United States has long been recognized as the country on wheels. Census estimates suggest that one U.S. household owned an average of 1.8 vehicles in 2013 (American Community Survey, 2014). To many Americans, cars are not only a basic necessity, but also a symbol of freedom and independence. Modeling car ownership behavior in the Baltimore and Washington metropolitan area becomes even more challenging since land use patterns in this area are more regulated (zoning restrictions and federal lands). The Washington metro system has attracted 271,160,000 passenger trips in 2014, only second to the New York City Subway (American Public Transportation Association, 2015). In July 2015, Maryland Governor Larry Hogan gave approval to the metro project Purple Line (McCartney et al., 2015). The expanded transit services have increased the complexity of the car ownership behavior in this region. However, there is limited effort to look at car ownership problems in the Maryland context. Cirillo (2010) developed a multinomial logit (MNL) model to explore factors associated with households’ auto ownership decisions in Maryland. But this study was based on data at national level which limits the number of observations and there was no land use or built environmental variables taken into consideration.

In this paper, car ownership decisions (number of cars owned at household level) are modeled using a discrete choice approach with the 2007/2008 Household Travel Survey (HTS) data collected in the Maryland and Washington area. Instead of assuming that the entire population share the same preference towards vehicle purchase decisions, we propose a latent class model (LCM) approach to capture the preference heterogeneity phenomenon in this study. This approach allows for existence of various
population classes, among which car ownership propensities can be different. In addition to household characteristics variables that are commonly seen in the literature, land use and built environment variables are also included in the model. The objective of this paper is twofold: to provide a comprehensive exploration on factors associated with the car ownership behavior in the Baltimore and Washington Metropolitan area, and to test how the LCM can enhance our understanding towards car ownership behavior compared to the standard MNL model.

The remainder of the paper is organized as follows: in Section 2, a critical review on disaggregate car ownership models is given. In Section 3, details on model specification are provided. Section 4 describes the main data sources and explanatory variables included in the model. Section 5 analyzes and discusses empirical results. Finally, major findings and future research directions are summarized in Section 6.

2. LITERATURE REVIEW

Given the importance of car ownership forecasting, car ownership modeling has been one of the most intensely researched transportation domains over the years. Various forms of modeling approaches have been proposed in the literature to analyze different aspects of car ownership problems. In 2004, de Jong et al. published a comprehensive literature review on car ownership models. In this review, car ownership models were categorized into ten types: aggregate time series model, aggregate cohort model, static disaggregate ownership model, static disaggregate type choice model, panel model, etc. In the literature, car ownership decisions are mainly considered as discrete choice behavior at the household level. Thus, the scope of this section focuses on reviewing studies on static disaggregate car ownership models and issues with the existing researches.

The earliest efforts of modeling changes in car ownership levels can be dated back to the 1930s (de Wolff, 1938). However, it was not until 1976 that disaggregate modeling of number of vehicles at the household level was first introduced by Lerman and Ben-Akiva (1976). The introduction of MNL models based on the random utility theory to car ownership modeling is considered as a significant progress compared to previous aggregate modeling. By estimating parameters at the household level, disaggregate models do a better job at diminishing the aggregation bias. Also, the random utility theory makes the model more structurally behavioral, which leads to better understanding of the causal relationship between factors influencing car ownership decisions and changes in number of cars owned (Potoglou and Kanaroglou, 2008).

Within the category of disaggregate models, discrete choice models are classified into two types based on the underlying choice response mechanism: the ordered-response mechanism and the unordered-response mechanism. The ordered response mechanism (e.g., ordered probit and ordered logit models) assumes that there exists a
unidimensional latent car ownership tendency index that impacts car ownership decisions (Bunch, 2000). The unordered-response mechanism (e.g., probit and logit models) is based on the random utility maximization theory. In 1998, Bhat and Pulugurta compared the ordered and the unordered-response mechanisms using different datasets. They found misspecification issues with the ordered-response mechanism, which may result in inaccurate prediction of car ownership levels. They drew the conclusion that the unordered-response mechanism is more appropriate in car ownership modeling and generates a better image of the decision-making process of households.

