A JOINT TOUR-BASED MODEL OF VEHICLE TYPE CHOICE AND TOUR LENGTH

Karthik C. Konduri
School of Sustainable Engineering and the Built Environment
Arizona State University
Room ECG252, Tempe, AZ 85287-5306
Tel: (480) 965-3549; Fax: (480) 965-0557
Email: karthik.konduri@asu.edu

Xin Ye
National Center for Smart Growth Research and Education
University of Maryland
1112D, Preinkert Field House (Building 054)
College Park, MD 20742
Tel: (301) 405-6788; Fax: (301) 314-5639
Email: xinye@umd.edu

Bhargava Sana
School of Sustainable Engineering and the Built Environment
Arizona State University
Room ECG252, Tempe, AZ 85287-5306
Tel: (480) 965-3549; Fax: (480) 965-0557
Email: bsana@asu.edu

Ram M. Pendyala
School of Sustainable Engineering and the Built Environment
Arizona State University
Room ECG252, Tempe, AZ 85287-5306
Tel: (480) 965-3549; Fax: (480) 965-0557
Email: ram.pendyala@asu.edu

Submitted for Presentation and Publication to
Committee ADB40: Transportation Demand Forecasting

90th Annual Meeting of the Transportation Research Board
January 23-27, 2011

Word count: 7718 (text) + 4(tables/figures) x 250 = 8718 equivalent words

August 2010

ABSTRACT

Tour-based microsimulation model systems are seeing increasing application for forecasting activity-travel patterns under a wide range of policy and system scenarios. In such models, the tour is the unit of analysis, thus offering a framework to account for inter-linkages across trips in a tour. This paper focuses on examining the relationship between two dimensions of tours, the type of vehicle (in a household that owns multiple vehicles of different types) chosen to undertake the tour and the overall length (distance traveled) for the tour. These two dimensions are of much interest in the current planning context where concerns about energy sustainability and greenhouse gas emissions are motivating planners to seek ways to mitigate the adverse impacts of automotive travel. Moreover, virtually all tour-based models currently used in practice do not explicitly account for vehicle type choice in modeling tour attributes, despite its critical importance for energy and emissions analysis. This paper presents a joint discrete-continuous model of tour vehicle type choice and length. Estimation results suggest that there are significant common unobserved factors that affect vehicle type choice and length of tours, justifying the use of joint simultaneous equations modeling approaches to model tour attributes. It was found that the model specification in which vehicle type choice affects tour length performed better than the specification in which tour length affects vehicle type choice, suggesting that vehicle type choice (and allocation among household members) is a longer term choice that influences shorter-term tour length choices.

Keywords: tour-based models, vehicle type choice, tour length, joint modeling, discrete-continuous models, causal relationship, error correlation

1. INTRODUCTION

There has been a growing interest in the application of microsimulation approaches to travel demand modeling and forecasting. Microsimulation models of travel demand simulate the activity-travel choices of individuals recognizing the inter-dependence among activities, trips, and persons subject to the various spatial, temporal, and resource constraints that individuals experience (Arentze et al 2000). The literature on travel demand modeling and forecasting is replete with examples of activity- (Kitamura and Fujji 1998, Pendyala et al 2004, Pinjari et al 2004) and tour- (Bowman and Ben-Akiva 2000, Vovsha et al 2002, Miller et al 2005, Bradley et al 2009, Yagi and Mohammadian 2009) based approaches that purport to represent and simulate individual activity-travel behavior. Alternative model systems may differ in the nature of the behavioral paradigm underlying the model, but the unit of analysis is invariably a trip chain or tour to explicitly recognize the inter-dependency of trips within a tour.

There have been a number of successful implementations of tour-based model systems both in the US and elsewhere (Algers et al 1995, Vovsha et al 2002, Bowman and Bradley 2006). Most of the tour-based models consider (to differing degrees) some basic dimensions that characterize tours including primary activity type, location, number of stops and identification of stop locations on the tour, sequencing and scheduling of stops, and mode choice at both the tour- and individual trip- level. Some models are also attempting to explicitly consider intra-household interactions to explicitly account for passenger accompaniment in simulating household tours. There is virtually no tour-based model, however, that explicitly includes choice of the type of vehicle used to undertake the tour. Given that the type of vehicle used (in terms of body type, fuel type, and/or vintage) and total distance traveled on a tour are two critical factors determining energy consumption and greenhouse gas (GHG) emissions (Hensher 2008, Spissu et al 2009), this paper focuses on the relationship between these two tour-level dimensions of interest.

Household vehicle ownership (and utilization) by type of vehicle has been the focus of several recent research efforts (Mohmmadian and Miller 2003, Bhat and Sen 2006, Cao et al 2006, Eluru et al 2010). However, much of this work is aimed at examining the household vehicle type holdings, the mix of vehicle types in a household fleet, and the overall utilization (mileage) of vehicles. While that work offers a valuable basis to represent overall household vehicle fleet ownership choices and vehicle utilization patterns, it does not provide the level of disaggregate detail that planners desire to analyze vehicle type choice and usage patterns at the individual tour level. Many households have different types of vehicles, including large utility vehicles or minivans, and smaller fuel-efficient compact cars or hybrid-fuel vehicles. One needs to understand the usage patterns of each vehicle type at a tour level so that demand characteristics can then be closely tied to their associated environmental impacts.

In most of the tour-based model implementations, a number of models are estimated to mimic the different choice dimensions of individual's tour making behavior. The models are often implemented sequentially (with logsum feedback loops) to simulate the different tour characteristics. Such a sequential application of models inherently involves making two assumptions. First, it assumes that tour attributes can be modeled independently without accounting for common unobserved factors (error correlations) that may simultaneously impact multiple tour attributes. Second, the sequential application assigns an order to the decision making behavior of individuals. However, in reality, people may make tour-related decisions jointly. It is of considerable interest and importance then to model different tour-attributes jointly using advanced simultaneous equation modeling frameworks (Pendyala and Bhat 2004, Ye and Pendyala 2009). The joint modeling approaches not only lend themselves to modeling different tour dimensions simultaneously but they also allow one to accurately represent decision making behavior by accommodating error correlations across tour dimensions which exist due to common unobserved variables (Mannering 1986).

