Scientia Iranica, Vol. 8, No. 1, pp 29–37
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SCIENTIA
IRANICA

Modeling Automobile Ownership Decisions: A Disaggregate Approach

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In this paper, a disaggregate model is developed for household car ownership based on a data set from the city of Mashad. The approach adopted in this study is a two-level nested logit in which conditional probability of owning one car vs two or more is modeled at level 1, then marginal probability of owning a car is modeled at level 2. Seven groups of descriptive variables, each including one or more variables divided into two separate classes for each level, were employed in the model building process. Household demographics and socio-economic indicators, including head of the household characteristics like gender, age and occupation, as well as life style and life cycle stage, were among the variables which showed significant effects on car ownership. Results demonstrate the appropriateness of the nested logit structure and reject the application of the simple multinomial logit models when the IIA property is not valid. Necessity of data sets with rich information, more appropriate for disaggregate modeling applications, is further recommended.

INTRODUCTION

The significant impact of car ownership on the socio-economic life of urban societies is evident. The level of car ownership and car usage has considerable effects on urban socio-economic activities, resulting in the final shapes of land use and urban plans to be highly affected. There are few aspects of urban life in which the effects of car ownership are not clearly observed. Many organizations and governments are interested in future level of car ownership and car usage, since without such information no planning effort can be accomplished and no correct solution for future demand can be expected. Moreover, car owners and users are considered important sources of government revenue [1].

Car ownership is considered an important element of the transportation performance structure. It is highly interlinked with demand for public transportation; as the level of car ownership increases public transportation patronage decreases [2]. Increasing car ownership is accompanied by more energy consumption and more car trips: consequently, inadequacy of transportation infrastructure is expected and more congestion is inevitable [3].

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BACKGROUND

Forecasting car ownership and car usage has been a subject of interest and attention for many researchers and transportation planners, playing an important role in the urban transportation planning process. Trip making behavior of a household is highly influenced by household car ownership. Historically, car ownership has been found to be the most important variable in trip generation models [4] and a major determinant of modal choice models [5]. Thus, understanding the decisions underlying the car ownership process is regarded as a prerequisite to demand analysis and forecasting.

In most transportation studies, car ownership has bridged the gap between urban land use models, which focus on the spatial pattern of urban activities and the 4-step urban transportation planning process of trip generation, trip distribution, modal split and route assignment [6]. In spite of car ownership playing a significant role in the usage of transportation systems in urban areas, car ownership forecasting has usually performed outside the main process of demand estimation. In the past, methods such as extrapolation or correlation with one or two variables (rather than causal relationships) have been widely employed for car ownership forecasts [6]. Most of these approaches are aggregate in their nature and describe car ownership as a function of residential density [7], family income [8] or zonal demographic and socio-economic characteristics [9]. In recent years, however, an extensive effort has been devoted to subjects like car ownership and car purchase [6,10,11] or car usage [12]. In these approaches, mainly behavioral attempts have been made to investigate the underlying structure of household car purchase decisions.

The main objective of this study is to investigate patterns of household car ownership and develop a disaggregate model based on household socio-economic characteristics. In this approach, factors affecting car purchase or loss possess socio-demographic identity, in the way that young members of a family create new households, or a member gets employed in a new position [13,14]. This study defines household as the unit of ownership investigation and analysis. Such a definition is compatible with disaggregate demand models.

STUDY APPROACH AND MODEL STRUCTURE

This study employs the utilitarian approach of microeconomic concepts [15] and uses the nested or hierarchical logit model structure [16]. Appropriateness of the approach in car ownership modeling has been indicated by many researchers [e.g.,17,18]. In this approach, when an individual or a household encounters a set of alternatives, they evaluate them based on their characteristics defined through utility functions. The alternative with the most utility is, then, selected. A brief description of the concept is as follows.

Let U represent utility of an alternative consisting of two parts of representative utility V and random term ε, i.e., for alternative i,

$$U_i = V_i + \varepsilon_i. \tag{1}$$

The measurable utility of the i alternative, V_i, is defined as a function of its characteristics as well as the socio-economic characteristics of the decision maker. The random term, ε_i, reflects unobservable attributes of both alternative and the decision maker.

The logit model assumes that the random term in utility function is independently and identically distributed with Gumbel extreme-value distribution [19]. The model formulation is as follows:

$$P_i = \frac{\exp(V_i)}{\sum_{j\in J}\exp(V_j)}, \tag{2}$$

where P_i represents the probability that i is selected and J is the set of alternatives.