Despite wide applications of the MNL model, its strong assumption on the preference homogeneity has driven researchers to develop alternative models to relax this limitation. Among these models, the mixed logit model (MLM) and the LCM have received the most attention from researchers and analysts (Greene and Hensher, 2003). The MLM relaxes the preference homogeneity assumption by allowing the parameters to change following a user-defined distribution across individuals. As an alternative to the MLM, the LCM assumes that individual behavior not only depends on observed attributes but also on heterogeneity that varies with unobserved factors. Since both models have its pros and cons, many comparisons between the two models exist in the literature. Greene and Hensher (2003) compared the MLM with the LCM using road type choice data from New Zealand. The results showed that both the models provided attractive features compared to the MNL model but they did not conclude which model is superior to the other. Shen (2010) carried out a comprehensive comparison using two stated choice survey datasets from Japan. His results suggested that the LCM outperformed the MLM in both datasets.

While LCM has been widely applied in marketing research, this model has limited application to discrete choice analyses or in transportation-related studies. Bhat (1997) and Srinivasan et al. (2009) have applied the LCM approach to look at mode choice behavior. Results indicated that the inherent preferences for travel modes and level-of-services sensitivity were distinctive among the population segments. Xiong et al. (2014) developed the LCM for the departure time choice analysis in the Maryland side of the Capital Beltway (I-495) where significant heterogeneity was revealed in drivers’ preference toward HOV/HOT lane usage. A couple of studies in transportation safety also employed the LCM approach to capture the existence of risk segmentation within the accident population (Eluru et al., 2012; Xie et al., 2012). In terms of car ownership behavior, Anowar et al. (2014) first introduced the LCM approach to this transportation domain. Using the data from Quebec City, Canada, their study focused on the comparison between the latent class unordered response model and the latent class ordered response model.

3. METHODOLOGY AND MODEL SPECIFICATION
This paper aims at exploring factors that influence the car ownership behavior of Maryland area residents. The correct estimation of parameters in the discrete choice model is critical in understanding what roles car ownership determinants actually play. The standard MNL models used in car ownership researches assume that model coefficients remain the same across the entire population. This strong assumption may not strictly hold and sometimes leads to bias in parameter estimation. Consider the following case for example: It is intuitive for households with higher income to own more vehicles. However, this may not be the case for people who enjoy transit. When commuting, transit could free users from driving and allow them to play with their smartphones, read the newspaper or relax. In the event of congestion, transit lovers tend to take metro rather than get stuck in the traffic. This is especially true for residents in our study area, since the State of Maryland and the Baltimore and Washington Metropolitan area consistently rank as two of the most congested areas in the country (Cheston et al., 2008). For those households, increasing level of income does not necessarily result in owning more cars. This example illustrates the importance of capturing the preference heterogeneity.

The LCM assumes that households can be probabilistically assigned to several behaviorally similar classes that are determined by observed/unobserved attributes. The car ownership behavior is conditioned on the probability which class the household belongs to (Bhat, 1997). Therefore, the preference heterogeneity is captured by the population segmentation. The term latent class comes from the fact that these classes are not directly observable to researchers. In this study, the fundamental behavioral model is a logit model where the class-dependent car ownership choice follows random utility maximization modeling form. The probability \( P_{ij|k} \) that household \( i \) belonging to class \( k \) owns \( j \) cars is formulated as:

\[
P_{ij|k} = \frac{\exp (\beta_j X_{ij})}{\sum_m \exp (\beta_m X_{im})}
\]

where \( \beta \) is the vector of class \( k \) dependent parameters for the vector of explanatory variables \( X_{ij} \). Explanatory variables in this study include two main types of variables: household socio-demographic and land use variables. Detailed description for the explanatory variables is carried out in Section 4.

The LCM simultaneously estimates the probability \( H_{ik} \) of segment membership (Equation 2). This could be considered as adding another level to the class-dependent car ownership choice model. The variables that influence a particular household \( i \) belonging to class \( k \) are termed segmentation variables.

\[
H_{ik} = \frac{\exp (\gamma_k Z_i)}{\sum_k \exp (\gamma_k Z_i)}
\]

where \( \gamma \) is the vector of parameters for the vector of segmentation variable \( Z_i \).
Then, the unconditional probability of household $i$ choosing alternative $j$ can be expressed as the product of the probabilities defined in Equation 1 and Equation 2.

$$P_{ij} = \sum_{k=1}^{K} P_{ij|k} H_{ik}$$  \hspace{1cm} (3)

The log-likelihood function for the whole dataset is

$$LL = \sum_{i} \sum_{j} y_{ij} \ln P_{ij}$$  \hspace{1cm} (4)

where $y_{ij}$ is a dummy variable which is equal to 1 when household $i$ made choice $j$ and 0 otherwise. The model estimation method follows the likelihood maximization method. The software used in this study is Python Biogeme Version 2.2 (Bierlaire and Fetiarison, 2009).

