Vehicle Ownership Modeling Framework for the State of Maryland: Analysis and Trends from 2001 and 2009 NHTS Data

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Abstract: This paper presents a vehicle ownership modeling framework for the state of Maryland estimated on data extracted from the 2001 and 2009 National Household Travel Survey. The framework consists of vehicle ownership models and vehicle usage models; the models are based on a wide variety of sociodemographics, land-use variables, and operating cost. The models' results and the deriving sensitivity analyses show that changes in income and unemployment rate or compact development have little effect on vehicle ownership rates. Nevertheless, the combined effect of high density and increase in fuel cost produce a significant reduction in vehicle usage. The vehicle ownership model estimated on 2001 data has been successfully incorporated into the Maryland Statewide Transportation Model (MSTM). **DOI: 10.1061/(ASCE)UP.1943-5444.0000128.** *© 2013 American Society of Civil Engineers.*

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Introduction

Over the last few decades, the average number of cars per household and the proportion of households with access to more than one vehicle has grown significantly in the United States. Increasing energy costs and awareness about climate change, however, are forcing citizens to reduce energy consumption and emissions and public authorities to study how policies might impact travel behavior. Understanding and predicting consumers' preferences regarding vehicle ownership and use is important given the consequent impacts on both transportation and land-use planning and the relationship to energy consumption, environment, and health (Sinha 2003; Tam and Lam 2004; Oakil et al. 2011). The number of cars in a household has been found to be a major determinant in trip/tour/chain-making behavior and mode choice for individuals and households (Nobile et al. 1996; Ghaeli and Hutchinson 1998). Greenhouse gas (GHG) emissions from the U.S. transportation sector accounts for 27% of the GHG emissions of the entire U.S. economy and 30% of the world's transportation GHG emissions (Greene and Plotkin 2011).

Models for predicting changes in the level of vehicle ownership have been developed and applied in several countries: the Netherlands (de Jong 1996; AVV 2000), Norway (Hague Consulting Group and TØI 1990), the U.K. (MVA Consultancy 1996; Romilly et al. 1998; Whelan 2007), Australia (Hensher et al. 1992), the United States (Mannering and Winston 1985; Train 1986), Singapore (Chin and Smith 1997), and Malaysia (Joevono et al. 2008). On a smaller geographical scale and given the focus of the present paper, it is necessary to note that the Baltimore Regional Transportation Board (Baber 2004) developed auto availability models using 2000 Public Use Microdata Sample (PUMS) and 2001 National Household Travel Survey (NHTS) data. These studies focus, in general, on vehicle ownership or car usage, but some are based on more comprehensive modeling framework, whose components are usually calibrated on disaggregate data.

Two decision mechanisms of disaggregate models have been used for vehicle ownership modeling in the literature: the unordered-response mechanism (MNL) (e.g., Mannering and Winston 1985; Train 1986; Hensher et al. 1992) and the ordered-response mechanism (ORL) (e.g., Golob 1990; Kitamura and Bunch 1992; Hanly and Dargay 2000; Cao et al. 2007). The latter has been recently fallen into disuse because the superiority of MNL over ORL has been demonstrated in a number of empirical studies on the basis of different data sets (Bhat and Pulugurta 1998; Potoglou and Karoglou 2008). The vehicle ownership attributes adopted in existing studies (e.g., Berkovec 1985; Train 1986; Kitamura and Bunch 1992; Dargay and Vythoulkas 1999; Whelan 2007) can be classified into four categories: (1) information on the household, (2) information on the household head or primary driver, (3) land-use factors, and (4) car attributes.

Vehicle usage is a major component in many vehicle ownership modeling frameworks. Early studies mainly estimated vehicle miles traveled (VMT) by general regression models (Mannering and Winston 1985; Train 1986; Hensher et al. 1992; Kitamura et al. 1999). However, ordinary least-squares estimation for regression models might be biased when some endogenous variables (such as operating cost) enter the model. To solve this problem, an instrumental variable estimation method could be adopted. Existing studies on vehicle usage with regression models mainly developed instrumental variables on the basis of household and household head characteristics, and on vehicle and land-use variables (Train 1986).

More recent research works have proposed discrete continuous extreme value model formulation to analyze the choice of vehicle

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type/vintage/make/model and usage. Household demographics, household location characteristics, built environment attributes, household head characteristics, and vehicle attributes are used to explain vehicle ownerships and use (Bhat et al. 2009). Mixed logit has been applied to investigate the reasons behind the erosion of the U.S. automobile manufacturers' market share during the past decade. The model accounts for the influence of vehicle attributes, brand loyalty, product line characteristics, and dealerships on choice (Train and Winston 2007).

Transportation analysts have also been trying to account for dynamic effects in vehicle ownership modeling to incorporate intertemporal (uncertainty of financial position in the future) and intratemporal (acquired taste for a certain lifestyle) dimensions. Nobile et al. (1996) estimated a random effect multinomial probit model for vehicle ownership using panel data drawn from several waves of surveys held between 1985 and 1988 in the Netherlands; the model accommodates both intratemporal and intertemporal correlation. A recent paper by Rashidi et al. (2010) uses panel data (10 waves from 1989 to 2002) collected in Seattle and its surrounding areas to calibrate a model system of hazard-based equations in which timing of residential relocation, job relocation, and vehicle transaction are the endogenous variables. In an earlier paper, Mohammadian and Miller (2003) proposed a market-based decision-making process, and a transaction approach was applied to solve inconsistency in decision makers' choices. Each year a decision maker was supposed to face four choices: add a new vehicle to the fleet, dispose of one vehicle, trade one of the vehicles in the fleet, or do nothing. A mixed (random parameters) logit model was used to investigate the effects of heterogeneity in the dynamic transaction model and distinguish between heterogeneity- and state-dependence-based explanations for the observed persistence in choice behavior. Finally, in the context of dynamic models for vehicle ownership, Russo and Chilà (2007) proposed a sequential approach on the basis of panel data to model vehicle ownership choices in time.

This study reports on disaggregate models of car availability and use developed for the state of Maryland by using data extracted from the National Household Travel Survey. The study aims at comparing results obtained from the 2001 sample to those that will be obtained by using the NHTS sample relative to 2009 and very recently released by the Federal Highway Administration (FHWA). The study intends to explore trends in demographic, household, and land-use characteristics and to understand their effects on issues related to auto availability and use. The analysis may help to better address emerging transportation issues in the state of Maryland.

