A Joint Vehicle Holdings (Type and Vintage) and Primary Driver Assignment Model with an Application for California

Gaurav Vyas
Parsons Brinckerhoff
One Penn Plaza, Suite 200
New York, NY 10119
Tel: 512-944-5319; Fax: 212-465-5096
Email: gavyas@gmail.com

Rajesh Paleti
The University of Texas at Austin
Dept of Civil, Architectural & Environmental Engr
1 University Station C1761, Austin TX 78712
Tel: 512-471-4535; Fax: 512-475-8744
Email: rajeshp@mail.utexas.edu

Chandra R. Bhat *(corresponding author)*
The University of Texas at Austin
Dept of Civil, Architectural & Environmental Engr
1 University Station C1761, Austin TX 78712
Tel: 512-471-4535; Fax: 512-475-8744
Email: bhat@mail.utexas.edu

Konstadinos G. Goulias
University of California
Department of Geography
Santa Barbara, CA 93106-4060
Tel: 805-308-2837, Fax: 805-893-2578
Email: goulias@geog.ucsb.edu

Ram M. Pendyala
Arizona State University
School of Sustainable Engr and the Built Environment
Room ECG252, Tempe, AZ 85287-5306
Tel: 480-727-9164; Fax: 480-965-0557
Email: ram.pendyala@asu.edu

Hsi-hwa Hu
Southern California Association of Governments
818 W. Seventh Street, 12th Floor
Los Angeles, CA 90017
Tel: 213-236-1834; Fax: 213-236-1962
Email: hu@scag.ca.gov

Thomas J. Adler
Resource Systems Group, Inc.
55 Railroad Row, White River Junction, VT 05001
Tel: 802-295-4999
Email: tadler@rsginc.com

Aniss Bahreinian
California Energy Commission
Fuels and Transportation Division
1516 Ninth Street, MS-29 Sacramento, CA 95814
Email: ABahrein@energy.state.ca.us

ABSTRACT

In this paper, we estimate a joint household-level model of the number of vehicles owned by the household, the vehicle type choice of each vehicle, the annual mileage on each vehicle, as well as the individual assigned as the primary driver for each vehicle. A version of the proposed model system currently serves as the engine for a household vehicle composition and evolution simulator, which itself has been embedded within the larger SimAGENT (for Simulator of Activities, Greenhouse emissions, Energy, Networks, and Travel) activity-based travel and emissions forecasting system for the Southern California Association of Governments (SCAG) planning region.

1. INTRODUCTION

In regional travel modeling and simulation, the combination of the *number of vehicles* owned by a household, the *type choice (defined as combination of body type and vintage)* of the vehicles, and the *usage (miles traveled)* of the vehicles are important on-road vehicular travel determinants of greenhouse gas (GHG) emissions, fuel consumption, and pollutant emissions (*1*, *2*). In the state-of-the-art practice, when TDMs are interfaced with EPA's MOBILE6 or the recently released MOVES model or the EMFAC model in California for emissions forecasting, default values (percent of vehicles in each of specified technology classes) are used to represent the VMT mix. The use of default values offers simplicity; however, these default values may not reflect local conditions with respect to vehicle fleet composition. Even if they do, there is no basis to forecast future vehicle fleet composition in response to changes in such factors as fuel prices, socio-economic shifts (for example, aging of the US population), and policy decisions (for example, allowing vehicles attaining a certain fuel efficiency to use high-occupancy vehicle or HOV lanes).[1] Besides, there is increasing interest in, and legislative initiatives to, proactively influence the regional fleet mix of vehicles through environmental policies aimed at reducing pollutants and greenhouse gas emissions (for example, CARB (*3*)), calling for models of household vehicle fleet composition. Of course, in addition to the need for household vehicle fleet models to better improve the ability to forecast regional fleet mix and use, such models are also fundamentally important for travel demand modeling and transportation policy analysis.

To be sure, the importance of modeling household vehicle fleet choices has been recognized for several decades now, though the urgency in terms of GHG emission and fossil-fuel energy dependence is definitively more recent. Also, until recently, studies were hampered by the availability of computationally efficient and econometrically appropriate methodological tools to jointly forecast the number of vehicles owned by a household as well as the vehicle types of each of the vehicles. For instance, most earlier studies have either (a) focused on the vehicle type characteristics of the most recently purchased or the most driven household vehicle (*4*, *5*), or (b) confined attention to vehicle type characteristics of the most frequently used vehicle (*6*), or (c) examined ownership and vehicle type choices for only households with two vehicles or less to reduce the number of possible vehicle type combinations (*7*-*10*), and even then using aggregate classifications of vehicle types such as car versus non-car or sports utility vehicles (SUV) versus non-SUV vehicles. A few of these studies have also considered the amount of use (annual mileage) of each household vehicle (*7*, *10*, *11*).

Within the broad context of the methodological challenge of modeling all dimensions of all vehicles owned by a household, as just discussed, Bhat and colleagues (*12*, *13*) recently proposed the use of a flexible multiple discrete-continuous extreme value model (MDCEV) model. The MDCEV model has a simple closed form structure for the probability expressions, and allows the choice of multiple alternatives jointly. Thus, a disaggregate vehicle typology can be used without much problems in the MDCEV approach, while doing so is virtually impossible in the traditional choice models because of the explosion in the number of choice alternatives for

[1] The FHWA offers some guidance on how default values on vehicle mix distributions can be adjusted using local vehicle registration data and vehicle classification counts (http://www.fhwa.dot.gov/environment/conformity/emission/emismeth7.htm). But these values are still aggregate-level numbers that offer little for forecasting future vehicle fleet composition.

multiple vehicle households.[2] The MDCEV model also incorporates the notion that households own and use different vehicles for different functional purposes as well as to accommodate different preferences of individuals within a household. As such, the MDCEV model framework offers an elegant, theoretically consistent, and econometrically integrated approach to model vehicle ownership, vehicle type, and vehicle usage decisions, and all of them simultaneously (see Feng *et al*. (*10*) for a discussion of the importance of doing so).

In this paper, we discuss efforts to estimate MDCEV-based household vehicle type choice and use model for the State of California. An important distinction between our current effort and earlier household vehicle holdings research, in addition to differences relating to methodology and the comprehensiveness of modeling vehicle types in a household, is that our vehicle ownership and type choice model serves as the engine for a household vehicle composition and evolution simulator, which itself has been embedded within the larger activity-based travel and emissions forecasting system labeled as SimAGENT (for Simulator of Activities, Greenhouse emissions, Energy, Networks, and Travel) developed for the Southern California Association of Governments (SCAG) region (see Goulias *et al.* (*15*) for an overview).