The number of population classes $C$ is determined based on the Akaike Information Criterion (AIC) and the Consistent AIC (CAIC) (Louviere et al., 2000; Xiong et al., 2014). They are specified as

$$\text{AIC} = -2[LL - C \cdot N_b - (C - 1) \cdot N_c]$$  \hspace{1cm} (5)

$$\text{CAIC} = -2LL - [C \cdot N_b + (C - 1) \cdot N_c - 1] \cdot [\log(2N_o) + 1]$$  \hspace{1cm} (6)

where $N_b$ is the number of parameters in the behavioral choice model. $N_c$ denotes the number of parameters in the class membership model. $N_o$ represents the total number of observations. In this study, the two population classes give the best AIC and CAIC values.

4. DATA AND VARIABLES

The proposed latent class model is developed using the 2007/2008 Household Travel Survey (HTS) data conducted jointly by the National Capital Region Transportation Planning Board (TPB) and Baltimore Metropolitan Council (BMC). The survey was carried out from February 2007 to April 2008 in the Washington and Baltimore metropolitan area where information of 14,365 households was collected. Information recorded includes demographic, socioeconomic and trip making characteristics of Baltimore and Washington metropolitan area residents (TPB, 2010). Descriptive statistics are presented in Table 1.
TABLE 1 Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household size</td>
<td>2.18</td>
<td>1.21</td>
</tr>
<tr>
<td># of workers</td>
<td>1.18</td>
<td>0.85</td>
</tr>
<tr>
<td># of vehicles</td>
<td>1.73</td>
<td>1.05</td>
</tr>
<tr>
<td># of lic. drivers</td>
<td>1.63</td>
<td>0.75</td>
</tr>
<tr>
<td>Residential location (1=urban)</td>
<td>0.29</td>
<td>0.45</td>
</tr>
<tr>
<td>Housing tenure (1=own)</td>
<td>0.77</td>
<td>0.42</td>
</tr>
<tr>
<td># of observations</td>
<td></td>
<td>14,365</td>
</tr>
</tbody>
</table>

The dependent variable in this study (number of cars owned at the household level) is categorized into four values: 0 (8.47%), 1 (35.95%), 2 (37.68%) and 3+ (17.90%). In this dataset, each household owns an average of 1.73 cars, which indicates high auto-dependence in the Maryland area. In terms of explanatory variables, mainly two types of variables are included in this study: household socio-demographic characteristics and land use characteristics. Household socio-demographic characteristic variables include household size, annual income, number of workers, number of licensed drivers and housing tenure (1=owned, 0=rented). In the literature, studies find that households with higher income, larger household size, more workers and drivers are more likely to own multiple cars (Bhat and Pulugurta, 1998; Chu, 2002).

As indicated in previous studies, land use patterns significantly influence households’ car ownership decisions (Bhat and Guo, 2007). The literature suggests that households living in urban areas, densely populated areas or transit-friendly areas are less likely to own a car. This is due to the limited parking availability and close access to non-driving travel modes in densely populated areas. Also, rural households are more auto-dependent. (Chu, 2002; Potoglou and Kanaroglou, 2008). In this paper, land use characteristic variables like population density, employment density, residential location (1=urban, 0=non-urban) and transit accessibility are included. Population density and employment density are calculated using the activity information from the Maryland Statewide Transportation Model (MSTM) at the traffic analysis zone (TAZ) level.

Transit accessibility is another important determinant of car ownership decisions. Past studies found that households living in transit-oriented development (TOD) areas have lower car ownership rates as opposed to non-TOD residents (Nasri and Zhang, 2014). It is also intuitive to have fewer cars when transit services are within easy reach. In this study, transit accessibility measures are calculated using the popular Hansen Accessibility approach (Hansen, 1959):

\[ A_i = \sum_j W_j^a \cdot \exp(-\beta \cdot t_{i,j}) \]  

(7)
where $A_i$ is the accessibility in zone $i$. $W_j$ denotes number of activities in zone $j$. $t_{i,j}$ represents the impedance (transit peak travel time) between zone $i$ and $j$. $\alpha$ and $\beta$ are parameters defining the weight of dense areas and the influence of travel time. In this study, $\alpha$ and $\beta$ are set to 1.5 and -0.3 respectively. These parameters were set heuristically. $\alpha$ helps emphasizing urban centers, while $\beta$ determines the burden of travel time. Various settings were tested by the authors ([http://tfresource.org/accessibilities](http://tfresource.org/accessibilities)), and the proposed setting was found to represent reasonably well access to transit in this study area. Figure 1 visualizes transit accessibility in Maryland and surrounding areas.