The remaining of this paper is organized as follows: the next section describes the main data sources and preliminary statistics for vehicle ownership and use in the state of Maryland. Then, the modeling framework and model development is described. Empirical results from model calibration are then described in two sections, followed by a comparison between results obtained for 2001 and 2009. Finally, conclusions and challenges for future research are presented.

Data Description

National Household Travel Survey

The vehicle ownership framework proposed is estimated on data extracted from the 2001 and 2009 National Household Travel Surveys conducted by the Federal Highway Administration. The NHTS collected travel data from a national sample of civilian, noninstitutionalized population of the United States. There are approximately 70,000 households in the final 2001 NHTS data set, of which 4,240 households are in the Maryland area, and 150,000 households in the final 2009 NHTS data set, which only has 355 households for the state of Maryland. The significant difference in the valid number of responses is because the State of Maryland was in the add-on program of NHTS in 2001 but not 2009. The NHTS was executed as a telephone survey using computer-assisted telephone interviewing (CATI) technology. The 2001 and 2009 NHTS data sets include the following information relevant to vehicle ownership modeling:

- Household data on the head and its relationship to other members, income, housing characteristics, and other sociodemographics;
- Information on each household's vehicles, including year, make, model, and estimates of annual miles traveled; and
- Data about drivers, including information on travel as part of work.

Descriptive Statistics

This section reports descriptive statistics obtained from the analysis of NHTS data relative to the state of Maryland with the focus on the attributes that are used subsequently for vehicle ownership modeling. Main indicators are derived for both 2001[part (a) of each figure] and 2009 [part (b) each figure].

Fig. 1 shows that vehicle ownership increases directly with income. About two-thirds of the households with annual incomes under $5,000 owned no vehicles in 2001, whereas only about 20% of low-income-level (<$30,000) households owned no vehicles in 2009. The average number of car per household rose from 1.92 vehicles in 2001 to 2.02 vehicles in 2009.

The number of licensed drivers in a household is closely related to vehicle ownership (Fig. 2). In 2001, the average number of

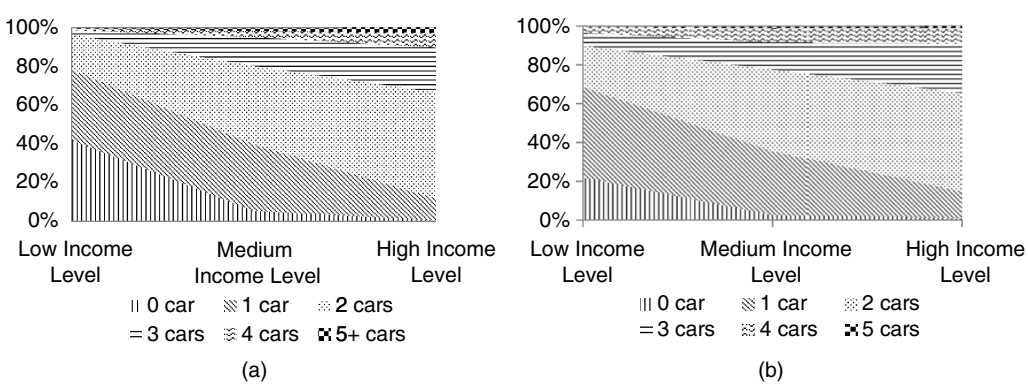

Fig. 1. Percent of households owning zero, one, or more vehicles by annual household income: (a) 2001 NHTS; (b) 2009 NHTS

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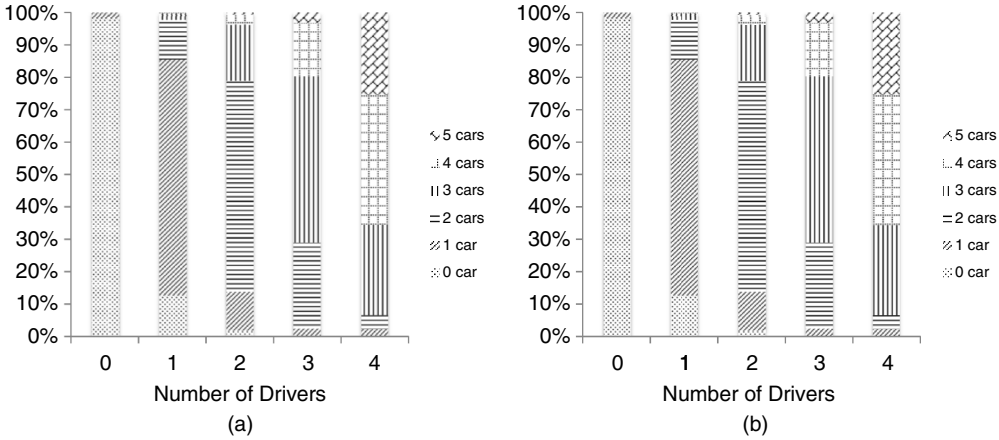

Fig. 2. Percent of households owning zero, one, or more vehicles by number of drivers: (a) 2001 NHTS; (b) 2009 NHTS

vehicles per household closely followed the number of drivers, ranging from 1.05 for one-driver households, 2.13 for two-driver households, 3.00 for three-driver households, 4.00 for four-driver households, to 4.86 for households with five or more drivers. Similar trends have been calculated for 2009 (The 2009 sample does not contain observations related to the "0 drivers" category), but with slightly higher proportions.

Concerning employment rates, the number of household members with jobs is also closely related to vehicle ownership (Fig. 3). The average number of vehicles per household in 2001 is approximately the number of workers, ranging from 1.53 for one-worker households, 2.14 for two-worker households, 2.81 for three-worker households, 3.89 for four-worker households, to 4.50 for households with five or more workers. In 2009, those rates are again slightly higher.

Fig. 4 shows the relationship between vehicle ownership and whether a household is in an urban or rural area. The results show that, on average, households in rural areas own more cars. In 2001, the average number of vehicles per household is 2.53 in an urban cluster, 1.77 in an urban area, 2.51 in an area surrounded by urban areas, and 2.83 in a nonurban area. In 2009, urban clusters, urban areas, and nonurban areas have, on average, a lower number of vehicles (1.90, 2.22, and 2.35, respectively).