In the process of the integration discussed above, another unique aspect of our model is that we jointly estimate the household vehicle fleet characteristics as well as identify a member of the household who will be the primary driver for each of the vehicles. This emphasis on the primary driver assignment is important for two reasons. First, household decisions of what body type and vintage of vehicles to own, and who the primary drivers would be for each vehicle, are not made independently. For instance, women of driving age, in general, may prefer newer vintage vehicles than men (as our own empirical results will show). Similarly, a household with a working couple and two children may prefer to get a car for the husband (*i.e.,* the husband is the primary driver of the car) and an SUV for the wife since the wife is likely to be primarily responsible for child-care (see (*16*)). Another example would be parents deciding whether and what type of vehicles to provide their teenage children. Some may prefer to provide the old "hand-me down" vehicle to their child and get a new vehicle, while others may overrule the preferences of their child for a sporty vehicle and purchase a new mid-sized sedan with substantial safety features. In all these instances, the preferences of each driving age individual, the anticipated activity-travel patterns of individuals, and the types of vehicles parents may want to provide for their teenage children will all certainly feature in the discussions at the household-level of what type of vehicles to own. Second, the assignment of a primary driver for each vehicle owned by a household enables us later in SimAGENT to assign a vehicle to each trip made by the household (we discuss this issue later in the conclusions section). The explicit trip-vehicle pairing enables us to develop a time-space vehicle use profile and associated vehicular emissions at the fine spatial and temporal resolution of SimAGENT. Overall, and considering that many metropolitan planning organizations (MPOs) and state agencies are moving toward activity-based models, the primary driver allocation will increasingly become a central behavioral consideration to produce more accurate travel and emissions forecasts.

---

[2] For instance, in the empirical analysis of the current paper, there are 54 vehicle types. This would lead to a total of 1486 alternative vehicle type choice bundles (including the no vehicle alternative) in the traditional choice models even if the analysis is confined to households with two or fewer vehicles. Extending the analysis to all households (with no restriction on the number of vehicles) would lead to a total of 6,564,834,826 choice bundles in the empirical sample of the current study. Note also that one cannot use a random sampling approach in estimation even if the restrictive multinomial logit model is used, because of the joint nature of the discrete (vehicle type) and continuous choices (amount of use of each vehicle) (see Bento (*14*)).

2. METHODOLOGY

The joint MDCEV-MNL model is briefly discussed in this section. For notational simplicity, we suppress the index for the household throughout the discussion. Let *K* be the different vehicle types (characterized by a combination of body type, size, and vintage) that a household can own. Also, let the different vehicle types be defined such that households own no more than one vehicle of each type (this may be achieved by defining the vehicle types in disaggregate body type, size, and vintage categories such as small SUV-new, small SUV 2-3 years old, small SUV 3-4 years old, mid-sized SUV-new, and mid-sized SUV 2-3 years old).[3] With this characterization of vehicle types, *K* effectively represents the total number of vehicles a household can possibly own. If a household owns a particular vehicle type, this vehicle type may be assigned to any one of the drivers in the household.[4] Let m_k be the annual mileage of each vehicle type *k* (*k* = 1, 2, …, *K*) and let *l* be the index for drivers in the household (*l*=1, 2, …, *N*). Let W_{lk} be the utility perceived by the household from assigning vehicle type *k* to driver *l* as the primary driver (this basically is a combination of individual *l*'s preferences for vehicle type *k* and the household's overall assessment of the value of holding vehicle type *k* and assigning it to driver *l*). Moreover, consider that all the households have a non-zero non-motorized mileage (as discussed later in Section 3). In our model, we consider the "non-motorized mode" as being the first vehicle "type", which then makes the total household motorized annual mileage endogenous to the formulation.[5] The underlying utility function that the household maximizes can be written as (see (*17*)):

$$\tilde{U} = [\exp(\beta' x_1 + \varepsilon_1)] m_1^{\alpha_1} + \sum_{k=2}^{K} \{[\exp(\sum_{l \in N} \delta_{lk} W_{lk})](m_k + 1)^{\alpha_k}\} \qquad (1)$$

subject to $\sum_{k=1}^{K} m_k = M$, $m_k \geq 0$ and $\sum_{l \in N_k} \delta_{lk} = 1 \; \forall \; k \geq 2$, where *M* is the total exogenous household annual mileage across all the *k* vehicle types (including non-motorized travel; *M* is determined in an earlier step in SimAGENT), δ_{lk} is a dummy variable that takes a value of 1 if the l^{th} member is the primary driver for vehicle type *k*, and α_k is the satiation parameter that influences the rate of diminishing marginal utility from using vehicle type *k* .

Given that there can only be one primary driver for each vehicle type, the household, if it chooses to own vehicle type *k*, will assign that vehicle to driver *l* so that there is maximum utility from that assignment. The utility expression in Equation (1) can thus be rewritten as:

$$\tilde{U} = [\exp(\beta' x_1 + \varepsilon_1)] m_1^{\alpha_1} + \sum_{k=2}^{K} \{[\exp(\max_{l \in N} \{W_{lk}\}](m_k + 1)^{\alpha_k}\} \qquad (2)$$

---

[3] In fact, the definition of the vehicle types (as characterized by body type, body size, and vintage) can always be constructed in such a way that there are no households with multiple vehicles of the same type. But, in practical modeling, a balance is warranted between the number of vehicle type categories and the percentage of households accommodated through the MDCEV modeling structure, as discussed further in Section 3.

[4] SimAGENT considers all individuals with a driver's license as a candidate for assignment as a primary driver for a vehicle (a module in an earlier demographic simulator in SimAGENT determines whether a driving age adult has a driver's license or not).

[5] We do not distinguish between different non-motorized modes (bicycling and walking) in the current analysis, because the focus is on motorized travel.