A major drawback of the logit structure is attributed to the lack of Independence of Irrelevant Alternatives (IIA) property [e.g., 20]. (The famous example of red bus-blue bus represents such a drawback very well.) In cases when the property is not valid anymore, the probit structure has been suggested [21]. However, more parameters need to be estimated when the probit model is employed, resulting in a less efficient model [22]. The nested or hierarchical logit model has been proposed as an alternative to the probit model in recent years [16,23]. The model can appropriately overcome the shortcomings of the simple logit model when lack of the IIA property is encountered [e.g., 23].

Car ownership decision can be formulated as a choice process among different alternatives using nested logit structure. Figure 1 demonstrates such a structure. The objective of the upper level logit model (Model B) is predicting the relative probability of owning a car as compared to not owning a car. The lower level logit model (Model A) provides information regarding the relative conditional probability of owning one car compared to owning two or more cars, given that car ownership exists. The methodology employed is to model the lower nest first (Model A at level 1) and then include its effect on the upper nest (Model B at level 2) through an inclusive value. The information is transferred from the lower level to the upper level through the inclusive value, or as sometimes called, the expected maximum utility of the members of the nest [23,24]. Steps in car ownership model development are as follows:

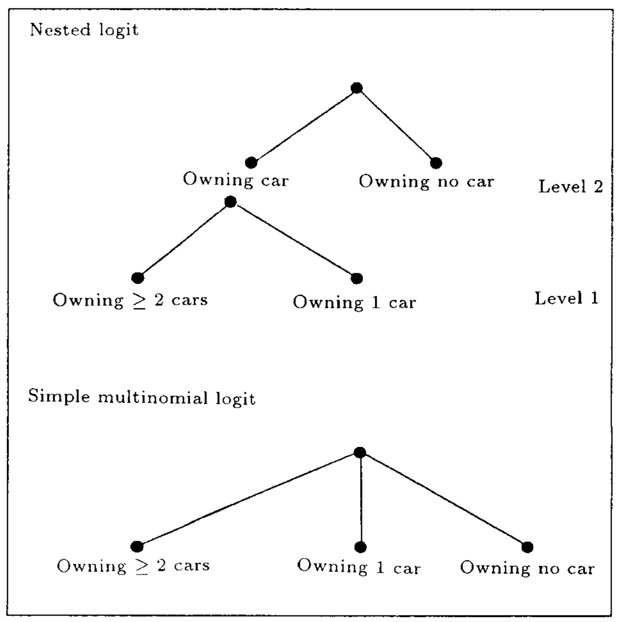

Figure 1. Nested logit and simple multinomial logit structures in car ownership models.

1. Conditional choice probability at level m for two alternatives "owning 1 car" vs. "owning ≥ 2 cars" is:

$$P(m^*\backslash k) = \frac{\exp(V_{m^*})}{\sum_{m\in M_k}\exp(V_m)}. \tag{3}$$

2. The inclusive value is calculated by the following equation:

$$I_k = \ln \sum_{m\in M_k} \exp(V_m). \tag{4}$$

3. Marginal choice probability at level k for two alternatives "owning car" vs. "owning no car" is :

$$P(k^*) = \frac{\exp(V_{k^*} + \theta_{k^*}.I_{k^*})}{\sum_{k\in K}\exp(V_k + \theta_k.I_k)} \tag{5}$$

4. Marginal choice probability at level m is as follows:

$$P(m^*) = P(k^*).P(m^*\backslash k^*), \tag{6}$$

where:

$m =$	index representing alternatives on level 1,
$k =$	index representing alternatives on level 2,
$m^* =$	one particular m,
$k^* =$	one particular k,
$P(m^*\backslash k^*) =$	probability that m^* is selected at level 1, given that k^* is selected at level 2,
$P(m^*) =$	probability that m^* is selected,
$P(k^*) =$	probability that k^* is selected,
$M_k =$	set of alternatives on level 1 related to alternative k on level 2,
$V_k =$	representative utility of alternative k,
$I_k =$	inclusive value for the set of alternatives M_k on level 1 related to alternative k on level 2,
$\theta_k =$	coefficient of the inclusive value term.