This paper presents a joint model of vehicle type choice and tour length for automobile tours undertaken by individuals in households that have a mix of vehicle body types. In this context, there are interesting questions regarding the relationship between vehicle type choice and tour length that arise. The joint consideration of vehicle type choice and tour length explicitly accounts for the endogeneity of tour length in the vehicle type choice process and vice-versa. Does vehicle type choice affect tour length, or does tour length affect vehicle type choice? Or is there a more contemporaneous relationship between these two choice dimensions that makes it impossible to choose one specification over the other? Interesting policy outcomes arise in the context of these questions. Consider the situation where tour length affects vehicle type choice, wherein shorter tour lengths are associated with the use of larger vehicle types that consume more energy and pollute more. In that situation, policies that promote land use density may actually have a counter-intuitive effect of not providing the intended benefits from an environmental perspective. If enhanced land use density results in shorter vehicle tours that households can monetarily afford to undertake using large utility vehicles, then the policy may not yield the intended environmental benefits. Similar policy implication arguments can be made for the reverse situation where vehicle type choice impacts tour length. Say, one provides tax incentives for the purchase of a fuel efficient automobile that motivates households to purchase such vehicles. Individuals can now monetarily afford to drive more miles using the fuel efficient vehicles, thus negating at least some of the potential benefits of incentives provided to households to acquire fuel efficient vehicles. Not only does this joint model system offer insightful policy implications, but it also offers a mechanism for incorporating vehicle type choice explicitly in emerging tour-based models – this choice dimension is often lacking in current models.

The paper utilizes a sample of tours undertaken by individuals in households that own a mix of vehicle types drawn from the 2009 National Household Travel Survey (NHTS) dataset of the United States. A joint model of vehicle type choice (discrete choice variable), and tour length (continuous choice variable) was estimated. A probit-based discrete-continuous model specification and simulation-based estimation approaches were employed. The methodology accommodates potential error correlations across choice dimensions due to the presence of common unobserved attributes. There are a number of discrete-continuous modeling methodologies in the literature (Pendyala and Bhat 2004, Ye and Pendyala 2009). Unlike some of the earlier discrete-continuous frameworks which make distributional transformations for ease of estimation (Bhat 1998, Pendyala and Bhat 2004), the probit-based approach accommodates error correlations by assuming a multivariate normal distribution structure. The authors have successfully used this approach in previous work to shed light on multiple choice dimensions underlying activity-travel demand (Ye and Pendyala 2009, Konduri et al 2010). The paper also modifies an earlier non-nested hypothesis test (Ye and Pendyala 2009) and uses it to compare alternative joint discrete-continuous specifications.

The remainder of the paper is organized as follows. The probit-based methodology and the modified non-nested hypothesis test are presented in Section 2 followed by a description of the data in Section 3. Model estimation and hypothesis test results are presented in Section 4 followed by conclusions in Section 5.

2. METHODOLOGY

This section presents an overview of the modeling methodology used in this study.

2.1. Model Formulation

The probit-based methodology adopted in this paper is presented only briefly here as complete details may be found elsewhere (Ye and Pendyala, 2009). The formulation is presented for a discrete choice variable with three choice alternatives. However, the formulation can easily be extended to accommodate discrete choice variables with any number of alternatives, although the estimation becomes increasingly computationally cumbersome with additional choice alternatives. The system of equations for the discrete-continuous model system may be formulated as:

$$\begin{cases} u_1^* = x_1\beta_1 + \delta_1 d + \varepsilon_1 \\ u_2^* = x_2\beta_2 + \delta_2 d + \varepsilon_2 \\ u_3^* = x_3\beta_3 + \varepsilon_3 \\ d \ = z\theta + \lambda_1 y_1 + \lambda_2 y_2 + \omega \end{cases} \tag{1}$$

where u_1^*, u_2^*, u_3^* are the latent utility functions for three alternatives corresponding to the discrete choice variable. β_1 , β_2 , β_3 are the coefficient vectors corresponding to the exogenous variables x_1, x_2, x_3 on the right-hand side of the latent utility functions. d is the continuous choice variable and enters the utility functions of the discrete choices with coefficients δ_1, δ_2. z is a vector of explanatory variables influencing d with a coefficient vector θ. y_1 and y_2 are indicator variables corresponding to the first and second discrete choice alternatives and are defined as follows:

$$\begin{aligned} y_1 &= I(u_1^* > u_2^* \, and \, u_1^* > u_3^*) \\ y_2 &= I(u_2^* > u_1^* \, and \, u_2^* > u_3^*) \end{aligned} \tag{2}$$

where y_1 and y_2 assume a value of 1 if the conditions in the parentheses are satisfied and 0 otherwise. λ_1 and λ_2 in Equation (1) are the coefficients corresponding to indicator variables y_1 and y_2. For the above model to be identified, either the λ or the δ parameters must be restricted to zero, and this results in two alternative model structures: (i) λ_1 and λ_2 equal to zero, corresponding to the joint model specification where the tour length affects vehicle type choice for the tour, and (ii) δ_1 and δ_2 equal to zero corresponding to the joint model specification where vehicle type choice affects tour length.

The random error terms ε_1, ε_2, ε_3, ω in the model are assumed to be multivariate normally distributed with the variance-covariance matrix as shown below:

$$\Sigma = \begin{bmatrix} 1 & 0 & 0 & \gamma_1 \\ 0 & 1 & 0 & \gamma_2 \\ 0 & 0 & 1 & \gamma_3 \\ \gamma_1 & \gamma_2 & \gamma_3 & \sigma^2 \end{bmatrix} \tag{3}$$

It can be seen from the variance-covariance matrix above that the emphasis in the model formulation is to accommodate the error correlations between the discrete choice alternatives and the continuous choice variable and the variance-covariance components corresponding to the discrete choice are fixed as shown. Theoretically, one could potentially identify two additional parameters of the six covariance elements corresponding to the discrete choice variable in the matrix. However, in this paper, the error correlation structure is limited to that shown in equation (3). The notation in Equation (1) may be simplified as shown in Equation (4):

$$\begin{cases} u_1^* = V_1 + \varepsilon_1 \\ u_2^* = V_2 + \varepsilon_2 \\ u_3^* = V_3 + \varepsilon_3 \\ d \ = U + \gamma_1\varepsilon_1 + \gamma_2\varepsilon_2 + \gamma_3\varepsilon_3 + \sigma'\xi \end{cases} \tag{4}$$

where V_1, V_2, V_3 constitute the deterministic part of the latent utility functions and U represents the deterministic component of the continuous model. The random error term in the continuous model has been parameterized as a linear combination of ε_1, ε_2, ε_3, and ξ, where ξ is a random error term that is standard normally distributed and is independent of ε_1, ε_2, and ε_3. σ'^2 is assumed to be equal to ($\sigma^2 - \gamma_1^2 - \gamma_2^2 - \gamma_3^2$) so that the covariance structure shown in equation (3) is preserved in the modified notation.