The optimization problem above can be solved by forming the Lagrangian and applying the Kuhn-Tucker conditions. Keeping the non-motorized alternative to which the household always allocates a non-zero mileage as the base alternative, the Kuhn-Tucker conditions may be written as (*17*):

$$H_k = H_1 \text{ if } m_k^* > 0 \qquad (k = 2,3,...K), \qquad (3)$$
$$H_k < H_1 \text{ if } m_k^* = 0$$

where,

$$\begin{aligned} H_1 &= \beta' x_1 + \ln\alpha_1 + (\alpha_1 - 1)\ln m_1^* + \varepsilon_1 \,, \\ H_k &= \max_{l \in N}\{W_{lk}\} + \ln\alpha_k + (\alpha_k - 1)\ln(m_k^* + 1), k \geq 2 \end{aligned} \qquad (4)$$

To complete the model specification, we assume the following functional form for $W_{lk} (k \geq 2)$:

$$W_{lk} = \beta' x_k + \gamma' z_{lk} + \varepsilon_{lk} \,, \qquad (5)$$

where $\beta' x_k$ is the overall observed utility component of vehicle type *k*, z_{lk} is an exogenous variable vector influencing the utility of the driver *l*-vehicle type *k* pairing, γ is the corresponding coefficient vector to be estimated, and ε_{lk} is an unobserved error component representing idiosyncratic preferences of driver *l* for vehicle type *k*. We assume that the ε_{lk} terms are identically Gumbel distributed. But the intrinsic preferences of all drivers in the household for vehicle type *k* may be generally high or generally low. For instance, all drivers in a "sporty" lifestyle family may have a higher preference for small vehicles (relative to their observationally equivalent peer households), or all drivers in a "luxury-minded" family may have a higher preference for large SUVs. This generates correlation (across drivers *l*) in the error terms ε_{lk}. Let this correlation be determined by a logsum (or dissimilarity) parameter θ_k. Then, the distribution function of the error terms of the drivers within a household can be written as:

$$F(\varepsilon_{1k}, \varepsilon_{2k}, ..., \varepsilon_{Lk}) = \exp\left\{ -\left[e^{-\varepsilon_{1k}/\theta_k} + e^{-\varepsilon_{2k}/\theta_k} + ... e^{-\varepsilon_{Lk}/\theta} \right]^{\theta_k} \right\} \qquad (6)$$

In this analysis, for convenience, we assume $\text{cov}(\varepsilon_{lk}, \varepsilon_{l'k'}) = 0$ if $k \neq k'$, though it is possible that some household-level unobserved factors (such as "luxury mindedness") can impact the preferences for multiple vehicle types (such as for an SUV of different vintages). Such covariances can be accommodated using the more general multiple discrete-continuous generalized extreme value (MDCGEV) model of Pinjari (*18*) for the upper level model instead of the MDCEV. This is left for future efforts.

Using the maximization property of the Gumbel distribution that $\text{Max}_j \, \varepsilon_j = G[\ln \sum_j e^{V_j/\theta}, \theta]$, Equation (4) can be written as:

$$\begin{aligned} H_1 &= \beta' x_1 + \ln\alpha_1 + (\alpha_1 - 1)\ln m_1^* + \varepsilon_1 = V_1 + \varepsilon_1 \,, \\ H_k &= \beta' x_k + \theta_k \ln \sum_{l \in N} \exp\left(\frac{\gamma' z_{lk}}{\theta_k} \right) + \ln\alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) + \varepsilon_k = V_k + \varepsilon_k, \; k \geq 2 \end{aligned} \qquad (7)$$

where ε_k is a standard Gumbel distributed random term. Also, since $\text{cov}(\varepsilon_{lk}, \varepsilon_{l'k'}) = 0$ if $k \neq k'$, $\text{cov}(\varepsilon_k, \varepsilon_{k'}) = 0$. The probability that the household chooses the first Q of K vehicle categories ($Q \geq 1$) and drives these vehicles for annual mileages $m_1^*, m_2^*, ..., m_Q^*$ may be written as:

$$P(m_1^*, m_2^*, ...m_Q^*, 0,0,0,....,0) = \left[\prod_{k=1}^{Q} r_k\right]\left[\sum_{k=1}^{Q} \frac{1}{r_k}\right]\left[\frac{\prod_{k=1}^{Q} e^{V_k}}{\left(\sum_{h=1}^{K} e^{V_h}\right)^Q}\right](Q-1)!,\ r_k = \left(\frac{1-\alpha_k}{m_k^* + 1}\right), \tag{8}$$

where V_1 and V_k $(k \geq 2)$ may be inferred from Equation (7).

The conditional probability of member l being the primary driver for vehicle k *(k* >1), given that vehicle k is owned by the household (*i.e.*, $m_k^* > 0$), can be obtained as[6]:

$$P(l \mid m_k^* > 0;\ l \in N_k) = \frac{\exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right)}{\sum_{l' \in N_k} \exp\left(\frac{\gamma' z_{l'k}}{\theta_k}\right)}, k \geq 2 \tag{9}$$

The unconditional probability that individual '*a*' is the primary driver for the second vehicle type, individual '*b*' is the primary driver for the third vehicle type, ….individual '*q*' is the primary driver for vehicle type *Q*, can be written as:

$$\begin{aligned} &P(m_1^*, m_{2a}^*, m_{3b}^*, ...m_{Qq}^*, 0,0,0,...0) \\ &= P(m_1^*, m_2^*, ...m_Q^*, 0,0,...0) \times P(a \mid m_2^* > 0) \times P(b \mid m_3^* > 0)...P(q \mid m_Q^* > 0) \end{aligned} \tag{10}$$

The parameters to be estimated include β, γ, and the dissimilarity parameters θ_k.

3. DATA SOURCE AND SAMPLE FORMULATION

We used the residential component of the 2008 California Vehicle Survey data collected by the California Energy Commission (CEC) to estimate the vehicle fleet composition and use model of this paper (see Paleti *et al.* (*19*) for more details on this data).

The vehicle type alternative in our study is defined as a combination of body type (including vehicle size) and vintage. For the MDCEV model, we cannot have households owning multiple vehicles of the same type. To ensure this does not happen, we attempted several different categorization schemes of vehicle types, while also retaining richness in body type and vintage. At the end, we defined nine body type/size categories and six vintage categories, for a total of 54 vehicle types, such that no more than 5% of the households have multiple vehicles of

[6] The implicit assumption here is that households do not own cars and keep them idle throughout the year.

the same vehicle type (we excluded this 5% subset of households from our analysis).[7] The 9 body types/sizes are: (1) Sub-compact car, (2) Compact car, (3) Mid-sized car, (4) Large car, (5) Small SUV, (6) Mid-sized SUV, (7) Large SUV, (8) Van, and (9) Pick-up, and the 6 vintage categories are: (1) Less than 2 years old, (2) 2 to 3 years old, (3) 4 to 5 years old, (4) 6 to 9 years old, (5) 10 to 12 years old, and (6) Older than 12 years (the vintage categories are based on taking the difference between the survey year and the reported year of manufacture of the vehicle). Overall, there are a total of 55 alternatives in the MDCEV model - 54 alternatives obtained as combinations of nine body types/sizes and 6 vintage categories + one non-motorized vehicle "type" category that is always "consumed" (that is, households travel using non-motorized modes for some positive amount). However, the survey data did not collect information about the household's non-motorized mileage. So, we estimated the non-motorized mileage of each household using a deterministic rule that each individual in the household walks or bikes for half a mile daily. The total annual non-motorized mileage for a household is obtained as 0.5*365*(household size).[8]