In 2001, the vast majority of the vehicles were autos (Fig. 5). The next largest segment was sport utility vehicles, followed by pickup trucks. The fourth largest portion was vans, including minivans, cargo, and passenger vans. In 2009, the rankings were the same, but the percentage of automobiles decreased and the SUV and pickup truck segments significantly increased.

There is also a slight increase in average vehicle age in the state Of Maryland (Fig. 6). The average household auto in 2001 was 7.47 years old. Only 10% of all autos were new models (1 year old or less), and 18% were less than 3 years old. The majority of autos, 56%, were more than 5 years old. In 2009, the cars were generally older than in 2001 in Maryland. The average household auto in 2009 was 8 years old. Only 4.76% of all autos were new models (1 year old or less), and 13.69% were 3 years old or less. The majority of autos, 63.54%, were more than 5 years old.

Modeling Framework

Structure of the Framework

The modeling framework applied in this paper is described in Fig. 7. According to this framework, for 2001 and 2009, vehicle ownership and use are estimated by using data derived from the National Household Travel Survey. The number of vehicles that the household owns (zero, one, two, three, four or more cars) is predicted by means of multinomial logit model (MNL), whereas the annual mileage traveled by all the vehicles is modeled using a two-stage least-squares regression. The models estimated are validated and then used to test a number of scenarios, including sensitivities to socioeconomic variables, land-use factors, and fuel price.

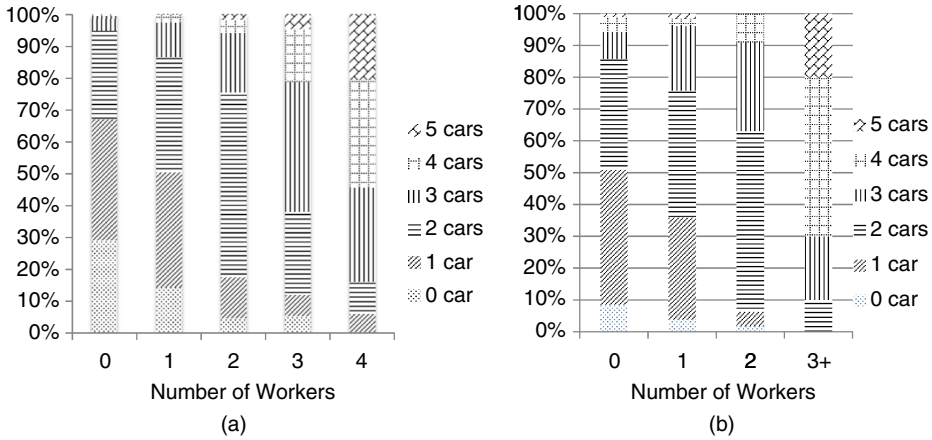

Fig. 3. Percent of households owning zero, one, or more vehicles by number of workers: (a) 2001 NHTS; (b) 2009 NHTS

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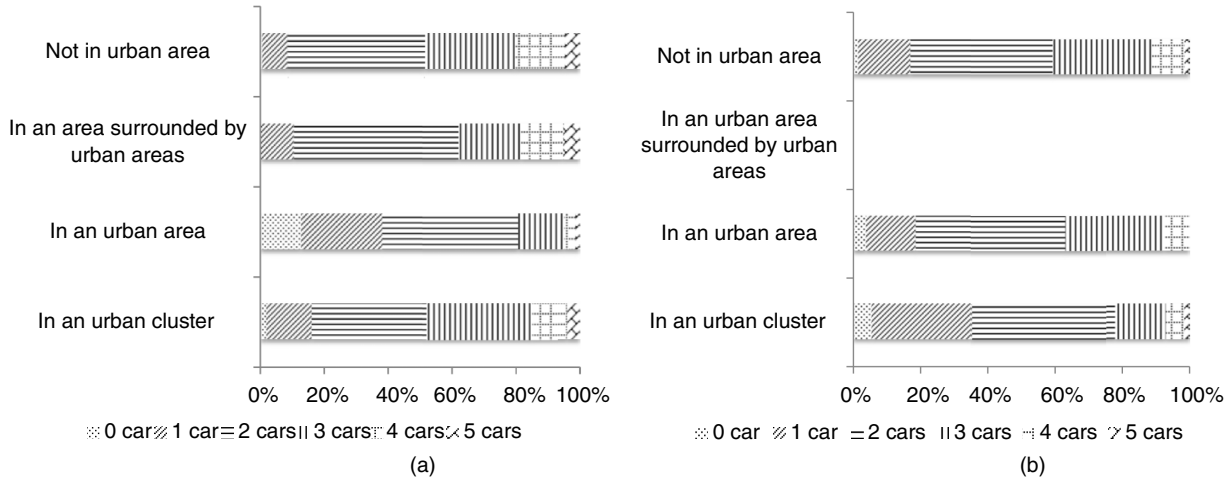

Fig. 4. Percent of households owning zero, one, or more vehicles by household location: (a) 2001 NHTS; (b) 2009 NHTS

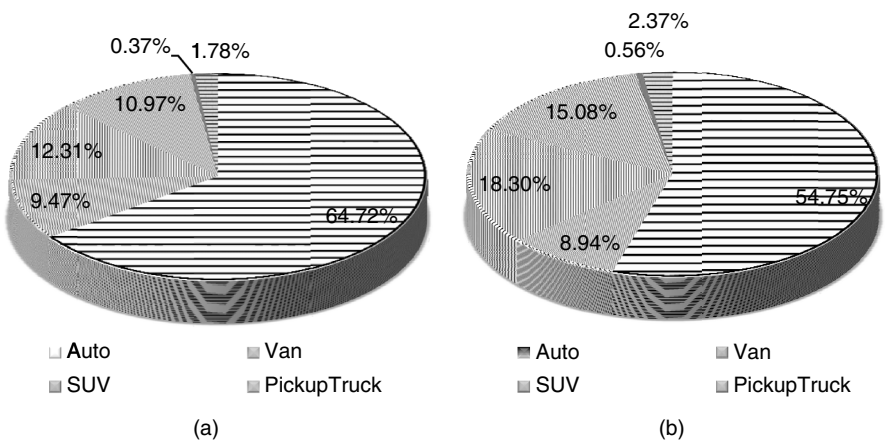

Fig. 5. Percent of types of vehicles owned by households: (a) 2001 NHTS; (b) 2009 NHTS

