Joint Vehicle Holdings, by Type and Vintage, and Primary Driver Assignment Model with Application for California

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In this paper an estimation is made of a joint household-level model of the number of vehicles owned by a household, the vehicle type choice of each vehicle, the annual mileage on each vehicle, and 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 in the larger Simulator of Activities, Greenhouse Emissions, Energy, Networks, and Travel (SimAGENT), an activity-based travel and emissions forecasting system for the Southern California Association of Governments planning region.

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 is an important on-road vehicular travel determinant of greenhouse gas (GHG) emissions, fuel consumption, and pollutant emissions (*1, 2*). In the state-of-the-art practice, when travel demand models are interfaced with the Environmental Protection Agency's MOBILE6 or the recently released MOVES model or the EMFAC model in California for emissions forecasting, default values (percentage of vehicles in each of the specified technology classes) are used to represent the vehicle miles traveled 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 factors such as fuel prices, socioeconomic shifts (for example, aging of the U.S. population), and policy decisions (for example, allowing vehicles attaining a certain fuel efficiency to use high-occupancy vehicle lanes). [FHWA offers some guidance on how default values on vehicle mix distributions can be adjusted by 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.]

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 GHG emissions [for example, the California Air Resources Board (*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, although the urgency in regard to GHG emissions 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 (*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 only for households with two vehicles or less, to reduce the number of possible vehicle type combinations, and even then using aggregate classifications of vehicle types such as car versus noncar or SUVs versus non-SUV vehicles (*7–10*). A few of these studies 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 recently proposed the use of a flexible multiple discrete-continuous extreme value (MDCEV) model (*12, 13*). 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 many problems in the MDCEV approach, whereas doing so is virtually impossible in the traditional choice models because of the explosion in the number of choice alternatives for multiple-vehicle households. For instance, in the empirical analysis of this paper, there are 54 vehicle types. This number would lead to a total of 1,486 alternative vehicle type choice bundles (including

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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. Also, 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 et al. (*14*)]. 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 in 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. for a discussion of the importance of doing so (*10*)].

In this paper, efforts to estimate the MDCEV-based household vehicle–type choice and use model for the state of California are discussed. An important distinction between the 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 the vehicle ownership and type choice model serves as the engine for a household vehicle composition and evolution simulator, which itself has been embedded in the larger activity-based travel and emissions forecasting system, the Simulator of Activities, Greenhouse Emissions, Energy, Networks, and Travel (SimAGENT), developed for the Southern California Association of Governments region [see Goulias et al. for an overview (*15*)].

In the process of the integration discussed above, another unique aspect of the current model is that the household vehicle fleet characteristics are jointly estimated and the member of the household who will be the primary driver for each of the vehicles is identified. This emphasis on the primary driver assignment is important for two reasons. First, household decisions on the body type and vintage of the vehicles the household will 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 do (as the authors' 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 because she is likely to be primarily responsible for child care [see Hilbrecht et al. (*16*)]. Another example would be parents deciding whether and what types of vehicles to provide for their teenage children. Some may prefer to provide the old "hand-me-down" vehicle to their child and get a new vehicle, whereas others may overrule the preferences of their child for a sporty vehicle and purchase a new midsize 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 allows a vehicle to be assigned later in SimAGENT to each trip made by the household (this issue is discussed later in the section on conclusions). The explicit trip–vehicle pairing allows for the development of 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 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.

METHODOLOGY

The joint MDCEV–multinomial logit (MNL) model is briefly discussed in this section. For notational simplicity, the index for the household is suppressed 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 to 3 years old; small SUV, 3 to 4 years old; midsize SUV, new; and midsize SUV, 2 to 3 years old). 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 later in the paper. 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. SimAGENT considers all individuals with a driver's license as candidates 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).

Let m_k be the annual mileage of each vehicle type k ($k = 1, 2, \ldots, K$) and let l be the index for drivers in the household ($l = 1, 2, \ldots, N$). 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 of the households have a nonzero nonmotorized mileage (as discussed later). In the model, the nonmotorized mode is considered as being the first vehicle type, which then makes the total household motorized annual mileage endogenous to the formulation. A distinction is not made between different nonmotorized modes (bicycling and walking) in the current analysis, because the focus is on motorized travel. The underlying utility function that the household maximizes can be written as [see Bhat (*17*)]

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

subject to

$$\sum_{k=1}^{K} m_k = M, m_k \geq 0$$

and

$$\sum_{l \in N_k} \delta_{lk} = 1 \qquad \forall\, k \geq 2$$

where

M = total exogenous household annual mileage across all k vehicle types (including nonmotorized travel) (M is determined in an earlier step in SimAGENT),
δ_{lk} = dummy variable that takes a value of 1 if the lth member is the primary driver for vehicle type k, and
α_k = satiation parameter that influences the rate of diminishing marginal utility from using vehicle type k.