The final dataset used in the analysis consists of 4711 households. Of these households, 3.4 % do not own any vehicles, 32.6 % own one vehicle, 45.2 % own two vehicles, 14.6 % own three vehicles, and 4.2 % own four or more vehicles. The average number of vehicles per household is 1.84. Across all the vehicles in the sample (across all households), the highest percentage by body type corresponds to a mid-size car (22.3% of all vehicles), while the lowest is for a sub-compact car (3.4%). Overall, half of all vehicles are passenger cars (sub-compact, compact car, mid-sized car, and large car). SUVs are the second most preferred body-type, with 26.2% of households owning an SUV (small, mid-sized, or large). Pick-ups also constitute a sizeable fraction, making up 17% of the vehicle fleet. By vintage category, vehicles of 6 to 9 years old are the most common (26.3% of the total vehicle fleet). The average vintage of vehicles in the sample is 7.78 years. On average, a vehicle is driven 13,328 miles annually. Compact cars are slightly more driven with an annual mileage of 14,319 miles. Old cars (10 years or older) are the least driven, as is reasonable to expect. In terms of the primary driver assignment, 80% of pick-up trucks are assigned to a male member of household. For the rest of the body types, the

---

[7] One could use an even more disaggregate classification of the vintage categories, with the result that the vehicle types (which are combinations of body type, body size, and vintage) are so disaggregate that households do not own more than one vehicle of each vehicle type. While there are no conceptual or implementation issues in doing so because of the relative flexibility of the MDCEV model, there is a need here for a trade-off and balance. For example, if we wanted to include more than 98% of households in the current analysis, we would have to go to 18 vintage categories rather than the six being used right now. However, such a very disaggregate vintage classification does not provide much additional information for vehicle policy analysis or GHG emissions analysis, and essentially becomes simply a device to accommodate more households within the MDCEV modeling scheme. At the same time, the number of alternatives rises to 163 alternatives in the MDCEV from the current 54 alternatives, which increases the number of parameters to be estimated and reduces econometric efficiency of the estimated parameters. So, we prefer to use the MDCEV modeling framework to estimate parameters in a theoretically consistent and econometrically efficient manner for the vast majority of households, and then use traditional (and simplistic) estimation approaches for the small fraction of remaining households. For instance, for the SCAG implementation, we first have a simple binary choice model to separate households into those that do not have multiple vehicles of each type within the 54-vehicle type categorization scheme and those that do. Then, the households that do not have multiple vehicles of each type are taken through the MDCEV approach to forecast number of vehicles, vehicle type, and vehicle usage decisions. For the 5% of households that do have multiple vehicles of the same type within the 54-vehicle type classification, more disjointed models using traditional single discrete choice methods are estimated and applied.

[8] The model results were not sensitive to the mileage value assigned to the non-motorized mode "type". This assignment is simply a devise to be able to apply the MDCEV model.

proportion of male primary drivers is more or less the same as that of female primary drivers. Of course, these results do not control for other variables, as does our multivariate and joint MDCEV-MNL model.

Several demographic variables are considered in the empirical analysis. For the MDCEV estimation, the exogenous variables include household race, household size, number of adults (> 15 years of age), household income, number of children in the household by age groups- 0 to 4 years, 5 to 12 years, 12 to 15 years, number of senior adults (aged more than 65 years), highest education level attained among all household members, number of workers, and mean distance to work calculated among workers (in miles). For the MNL estimation, individual characteristics including age, gender, race, education level, employment status, and distance to work place (in miles) are used.

4. EMPIRICAL RESULTS

In the most general way of specifying the MDCEV model, we can estimate 54 coefficients for each covariate. However, estimating such a model is not only practically infeasible but also inefficient. Instead, to avoid the explosion in the number of parameters to be estimated, we consider the total baseline utility associated for each MDCEV alternative as the sum of independent utilities for the body type and vintage dimensions. We also attempted interaction effects of variables across the two dimensions, but these did not come out to be statistically significant.

Since only differences in utilities matter, and because of our way of specifying dimension-specific utilities, a base category needs to be specified for both the body type and vintage dimensions. We used the non-motorized annual mileage as the base category for the body type dimension (for ease in presentation, we will refer to the body type/size combination dimension simply as the body type dimension from hereon), and the "New" vehicle category (less than 2 years old) as the base category for the vintage dimension. This type of formulation reduces the number of coefficients to be estimated for each exogenous variable to 14 (9 for body type + 5 for vintage type). The effects of exogenous variables can then be calculated by combining the appropriate coefficients. For example, for the small SUV which is more than 12 years old, the total impact of number of workers on the baseline utility can be obtained as: $\beta_{\#worker,SmallSUV} + \beta_{\#worker,aged>12\,years}$. The satiation parameters are also specified in a similar manner. Specifically, the α_k satiation parameters in Equation (1) are specified as $\frac{1}{1+\exp(-\delta_k - \mu_k)}$, where the first component δ_k corresponds to the effect originating from the body type dimension of vehicle type *k*, and the second component μ_k originates from the vintage dimension of vehicle type *k*. The functional form used guarantees that α_k is bounded between 0 and 1.

For the MNL estimation, the maximum number of alternatives is 6, which corresponds to the maximum number of drivers in any household in the estimation data. But the number of alternatives varies across households because of varying numbers of driving-age adults. Further, each alternative in the MNL model corresponds to an individual, who is identified by her/his characteristics rather than by labels of A or B or C. Thus, this estimation corresponds to that of an "unlabelled" estimation, with the alternatives being purely characterized by individual-associated attributes.

4.1 MDCEV Model Results

Table 1 presents the estimation results of MDCEV component of the final model. As mentioned earlier, the non-motorized annual mileage is the base category for the body type dimension and "New" (age less than 2 years) is the base category for the vintage dimension. Thus, these categories do not appear in Table 1. Further, a "--" in Table 1 indicates that the effect of the corresponding variable (described in the column) on the corresponding dimension (as described in the rows) is the same as that on the base category. Also, values in parentheses are the t-statistics corresponding to each parameter estimate.

Household race: We used 5 race variables: (1) African-American, (2) Hispanic, (3) Asian, and (4) Caucasian and (5) Other race. The base race constitutes "other races" which are not included in above four categories. If all the individuals in the household have the same race, then we coded the household race as the race of any of these members. If members in the household were of different race groups, the household was assigned to the "other race" category. The results in Table 1 show that race has a statistically significant effect on the household's vehicle holdings. African-Americans are likely to own large cars and vehicles that are 4-5 years old, suggesting a preference for vehicles in the medium age range. Hispanic households have the same preferences as households belonging to the "other" race category. Asian households do not hold preferences for any particular body type, but, similar to African-American households, they have a high preference for vehicles 4 to 5 years old. Also, Caucasian households are disinclined to own compact cars and large SUVs. These results may be reflective of different lifestyle, cultural, and attitudinal factors among different races/ethnic groups.