![Transit Accessibility Index in Maryland and Surrounding areas](image)

**FIGURE 1 Transit Accessibility Index in Maryland and Surrounding areas**

5. **ESTIMATION RESULTS**

In this paper, a standard MNL model serves as the benchmark model. The LCM then is compared with the benchmark model in terms of model interpretation capability and goodness-of-fit. Various performance measures are then presented to facilitate the comparison. Detailed information is given as follows.

5.1 **Multinomial Logit Model**

Estimation results of the MNL model are listed in Table 2. In this model, car ownership levels are specified as four choices (0, 1, 2 and 3+). Households owing zero car are set as the reference level. The overall effects of explanatory variables to the car ownership decision are mostly as expected and in accordance with the literature. Households with more workers, higher annual income, more licensed drivers and owned houses are more
likely to own multiple cars. Also households who live in the more urban areas or areas with higher household and employment density are less likely to own multiple cars.

However, we can observe some counter-intuitive results as well. For the impacts of household size variable, it is naturally to assume that households with more people are more likely to own more vehicles. But the negative signs of the household size coefficients in this study indicate the opposite. This may be due to the complication of the racial composition in Maryland and larger size households do not necessarily result in owning more cars. For instance, a large family with few workers or low income would not guarantee owning more cars. The effects of the variable number of workers are more persuasive since households with more workers tends to have higher income levels.

Another important finding from Table 2 is that transit accessibility has mixed effects on car ownership decisions in Maryland. Households with more convenient access to transit are less likely to own 1 car but more likely to own 2 or more cars. This mixed phenomenon has motivated us to explore alternative modeling tools to look at the impacts of transit accessibility on car ownership choices. Results indicate that the LCM can provide a better explanation on the effects of transit accessibility. Detailed information is carried out in the following sections.

<table>
<thead>
<tr>
<th>Variables</th>
<th># of Vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Values</td>
</tr>
<tr>
<td>ASC</td>
<td>-0.949</td>
</tr>
<tr>
<td># of workers</td>
<td>0.34</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.373</td>
</tr>
<tr>
<td>Household income</td>
<td>0.122</td>
</tr>
<tr>
<td># of lic. drivers</td>
<td>2.78</td>
</tr>
<tr>
<td>Housing tenure</td>
<td>1.02</td>
</tr>
<tr>
<td>Residential location</td>
<td>-0.727</td>
</tr>
<tr>
<td>Household density</td>
<td>-0.0772</td>
</tr>
<tr>
<td>Employment density</td>
<td>-0.0257</td>
</tr>
<tr>
<td>Transit accessibility</td>
<td>-0.036</td>
</tr>
</tbody>
</table>

# of observations 14365
Log likelihood -10878.315
Pseudo $R^2$ 0.454

5.2 Latent Class Model
For the LCM approach, results of both the behavioral part and the membership part of the model are listed in Table 3. For the membership model, two population classes are identified and two segmentation variables are specified to characterize the population classes (household income, household size). The selection of the segmentation variables is carried out by trial and error and removing insignificant variables. Results illustrate that households with more annual income and larger household size are more likely to be assigned to Class 2. So Class 2 members can be characterized as higher-income households with more family members. These households tend to be families with children. In contrast, households in Class 1 tend to have lower income and smaller family size, which usually consists of families without kids.

Results show that households in Class 1 are more positively influenced by household size while it is the opposite in Class 2. This may be due to the reason that Class 2 households usually have children who are not able to drive. Therefore, increased family size does not result in owning more cars. In terms of transit accessibility, households in both classes become overall negatively impacted by higher access to transit. These result interpretations are more intuitive and can indicate that after capturing the preference heterogeneity, the estimation results become more plausible and class-specific. In terms of coefficient magnitude, while the number of workers has positive effects on both Class 1 and Class 2, the magnitude of the influence is distinct. The number of workers has a larger impact on households in Class 1 than those in Class 2. This is because households in Class 1 usually do not have children and their car ownership decision is more related to how many people in this household have a job and need access to cars. In contrast, the variable number of workers has less impacts on the car ownership decision of Class-2 households due to other determinants (e.g. child-related needs). This also indicates that the LCM could capture additional latent information than the MNL model.