Given that there can be only 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

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

The optimization problem above can be solved by forming the Lagrangian and applying the Kuhn–Tucker conditions. By keeping the nonmotorized alternative to which the household always allocates a nonzero mileage as the base alternative, the Kuhn–Tucker conditions may be written as (*17*)

$$\begin{aligned} &H_k = H_1 \qquad \text{if } m_k^* > 0 \qquad \left(k = 2, 3, \ldots, K\right) \\ &H_k < H_1 \qquad \text{if } m_k^* = 0 \end{aligned} \tag{3}$$

where

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

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

$$W_{lk} = \beta' x_k + \gamma' z_{lk} + \varepsilon_{lk} \tag{5}$$

where

- $\beta' x_k$ = overall observed utility component of vehicle type k,
- z_{lk} = exogenous variable vector influencing the utility of the driver l–vehicle type k pairing,
- γ = corresponding coefficient vector to be estimated, and
- ε_{lk} = unobserved error component representing idiosyncratic preferences of driver l for vehicle type k.

It is assumed 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 preference 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 in a household can be written as

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

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

With the maximization property of the Gumbel distribution that $\max_j \varepsilon_j = G\left[\ln \sum_j e^{V_j/\theta}, \theta\right]$, Equation 4 can be written as

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

where ε_k is a standard Gumbel distributed random term and V is the observed part of the utility associated with a vehicle type alternative. Also, because $\mathrm{Cov}(\varepsilon_{lk}, \varepsilon_{l'k'}) = 0$ if $k \neq k'$, $\mathrm{Cov}(\varepsilon_k, \varepsilon_{k'}) = 0$. The probability that the household chooses the first Q of K vehicle categories $(Q \geq 1)$ and drives these vehicles for annual mileages $m_1^*, m_2^*, \ldots, m_Q^*$ may be written as

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

where r_k is a function of α_k and m_k^* and 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 follows (the implicit assumption here is that households do not own cars and keep them idle throughout the year):

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

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

$$\begin{aligned} &P\left(m_1^*, m_{2a}^*, m_{3b}^*, \ldots, m_{Qq}^*, 0, 0, 0, \ldots, 0\right) \\ &\quad = P\left(m_1^*, m_2^*, \ldots, m_Q^*, 0, 0, \ldots, 0\right) \times P\left(a \middle| m_2^* > 0\right) \\ &\quad \times P\left(b \middle| m_3^* > 0\right) \ldots P\left(q \middle| m_Q^* > 0\right) \end{aligned} \tag{10}$$

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

DATA SOURCE AND SAMPLE FORMULATION

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

The vehicle type alternative in this study is defined as a combination of body type (including vehicle size) and vintage. For the MDCEV model, one cannot have households owning multiple vehicles of the same type. To ensure this does not happen, several different categorization schemes of vehicle types were attempted, and the richness in body type and vintage were also retained. Finally, nine body type–size categories and six vintage categories were defined, for a total of 54 vehicle types, such that no more than 5% of the households have multiple vehicles of the same vehicle type (this 5% subset of households was excluded from the analysis). 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. Although 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 one wanted to include more than 98% of households in the current analysis, 18 vintage categories would be needed 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 in the MDCEV modeling scheme. At the same time, the number of alternatives rises to 163 in the MDCEV from the current 54 alternatives, which increases the number of parameters to be estimated and reduces the econometric efficiency of the estimated parameters. So, the preference is 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 Southern California Association of Governments implementation, first a simple binary choice model is used to separate households into those that do not have multiple vehicles of each type in 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 in the 54-vehicle type classification, more disjointed models using traditional single discrete choice methods are estimated and applied.