Let V_{12} represent the difference in the deterministic components of the latent utility functions of discrete alternatives 1 and 2, i.e., $V_{12} = V_1 - V_2$. Similarly $V_{13} = V_1 - V_3$. One can then derive a joint discrete-continuous probability function conditional on ε_1, ε_2, ε_3. Equation (5) illustrates the probability formulation for discrete choice alternative 1 (y_1 = 1). The probability formulations for the other discrete choice alternatives can be derived in a similar manner.

$$\begin{aligned}
\Pr(y_1 = 1, d \mid \varepsilon_1) &= \Pr(u_1^* > u_2^*, u_1^* > u_3^*, d \mid \varepsilon_1) \\
&= \Pr(\varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1, d \mid \varepsilon_1) \\
&= \Pr(\varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1 \mid \varepsilon_1) \times \\
&\quad \Pr\left[(d \mid \varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1) \mid \varepsilon_1\right] \\
&= \left[\Phi(V_{12} + \varepsilon_1)\Phi(V_{13} + \varepsilon_1)\right] \times \\
&\quad \left\{ \frac{1}{\sigma'} \phi\left(\frac{d - U - \gamma_1\varepsilon_1 - \gamma_2\varepsilon_2 - \gamma_3\varepsilon_3}{\sigma'} \right) \middle| \varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1 \right\}.
\end{aligned} \tag{5}$$

$\phi(.)$ and $\Phi(.)$ in equation (5) denote the probability density function and the cumulative probability density functions respectively. The unconditional probability for discrete choice alternative 1 may then be derived by integrating the probability function over the distributional domains of ε_1, ε_2, ε_3. As can be seen, the distributional domain of ε_1 extends from -∞ to ∞, ε_2 extends from -∞ to $V_{12} + \varepsilon_1$, and ε_3 extends from -∞ to $V_{13} + \varepsilon_1$. The unconditional probability does not have a closed form solution and simulation based techniques may be employed to evaluate the unconditional probability. In order to simulate the unconditional probability, randomly draw ε_{1r} (r = 1, 2, … R) from a standard normal distribution and let $\varepsilon_{2r} = \Phi^{-1}[u_{2r}\Phi(V_{12} + \varepsilon_{1r})]$ and $\varepsilon_{3r} = \Phi^{-1}[u_{3r}\Phi(V_{13} + \varepsilon_{1r})]$, where u_{2r} and u_{3r} are two independent draws from a standard uniform distribution. ε_{2r} and ε_{3r} are now draws from the corresponding truncated normal distributions for ε_2 and ε_3. By repeating this procedure R times, the unconditional probability function may be approximated as:

$$\Pr(y_1 = 1, d) \approx \left\{ \sum_{r=1}^{R} \Phi(V_{12} + \varepsilon_{1r})\Phi(V_{13} + \varepsilon_{1r}) \frac{1}{\sigma'} \phi\left(\frac{d - U - \gamma_1\varepsilon_{1r} - \gamma_2\varepsilon_{2r} - \gamma_3\varepsilon_{3r}}{\sigma'} \right) \right\} \Big/ R \tag{6}$$

The unconditional probability functions for the other two alternatives of the discrete choice variable may be derived in an analogous manner. The Maximum Simulated Likelihood Estimation (MSLE) procedure can then be applied to estimate the parameters using quasi-random Halton sequences (Bhat 2001).

As with any joint discrete-continuous model system, careful consideration must be given to issues of identification and normalization. To avoid any issues with normalization it is recommended that the γ_j in Equation (3) with the smallest absolute value be normalized to zero. This assumption is consistent with Walker (2002) and a detailed discussion on the normalization assumption and its validity is presented elsewhere (Ye and Pendyala, 2009).

The model formulation presented above can be applied to any discrete-continuous type problem where the choice set of alternatives is constant for all decision makers. However, in this particular study, the discrete variable considered in the analysis – vehicle body type – may vary across decision makers (as different households own different vehicle fleets). Therefore, the methodology described above is modified to accommodate varying choice sets. Let k_1, k_2, k_3 be three indicator variables denoting the availability of each of three choice alternatives for the decision maker. The indicator variable assumes a value of 1 if a particular choice alternative is available and 0 otherwise. The deterministic component in the original utility expressions may be modified as:

$$\begin{cases} u_1^* = k_1 x_1 \beta_1 + (1-k_1)(-\infty) + \delta_1 d + \varepsilon_1 \\ u_2^* = k_2 x_2 \beta_2 + (1-k_2)(-\infty) + \delta_2 d + \varepsilon_2 \\ u_3^* = k_3 x_3 \beta_3 + (1-k_3)(-\infty) + \varepsilon_3 \\ d = z\theta + \lambda_1 y_1 + \lambda_2 y_2 + \omega \end{cases} \tag{7}$$

It can be seen that whenever an alternative is available, the deterministic component of the utility remains the same as in the earlier formulation. However, if a particular alternative is not available then the alternative is made highly unattractive (by adding a very large negative value). As a result the probability of any missing alternative (vehicle type) being chosen is forced to be zero. One can then proceed with the model estimation by using the modified deterministic components. Thus the model formulation presented in Equation (7) can accommodate varying choice sets for the discrete choice model component in a joint discrete-continuous problem.

2.2. Non-nested Hypothesis Test

As mentioned earlier, based on whether the parameter λ or δ is set to zero, two different specifications of the joint discrete-continuous models arise. It is entirely possible that both specifications of the joint discrete-continuous model will provide behaviorally plausible results with statistical goodness-of-fit measures that are quite similar. Therefore, rigorous statistical hypothesis tests are required to compare alternative model specification and choose the appropriate model specification.

One cannot use standard likelihood ratio tests when model specifications are non-nested. One of the earliest tests to compare models from different families was proposed by Cox (1961, 1962). Horowitz (1983) presented a more compact form of the Cox test for comparing non-nested discrete choice models. The test was modified by Ben-Akiva and Swait (1984) to accommodate the comparison of standard goodness-of-fit statistics obtained from discrete choice model estimation results. This test has been applied to compare both single equation (McCarthy and Tay 1998) and simultaneous equation model systems (Pendyala and Bhat 2004, Ye et al 2007). However, the test was initially proposed to compare single equation discrete model systems and its appropriateness for comparing simultaneous equation model systems is unknown. In order to address this issue, Ye and Pendyala (2009) proposed a new hypothesis test for comparing non-nested joint discrete-continuous model systems. However, their hypothesis test is not applicable when the set of alternatives for the discrete choice varies across decision makers. In this paper, a modified version of the non-nested hypothesis test is proposed for comparing non-nested joint discrete-continuous model systems where the choice set for the discrete choice varies across decision makers.