Model Development

- **Vehicle Ownership Model**
  The decision maker in this framework is the household, as it is assumed that the household has the overall responsibility for the number of vehicles owned. The choice set includes zero, one, two, three, and four or more vehicles. Consideration was given to extending the choice set and to include five or more cars but data showed that this segment accounts for less than 2% of the entire sample. The model is specified as a multinomial logit model:

$$P_i = \frac{e^{V_i}}{\sum_{j=0,1,2,3,4+} e^{V_j}}$$

where P_i = probability of owning each number of vehicles in the choice set (0, 1, 2, 3, 4+); and V_i (the utility of ownership) = weighted sum of factors that affect households' decisions. Table 1 lists the variables that enter the utility function. Differences exist between the specification used for the 2001 and 2009 models; in particular, the variables "education," "housing units per sq. mile," and "percentage renter-occupied housing" are not available in 2009 NHTS, "urban size" is essentially the same variable although on a different scale, household size and owning a house variables have been selected on the basis of their significance in model calibration.

- **Vehicle Usage Model**
  The regression model predicts the annual VMT per household. It is specified as a log-linear regression model with a function of household socioeconomic variable, land-use attributes, and vehicle specifications. The formulation of the model follows:

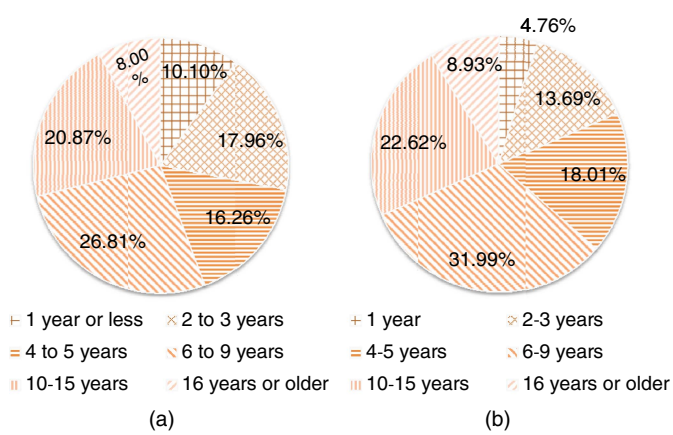

Fig. 6. Percent of vehicle age owned by households: (a) 2001 NHTS; (b) 2009 NHTS

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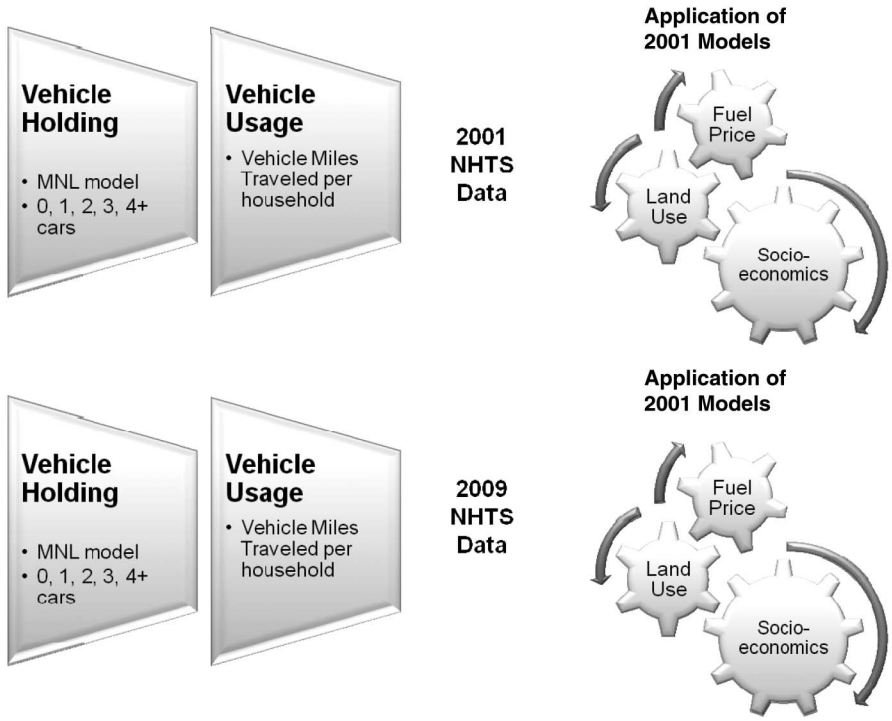

Fig. 7. Modeling framework

$$\log(\mathrm{VMT}) = f(X)$$

The variables that enter the regression model are listed in Table 2.

The parameters are estimated with an instrumental variable approach. This approach (rather than ordinary least squares) is required because the operating cost is entered in the regression equation as an explanatory variable. Because the household chooses which vehicle(s) it owns, it effectively chooses the operating cost of driving the selected vehicle(s) (Train 1986). Therefore, the operating cost is endogenous in the model, and the ordinary least-squares estimation is biased. To avoid this bias, instrumental variable approach with two-stage least-squares estimation method is applied. In the first stage, the operating cost (endogenous variable) is regressed on the exogenous variables in the model. The predicted values from these regressions are obtained. In the second stage, the regression of VMT is estimated as usual, except that in this stage operating cost is replaced with the predicted values from the first stage. The exogenous variables used to predict operating cost include household income, household size, housing density, number of adults, and number of workers.

Empirical Results

Empirical Results of Vehicle Ownership Model

Table 3 presents the estimated model of vehicle ownership. The 2009 sample, only recently released, contains a very limited number of variables; this explains why some variables are not included in the 2009 model. In terms of the estimated coefficients, most of them have the expected sign and value. For those that present significant t-statistics, the coefficients have intuitive meaning.