The nine body types/sizes are (*a*) subcompact car, (*b*) compact car, (*c*) midsize car, (*d*) large car, (*e*) small SUV, (*f*) midsize SUV, (*g*) large SUV, (*h*) van, and (*i*) pickup; and the six vintage categories are (*a*) less than 2 years old, (*b*) 2 to 3 years old, (*c*) 4 to 5 years old, (*d*) 6 to 9 years old, (*e*) 10 to 12 years old, and (*f*) 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 six vintage categories + one nonmotorized vehicle type category that is always consumed (that is, households travel by using nonmotorized modes for some positive amount). However, the survey data did not collect information about the household's nonmotorized mileage. So, the nonmotorized mileage of each household was estimated by using a deterministic rule that each individual in the household walks or bikes for half a mile daily. The total annual nonmotorized mileage for a household is obtained as 0.5 * 365 * (household size). The model results were not sensitive to the mileage value assigned to the nonmotorized mode type. This assignment is simply a device to allow applying the MDCEV model.

The final data set used in the analysis consists of 4,711 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 midsize car (22.3% of all vehicles); the lowest is for a subcompact car (3.4%). Overall, half of all vehicles are passenger cars (subcompact, compact car, midsize car, and large car). SUVs are the second most preferred body type, with 26.2% of households owning an SUV (small, midsize, or large). Pickups also constitute a sizable fraction, making up 17% of the vehicle fleet. By vintage category, vehicles 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 mi annually. Compact cars are driven slightly more with an annual mileage of 14,319 mi. Old cars (10 years or older) are the least driven, as is reasonable to expect. In regard to the primary driver assignment, 80% of pickup trucks are assigned to a male member of the household. For the rest of the body types, the 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 the 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, 13 to 15 years), number of senior adults (more than 65 years old), 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 workplace (in miles) are used.

EMPIRICAL RESULTS

In the most general way of specifying the MDCEV model, 54 coefficients for each covariate can be estimated. 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, the total baseline utility associated for each MDCEV alternative is considered as the sum of independent utilities for the body type and vintage dimensions. Interaction effects of variables across the two dimensions were also attempted, but were not found to be statistically significant.

Because only differences in utilities matter, and because of the way of specifying dimension-specific utilities, a base category needs to be specified for the body type and vintage dimensions. The nonmotorized annual mileage was used as the base category for the body type dimension (for ease in presentation, the body type/size combination dimension will be referred to simply as the body type dimension from here on), and the new vehicle category (less than 2 years old) will be referred to 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 (nine for body type + five for vintage type). The effects of exogenous variables can then be calculated by combining the appropriate coefficients. For example, for the small SUV that is more than 12 years old, the total impact of number of workers on the baseline utility can be obtained as $\beta_{\#\text{worker,SmallSUV}} + \beta_{\#\text{worker,aged}>12\text{ years}}$. The satiation parameters are also specified in a similar manner. Specifically, the α_k satiation parameters in Equation 1 are specified as $1/1 + \exp(-\delta_k - \mu_k)$, 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 six, 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 or his characteristics rather than by labels of A or B or C. Thus, this estimation corresponds to that of an unlabeled estimation, with the alternatives being characterized purely by individual-associated attributes.

MDCEV Model Results

Table 1 presents the estimation results of the MDCEV component of the final model. As mentioned earlier, the nonmotorized 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

Five race variables were used: (*a*) African-American, (*b*) Hispanic, (*c*) Asian, (*d*) Caucasian, and (*e*) other race. The base race constitutes other races that are not included in the first four categories. If all individuals in the household are of the same race, then the household race was coded 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 to 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, Asian households 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 and ethnic groups.

Number of Adults (>15 Years Old)

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

Number of Male Adults (>15 Years Old)

The number of male adults variable provides the marginal utility differential between an additional male in the household compared with 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 midsize SUVs compared with women. The general social perception is that SUVs are driven by middle-aged working women with children [see Walsh (*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 finding 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 Fang (*11*), Kitamura et al. (*21*), and Cox et al. (*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 [Ong and Lee (*23*) and Yurko (*24*) also find a similar result].

Number of Senior Adults (>65 Years Old)

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 pickup trucks. These results might be indicative of the fact that senior adults prefer vehicles that are more affordable and comfortable and easy to get into and out of. 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

The effect of number of children was considered 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 subcompact cars. These effects permeate across all age groups, perhaps because of a perceived need for additional cargo and luggage space (to carry tricycles, childcare equipment, etc.) and additional passenger room for carpooling arrangements of children within and across households. The number of children does not have any substantial effects on preferences on the basis of vehicle vintage.