According to Horowitz (1983), the probability that the goodness-of-fit statistic for a model B is greater than the goodness-of-fit statistic for model A by a value $t > 0$ assuming that model A is the true model is asymptotically bounded as:

$$\Pr\left[\bar{\rho}_B^2 - \bar{\rho}_A^2 > t\right] \le \Phi\left[-\sqrt{-2L^* t}\right] \tag{8}$$

where

$\bar{\rho}_m^2$ = likelihood ratio index for model m and is calculated as shown in Equation (9)

L_m = log-likelihood function value for model m at convergence

K_m = number of parameters being estimated in model m

L^* = log-likelihood function value of model m when all the parameters are assumed to be zero

$$\bar{\rho}_m^2 = 1 - \frac{L_m - \frac{K_m}{2}}{L^*} \tag{9}$$

In the original formulation of Horowitz (1983), L^* was defined as $N \ln(1/J)$ where N is the number of observations and J is the number of choice alternatives. In the hypothesis test proposed by Ye and Pendyala (2009) for comparing non-nested joint discrete-continuous models, a modified L^* was proposed. The modified L^* was comprised of two components as shown in Equation (10).

$$L^*(Joint\ Model) = L^*(Continuous\ \ Model) + L^*(Discrete\ Model) \tag{10}$$

The equations for calculating L^* for the continuous and discrete model components are shown in equations (11) and (12) respectively:

$$L^*(Continuous\ Model) = -\frac{N-1}{2} - N\ln\left(\sqrt{2\pi}\,\hat{\sigma}\right) \tag{11}$$

where $\hat{\sigma}$ = standard deviation of the continuous variable

$$L^*(Discrete\ Model) = -N\ln(J) \tag{12}$$

As can be seen in equation (12), the formulation of L^* for the discrete choice assumes that the choice set is the same for all decision makers. In order to accommodate varying choice sets for different decision makers, the following form is proposed for the contribution of the discrete model component to L^*.

$$L^*(Discrete\ Model) = -\sum_{i=1}^{N} \ln(j_i) \tag{13}$$

where j_i is the number of choice alternatives in the choice set for individual observation i. Therefore, the modified L^* value for the joint discrete-continuous model with varying choice sets for the discrete choice variable is given by:

$$L^*(JointModel) = -\frac{N-1}{2} - N\ln\left(\sqrt{2\pi}\,\hat{\sigma}\right) + -\sum_{i=1}^{N} \ln(j_i) \tag{14}$$

Substituting equation (14) in equation (8) gives the following form for the probability statistic and its asymptotic bound:

$$\Pr\left[\bar{\rho}_B^2 - \bar{\rho}_A^2 > t\right] \le \Phi\left[-\sqrt{-2\left(-\frac{N-1}{2} - N\ln\left(\sqrt{2\pi}\,\hat{\sigma}\right) + -\sum_{i=1}^{N}\ln(j_1)\right)t}\right] \tag{15}$$

Using this formulation, one can compare non-nested discrete-continuous model specifications with varying choice sets across decision makers.

3. DATA SET AND SAMPLE COMPOSITION

In this paper, data drawn from the 2009 National Household Travel Survey (NHTS) of the United States is used. Only home and work-based tours are considered as these two locations are often considered anchors of trip making. The subsample employed for analysis in this paper includes only those tours made by individuals residing in households that own multiple vehicles of different body types. In addition, the analysis is limited to the modeling of automobile-only tours undertaken by individuals of driving age (15 years or above) on regular weekdays (Monday through Thursday). This resulted in a total of 102,352 tours performed by 64,568 respondents residing in 37,938 households. The average number of tours per person was about 1.6 and that per household was nearly 2.7.

Nearly 29.4 percent of all tours were home-based work (HBW) tours, 64.5 percent were home-based non-work tours (HBNW), and about 6.1 percent were work-based tours mostly comprising of eat-lunch activities pursued by employed individuals between work episodes. The HBNW tours are of particular interest in this study because people potentially have greater flexibility in the choice of destinations (and therefore distance traveled) and vehicle type for these tours as opposed to home-based work tours and work-based tours which are more temporally and spatially constrained. Also, in order to avoid the inflation of t-statistics resulting from the use of a very large sample dataset that may lead to erroneous inferences, a random sample of a little less than 10 percent of the 66,030 home-based non-work tours was selected. The subsample comprised of 6,478 tours and all descriptive analysis and model estimation results presented from this point forward correspond to the use of this random sample.

Table 1 provides a summary of some key variables at the tour-, household-, and person- level. Each HBNW tour involved an average of 1.7 stops with average travel duration of 37 minutes and average tour length of 15.7 miles. On an average, there were about 1.7 persons on each tour. If one were to observe the descriptive statistics at the household level, the averages may appear to be a little higher than in the general population, but this is presumably because the sample consists exclusively of multiple vehicle households that own a mix of vehicle body types. Such households are likely to be larger with a greater number of children. On average, there are nearly three persons in a household with one child. Most of the households in the sample (68 percent) reside in urban areas. There is a slightly higher percentage (56 percent) of females than males. This may be due to the higher number of household maintenance and serve-child activities that women generally undertake compared to men.

Table 2 provides a distribution of tour characteristics by vehicle type chosen. As expected, larger vehicle body types (van, sports utility vehicle) are typically associated with larger vehicle occupancy compared to other vehicle types. Households probably like to use larger vehicles for trips involving multiple individuals in the traveling group. It is interesting to note that, when the vehicle fleet composition of the household is ignored, car appears to be the preferred body type, being chosen for nearly 42 percent of the HBNW tours. The car vehicle type is followed in preferential order by sports utility vehicle (SUV), pickup truck and van. It is also found that the difference in tour lengths across vehicle types chosen for the tour appears to be only marginal. These statistics might give one the impression that vehicle type choice and tour length have no relationship. However, the differences in tour length across vehicle types are more pronounced when one controls for vehicle fleet composition. Whenever van is part of the household vehicle fleet, it appears to be the preferred alternative. In households where both a car and a SUV are present, SUV is chosen for more tours than car. The pickup truck appears to be the least preferred vehicle type. Pickup trucks may not be used as commonly as other vehicle types for routine HBNW tours. Tours where SUV is the chosen body type have the highest occupancy, followed in order by van, car and pickup truck. These findings show that one needs to consider the vehicle availability (fleet composition) choice set when attempting to model the relationships between vehicle type choice and other tour attributes. Otherwise, one is merely observing the average characteristics resulting from the assumption that all vehicle types are available to every decision maker.