The representative utility for alternative $i(V_i)$ in the above equations has the following general specification:

$$V_i = B_o + B_1\ X_{i1} + B_2\ X_{i2} + ... + B_k\ X_{ik} = X_iB', \tag{7}$$

where V_i is the utility of alternative i, B is the coefficient of variables, X is the explanatory variable for alternative i, $B' = (B_o, B_1, ..., B_k)'$ and $X_i = (1, X_{i1}, X_{i2}, ..., X_{ik})$.

The significant attribute of the nested logit structure is related to the acceptable range of the coefficient of the expected maximum utility variable (I_k). Accepted range of $0 < \theta \leq 1$ has been reported in relevant literature [16,23,24]. Any other result for θ would lead to incorrect forecasts. For $\theta = 1$, the nested logit structure is equivalent to simple logit model. The result may indicate the appropriateness of the nested logit model when employed for car ownership modeling.

One important limitation of using the sequential or nested logit estimation procedure is that the same explanatory variables cannot be used in the two different levels of the structure. This implies that the set of independent variables has to be partitioned into two sets, in order to be used for estimation of the lower and upper level models, respectively. Categorical data analysis is conducted on a set of potential explanatory variables for such partitioning. The variables are partitioned based on whether they are more significant at the lower level or the upper level.

The model goodness of fit statistic $L^*(C)$ is defined as:

$$L^*(C) = \sum x_i \ln(x_i/y_i), \tag{8}$$

where x_i is the number of observations in the estimation data set that have selected alternative i and y_i is the total number of observations with alternative i available (including those who selected alternative i). The overall measure of goodness of fit, ρ^2, is similar to R^2 with its value between 0 and 1 [19,25]. The index for a sequential nested logit model is given by the following formula:

$$\begin{aligned}\rho^2 =& 1 - \{[L_1^*(\beta) + L_2^*(\beta) + ... + L^*j(\beta)]/\\ &[L_1^*(0) + L_2^*(0) + ... + L^*j(0)]\},\end{aligned} \tag{9}$$

where the subscripts 1 through j refer to the j simple logit model in the structure of interest, $L_i(0)$ is the initial log-likelihood of the ith model and $L_i(\beta)$ is the log-likelihood at the convergence.

Model calibration in this research was conducted by Maximum Likelihood Estimation (MLE) method using GAUSS software.

DATA SET AND VARIABLES

This section briefly describes the data set and the procedure employed for developing the key descriptive variables in car ownership model estimation for the city of Mashad. The holy city of Mashad is the capital of Khorasan, a province in the north east of Iran. With a population of around 2.0 million in 1994, the average age in the city is young. The importance of Mashad is in commerce and tourism, mainly pilgrims of the eighth Shiite leader, Imam Reza. A rather large university and many educational religious centers in the city have made Mashad a major center of education in that region of the country. In recent years, the city has also been the host of many Afghanis, as well as people from new independent states in the north.

A 25% random sample from the Mashad Comprehensive Transportation Study (MCTS) has been employed in this study. The data were gathered in 1994 from the city of Mashad. The data set utilizes 3,964 households from population of about 400,000 households. The resulting sample households are scattered throughout the city of Mashad consisting of 141 traffic zones. The sample includes household information on residence location, size, car ownership, individual's characteristics including, sex, age, occupation and trip records. Table 1 presents car ownership distributions for the sample employed in this research and for its population. As it is expected, the sample is well representative of population with respect to car ownership characteristic.

The extensive set of explanatory variables used in the model development process are presented in Table 2. The variables are grouped into seven categories. Some variables have been defined as dummies in order to capture irregularities as nonlinearities in household car ownership patterns more properly. (For two different applications of dummies in relevant subjects, see e.g., [2,26].) The first category of variables describes the demographic characteristics of the household by number of household members, i.e., household size. Household life cycle, shown in the second group, has been defined by the presence and age of children. The third group includes household socio-economic characteristics such as number of workers and zonal average residential land area per person. Information on land area has been obtained from a separate survey conducted on residential units sold in Mashad in 1994. This variable is employed as an approximate surrogate for households economic status. Head of household demographics comprise the fourth category of the descriptive variables, which are age and gender. The fifth group of variables consists of head of household occupation. A set of dummy variables classifies earlier 16-group job categories. In the sixth group, household life-style is represented by the household level of out of home activity participation, i.e., trip making patterns. Average number of trips made by a household member has been categorized into three ranges of low, medium and high represented by dummy variables. Finally, the last category indicates transportation systems availability to the household. Highly available systems make households spend less time traveling, using more probably family cars.