Number of adults (> 15 years of age): Households with many adults have the least preference for small SUVs and the highest preference for vans/compact/large cars, results that need further exploration in future studies. The negative sign on these coefficients (relative to the base of non-motorized travel) is simply an artifact of the way the non-motorized travel mileage was created, and should not be interpreted in any behavioral sense.

Number of male adults (>15 years of age): This variable provides the marginal utility differential between an additional male in the household compared to an additional female adult in the household (because of the presence of the number of adults variable earlier). The results indicate that males tend to be less drawn toward compact cars and mid-sized SUVs compared to women. The general social perception is that SUVs are driven by middle-aged working women with children (see (*20*)), which is consistent with the finding here. Also, the lower preference for compact cars among males may simply be a reflection of body frame size differences between men and women.

Household income (\$): Several functional forms of the household income variable were considered in the baseline utility specification, including a continuous income specification, and spline variables and dummy variables for different income ranges. However, the simple continuous income specification provided the best statistical fit. Table 1 shows that, along the body-type dimension, the sign of the coefficients on the income variable is generally positive. That is, households with high income are likely to own multiple vehicles. This is expected because high income households have more purchasing power. In addition, such households have a high preference for large SUVs and a low preference for compact cars, suggesting an emphasis on luxury vehicles (see also (*11*, *21*, *22*)). Along the vintage dimension, the coefficient on income is negative for all categories above 4 years, suggesting that, as the income of a household increases, the preference for older vehicles decreases ((*23*) and (*24*) also find a similar result).

Number of senior adults (aged > 65 years): Households with many senior members are more likely (relative to those with few senior members) to own large cars. Moreover, households with senior adults are also found to be less likely to own pick-up trucks. These results might be indicative of the fact that senior adults prefer vehicles which are more affordable and comfortable, and easy to get into and out of. Interestingly, as with the number of children, the number of senior members in households does not have any influence on the vintage dimension.

Number of children: We considered the effect of number of children by three age categories, as mentioned before. Overall, households with children have a high preference for spacious body-types such as SUVs and vans, and a low preference for compact and sub-compact cars. These effects permeate across all age groups, perhaps because of a perceived need for additional cargo/luggage space (to carry tricycles, childcare equipment *etc*.), and additional passenger room for car-pooling arrangements of children within and across households. The number of children does not have any substantial effects on preferences based on vehicle vintage.

Highest education in household: Households with bachelor's or associate (highest) degree (as the highest degree across all household members) are less likely to own sub-compact cars, large cars, large SUVs and pick-up trucks relative to other body types. Also, these households are most likely to own vehicles that are 6 to 9 years old. A higher education probably makes these households less prone to hold vehicles that are not fuel efficient (such as large cars, SUVs, and pick-up trucks). Households having individuals with post graduate degrees are particularly unlikely to prefer pick-up vehicles. It is possible that, when making vehicle type choice decisions, individuals with the highest education level in the household tend to bring their environmentally conscious outlook to overall household decisions, thus avoiding large vehicles. Taken along with the household income effect, the suggestion is that households with high incomes are likely to gravitate toward luxury large vehicles, but this effect is attenuated by the high education status of the person with the highest education level in the household. Thus, for example, consider two two-worker households, both with high household income earnings– one has a very highly educated individual who earns a substantial fraction of the overall household income, and the other has two individuals of moderate education levels earning about equal fractions of the overall household income. Our results suggest that the first household can be expected to own smaller sized cars than the second household.

Number of workers: Households with many workers are likely to own mid-sized SUVs and the least likely to own vans, as also observed by Chao and Shen (*25*). Interestingly, the vintage of the vehicle owned by a household is not affected by the number of workers in that household.

Mean distance to work: Households with a longer mean distance to work are the most likely to own pick-up trucks. This is perhaps a reflection of the type of jobs that people who reside at places far from home get to do. It is possible that people involved in the construction and repair industry, who usually prefer pick-up trucks to carry work equipment, work at multiple locations on a given day because of the nature of their job.. Thus, they might report longer commute durations compared to employees with a fixed work place in other industry sectors (*26*). Unfortunately, we did not have information on occupation categories in our data to examine this interaction effect of distance to work and occupation, an issue that needs additional attention in future research efforts. Along the vintage dimension, households with workers having longer commute distances prefer newer vehicles aged 2-3 years.

Constants and satiation parameters: The baseline constants in the model do not have any substantive interpretation because of the presence of several continuous variables in the model (these constants are not presented here to conserve on space). In addition to constants for the body type and vintage dimensions, we also explored specifications for constants corresponding to interactions of body type and vintage. Several of these interaction constants came out to be highly significant. Specifically, the interaction constants for older (more than 10 years old) pickup trucks, new (less than 5 years old) small SUVs, and 2-to-3 year old large cars are positive, indicating, respectively, that pickup trucks retain more value (relative to other body types) over time, small SUVs are preferred as new vehicles, and large cars generally are likely to be held in the intermediate vintage categories.

Satiation parameters: The satiation parameters need to be computed from the δ_k and μ_k estimates, as discussed earlier. This will provide a separate satiation parameter for each of the 55 vehicle types. However, due to space considerations, we present the implied satiation parameters α_k (and corresponding standard errors) separately for the body type dimension (assuming a vehicle less than 2 years of age) and the vintage dimension (assuming a sub-compact vehicle). The satiation parameter for the non-motorized mode, not shown in Table 1, is effectively zero, consistent with the very low mileage by non-motorized modes. The results for other body types and vintages are presented in Table 1. Several results may be observed from Table 1. First, the satiation parameters for all alternatives are significantly different from 1, indicating the presence of satiation effects in vehicle holding and usage decisions (the t-statistics in Table 1 for the satiation parameters are computed with respect to the value of 1). Second, the relative magnitudes of the α_k parameters suggest that pick-up trucks have the highest satiation effects among all vehicle body types. Third, along the vintage dimension, the satiation effect is highest for vehicles older than 12 years, consistent with the lower average annual mileage value for vehicles in this age group.

4.2 MNL Results

Table 2 presents the estimation results of the MNL component of the final model. The variables below correspond to characteristics associated with the individual.