Coefficients of household income are positive and very significant for models calibrated on both 2001 and 2009 data; the value of the coefficients is larger with respect to households with more cars. Therefore, households with higher income tend to own multiple cars, and the higher their income, the more likely that they will own more cars. The variables relative to the number of household members have negative coefficients but turn out to be not significant except for the one vehicle alternative specific variable.

Households with more workers and drivers own more vehicles. The coefficients of number of drivers are extremely significant, which means that this attribute greatly influences the vehicle ownership in the household. The number of employed people results is significant in the three-vehicle and four-or-more-vehicle alternatives only for 2001 but not significant for 2009, thus they are eliminated from the model. The number of children in a household is a significant factor in the one-vehicle alternative only in the 2001 model.

When it comes to the characteristics of the household head, the coefficients relative to education are estimated for the 2001 model only, given that the information was not available in the 2009 data set. The coefficients in the one-vehicle and two-vehicle alternatives are positive but not significant at the 95% level; however, they are kept in the final specification to emphasize that the lack of this variable does not affect the final fit of the 2009 vehicle ownership model.

The 2001 model contains three land-use factors: location of the household (from urban to rural area), housing density, and the percentage of rental properties. These variables have a strong influence on household vehicle ownership. In particular, moving from urban to rural areas produces a positive effect on the number of cars owned (as expected); housing density has a negative effect as well as does the percentage of rental properties.

To characterize land use, in the 2009 model the location of the household by urban size was used. This variable ranges on an ordinal scale from 1 to 5 in the 2001 data set and from 1 to 6 in the 2009 data set. The lowest level represents nonurban areas, whereas the 2 through 5(6) categories represent increasing density level, ranging from the least dense to the densest urban area. This variable

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Table 1. Variables in the Utility Function of Vehicle Ownership Model

Variable	Meaning	2001	2009
Income	Annual income level of the household 01 = < $5,000 02 = $5,000–$9,999 03 = $10,000–$14,999 04 = $15,000–$19,999 05 = $20,000–$24,999 06 = $25,000–$29,999 07 = $30,000–$34,999 08 = $35,000–$39,999 09 = $40,000–$44,999 10 = $45,000–$49,999 11 = $50,000–$54,999 12 = $55,000–$59,999 13 = $60,000–$64,999 14 = $65,000–$69,999 15 = $70,000–$74,999 16 = $75,000–$79,999 17 = $80,000–$99,999 18 = ≥ $100,000	√	√
HHSIZE	Household size (number of household members)	√	
Cld	Number of children in the household	√	
Wrk	Number of workers in the household	√	
Drv	Number of licensed drivers in the household	√	√
Edu	Education level of household head 1 = Less than high school graduate 2 = High school graduate, include GED 3 = Vocational/technical training 4 = Some college, but no degree 5 = Associate's degree (e.g., A.A.) 6 = Bachelor's degree (e.g., B.A., A.B., B.S.) 7 = Some graduate or professional school, but no degree 8 = Graduate or professional school degree (for example, M.A., M.S., M.B.A., M.D., D.D.S., Ph.D., Ed.D., J.D.)	√	
Loc	Household location at five levels of variation (five levels: 1 = urban, 2 = second city, 3 = suburban, 4 = town, 5 = rural)	√	
Urb	Urban size at six levels of variation 1 = Not in an urbanized area 2 = 50,000–199,999 3 = 200,000–499,999 4 = 500,000–999,999 5 = 1 million or more without subway or rail 6 = 1 million or more with subway or rail		√
HHDen	Housing units per square mile—block group 25 = 0 to 50 150 = 50 to 250 700 = 250 to 1,000 2,000 = 1000 to 3,000 4,000 = 3,000 to 5,000 6,000 = 5,000 to 999K	√	
Rnt	Percentage renter-occupied housing at block level (%)	√	
Home	Dummy variable (1 = owned home, 0 = rental home)		√

Note: Variable selections are based on data availability.

has a strong influence on household vehicle ownership. In particular, it is very significant in the two-vehicle, three-vehicle, and four-or-more-vehicle alternatives. As expected, urban size has a negative effect on vehicle ownership and the effect becomes greater for three-or-more-vehicle households. Again for 2009, the home owned or rented variable is only significant in the two-vehicle and three-vehicle alternatives. The positive sign means that households with owned homes are more likely to own more cars. Although, one might think that the variables used could cause high correlation across the coefficient estimated, the correlation matrix has not revealed any serious problem on this regard.

Table 2. Variables in the Utility Function of Vehicle Usage Model

Variable	Meaning	2001	2009
log(Income)	*Income*, annual income level of the household	√	√
HHSIZE	Household size	√	
Cld	Number of children in the household	√	√
Wrk	Number of workers in the household	√	√
Drv	Number of licensed drivers in the household	√	√
Edu	Education level of household head	√	
Loc	Household location at five levels of variation	√	
Urb	Urban size at six levels of variation		√
Hmtp	Household housing type (1 = single house, 2 = townhouse, 3 = condo or apartment)		√
log(HHDen)	*HHDen*, housing units per square mile—block group	√	
Rnt	Percentage renter-occupied housing at block level	√	
log(cost)	*Cost*, operating cost, represented by cents per mile	√	√

Note: Variable selections are based on data availability.

The 2001 model has been validated by using an out-of-sample approach (Table 4). Overall the model does well, predicting 1.13 vehicles per household, which is very close to the observed value of 1.10 cars per household. The model slightly underpredicts the 0-vehicle household and 3-vehicle household, and it overpredicts 1- and 2-vehicle households. The validation of the 2009 model was not attempted, given the small sample size available.

Empirical Results of Vehicle Usage Model

Results relative to vehicle use (VMT per household) and derived from the regression model are presented in Table 5. Most of the estimated coefficients have the expected sign and values. Both 2001 and 2009 models indicate that household income and the number of workers and drivers have a positive influence on vehicle use. In particular, the number of workers in the household significantly contributes to household vehicle use. The coefficient of the variable "number of children" is negative but not significant in 2001, whereas it it positive and significant at the 90% level in 2009.

Among the land-use factors used for the 2001 analysis, variables related to household location and population density are significant at the 90% level. Households in more dense areas tend to drive less as the coefficient of log of population density is negative. Household location is measured on a 5-level scale, which represent urban, second city, suburban, town, and rural areas. The positive coefficient means that households tend to drive more in rural areas.