4. MODEL ESTIMATION RESULTS

Joint discrete-continuous models of vehicle type choice and length were estimated for HBNW tours using the modified formulation presented in Equation (7). The vehicle type choice is modeled as a multinomial probit model and the tour length is modeled as a log-linear regression model. The vehicle type choice included four discrete choices, namely, car, van, SUV, and pickup truck, with pickup truck considered the base alternative. Independent models with no error correlations across the choice dimensions were also estimated for assessing the benefits of joint modeling frameworks in this context. The coefficient estimates from the independent models served as the starting values for estimating the joint models. The MSLE procedure was used for estimating the coefficients in the joint model using 100 quasi-random Halton sequences (Bhat, 2001).

In this study, two alternative joint discrete-continuous model specifications were explored. In the first model specification, tour length was assumed to affect vehicle type choice. In the other model specification, vehicle type choice was assumed to affect tour length. The two model specifications are behaviorally plausible and could potentially provide a way to evaluate some interesting policy outcomes. According to the first specification, an individual may choose a set of destinations to visit during a tour – in other words he or she determines the distance to travel, and then chooses the type of vehicle dependent on the distance. For longer distances, an individual may choose to use the more fuel efficient vehicle for monetary benefits or the larger less fuel efficient vehicle for comfort and capacity. For shorter distances, the individual may be indifferent to the type of vehicle. In the second model specification, one is postulating that individuals within a household probably have a car assigned to them based on their household roles. For example, in a household with a car and van, if the female head in the household is responsible for chauffeuring kids, then she may be allocated the larger vehicle (van), whereas the car may be assigned to the male head of the household. If that is the case, then the choice of tour length (destinations) may depend on the type of vehicle that the person is assigned (and drives primarily). The male head of the household may choose to travel farther because he is driving the smaller more fuel efficient vehicle (and it is monetarily affordable to do so), or may choose to drive short distances because the small car is not as comfortable as the large vehicle. Table 3 provides model estimation results for the specification where the tour length is assumed to affect the vehicle type choice, and Table 4 provides results of the specification where vehicle type choice is assumed to affect the tour length. The tables include estimation results for both independent and joint models.

4.1. Non-nested Hypothesis Test

It is found that both model specifications presented in Tables 3 and 4 offer plausible results. In order to select an appropriate model specification that best fits the data, the non-nested hypothesis test presented earlier was applied. The model with higher likelihood ratio index is generally selected as the appropriate one. The test gives bounds on the probability that the incorrect model is selected when one does so. In this study, the joint model where vehicle type choice affects tour length produces a higher likelihood ratio index. The non-nested test indicates that the probability with which this model will be an incorrect model is less than 0.007. Therefore the model where the vehicle type choice affects the tour length can be regarded as the more appropriate model specification. This supports the notion that households probably allocate vehicles among household members a priori at a higher longer-term choice dimension level, and then individual tour destinations and travel distance are dependent on the type of vehicle the person is allocated, other tour attributes such as accompaniment type and number of stops on the tour, and usual socioeconomic characteristics. The joint model specification where the vehicle type affects the tour length also has significant error correlations (discussed further later) pointing to the need for modeling the choice dimensions using a simultaneous equations framework that can explicitly accommodate error correlations across choice dimensions. As this model specification is best supported by the data, the remaining discussion focuses on findings reported in Table 4.

From a more qualitative perspective, an examination of the statistical significance of coefficients associated with right hand side endogenous variables sheds further light on the appropriateness of one model specification over another. In the model where tour length affects vehicle type choice, the tour length variable is statistically insignificant in affecting the utility of all vehicle types. All three coefficients are statistically insignificant. On the other hand, in the joint model where vehicle type choice affects tour length, it is found that all three vehicle types have statistically significant coefficients, clearly indicating that there is a significant joint relationship between vehicle type choice and tour length. When faced with the choice between models in which one demonstrates a statistically significant relationship between choice dimensions that are likely linked together from a behavioral perspective, and another demonstrates no such relationship, it is reasonable to prefer the one depicting statistically significant relationships unless the behavioral relationships represented in the model are completely inconsistent with basic logic, past research, and known behavioral theories.

4.2. Influence of Tour Attributes

The constant terms in the joint model reveal that SUV and van vehicle types are preferred over cars for HBNW tours. This result is reasonably consistent with what was observed in the descriptive analysis where SUV and van were chosen more frequently compared to other body types when these vehicle types existed in the fleet. Note that the other model specification where length affects vehicle type provides results that are different and inconsistent with those found in the specification of Table 4. The results in Table 4 show a slight baseline preference for SUV over van, whereas the results in Table 3 show a baseline preference for van over SUV. Thus, the choice of model specification can have an important impact on inferences.

In addition to the impact of vehicle type choice on tour length, the effect of number of stops and accompaniment type were also explored. One may contend that accompaniment and number of stops are also endogenous tour attributes and that they should also be modeled along with vehicle type choice and tour length. However, the modeling methodology employed in this paper can only accommodate one continuous variable and one discrete choice variable in its current form. The exploration of all four choice dimensions in an integrated joint modeling framework is left for a future exercise. The number of stops on the tour appears to have a positive influence on the use of van, presumably because these are more complex trip chains involving multiple passengers. The number of stops also has a positive impact on tour length. Solo tours are more likely undertaken by car, consistent with the notion that larger vehicle type may not be needed in the absence of multiple passengers. Solo tours are also likely to be shorter tours in comparison to joint tours. This result is reasonable given that joint tours may involve visiting destinations (that could be farther away, but more preferred) that satisfy the preferences of multiple individuals on the journey. All three vehicle types have a positive impact on tour length compared to the pickup truck (omitted base alternative). Among the three vehicle types included in the model, the car and van are associated with longer tour lengths than the SUV. Thus it appears that, whereas the SUV is more preferred for tour-making (see vehicle type choice model component), the SUV is utilized (mileage driven) less – perhaps because drivers are making a conscious decision to conserve on driving expense. As van tours tend to be more complex (multi-stop) and multi-passenger in nature, it is not surprising that this vehicle type has the largest positive impact on tour length. However, it should be noted that the vehicle type choice has an impact on tour length even after controlling for other tour attributes.