Table 1. Household car ownership distribution.

No. of Cars	0	1	2	>= 3
Population	74.45	24.2	1.26	0.09
Sample	72.15	26.51	1.24	0.1

ESTIMATION OF CAR OWNERSHIP MODELS

Model A: "Owning 1 Car" vs "Owning ≥ 2 Cars"

Alternative	Name	Frequency
1	owning 1 car	1051
2	owning ≥ 2 cars	53

This is the lower level of logit model. A positive sign on the coefficient of a variable in the model means that the condition represented by that variable increases the relative probability of owning 2 or more cars (Alternative 2). A negative sign on the coefficient shows that the condition represented by that variable increases the relative probability of owning 1 car (Alternative 1). As mentioned earlier, the variables used in the formulation of Model A differ from those being used in the development of Model B. The variables have been selected after conducting a categorical (frequency) analysis on the data.

Table 3 shows the estimation results and summary of statistics of Model A. The model predicts a higher tendency of owning one car compared to two or more cars among large households. (A rather similar result has been reported elsewhere [14].) However, potential irregularities that may exist and can be depicted by dummy variables will be discussed later. The forementioned result might be attributed to the fact that in many instances negative association between household size and income has been reported (this is observed in Mashad as well). As expected, higher number of workers in the household increases the chance of owning 2 or more cars. The finding reveals that higher level of income may originate from the greater number of employed members in the household.

In households with heads at older ages, there is a higher probability of owning 2 or more cars than in younger ages. This means that most young couples in the early stages of their lives cannot afford a second car. The tendency, however, does not consistently hold in the whole range of head age, as will be seen later.

The significant effect of head of the household occupation on car ownership decision is observed from the relevant variable coefficients. The highest tendency of owning the second car is among households with heads that are employers (HDJOB4) and next are families with heads as retailers with a coefficient of about 50% (HDJOB5). When the head is a government employee, teacher or army personnel, the household most likely tends to own one car compared to two or more cars (the negative sign of HDJOB1 indicates such tendency). Regarding car ownership decisions, no significant difference was found among households with their heads unemployed compared to those involved in any other jobs not mentioned above. As a whole,

Table 2. Variables used in model formulation.

	1. Household Demographics
HHSIZE	Number of persons in the household
HHSIZE2	1 if household has 1 or 2 members
HHSIZE3	1 if household has 3 members
HHSIZE4	1 if household has 4 members
HHSIZE5*	1 if household has 5 or more members
	2. Household Life Cycle
NOCHLD	1 if household has no child
CHLDAGE < 6*	1 if age of the eldest child is less than 6
CHLDAGE: 6-11	1 if age of the eldest child is between 6 to 11
CHLDAGE: 12-18	1 if age of the eldest child is between 12-18
CHLDAGE > 18	1 if age of the eldest child is more than 18
CHLDAGE	Age of the eldest child
	3. Household Socio-Economic
WORKER	Number of employed persons in the household
WORKER1*	1 if at most one person is employed in household
WORKER2	1 if two persons are employed in household
WORKER3	1 if three or more persons are employed in household
LAND	Residential land per person (m^2)
LAND1*	1 if residential land per person is less than 50 m^2
LAND2	1 if residential land per person is between 50 to 100 m^2
LAND3	1 if residential land per person is between 100 to 150 m^2
LAND4	1 if residential land per person is greater than 150 m^2
	4. Household Head Demographics
MHEAD	1 if head is male
FHEAD*	1 if head is female
HEADAGE	Age of head
HEADAGE < 31	1 if age of head is less than 31 years
HEADAGE: 31-40	1 if age of head is between 31 and 40 years
HEADAGE: 41-50	1 if age of head is between 41 and 50 years
HEADAGE: 51-65	1 if age of head is between 51 and 65 years
HEADAGE > 65*	1 if age of head is greater than 65 years
	5. Household Head Occupation
HDJOB1	1 if head is government employee
HDJOB2	1 if head is worker or farmer
HDJOB3	1 if head is driver, foreman, or others
HDJOB4	1 if head is employer
HDJOB5	1 if head is shopkeeper or salesman
HDJOB6*	1 if head is not employed
	6. Household Life-style
NTRIP	Average number of trips per household member
LTRIP*	1 if number of trips per household member is less than 3
MTRIP	1 if number of trips per household member is 3 or 4
HTRIP	1 if number of trips per household member is more than 4
	7. Household Accessibility
TIME	Average household trip time (min.)
TIME < 40*	1 if average trip time is less than 40 min.
TIME: 40-80	1 if average trip time is between 40 and 80 min.
TIME: 80-120	1 if average trip time is between 80 and 120 min.
TIME > 120	1 if average trip time is greater than 120 min.