As expected, people drive less when the operating cost increases. Another interesting result is that the estimated coefficient of operating cost is exactly the elasticity.

With reference to 2001, the education of the household head is very significant. Higher education levels usually imply higher incomes; therefore, the resulting estimated coefficient confirms that

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Table 3. Vehicle Ownership Model Estimation

Explanatory variables	Alternatives	Year 2001 Estimated coefficient	Year 2001 *t*-statistic	Year 2009 Estimated coefficient	Year 2009 *t*-statistic
Alternative specific constant	1 vehicle	−1.403	−2.2	−1.473	−1.9
	2 vehicle	−7.514	−10.0	−5.984	−5.4
	3 vehicle	−12.17	−13.5	−8.988	−6.4
	4 + vehicle	−13.73	−11.6	−11.41	−7.2
Household income	1 vehicle	0.1573	4.5	0.1742	2.2
	2 vehicle	0.2850	7.6	0.2853	3.4
	3 vehicle	0.3610	9.1	0.3313	3.7
	4 + vehicle	0.3504	7.5	0.3091	3.1
Household size	1 vehicle	−0.7382	−4.8	—	—
	2 vehicle	−0.1738	−1.3	—	—
	3 vehicle	−0.211	−1.5	—	—
	4 + vehicle	−0.2613	−1.6	—	—
Number of children	1 vehicle	0.5070	3.2	—	—
Number of workers	2 vehicle	—	—	—	—
	3 vehicle	0.3489	3.5	—	—
	4 + vehicle	0.4900	2.8	—	—
Number of drivers	1 vehicle	3.888	13.0	1.836	2.6
	2 vehicle	6.387	18.4	3.887	5.1
	3 vehicle	7.567	20.0	5.179	6.3
	4 + vehicle	8.011	19.2	6.174	7.2
Education level of household head	1 vehicle	0.1343	13.7	—	—
	2 vehicle	0.1101	3.7	—	—
Household location	1 vehicle	0.1862	1.2	—	—
	2 vehicle	0.4309	2.6	—	—
	3 vehicle	0.5767	3.1	—	—
	4 + vehicle	0.5180	2.3	—	—
Urban size	2 vehicle	—	—	−0.2100	−2.4
	3 vehicle	—	—	−0.3910	−3.7
	4 + vehicle	—	—	−0.3449	−2.5
Housing density	1 vehicle	−0.00006652	−0.8	—	—
	2 vehicle	−0.0001791	−1.9	—	—
	3 vehicle	−0.0003208	−3.0	—	—
	4 + vehicle	−0.0007163	−4.1	—	—
Percentage renter-occupied housing	1 vehicle	−0.02801	−5.1	—	—
	2 vehicle	−0.02671	−4.8	—	—
	3 vehicle	−0.03221	−5.0	—	—
	4 + vehicle	−0.04451	−4.5	—	—
Home owned or rented	2 vehicle	—	—	1.456	2.6
	3 vehicle	—	—	0.9034	1.2
Likelihood with zero coefficients		−4218.3368		−523.0673	
Likelihood with constants only		−3643.9357		−445.3020	
Final value of likelihood		−2041.3362		−319.5435	
"Rho-squared" with respect to zero		*0.5165*		0.3891	
"Rho-squared" with respect to constants		*0.4398*		0.2824	

households with higher education levels have higher vehicle usage rates.

Land-use factors are represented by the variable "urban size" in the 2009 model; its coefficient is negative and significant at the 95% level; households tend to drive less in denser areas. The coefficient of housing type is negative; households owning condos or apartments usually have lower incomes and travel less than those owning single houses. As expected, vehicle miles traveled are reduced when operating costs rise.

Table 4. 2001 Model Validation

Vehicle ownership	Current	Forecast	Difference
0 vehicle household	28.04%	25.76%	−2.28%
1 vehicle household	41.06%	42.75%	1.69%
2 vehicle household	24.32%	25.05%	0.73%
3 vehicle household	6.01%	5.67%	−0.34%
4 + vehicle household	0.57%	0.77%	0.20%
Cars per household	1.10	1.13	0.03

Sensitivity Analysis

Sensitivity Analysis of Vehicle Ownership Model

The vehicle ownership models were then applied to test a number of policies and to measure their effects on vehicle ownership in Maryland. The following scenarios were tested:

1. Change in household income: both a 25% decrease (reflecting a possible economic downturn) and a 25% increase;
2. Change in housing density: in particular, the effect of the increase of density in second/city and urban areas by 100%;
3. Change in employment: 10% of households lose one worker and all households lose one worker (2001 model only); and
4. Application of the 2001 model estimates to the 2009 data set.

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Table 5. Estimation Results of Regression Model

Variable	Year 2001 Estimated coefficient	Year 2001 *t*-statistic	Year 2009 Estimated coefficient	Year 2009 *t*-statistic
Intercept	10.10	6.0	7.374	9.1
Log(household income)	0.501	6.9	0.593	5.7
Household size	0.060	0.6	—	—
Number of children	−0.010	−0.1	0.090	1.7
Number of workers	0.193	5.3	0.241	3.1
Number of drivers	0.151	2.7	0.092	1.1
Education level of household head	0.033	4.2	—	—
Household location	0.061	2.3	—	—
Urban size	—	—	−0.053	−2.1
Housing type	—	—	−0.116	−1.4
Log(population per square mile)	−0.062	−2.3	—	—
Percentage of rental properties	−0.00033	−0.4	—	—
Log(operating cost by cents/mile)	−0.450	−1.3	−0.186	−0.8
**Rho-squared*	*0.194*		*0.348*	

From the results shown in Table 6, in 2001, a decrease in household income will produce a decrease in the total number of cars owned by households in Maryland; a 25% decrease in household income is expected to lower the number of cars by about 4.5%. An increase in household income of 25% will result in 5.1% more cars in the state. Households with three cars are the most affected by this scenario.

It can be observed that small changes in housing density do not affect vehicle ownership very much and that a 4% reduction in the total number of cars in Maryland is obtained by doubling the density of urban/suburban areas. Fang (2008) reached a similar conclusion: increasing residential density within feasible ranges will have a very small impact on household vehicle ownership and vehicle fuel usage. In general, it can be said that the number of households with zero or one car increases, whereas the percentage of households with multiple cars decreases.