It is also interesting to note the difference in the significance of the variables between the independent models and the joint models. One can see that if the error correlations across choice dimensions are ignored as is the case of the independent model, incorrect inferences may be drawn. For example, the impact of van vehicle type on tour length is insignificant in the independent model, while the same variable has a statistically significant impact on tour length after accounting for potential error correlations. Not only is it statistically significant, but it is also the highest in magnitude. In general, parameter estimates between the independent and joint model specifications are quite different. These observations lend credence to the need for jointly modeling activity-travel choices by accommodating error correlations across choice dimensions.

4.3. Influence of Socioeconomic Attributes

A host of household and person level socioeconomic characteristics were included to account for their impacts on vehicle type choice and tour length. The ratio of household size to vehicle count has a negative impact on tour length, presumably because households with a greater ratio have a deficit of vehicles. Individuals in such households may have to choose destinations that are closer to home (small travel distances) so that they can return quickly and make the vehicle available to other members of the household. Van is the least preferred vehicle type for males and the pickup truck (when it is in the fleet of vehicles of a household) is the most preferred vehicle type. Males also have a tendency to engage in longer tours compared to females. It is possible that females take care of household maintenance and serve-child activities that are closer to home, contributing to shorter tour lengths as a whole. Older individuals prefer using a van and engage in shorter tours. It is possible that these individuals prefer the comfort and smooth drive of a van. In addition, these individuals may include grandparents who undertake tours with family members. As the number of children in the household increases, people have a propensity to use a larger vehicle (van) compared to the car. It is interesting to note that the number of children has a negative effect on tour length. There are two plausible explanations for this result. First, if the parents choose to leave a child at home, they may engage in shorter tours so that they can be back home relatively quickly and tend to their kids. Alternatively, if the parents choose to take their kids with them, they may still choose to engage in shorter tours for purposes of efficiency and for avoiding long tours that can be tough on children. Households in non-urban areas are less likely to use large vehicle types, but undertake tours of longer length. While the latter result is quite consistent with expectations in that such households are probably farther away from desirable destinations, the former result is somewhat surprising. It appears that these households prefer to use the car, possibly for trips that do not involve hauling goods or people, or the pick-up truck, possibly for trips that do involve hauling goods and/or people. People with flexible work start times engage in shorter tours suggesting that they may be engaging in more frequent and shorter tours, consistent with the notion that they are less time constrained than workers who do not have temporal flexibility in work start times. The latter group must probably engage in fewer, but more efficient, multi-stop tours that are inevitably longer in length.

In the case of the impact of socio-economic attributes on the endogenous variables, it is found that there are substantive differences in coefficient estimates between the independent and joint model specifications. Thus, accounting for error correlations is clearly important in the joint modeling of vehicle type choice and tour length. However, differences in coefficient estimates between the two model structures are less pronounced. Both the model where tour length affects vehicle type choice and the model where vehicle type choice affects tour length provide very similar indications in terms of the effects of socio-economic attributes on these choice dimensions.

5. CONCLUSIONS

Growing concerns about energy sustainability and greenhouse gas (GHG) emissions attributable to vehicular travel has transportation modelers increasingly relying on disaggregate microsimulation models of activity-travel choices to represent underlying behavioral relationships that influence how people respond to alternative policy scenarios aimed at curbing vehicular use. In this context, two choice dimensions of particular interest are the choice of vehicle (body type) and the distance traveled to undertake activities distributed in time and space. As activity-travel microsimulation models are increasingly considering the trip chain or tour as the unit of analysis, these choice dimensions are best examined in the context of tours as opposed to individual unlinked trips.

This paper aims to present a joint model system capable of representing the relationship between tour length and the choice of vehicle (body type) for undertaking the tour. Two plausible structural relationships between these two choice dimensions are considered. In the first, tour length may impact vehicle type choice and in the second, vehicle type choice may affect tour length.

In order to examine the nature of the relationship between vehicle type choice and tour length, this paper estimates a joint probit-based discrete-continuous model system that recognizes the multinomial nature of the vehicle type choice and the continuous nature of the length dimension. The paper extends the previous model formulation (Ye and Pendyala, 2009) to accommodate variable choice sets. In addition, the paper presents a modified non-nested test that can be used to compare alternative discrete-continuous model structures when choice sets vary across individuals. The simultaneous equations model system is capable of accounting for error correlations that may exist across choice dimensions, arising from the presence of common unobserved attributes that may affect both choice variables.

Model estimation was conducted on a random sample of more than 6,500 tours drawn from the 2009 NHTS. As expected, it is found that the preferences with respect to choice of vehicle body type vary according to the household vehicle fleet composition. In households where a SUV is present, it tends to be the most preferred vehicle type; however, the tour length for this vehicle type tends to be less than that of other vehicle types, suggesting that there is an important relationship between vehicle type choice and tour length that should be modeled while accounting for variable choice sets across observations.

Tour level models relating tour length and vehicle body type choice were estimated. The application of the non-nested test showed that the structure in which vehicle type choice influenced tour length (as opposed to the one where tour length affected vehicle type choice) performed statistically significantly better. Moreover, the coefficients of the vehicle type choice variables were found to be statistically significant in the tour length equation, suggesting that vehicle type choice has a significant impact on tour length. This lends credence to the behavioral paradigm in which vehicle type choice is a higher level household decision process wherein different household members are allocated vehicles among the fleet a priori. Then, the tour length undertaken by individuals is dependent on the vehicle type that has been allocated to each of them. Indeed, vehicle ownership and allocation processes may be viewed as longer term choice decisions that occur at the household level, and tour length may be viewed as a shorter term choice decision that occurs at the individual tour level. In general, it appears that vans are associated with longer trip lengths, followed respectively by cars, SUVs, and pick-up trucks. This significance is found even after accounting for the fact that van trips may be multi-passenger multi-stop journeys that are likely to be longer. A comparison of coefficients across model specifications shows that the independent models which do not account for error correlations across choice dimensions offer substantively different coefficient estimates and statistical significance than the joint model specifications that account for error correlations.

Among the three error correlations estimated, the one representing error covariance between van choice and tour length choice is found to be statistically significant. The correlation is found to be negative. What this means is that the unobserved attributes that make one positively inclined to choose the van as the vehicle type choice negatively impact tour length. This is consistent with expectations. Suppose an individual in a household has more household maintenance and serve-child obligations than another household member. Then, this household member may be more inclined to choose the van as their vehicle of choice as it is convenient to haul people and goods and is comfortable. However, this individual may also be inclined to choose destinations close to home for non-work activities, thus choosing to undertake tours of shorter length. This is because the same factors that made an individual choose the van (household obligations, serve children, desire for comfort) also contribute to the individual choosing to undertake shorter tours because such an individual is time-constrained. Such considerations are critical to the correct specification of multi-dimensional choice models of activity-travel demand.