Highest Education in Household

Households with a bachelor's or associate (highest) degree (as the highest degree across all household members) are less likely to own subcompact cars, large cars, large SUVs, and pickup 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

TABLE 1 Estimation Results of MDCEV Component for Vehicle Holdings

	Household Race							
Vehicle Category	African-American[a]	Hispanic	Asian[a]	Caucasian[a]	Number of Adults[a]	Number of Male Adults[a]	Household Income[a]	Number of Senior Members[a]
Subcompact	–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)	—	—
Midsize 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)	—
Midsize 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)	—

	Number of Children by Age Group			Highest Education Level Attained in Household				
	0–4 Years[a]	5–12 Years[a]	13–15 Years[a]	Bachelor's or Associate[a]	Postgraduate[a]	Number of Workers[a]	Mean Distance to Work Calculated Among Workers[a]	Satiation Parameters[b]
Subcompact	–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)
Midsize 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)
Midsize 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)

NOTE: — = effect of corresponding variable on corresponding dimension is same as effect on base category.
[a]Values shown in parentheses are *t*-statistics.
[b]The *t*-statistics for the satiation parameters are computed with respect to value of 1.

these households less prone to hold vehicles that are not fuel-efficient (such as large cars, SUVs, and pickup trucks). Households having individuals with postgraduate degrees are particularly unlikely to prefer pickup 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. 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 midsize 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 pickup trucks. This likelihood is perhaps a reflection of the types 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 pickup trucks to carry work equipment, work at multiple locations on a given day because of the nature of their jobs. Thus, they might report longer commute durations compared with employees with a fixed workplace in other industry sectors (*26*). Unfortunately, there was no information on occupation categories in the 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 2 to 3 years old.

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 (to conserve space, these constants are not presented here). In addition to constants for the body type and vintage dimensions, specifications for constants corresponding to interactions of body type and vintage were also explored. Several of these interaction constants were found 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 need will provide a separate satiation parameter for each of the 55 vehicle types. However, because of space considerations, the implied satiation parameters α_k (and corresponding standard errors) are presented separately for the body type dimension (assuming a vehicle less than 2 years of age) and the vintage dimension (assuming a subcompact vehicle). The satiation parameter for the nonmotorized mode, not shown in Table 1, is effectively zero, consistent with the very low mileage by nonmotorized modes. Results for other

TABLE 2 Estimation Results of MNL Component for Primary Driver Allocation

	Age			
Vehicle Category	16–25 Years[a]	26–40 Years[a]	41–65 Years[a]	Female[a]
No vehicle	—	—	—	—
Subcompact	—	–0.271 (–3.062)	–0.294 (–4.250)	–0.248 (–4.590)
Compact car	—	–0.271 (–3.062)	–0.294 (–4.250)	–0.248 (–4.590)
Midsize car	–0.359 (–3.436)	–0.260 (–2.713)	–0.239 (–3.030)	–0.249 (–4.910)
Large car	0.359 (–3.436)	–0.260 (–2.713)	–0.239 (–3.030)	–0.614 (–8.716)
Small SUV	—	—	—	–0.614 (–8.716)
Midsize SUV	—	—	0.172 (2.087)	—
Large SUV	–0.627 (–3.449)	—	0.151 (1.721)	–0.231 (–3.204)
Van	–0.951 (–4.826)	–0.400 (–3.368)	—	—
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)
2 to 3 years	—	—	—	0.573 (11.067)
4 to 5 years	—	—	—	0.581 (9.616)
6 to 9 years	—	—	—	0.430 (8.522)
10 to 12 years	—	—	—	—
More than 12 years	—	—	—	—

NOTE: — = Effect of corresponding variable on corresponding dimension is same as effect on base category.
[a]Values shown in parentheses are *t*-statistics.

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 pickup 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.

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: (*a*) age between 16 and 25 years, (*b*) age between 26 and 40 years, and (*c*) age between 41 and 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 pickup, and additional comfort considerations may draw these individuals toward more spacious and safer SUVs. Last, household members between 41 and 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 with men. Also, women prefer new vehicles more so than do men. There are no race differences of any consequence.

Education

Household members with a bachelor's or associate degree are indifferent concerning body types, but have a low preference to drive older vehicles (relative to individuals with a high school diploma).