* Omitted variable

the model was noteable ($\rho^2 = 0.756$) and all variables appearing in the model had their expected signs.

In order to depict nonlinear effects by Model A, three interval variables; household size, number of workers and head age were substituted with three sets of dummy variables. Table 4 presents the results of Model A.1. The model predicts a higher chance of owning a second car among households with sizes 3 or 4. However, crowded households (indicated by HHSIZE5) are not significantly different from 2-member households as far as car ownership decisions are concerned. As seen, Model A was incapable of reflecting such nonlinear, yet significant, effects among households with different sizes.

Once again, the model supports the earlier findings that there is a higher tendency to purchase the second family car among families with a greater number of working members. Both WORKER2 and WORKER3 variables appeared with positive signs in the model, implying the higher probability of owning two or more cars as the number of workers increases. This strong tendency can also be observed as the coefficient of WORKER3 is greater than that of WORKER2 at higher confidence levels (1.558 vs 0.601). Note that the base households in the model are those with, at most, one member employed and the relevant variable (WORKER1) does not appear in Model A.1.

The households with the head aged between 41-65, in general, tend to own the second family car with higher probability compared to other households. The result is consistent with the earlier tendency presented by Model A. This could be explained by the fact that heads in this category are very active with a higher chance of money-making, which allows them to buy a second car. (The two groups, in fact, can be pooled into a single group as their coefficients and t values are almost identical.) Households with heads more than 65 are not found to be very different from those with heads younger than 41, where car ownership decisions are concerned. A rather similar effect of head's occupation on car ownership pattern is resulted from both Models A and A.1. Marginal superiority of Model A.1 over Model A may be attributed to the fact that Model A.1 has employed the same type of information more appropriately. The estimation results by Model A or A.1 can be used in the process of model calibration at level 2, with final models named Models B and B.1, respectively.

Interaction terms between household size and number of workers and between head age and head employment seemed to be insignificant, therefore, they were dropped from the final models. The goodness of fit of the model with $\rho^2 = 0.756$ is significant.

Table 3. Car ownership model: Model A.

Variable	Coefficient	t-Value
Constant	-4.430	-4.74
HHSIZE	-0.199	-1.91
WORKER	0.533	2.32
HEADAGE	0.033	2.07
HDJOB1	-0.909	-1.96
HDJOB4	1.785	3.61
HDJOB5	0.913	2.67

Statistics Summary of Model A	
Number of observations	1104
Number of parameters	7
Number of iterations	20
$L^*(0)$	-765.23
$L^*(C)$	-212.64
$L^*(\beta)$	-186.53
ρ^2	0.756

Table 4. Car ownership model: Model A.1.

Variable	Coefficient	t-Value
Constant	-4.442	-10.97
HHSIZE3	1.025	2.25
HHSIZE4	1.012	2.78
WORKER2	0.601	1.93
WORKER3	1.558	2.86
HDAGE: 41-50	1.076	2.71
HDAGE: 51-65	1.055	2.60
HDJOB1	-1.124	-2.32
HDJOB4	1.760	3.36
HDJOB5	0.883	2.54

Statistics Summary of Model A.1.	
Number of observations	1104
Number of parameters	10
Number of iterations	17
$L^*(0)$	-765.23
$L^*(C)$	-212.64
$L^*(\beta)$	-181.57
ρ^2	0.763

Model B: "Owning Car" vs "Owning No Car"

Alternative	Name	Frequency
1	owning no car	2860
2	owning car	1104

This model is the upper level logit model. As before, a positive sign on the coefficient shows that the condition represented by that variable increases the probability of owning a car (Alternative 2). A negative sign on the coefficient illustrates that the condition represented by that variable increases the probability of not having a car (Alternative 1).

The results and statistics summary of Models B and B.1 are shown in Tables 5 and 6, respectively. In this section, however, only a description of Model B.1 is presented in detail (A rather similar description may be expected from Model B in Table 5.) As seen from Table 6, the continuously increasing positive effects of the LAND variables (proxy variables for household income) imply the higher probability of car ownership in households with greater land ownership per household member. The effects of the variables are highly significant.