From a policy perspective, the finding that vehicle type choice affects tour length has important implications. Suppose the government offers rebates, tax incentives, and other price breaks that induce individuals to purchase smaller fuel efficient vehicles. The idea behind offering such incentives is that energy consumption and greenhouse gas (GHG) emissions can be reduced by motivating people to acquire and drive such vehicles. However, the joint model considered most appropriate in this study shows that tours undertaken by cars are likely to be of longer length than tours undertaken by SUV and pick-up trucks and only marginally shorter than van tours. In other words, any gains in energy and environmental sustainability garnered through the increased acquisition of smaller cars may, at least in part, be negated or offset by the longer tour lengths (and therefore miles of travel) undertaken by these vehicles. It appears that individuals, even after controlling for a range of other attributes, may be consciously exercising trade-offs in their utilization of vehicles. Thus, joint models of the type presented in this paper can have important implications in terms of the policy impacts estimated for a variety of public policy scenarios. Future research in this area should attempt to treat other tour attributes such as accompaniment type and number of stops as endogenous variables in a multidimensional integrated choice modeling framework.

6. REFERENCES

Algers, S., A. Daly, P. Kjellman, and S. Widlert (1995) Stockholm Model System (SIMS): Application. *Proceedings of the 7th World Conference of Transportation Research (WCTR)*, Volume 2, Sydney, Australia, 345–361.

Arentze, T., F. Hofman, H. van Mourik, and H. Timmermans (2000) Albatross: Multiagent, Rule-based Model of Activity Pattern Decisions. *Transportation Research Record: The Journal of the Transportation Research Board*, 1706, National Academies, Washington, D.C., 136-144.

Ben-Akiva, M.E., and Swait, J.D. (1984) The Akaike Likelihood Ratio Index. *Transportation Science*, 20(2), 133-136.

Bhat, C.R. (1998) A Model of Post Home-Arrival Activity Participation Behavior. *Transportation Research Part B*, 32(6), 387-400.

Bhat, C.R. (2001). Quasi-random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model. *Transportation Research Part B*, 35(7), 677-693.

Bhat, C.R. and S. Sen (2006) Household Vehicle Type Holdings and Usage: An Application of the Multiple Discrete-Continuous Extreme Value (MDCEV) Model. *Transportation Research Part B*, 40(1), 35-53.

Bowman, J.L. and M. Ben-Akiva (2000) Activity-based Disaggregate Travel Demand Model System with Activity Schedules. *Transportation Research Part A*, 35(1), 1-28.

Bradley, M., J.L. Bowman, and B. Griesenbeck (2009) SACSIM: An Applied Activity-based Model System with Fine Level Spatial and Temporal Resolution. *International Journal of Choice Modelling*, 3(1), 5-31.

Cao, X., P.L. Mokhtarian, and S.L. Handy (2006) Neighborhood Design and Vehicle Type Choice: Evidence from Northern California. *Transportation Research Part D*, 11(2), 133-145.

Cox, D. (1961) Tests of Separate Families of Hypotheses. *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability*, 1, Berkeley: University of California Press.

Cox, D. (1962) Further Results on Tests of Separate Families of Hypotheses. *Journal of Royal Statistical Society B*, 24, 406-424.

Eluru, N., C.R. Bhat, R.M. Pendyala, and K.C. Konduri (2010) A Joint Flexible Econometric Model System of Household Residential Location and Vehicle Fleet Composition/Usage Choices. *Transportation,* 37(4), 603-626.

Hensher, D.A. (2008) Climate Change, Enhanced Greenhouse Gas Emissions and Passenger Transport – What Can We Do to Make a Difference? *Transportation Research Part D*, 13(2), 95-111.

Horowitz, J.L. (1983) Statistical Comparison of Non-nested Probabilistic Discrete Choice Models. *Transportation Science*, 17(3), 319-350.

Kitamura, R. and S. Fujji (1998) Two Computational Process Model s of Activity-travel Behavior. In T. Garling, T. Laitala and K. Westin (eds) *Theretical Foundations of Travel Choice Modeling*, Pergamon Press, Oxford, 251-279.

Konduri, K.C., X. Ye, and R.M. Pendyala (2010) A Probit-based Joint Discrete Continuous Model of In-Home and Out-of-Home Activity Type Choice and Duration Incorporating History Dependency. *Transportation Research Record: The Journal of the Transportation Research Board*, TRB, National Academies, Washington, D.C. (in press).

Mannering, F.L. (1986) A Note on Endogenous Variables in Household Vehicle Utilization Equations. *Transportation Research Part B*, 20(1), 1-6.

Miller, E., M. Roorda, and J. Carrasco (2005) A tour-based Model of Travel Mode Choice. *Transportation*, 32(4), 399-422.

Mohmmadian, A. and E.J. Miller (2003) An Empirical Investigation of Household Vehicle Type Decisions. *Transportation Research Record: The Journal of the Transportation Research Board*, 1854, National Academies, Washington, D.C., 99-106.

Pendyala, R.M., R. Kitamura, A. Kikuchi, T. Yamamoto, and S. Fujji (2005) FAMOS: The Florida Activity Mobility Simulator. *Transportation Research Record: The Journal of the Transportation Research Board*, 1921, National Academies, Washington, D.C., 123-130.

Pendyala, R.M. and C.R. Bhat (2004) An Exploration of the Relationship Between Timing and Duration of Maintenance Activities. *Transportation*, 31(4), 429-456.

Pinjari, A.R., N. Eluru, S. Srinivasan, J.Y. Guo, R.B. Copperman, I.N. Sener, and C.R. Bhat (2004) CEMDAP: Modeling and Microsimulation Frameworks, Software Development, and Verification. *Transportation Research Record: The Journal of the Transportation Research Board*, 1894, National Academies, Washington, D.C., 57-66.

Spissu, E., A.R. Pinjari, R.M. Pendyala, and C.R. Bhat (2009) A Copula-Based Joint Multinomial Discrete-Continuous Model of Vehicle Type Choice and Miles of Travel. *Transportation*, 36(4), 403-422.