Age: The best fit was obtained with three dummy variables: (1) Age between 16 to 25 years, (2) age between 26 to 40 years, and (3) age between 41 to 65 years. The household members belonging to the first age category are the least likely to prefer SUVs and vans. This category belongs to young people, and such individuals may have a tendency to prefer sporty vehicles rather than what they consider to be "uncool" or "family" vehicles. Individuals in the second age category are found to prefer SUVs. This category belongs to middle aged individuals, and additional responsibilities such as child care, child's school drop-off and pick-up, and additional comfort considerations may draw these individuals toward more spacious and safer SUVs.

Lastly, household members between 41 to 65 years old have the highest tendency for SUVs. Comfort and convenience (getting in and out of vehicles) might be the main criterion for these individuals.

Gender and race: Women are less likely to use body types other than vans, and are particularly unlikely to drive large cars and small SUVs, compared to men. Also, women prefer new vehicles more so than men. There are no race differences of any consequence.

Education: Household members with bachelor or associate degree are indifferent between body-types, but have a low preference to drive older vehicles (relative to individuals with high school or college degree).

Worker: Employed members in the household have a higher preference for sub-compact cars relative to unemployed members, perhaps reflecting a desire for balance in size and comfort. That is, employed individuals may prefer a smaller car for the commute in peak hours to save on fuel expenses, but may not also want to compromise on comfort. Along the vintage dimension, it is observed that workers have a tendency to drive vehicles that are less than 4 years old.

Distance to work (in miles): Several distance specification were explored, but the best specification was obtained with a dummy variable for “distance to work less than 10 miles”. For workers whose commute distance is less than 10 miles, mid-sized SUVs are the most preferred vehicle, possibly indicative of additional responsibilities toward children (such as dropping children at school). Along the vintage dimension, new vehicles are less preferred, perhaps because of less of a perceived need for the safety features of newer cars given the short commute or because of less concern about commute-related fuel costs.

4.3 Logsum Parameters

A total of 54 log-sum parameters (θ_k) may be estimated, capturing correlation in the preferences of individuals within a household for each of the 54 motorized vehicle types. However, 22 of these did not come out to be different from the value of 1, suggesting lack of correlation. For the remaining 32 vehicle types, we examined patterns of correlation and finally constrained the logsum parameters among these vehicle types to obtain three distinct values of the logsum parameters. We do not present these here to conserve on space, but the general trend indicated higher correlations (or generic inclinations or dis-inclinations within individuals in a family) for the car alternatives (compact car, mid-sized sedan, and large car) of recent vintage (less than 4 to 5 years old). That is, there is more volatility (across households) in the overall household-level preferences (due to unobserved factors) for the car alternatives of recent vintage. On the other hand, the logsum parameters indicated relatively less volatility (across households) in preferences for the small, mid-sized, and large SUV categories. This suggests that SUVs have a more consistent “value” position in the cognitive maps of households when making vehicle type choice decisions.

4.4 Model Fit

The final log-likelihood value at convergence of the joint MDCEV-MNL model is –54003.2. We estimated another model with just constants for the vehicle body type and vintage both in the baseline utility specification and the satiation parameters, with no variables in the primary driver allocation model, and with all logsum parameters fixed at 1. The log-likelihood of that model is –56883.00. The log-likelihood ratio test statistic value for comparison between these two models is 5759.60, which is higher than the critical chi-squared value for 107 degrees of freedom at any level of significance. This clearly indicates the value of the model estimated in this paper to predict vehicle holdings, usage, and primary driver assignment.

5. CONCLUSION

In this paper, we discuss efforts to estimate and apply a joint MDCEV-MNL household-level model of the number of vehicles owned by the household, the vehicle type choice of each vehicle, the annual mileage on each vehicle, as well as the individual assigned as the primary driver for each vehicle. The empirical results of our model indicate that several household and individual demographic variables have significant impacts on the vehicle holdings decisions. The resulting model can also be incorporated easily in any activity-based micro-simulation framework, thanks to the recent advances in the design of efficient forecasting algorithms for predicting using the MDCEV model (see Pinjari and Bhat (*27*)). The model developed in this study currently serves as the engine for a household vehicle composition and evolution simulator, which itself has been embedded within the larger SimAGENT activity-based travel and emissions forecasting system for the SCAG region. To our knowledge, this is the first such effort to integrate a complete household vehicle ownership and type choice simulator within a larger activity-based model micro-simulator system. Further, the assignment of a primary driver for each vehicle owned by a household allows us later in SimAGENT to assign a vehicle to each trip made by a household.

In the current version of SimAGENT, we first predict the household vehicle fleet, and the usage (annual mileage) and primary driver of each vehicle in the fleet. Subsequently, we estimate and apply a make/model MNL model within each body/vintage type. We also assume that all tours/trips made during the day by an individual are made using his/her primary vehicle. Further, we have an explicit vehicle type MNL model to determine the type of vehicle which is used for joint tours. The primary vehicles of all the individuals participating in the joint tours form the alternate choice set for this model. Thus, SimAGENT's output includes the complete travel pattern of all individuals in the household on a continuous time scale along with the information about the body type, vintage, make, and model of the vehicle used for every vehicular trip/tour made during the day. In addition, the structure of the MDCEV model also provides aggregate forecasts of annual mileage of each of the vehicles in the household. This is used by SimAGENT as a measure of the overall use of each vehicle when assigning tours (trips) to vehicles. At the same time, the aggregate mileage predictions serve another useful role. They allow SimAGENT to be used as a quick-response tool to examine the impact of a variety of land-use and transportation policies on GHG emissions and energy consumption, without needing to run the complete SimAGENT system for each policy. This allows a "first-order pruning" of policy alternatives, so that only those that seem most promising get taken further for a comprehensive SimAGENT evaluation (see Goulias *et al.* (*15*)).

Our latest efforts are focused on enhancing the implementation of the simulator within the larger activity-travel generation model system. For instance, it need not be the case that each (and all) of person A's tours (trips) should be assigned to the vehicle whose primary driver is person A (though this is the deterministic assignment in SimAGENT at this point). Other contextual information, such as the estimated annual mileage of each vehicle as predicted by the MDCEV model, availability of other household vehicles in the time window of activity participation and travel, the attributes of the available vehicles (fuel efficiency, vehicle size, trunk space, *etc.*), the characteristics of the activity episodes (such as location vis-à-vis origin point, destination zone characteristics/parking tightness, and activity purpose), and individual characteristics may also be considered in the individual trip assignment. Accordingly, we are developing an additional model for the vehicle-to-trip/tour assignment, with the primary driver being an important (but not sole) exogenous variable in the model. Another important enhancement being pursued is to use the vehicle holdings and primary driver assignment information (predicted upstream of all the activity generation and scheduling modules of SimAGENT) not only to facilitate the process of post-assigning vehicles to generated tours (and trips), but also more directly to influence household activity generation and scheduling patterns in SimAGENT. Concurrent with these modeling improvements, we are also in the process of obtaining information on the geo-locations of the households surveyed in the California Energy Commission (CEC) data to append relevant built environment measures, and include such measures in the vehicle type choice and primary driver assignment model.