Table 5. Car ownership model: Model B.

Variable	Coefficient	t-Value
Constant	-7.010	-11.61
LAND	0.017	14.74
CHLDAGE	0.029	4.98
MHEAD	1.567	4.10
NTRIP	0.786	16.61
TIME	-0.022	-17.69
I_K from Model A	0.479	5.79

Statistics Summary of Model B	
Number of observations	3964
Number of parameters	7
Number of iterations	14
$L^*(0)$	-2747.64
$L^*(C)$	-2344.85
$L^*(\beta)$	-2020.69
ρ^2	0.265

Table 6. Car ownership model: Model B.1.

Variable	Coefficient	t-value
Constant	-6.118	-11.49
LAND2	0.840	10.18
LAND3	1.144	8.12
LAND4	1.358	5.43
CHLDAGE: 6-11	0.300	2.28
CHLDAGE: 12-18	0.585	5.56
CHLDAGE > 18	0.623	5.05
MHEAD	1.739	4.64
MTRIP	0.942	9.94
HTRIP	1.330	5.32
TIME: 40-80	-0.656	-6.66
TIME: 80-120	-1.485	-8.67
TIME > 120	-1.748	-7.77
I_K from Model A.1	0.543	7.13

Statistics Summary of Model B.1	
Number of observations	3964
Number of parameters	15
Number of iterations	8
$L^*(0)$	-2747.64
$L^*(C)$	-2344.85
$L^*(\beta)$	-2101.09
ρ^2	0.235

Age of the eldest child demonstrates significant effect on household willingness to buy a car. Households with no child or with a child (children) at preschool age are less likely to purchase a car compared to others. It seems that as the first child gets older, households' feelings about their mobility requirements become stronger. The tendency might be attributed to the household life cycle stage with its special needs and priorities.

Being male as the head of the household shows significant effect on car ownership decision. The result may be explained by the fact that the female heads are likely to be less active economically. The result, however, is not conclusive and needs further investigations, as few households in the sample have reported females as their breadwinners.

As the number of trips made by the household members increases, the probability of owning a car increases. Household life-style reflected by the level of out of home activity participation shows a significant effect on car ownership decisions as indicated in Table 6. Positive coefficients of MTRIP and HTRIP variables reveal such tendency adequately. Households with higher activity involvement (represented by HTRIP) display a higher probability of car purchase than other households.

The lack of access to transportation systems has been well captured by the continuously negative effect of TIME variables. The variables predict a higher chance of having no car among the households who spend greater daily travel time per person. Household members with no access to family cars have to ride public transportation more often and, as a result, encounter longer trip times and delays.

The expected utility variable (I_k) with its coefficient less than one ($= 0.543$) is highly significant at 0.05 level. The coefficient confirms the appropriateness of the nested logit structure employed in this study. The result suggests that there is a significant similarity between owning one car and two or more cars (Model A), thereby justifying the grouping of these two alternatives into a single alternative(owning car). It also proves that developing a simple multinomial logit model with three types of ownership as an alternative would have yielded incorrect results. In fact, Figure 2 compares the appropriateness of the nested logit vs simple multinomial logit with three alternatives. Nested logit structure shows a better fit than simple logit one.

While the goodness of fit for Model B.1 is significant ($\rho^2 = 0.235$), the overall fit for car ownership nested logit structure model (both A and B models) with $\rho^2 = 0.351$ is noticeable.