Rising rates of unemployment produces fewer cars in suburban areas and towns, but the 10% rate of unemployment scenario does not produce an overall decrease in the total number of cars. To quantify the total effect of each scenario, the actual number of cars in the state and the predictions calculated by applying this model are compared and shown in Table 6; it can be seen that the small changes predicted by these scenarios have strong effects on the total number of cars in Maryland.

As expected, a decrease in household income in 2009 (as seen in Table 7) will produce a decrease in the total number of cars owned by households in Maryland; a 25% decrease in household income is expected to lower the number of cars by approximately 3.74%. An increase in household income of 25% will result in 3.44% more cars in the state. Households with one car and households with three cars are the most affected by this scenario.

Changes in urban size affect vehicle ownership and a 10% reduction in the total number of cars in Maryland is obtained by doubling the density of urban/suburban areas. In general, the number of households with zero or one car is increasing while households with multiple cars decrease. In particular, there is a large increase in one-car households and a large decrease in three-car households.

Table 6. Application Results for 2001 Vehicle Ownership Model

Vehicle ownership	Current	Income 25%	Income −25%	Housing Density + 100%	10% households lose one worker
0 car households	14.70%	13.34%	15.27%	15.55%	14.22%
1 car households	33.25%	31.40%	36.04%	35.55%	33.91%
2 car households	35.49%	35.78%	34.89%	34.23%	38.22%
3 car households	13.31%	15.71%	10.96%	11.79%	11.06%
4 + car households	3.25%	3.77%	2.84%	2.88%	2.59%
Total	100.00%	100.00%	100.00%	100.00%	100.00%
Average car ownership per household	1.57	1.65	1.50	1.51	1.54
Total car ownership in state of Maryland	3,186,009	3,348,353	3,043,958	3,064,251	3,125,130
Change of total cars in state of Maryland	—	162,344	−142,051	−121,758	−60,879
Percent change of total cars in state of Maryland	—	5.10%	−4.46%	−3.82%	−1.91%

Note: From Census (2000), the population in state of Maryland was 5,296,486 and the average household was 2.61 persons/household. Total number of households is 2,029,305.

Table 7. Application Results for 2009 Vehicle Ownership Model

Vehicle ownership	Current	Income 25%	Income −25%	Urban density + 100%
0 car households	4.92%	4.12%	6.06%	5.14%
1 car households	24.92%	22.70%	27.23%	32.63%
2 car households	43.39%	43.59%	42.65%	39.64%
3 car households	19.08%	21.74%	16.55%	15.94%
4+ car households	7.69%	7.85%	7.51%	6.65%
Total	100.00%	100.00%	100.00%	100.00%
Average car ownership per household	2.02	2.07	1.92	1.86
Total car ownership in state of Maryland	4,334,703	4,483,646	4,172,402	4,037,485
Change of total cars in state of Maryland	—	148,943	−162,301	−297,218
Percent change of total cars in state of Maryland	—	3.44%	−3.74%	−6.86%

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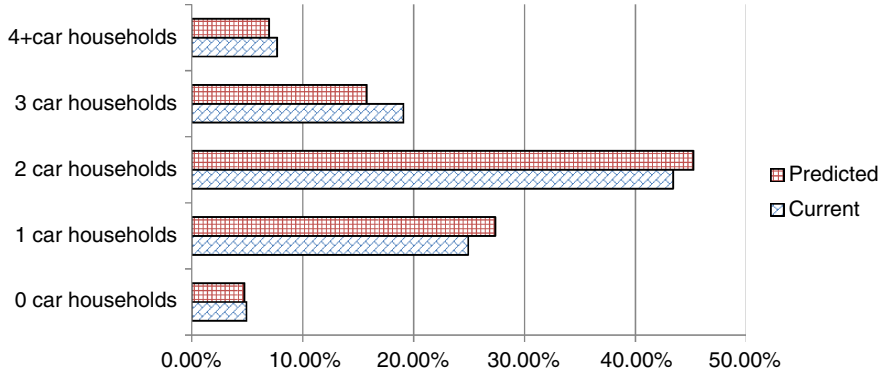

Fig. 8. Application of 2001 model to 2009 data

Households with zero cars increase only slightly. It can be concluded that increasing density will result in households owning fewer cars, but people will still need to have at least one car per household.

Finally, the 2001 model has been applied to the 2009 data (Fig. 8). The results show that the 2001 model overpredicts the one- and two-vehicle households and underpredicts three- and four-vehicle households; however, discrepancies are on the order of 3–4%.

Sensitivity Analysis of Vehicle Usage Model

The vehicle usage models have been applied to conduct a number of sensitivity analysis; the following scenarios were tested:

1. Change in household income: both a 25% decrease (reflecting a possible economic downturn) and a 25% increase;
2. Change in employment: 10% of households lose one worker and all households lose one worker;
3. Change in housing density: in particular the effect of the increase in the actual values of density by 100%;
4. Change in fuel cost: for year 2001, apply the model with fuel cost of $4 per gallon as the approximate highest fuel cost in 2008 ($3.16 per gallon in 2001 dollars with an inflation rate of 3% per year); for year 2009, apply the model with both a 50% decrease and a 50% increase of fuel cost (Information on historical fuel price is from the U.S. Energy Information Administration); and
5. Combined effect of higher density and increase of fuel price.

Table 8 summarizes the results obtained from the preceding scenarios. In 2001, VMT increases significantly with income; a 25% decrease in income produces just a 8.15% reduction in VMT. In terms of employment rates, VMT does not change much (−1.91%) when 10% of households lose a worker, but it decreases significantly (−17.54%) when all households lose one worker, although such an assumption is not very realistic. Thus, bad unemployment rates do not markedly change vehicle usage.

Changes in urban levels of household location and housing density are used to measure the influence of urbanization; if density is doubled, VMT decreases, but not dramatically (−8.05% and −12.31%, respectively).

For operating costs, it appears that people are very sensitive to fuel cost. By processing historical data on fuel prices, it was found that the highest fuel price of approximately $4 occurred in 2008. The operating cost was then recalculated and adjusted to remove the inflation factor. At that rate, vehicle usage is seen to drop by about a quarter (−25.92%).