ACKNOWLEDGEMENTS
The authors would like to thank the California Energy Commission for providing access to the data used in this research, and the Southern California Association of Governments for facilitating this research. The authors are also grateful to Lisa Macias for her help in formatting this document. Four anonymous reviewers provided valuable comments on an earlier version of this paper.

REFERENCES

1. Environmental Protection Agency (EPA). Report on the Environment: Science Report (SAB Review Report). National Center for Environmental Assessment, Report EPA/600/R-07/045, 2007.
2. Schrank, D., T. Lomax, and S. Turner. Urban Mobility Report 2010. Texas Transportation Institute, Texas A&M University, College Station, TX, 2010.
3. California Air Resources Board (CARB). *Incentive Programs for Alternative Fuels and Vehicles*. California Environmental Protection Agency, 2011. http://www.arb.ca.gov/fuels/altfuels/incentives/incentives.htm. Accessed July 15, 2011.
4. Train, K.E., and C. Winston. Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers. *International Economic Review*, Vol. 48, No. 4, 2007, pp. 1469-1496.
5. Spissu, E., A.R. Pinjari, R.M. Pendyala, and C.R. Bhat. A Copula-Based Joint Multinomial Discrete-Continuous Model of Vehicle Type Choice and Miles of Travel. *Transportation*, Vol. 36, No. 4, 2009, pp. 403-422.
6. Choo, S., and P.L. Mokhtarian. What Type of Vehicle Do People Drive? The Role of Attitude and Lifestyle in Influencing Vehicle Type Choice. *Transportation Research Part A*, Vol. 38, No. 3, 2004, pp. 201-222.
7. Mannering, F., and C. Winston. A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization. *Rand Journal of Economics*, Vol. 16, No. 2, 21985, pp. 15-236.
8. West, S. Distributional Effects of Alternative Vehicle Pollution Control Policies. *Journal of Public Economics*, Vol. 88, No. 3-4, 2004, pp. 735-757.
9. Brownstone, D., and H.A. Fang. A Vehicle Ownership and Utilization Choice Model with Endogenous Resident Density. Compendium of Papers DVD, Transportation Research Board 88th Annual Meeting, Washington, D.C, 2009.
10. Feng, Y., D. Fullerton, and L. Gan. Vehicle Choices, Miles Driven, and Pollution Policies. National Bureau of Economic Research, NBER Working Paper No. 11553, 2005.
11. Fang, H.A. A Discrete-Continuous Model of Households' Vehicle Choice and Usage, with an Application to the Effects of Residential Density. *Transportation Research Part B*, Vol. 42, No. 9, 2008, pp. 736-758.
12. Bhat, C.R., and S. Sen. Household Vehicle Type Holdings and Usage: An Application of the Multiple Discrete-Continuous Extreme Value (MDCEV) Model. *Transportation Research Part B*, Vol. 40, No. 1, 2006, pp. 35-53.
13. Bhat, C.R., S. Sen, and N. Eluru. The Impact of Demographics, Built Environment Attributes, Vehicle Characteristics, and Gasoline Prices on Household Vehicle Holdings and Use. *Transportation Research Part B*, Vol. 43, No. 1, 2009, pp. 1-18.
14. Bento, A.M., L.H. Goulder, M.R. Jacobsen, and R.H. von Haefen. Distributional and Efficiency Impacts of Increased US Gasoline Taxes. *American Economic Review*, Vol. 99, No. 3, 2009, pp. 667-699.

15. Goulias, K.G., C.R. Bhat, R.M. Pendyala, Y. Chen, R. Paleti, K.C. Konduri, T. Lei, D. Tang, S.Y. Youn, G. Huang, and H.H. Hu. Simulator of Activities, Greenhouse Emissions, Networks, and Travel (SimAGENT) in Southern California. Presented at the 91st Annual Meeting of the Transportation Research Board, Washington, D.C., January 2012.
16. Hilbrecht, M., S.M. Shaw, L.C. Johnson, and J. Andrey. I'm Home for the Kids': Contradictory Implications for Work-Life Balance of Teleworking Mothers. *Gender, Work and Organization*, Vol. 15, No. 5, 2008, pp. 454-476.
17. Bhat, C.R. The Multiple Discrete-Continuous Extreme Value (MDCEV) Model: Role of Utility Function Parameters, Identification Considerations, and Model Extensions. *Transportation Research Part B*, Vol. 42, No. 3, 2008, pp. 274-303.
18. Pinjari, A.R. Generalized Extreme Value (GEV)-Based Error Structures for Multiple Discrete-Continuous Choice Models. *Transportation Research Part B*, Vol. 45, No. 3, 2011, 474-489.
19. Paleti, R., N. Eluru, C.R. Bhat, R.M. Pendyala, T.J. Adler, and K.G. Goulias. Design of Comprehensive Microsimulator of Household Vehicle Fleet Composition, Utilization, and Evolution. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 2254, Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 44-57.
20. Walsh, M. Gendering Mobility: Women, Work and Automobility in the United States. *History*, Vol. 93, No. 311, 2008, pp. 376-395.
21. Kitamura, R., T.F. Golob, T. Yamamoto, and G. Wu. Accessibility and Auto Use in a Motorized Metropolis. Presented at the 79th Annual Meeting of the Transportation Research Board, Washington, D.C., January, 2000.
22. Cao, X., P.L. Mokhtarian, S.L. Handy. Neighborhood Design and Vehicle Type Choice: Evidence from Northern California. *Transportation Research Part D*, Vol. 11, No. 2, 2006, pp. 133-145.
23. Ong, P., and C. Lee. Spatial Pattern of Vehicle Ownership by Vintage. University of California Transportation Center, UC Berkeley, 2007.
24. Yurko, A. From Consumer Incomes to Car Ages: How the Distribution of Income Affects the Distribution of Vehicle Vintages. University Library of Munich, Germany, MPRA Paper No. 8849, 2008.
25. Chao, L., and Q. Shen. An Empirical Analysis of the Influence of Urban Form on Household Travel and Energy Consumption. *Computers, Environment and Urban Systems*, Vol. 35, No. 5, 2011, pp. 347-357.
26. Zolnik, E.J. The Effect of Sprawl on Private-Vehicle Commuting Outcomes. *Environment and Planning A*, Vol. 43, No. 8, 2011, pp. 1875-1893.
27. Pinjari, A.R., and C.R. Bhat. Computationally Efficient Forecasting Procedures for Kuhn-Tucker Consumer Demand Model Systems: Application to Residential Energy Consumption Analysis. Technical paper, Department of Civil and Environmental Engineering, University of South Florida, 2011.