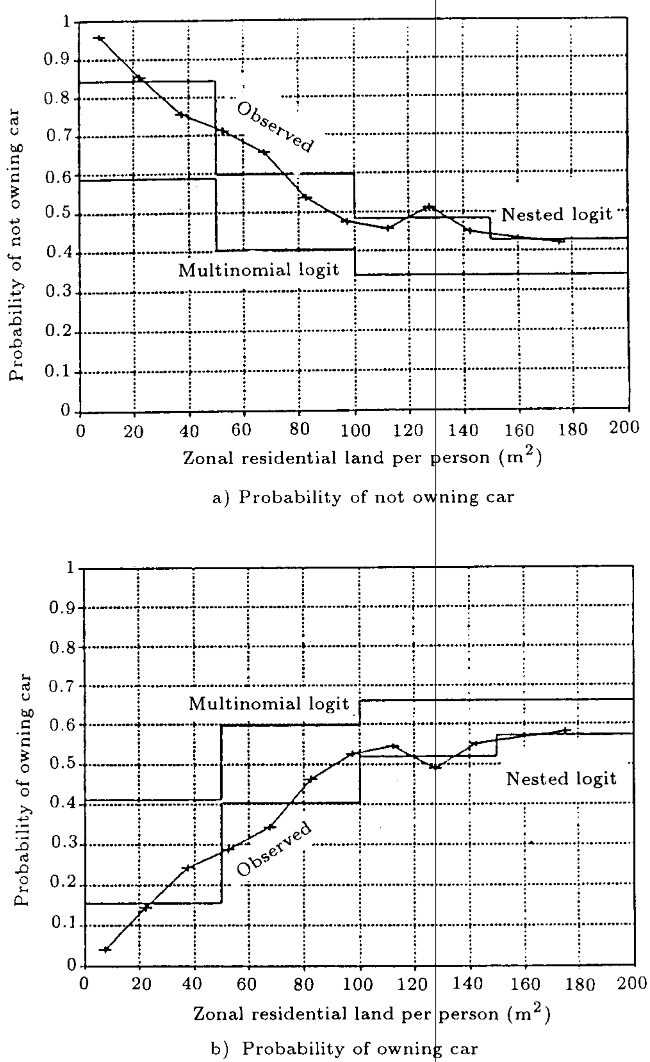

Figure 2. A comparative illustration of car ownership probability estimations by the nested logit and simple multinomial logit models for a given household HHSIZE = 3, WORKER = 1, CHLDAGE = 10, MHEAD = 1, HEADAGE = 40, HDJOB1 = 1, NTRIP = 2.5, TIME = 60.

SUMMARY AND CONCLUSIONS

This study, based on the utilitarian concept of choice theory and employing the nested logit model structure, develops a disaggregate model for car ownership. The nested model provides an appropriate tool when violation of the independence of irrelevant alternative assumption underlying the simple logit model is expected. The model, however, is as simple as the logit one.

Two-level model of car ownership was developed for the sample of households from the city of Mashad. In the lower level of car ownership model, the conditional choice probabilities of a household's two alternatives: owning one car vs owning two or more cars, given that household owns a car, were determined by a simple binary logit model. Household size, number of workers and head of the household's age and occupation were identified as factors with significant effects on household car ownership. Larger households are less likely to purchase the second family car. Households with their heads in high income positions tend to have more than one car. Government employees and teachers usually own one car. Greater number of moneymakers in a household increases the probability of a second car purchase.

In the upper level, the marginal choice probabilities of two alternatives: owning car vs owning no car were determined by a binary logit model. Households with a better socio-economic status indicate a higher tendency to owning car. Late stages in household life cycle, represented by the age of the eldest child, showed significant effect on car purchase. A rather similar tendency was observed among households with male heads.

Furthermore, life-style and household access to transportation systems had a significant effect on car ownership decisions. Any improvement on transportation systems leading to lower values of trip time would imply a lower probability of car ownership. The expected maximum utility from the lower level indicated a positive effect on car ownership decisions. The coefficient value of less than one approves the validity of the nested logit structure employed in this study.

The results of the car ownership models developed in this study are promising. While the nested logit structure, employed in this study, benefits from the advantages of the simple logit, it also handles possible association among alternatives appropriately. This study is also regarded as the first disaggregate car ownership model developed based on a sample from a city in Iran.

As a first step towards the development of a disaggregate model of car ownership in Iran, this study faced several limitations. In general, the data set was not designed for developing disaggregate models. Not all the information usually required for descriptive variables of car ownership models was found in the data set. For example, no data was available on possession of driver's licence by household members, or information about household income was not collected during the survey in Mashad in 1994.

As a whole, the research presents some significant characteristics of car ownership models which can be extended and improved in future. In this regard, preparing well structured questionnaries including more appropriate pieces of information is very important. Also, more precise and appropriate assignments of dummy variables to interval variables may be accomplished through the one-way analysis of variance process. The result would lead to better definitions of groups to be represented by the dummies.

ACKNOWLEDGMENT

The authors wish to thank Mashad Traffic Organization for providing 1994 Mashad Comprehensive Transportation Study (MCTS) available for this research. Also, the support of Sharif University of Technology is fully appreciated.

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