Table 8. Application Results for 2001 and 2009 Vehicle Usage Models

Policy		Percent change of vehicle miles traveled (%) 2001	2009
Income + 25%		18.61	14.14
Income − 25%		−8.15	−3.75
10% households lose one worker		−1.91	−2.38
All households lose one worker		−17.54	−21.40
Housing density +100%		−8.05	−12.31
Housing density +100% and fuel cost +25%		−16.85	−15.88
Fuel Price	$4.0 per gallon ($3.16 per gallon in 2001 dollars)	−25.92	—
	−50%	—	13.78
	+50%	—	−7.27

In 2009, The VMT increases (14.14%) with income; however, when income decreases, VMT decreases much less (−3.75%). In terms of employment rates, VMT does not change much (−2.38%) when 10% of households lose workers; but it decreases greatly (−21.40%) when all households lose a worker. The results obtained for 2009 data are consistent with those derived from the 2001 analysis, although less sensitive to changes in income.

Urban size is used to measure the influence of urbanization. The results show that even if urban density is doubled, VMT does not decrease a lot (−12.31%). As to operating costs, people are not as sensitive to automobile costs in 2009 as they were in 2001. A price was supposed that would either increase or decrease by 50%, and the vehicle usage was then recalculated. Vehicle usage increased 13.78% as the fuel price decreased by 50%, which is reasonable. When fuel price increases by 50%, vehicle usage did not decrease much (only −7.27%).

The joint effect of increased density and of rising fuel costs produces about 15% decrease in the total VMT for both 2001 and 2009 models.

Conclusions

This study has presented a model system for vehicle ownership in the state of Maryland on the basis of a two-stage formulation: (1) the vehicle ownership model and (2) the vehicle usage model. A multinomial logit model is used in the vehicle ownership models. A regression model and an instrumental variable estimation approach are used for the vehicle usage model. The system of models calibrated on 2001 and 2009 NHTS data contains a wide variety of

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Table 9. Comparison of 2001 and 2009 Vehicle Ownership Models

Scenarios	2001 (%)	2009 (%)
Vehicle Ownership		
Income + 25%	5.10	3.44
Income − 25%	−4.46	−3.74
Density + 100%	−3.82	−6.86
10% households lose one worker	−1.91	—
Vehicle Usage		
Income + 25%	18.61	14.14
Income − 25%	−8.15	−3.75
Density + 100%	−8.05	−12.31
10% households lose one worker	−1.91	−2.38
All households lose one worker	−17.54	−21.40
Housing density + 100% and fuel cost + 25%	−16.85	−15.88
Fuel price	−25.92 (from $1.6 to $4)	−7.27 (increase by 50%) 13.78 (decrease by 50%)

coefficients, including sociodemographics, land-use variables, and operating cost (fuel price). The models were then applied to study individual preferences regarding vehicle ownership and use under a number of scenarios. Predictions, not always intuitive, provided a good ground for discussion and were found to be significant for the understanding of travel behavior and attitude towards car use in Maryland. The following discussion summarizes the main findings (see also Table 9 and Fig. 9).

Income, which is here used as a proxy variable for economic growth, affects vehicle usage more than it affects the number of vehicles per household. In particular, when comparing 2009 and 2001 results, households have become less sensitive to changes in income; there is also asymmetry in the sensitivity to income; a larger effect on vehicle use is predicted with raising income.

In terms of the land-use factor; changes in vehicle ownership attributable to more compact development are relatively low. Even scenarios where the density of urban area is doubled produce very little effects; this result is quite disappointing when considering that smart growth developments advocate denser urban areas to reduce congestion and greenhouse gas emissions. However, there is a much higher sensitivity to density for 2009 than for 2001. The combined effect of more dense development and fuel cost increase produce a significant reduction in car usage of approximately 16%; this result is stable across the two samples considered.

High unemployment rates have very little effect on vehicle ownership in Maryland; even if 10% of the households lose one worker, vehicle ownership remains almost unchanged. Nationwide, only about one-quarter of jobs in low- and middle-skill industries are accessible via public transit within 90 min for the typical metropolitan commuter (Puentes 2011), thus the necessity of owning and operating a car, particularly for lower-skilled workers.

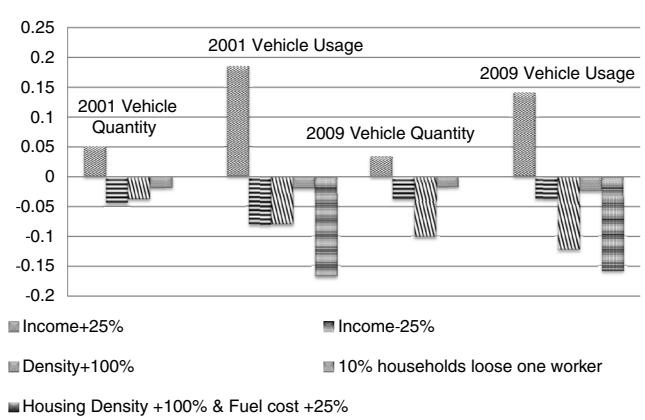

Fig. 9. Comparison of 2001 and 2009 car ownership models

For vehicle usage, the comparison of the results from changes in fuel price was especially notable. By increasing the 2001 fuel price to its 2009 level, vehicle usage sharply decreases by about 25%, which is a realistic drop reflecting the huge change from $1.60 to $4 per gallon. The 2009 model predicts about 14% increase in vehicle usage when fuel price drops by 50%. Households are not that sensitive to fuel price decrease; a 50% percent increase produces only about 7% decrease in mileage traveled. The fuel price in 2008 was very high and at one point reached $4/gallon; the same year the national VMT was down of 3.5% and government tax receipts went 9% down (Brand 2009).

The 2001 vehicle ownership model presented in this paper has been successfully implemented into the Maryland Statewide Transportation Model. Conditional on the availability of data, more accurate models including vehicle type choice can be estimated and added to this framework; the use of advanced models for vehicle usage is under consideration. Finally, the authors are actively working on the development of a dynamic discrete choice framework specified as an optimal stopping problem, in which households decide when to make a change in vehicle ownership. The introduction of a temporal dimension will add more realism to the sensitivity analysis for policy scenarios testing.

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