LIST OF TABLES

TABLE 1 Estimation Results of MDCEV Component for Vehicle Holdings

Variable →	Household Race				Number of Adults	Number of Male Adults	Household Income	Number of Senior Member
	Black	Hispanic	Asian	Caucasian				
Sub-compact	-1.017 (-1.896)	--	--	--	-0.266 (-2.321)	--	0.025 (1.816)	-0.182 (-3.358)
Compact car	--	--	--	-0.073 (-1.186)	-0.147 (-1.712)	-0.142 (-2.445)	--	--
Mid-sized car	--	--	--	--	-0.263 (-3.206)	--	0.033 (4.943)	--
Large car	0.530 (2.035)	--	--	--	-0.151 (-1.419)	--	0.068 (6.134)	0.207 (3.142)
Small SUV	--	--	--	--	-0.488 (-4.637)	--	0.037 (2.890)	--
Mid-sized SUV	--	--	--	--	-0.469 (-4.312)	-0.085 (-0.982)	0.052 (5.697)	--
Large SUV	--	--	-0.316 (-1.575)	-0.186 (-2.374)	-0.195 (-2.102)	--	0.090 (10.701)	--
Van	--	--	-1.336 (-4.158)	--	-0.121 (-1.252)	--	--	--
Pickup	-0.888 (-2.898)	--	--	--	-0.254 (-3.181)	--	0.030 (3.475)	-0.097 (-1.690)
Less than 2 years	--	--	--	--	--	--	--	--
2 to 3 years	--	--	--	--	--	--	--	--
4 to 5 years	0.234 (1.305)	--	0.334 (2.286)	--	--	--	-0.011 (-1.431)	--
6 to 9 years	--	--	--	--	--	--	-0.031 (-5.205)	--
10 to 12 years	--	--	--	0.089 (1.659)	--	--	-0.062 (-7.926)	--
More than 12 years	--	--	--	0.089 (1.659)	--	--	-0.099 (-14.271)	--

TABLE 1 (Continued) Estimation Results of MDCEV Component for Vehicle Holdings

Variable	Number of Children by age group			Highest education level attained in household		Number of Workers	Mean distance to work calculated among workers	Satiation Parameters*
	0-4 years	5-12 years	13-15 years	Bachelor or Associate	Postgraduation			
Sub-compact	-0.468 (-2.718)	--	-0.373 (-1.921)	-0.202 (-1.571)	--	--	--	0.806(4.797)
Compact car	-0.138 (-2.032)	-0.119 (-1.888)	--	--	0.308 (4.145)	--	--	0.830 (7.590)
Mid-sized car	--	-0.201 (-3.230)	--	--	0.146 (2.005)	--	-0.465 (-2.126)	0.831 (7.811)
Large car	--	-0.232 (-1.761)	--	-0.139 (-1.319)	--	-0.320 (-4.254)	--	0.825 (5.573)
Small SUV	-0.238 (-1.408)	-0.219 (-1.522)	--	--	--	--	--	0.737 (6.643)
Mid-sized SUV	--	--	--	--	--	0.082 (1.488)	--	0.842 (6.328)
Large SUV	0.376 (5.714)	0.229 (3.513)	0.334 (4.374)	-0.179 (-1.962)	-0.375 (-3.434)	--	--	0.806 (6.749)
Van	0.353 (4.187)	0.476 (6.427)	0.481 (5.382)	--	0.281 (2.577)	--	--	0.847 (5.619)
Pickup	--	--	--	-0.142 (-1.738)	-0.595 (-5.542)	--	0.469 (1.999)	0.793 (7.418)
Less than 2 years	--	--	--	--	--	--	--	--
2 to 3 years	0.106 (1.879)	--	--	0.072 (1.078)	--	--	0.598 (2.665)	0.836 (4.109)
4 to 5 years	--	--	--	--	--	--	--	0.830 (4.101)
6 to 9 years	--	--	--	0.113 (2.082)	--	--	--	0.826 (4.305)
10 to 12 years	--	--	--	-1.017 (-1.896)	--	--	--	0.808 (4.23)
More than 12 years	-0.156 (-2.308)	--	--	--	--	--	--	0.737 (4.57)

* The t-statistics for the satiation parameters are computed with respect to the value of 1.

TABLE 2 Estimation Results of MNL Component for Primary Driver Allocation

Variable →	Age			Female	Race	Education Level	Employment Status	Work distance less than 10 miles
	16-25 years	26-40 years	41-65 years		Caucasian	Bachelor or Associate	Worker	
No vehicle	--	--	--	--	--	--	--	--
Sub-compact	--	-0.271 (-3.062)	-0.294 (-4.250)	-0.248 (-4.590)	-0.274 (-2.057)	--	0.143 (2.346)	--
Compact car	--	-0.271 (-3.062)	-0.294 (-4.250)	-0.248 (-4.590)	--	--	0.143 (2.346)	--
Mid-sized car	-0.359 (-3.436)	-0.260 (-2.713)	-0.239 (-3.030)	-0.249 (-4.910)	--	--	0.090 (1.434)	--
Large car	0.359 (-3.436)	-0.260 (-2.713)	-0.239 (-3.030)	-0.614 (-8.716)	--	--	0.070 (0.829)	--
Small SUV	--	--	--	-0.614 (-8.716)	--	--	0.070 (0.829)	--
Mid-sized SUV	--	--	0.172 (2.087)	--	--	--	--	0.073 (0.903)
Large SUV	-0.627 (-3.449)	--	0.151 (1.721)	-0.231 (-3.204)	--	--	-0.231 (-3.626)	0.073 (0.903)
Van	-0.951 (-4.826)	-0.400 (-3.368)	--	--	--	--	-0.231 (-3.626)	--
Pickup	-0.825 (-6.856)	-0.215 (-2.242)	--	-1.987 (-23.144)	--	--	--	--
Less than 2 years	-0.468 (-3.756)	--	--	0.573 (11.067)	0.086 (1.889)	0.060 (1.310)	0.103 (2.217)	-0.062 (-1.208)
2 to 3 years	--	--	--	0.573 (11.067)	0.086 1.889)	0.060 (1.310)	0.103 (2.217)	-0.062 (-1.208)
4 to 5 years	--	--	--	0.581 (9.616)	0.086 (1.889)	0.060 (1.310)	--	--
6 to 9 years	--	--	--	0.430 (8.522)	0.086 (1.889)	--	--	--
10 to 12 years	--	--	--	--	--	--	--	--
More than 12 years	--	--	--	--	--	--	--	--