Worker

Employed members in the household have a higher preference for subcompact 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 specifications 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 mi, midsize SUVs are the most preferred vehicle, possibly indicative of additional responsibilities concerning children (such as dropping children off 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.

Race (Caucasian)[a]	Education Level (Bachelor's or Associate)[a]	Employment Status (Worker)[a]	Work Distance Less Than 10 mi[a]
—	—	—	—
−0.274 (−2.057)	—	0.143 (2.346)	—
—	—	0.143 (2.346)	—
—	—	0.090 (1.434)	—
—	—	0.070 (0.829)	—
—	—	0.070 (0.829)	—
—	—	—	0.073 (0.903)
—	—	−0.231 (−3.626)	0.073 (0.903)
—	—	−0.231 (−3.626)	—
—	—	—	—
0.086 (1.889)	0.060 (1.310)	0.103 (2.217)	−0.062 (−1.208)
0.086 (1.889)	0.060 (1.310)	0.103 (2.217)	−0.062 (−1.208)
0.086 (1.889)	0.060 (1.310)	—	—
0.086 (1.889)	—	—	—
—	—	—	—
—	—	—	—

Logsum Parameters

A total of 54 logsum parameters (θ_k) may be estimated, thus capturing correlation in the preferences of individuals in a household for each of the 54 motorized vehicle types. However, 22 of these logsum parameters were not found to be different from the value of 1, suggesting lack of correlation. For the remaining 32 vehicle types, patterns of correlation were examined and finally the logsum parameters among these vehicle types were constrained to obtain three distinct values of the logsum parameters. These values are not presented here to conserve space, but the general trend indicated higher correlations (or generic inclinations or disinclinations in individuals in a family) for the car alternatives (compact car, midsize 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. However, the logsum parameters indicated relatively less volatility (across households) in preferences for the small, midsize, and large SUV categories. This lower volatility suggests that SUVs have a more consistent value position in the cognitive maps of households when decisions are made about vehicle type choice.

Model Fit

The final log likelihood value at convergence of the joint MDCEV–MNL model is −54,003.2. Another model was estimated with just constants for the vehicle body type and vintage 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 −56,883.00. The log likelihood ratio test statistic value for comparison between these two models is 5,759.60, which is higher than the critical chi-squared value for 107 degrees of freedom at any level of significance. This result clearly indicates the value of the model estimated in this paper to predict vehicle holdings, usage, and primary driver assignment.

CONCLUSION

In this paper, there was a discussion on 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, and the individual assigned as the primary driver for each vehicle. The empirical results of the model indicate that several household and individual demographic variables have significant effects on the vehicle holdings decisions. The resulting model can also be incorporated easily in any activity-based microsimulation framework, thanks to the recent advances in the design of efficient forecasting algorithms for predicting with 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 in the larger SimAGENT activity-based travel and emissions forecasting system for the Southern California Association of Governments region. To the authors' knowledge, this is the first such effort to integrate a complete household vehicle ownership and type choice simulator into a larger activity-based model microsimulator system. Further, the assignment of a primary driver for each vehicle owned by a household allows one later in SimAGENT to assign a vehicle to each trip made by a household.

In the current version of SimAGENT, the household vehicle fleet and the usage (annual mileage) and primary driver of each vehicle in the fleet are first predicted. Subsequently, a make and model MNL model in each body and vintage type is estimated and applied. It is also assumed that all tours (or trips) made during the day by an individual are made by using his or her primary vehicle. Further, an explicit vehicle type MNL model is used to determine the type of vehicle that is used for joint tours. The primary vehicles of all 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 or tour made during the day. In addition, the structure of the MDCEV model provides aggregate forecasts of annual mileage of each vehicle in the household. This forecast is used by SimAGENT as a measure of the overall use of each vehicle when tours (trips) are assigned 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 effect 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 tool allows a first-order pruning of policy alternatives, so that only those that seem most promising are taken further for a comprehensive SimAGENT evaluation [see Goulias et al. (*15*)].

The 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 (although 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 and parking tightness, and activity purpose), and individual characteristics may also be considered in the individual trip assignment. Accordingly, an additional model is being developed for the vehicle-to-trip or 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 postassigning 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, also being pursued is the process of obtaining information on the geolocations of the households surveyed in the California Energy Commission data to append relevant built environment measures and include such measures in the vehicle type choice and primary driver assignment model.

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