However, limitations still exist in the LCM approach. There are still a couple of parameters in the LCM that are unreasonable (e.g. higher transit accessibility massively increasing the probability for 3+ autos for Class 1). Additionally, the pseudo $R^2$ is only improved from 0.454 to 0.457, which indicates that the LCM fails to significantly enhance the goodness-of-fit. Inclusion of the error components could potentially account for unobserved heterogeneity across the observations, which is likely to improve the goodness-of-fit.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Class 1</th>
<th></th>
<th>Class 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>ASC</td>
<td>-</td>
<td>-46.1 -0.03</td>
<td>-54.1 -0.03</td>
<td>-64.5 -0.04</td>
</tr>
<tr>
<td># of workers</td>
<td>-</td>
<td>0.962 2.78</td>
<td>1.55 4.28</td>
<td>1.89 5.07</td>
</tr>
<tr>
<td>Household size</td>
<td>-</td>
<td>0.188 0.08</td>
<td>1.75 0.7</td>
<td>0.195 0.08</td>
</tr>
<tr>
<td>Household income</td>
<td>-</td>
<td>0.51 5.28</td>
<td>0.594 6.11</td>
<td>0.629 6.43</td>
</tr>
<tr>
<td># of lic. drivers</td>
<td>-</td>
<td>46.7 0.03</td>
<td>50.4 0.03</td>
<td>54.9 0.03</td>
</tr>
<tr>
<td>Housing tenure</td>
<td>-</td>
<td>1.53 4.5</td>
<td>2.94 7.79</td>
<td>3.68 7.2</td>
</tr>
<tr>
<td>Residential location</td>
<td>-</td>
<td>-0.25 -0.7</td>
<td>0.73 1.63</td>
<td>-0.812 -1.09</td>
</tr>
<tr>
<td>Household density</td>
<td>-</td>
<td>-0.111 -5.52</td>
<td>-0.26 -9.83</td>
<td>-0.968 -9.93</td>
</tr>
<tr>
<td>Employment density</td>
<td>-</td>
<td>0.252 1.98</td>
<td>0.178 1.29</td>
<td>-1.72 -3.02</td>
</tr>
<tr>
<td>Transit accessibility</td>
<td>-</td>
<td>-0.669 -2.39</td>
<td>-0.422 -1.4</td>
<td>3.41 4.59</td>
</tr>
</tbody>
</table>

### Membership Probabilities

<table>
<thead>
<tr>
<th>Variables</th>
<th>Values</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC</td>
<td>1.4</td>
<td>6.98</td>
</tr>
<tr>
<td>Household income</td>
<td>-0.0367</td>
<td>-2.55</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.271</td>
<td>-3.93</td>
</tr>
<tr>
<td>Income * HH Size</td>
<td>0.0117</td>
<td>2.3</td>
</tr>
</tbody>
</table>

| # of observations | 14365 |
| Log likelihood    | -10458.145 |
| Pseudo $R^2$      | 0.457  |
6. IMPLICATIONS OF FINDINGS AND FUTURE DIRECTIONS

The primary objective of this paper is to explore the factors that influence household car ownership decisions in the Washington and Maryland area. Despite the popularity of the MNL model in car ownership modeling, its assumption of preference homogeneity might lead to biased results. Recognizing this modeling limitation, we propose a LCM approach to capture the preference heterogeneity in car ownership choices. Results confirm the existence of population segmentations and the distinct behavior of the segments. Compared with the MNL model, the LCM further explores the decision determinants and provides more in-depth behavioral interpretation. These advantages of the LCM could further assist the decision-making process.

Two population classes are identified in this study. Two segmentation variables (household size and household income) are employed to characterize the population classes. We notice that transit accessibility, which previously tends to have an overall positive in the MNL models, has an overall negative impact on car ownership model in the LCM. These different coefficient interpretations illustrate better analysis capability of the LCM over the MNL. Compared with variables in the MNL, variables in the LCM are more consistent and illustrative. Results indicate that mixed/unclear effects can be better documented by means of the LCM approach.

With the rapid development and advances in technologies, it has been more and more recognized by researchers in various domains that choice behavior occurs in a dynamic context. This is especially the case for car ownership behavior due to the strong correlation among car-purchasing decisions at different time points. Future research could focus on taking into account the temporal interdependence in the decision-making process. Dynamic models could provide more accurate results in the mid-term and long-term travel demand forecasting (Xiong and Zhang, 2015; Xiong et al., 2015).
7. REFERENCES


Cirillo, C. (2010). Automobile Ownership Model. Published by The National Center for Smart Growth Research and Education at the University of Maryland.