Vovsha, P., E. Petersen, and R. Donnelly (2002) Microsimulation in Travel Demand Modeling: Lessons Learned from the New York Best Practice Model. *Transportation Research Record: The Journal of the Transportation Research Board*, 1805, National Academies, Washington, D.C., 68-77.

Walker, J. (2002). The Mixed Logit (or Logit Kernel) Model: Dispelling Misconceptions of Identification. *Transportation Research Record: Journal of the Transportation Research Board*, 1805, 86-98.

Yagi, S. and A. Mohammadian (2009) An Activity-based Microsimulation Model of Travel Demand in the Jakarta Metropolitan Area. *International Journal of Choice Modelling*, 3(1), 32-57.

Ye, X., Pendyala, R.M., and Gottardi, G. (2007). An Exploration of the Relationship Between Mode Choice and Complexity of Trip Chaining Patterns. *Transportation Research Part B*, 41(1), 96-113.

Ye, X. and R.M. Pendyala (2009) A Probit-based Joint Discrete-Continuous Model System: Analyzing the Relationship between Timing and Duration of Maintenance Activities. *DVD Proceedings of the 88th Annual Meeting of the Transportation Research Board*, January, Washington, D.C.

TABLE 1 Sample Descriptive Statistics

Variable Description	Mean	Std. Deviation
Tour-level		
Number of passengers/tour	1.7	0.9
Number of trips/tour	2.7	1.2
Number of stops/tour	1.7	1.2
Travel travel duration/tour	37.0	29.7
Travel travel distance/tour	15.7	14.4
Household-level		
Household size	3.1	1.3
Household vehicle ownership	2.8	1.1
Number of adults	2.3	0.7
Number of children	0.8	1.1
Percentage of households in non-urban area	30%	0.5
Percentage of households with income less than $40K	20%	0.4
Person-level		
Percentage of males	50%	0.5
Percentage of people less than 18 years old	10%	0.2
Percentage of people 65 or older	30%	0.4
Percentage of people with some level of college education	70%	0.5

1 **TABLE 2 Tour Characteristics by Vehicle Type Chosen for the Tour**

Household Vehicle Fleet Composition by Body Type	Frequency	Vehicle Body Type Selected for Tour	Tour Distance	Tour Travel Time	Number of passengers on Tour	Number of Stops on Tour
Average Tour Attributes (Not Considering Vehicle Fleet Composition)						
	2716	Car	16.0	37.7	1.6	1.6
	911	Van	15.2	37.0	2.1	1.8
	1647	SUV	15.4	36.0	1.8	1.7
	1204	Pickup	15.6	36.5	1.5	1.6
Average Tour Attributes (Considering Vehicle Fleet Composition)						
SUV, Pickup	412	SUV	17.0	37.4	1.9	1.8
SUV, Pickup	221	Pickup	15.6	37.4	1.5	1.6
Van, Pickup	169	Van	14.4	35.9	2.0	1.8
Van, Pickup	111	Pickup	15.9	37.5	1.4	1.7
Van, SUV	100	Van	17.2	39.6	2.1	1.7
Van, SUV	76	SUV	16.4	40.3	1.7	1.7
Van, SUV, Pickup	28	Van	15.4	31.9	1.9	1.3
Van, SUV, Pickup	31	SUV	17.9	38.4	1.9	1.6
Van, SUV, Pickup	12	Pickup	17.4	61.4	1.3	1.3
Car, Pickup	1204	Car	17.1	39.3	1.6	1.7
Car, Pickup	662	Pickup	15.4	35.8	1.5	1.6
Car, SUV	767	Car	14.3	36.1	1.5	1.6
Car, SUV	824	SUV	14.1	34.3	1.7	1.6
Car, SUV, Pickup	196	Car	16.6	36.9	1.6	1.6
Car, SUV, Pickup	241	SUV	16.0	37.4	1.7	1.7
Car, SUV, Pickup	137	Pickup	16.9	36.9	1.4	1.6
Car, Van	392	Car	15.2	36.5	1.7	1.6
Car, Van	450	Van	15.0	37.5	2.1	1.8
Car, Van, Pickup	99	Car	15.8	35.6	1.6	1.5
Car, Van, Pickup	102	Van	17.0	38.9	2.1	1.9
Car, Van, Pickup	51	Pickup	14.0	33.5	1.6	1.4
Car, Van, SUV	47	Car	17.2	41.2	1.5	1.6
Car, Van, SUV	50	Van	11.1	28.8	1.8	1.6
Car, Van, SUV	46	SUV	15.4	36.4	1.5	1.9
Car, Van, SUV, Pickup	11	Car	20.3	42.4	1.6	1.6
Car, Van, SUV, Pickup	12	Van	21.7	43.8	2.3	1.8
Car, Van, SUV, Pickup	17	SUV	18.3	40.4	2.1	1.9
Car, Van, SUV, Pickup	10	Pickup	15.0	33.6	1.4	1.6

TABLE 3 Estimation results for the model specification where tour length affects vehicle type choice

	Independent Vehicle Type Choice Model						Independent Tour Length Model		Joint Vehicle Type Choice Model						Joint Tour Length Model	
	Car		Van		SUV				Car		Van		SUV			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	1.686	13.3	2.077	10.8	1.957	13.7	1.913	36.3	1.259	6.5	1.960	4.6	1.456	6.5	1.921	35.9
Tour Attributes																
Log of tour length in miles	0.076	2.0	-0.054	-0.9	0.052	1.1			0.093	1.3	-0.191	-1.0	0.089	1.0		
More than one stop			0.294	2.6			0.793	32.4			0.390	2.3			0.793	32.5
Solo tour	-0.381	-4.5	-0.921	-7.2	-0.670	-6.8	-0.063	-1.8	-0.267	-3.7	-0.763	-6.8	-0.510	-6.1	-0.065	-1.8
Joint tour							0.235	6.7							0.232	6.6
Socio-economic Attributes																
Ratio of household to number of vehicles							-0.061	-1.8							-0.067	-2.0
Male	-1.825	-21.1	-2.287	-18.3	-1.910	-18.9	0.047	2.0	-1.474	-21.4	-1.839	-17.8	-1.538	-18.9	0.047	2.0
Age 65 years or older			0.221	1.6			-0.061	-2.1			0.170	1.5			-0.061	-2.1
Number of children	-0.089	-2.7	0.141	2.9			-0.058	-3.4	-0.073	-2.5	0.104	2.4			-0.056	-3.2
Household in non-urban area					-0.197	-2.4	0.452	17.8					-0.192	-2.4	0.452	17.8
Education level (atleast college)							0.048	1.9							0.046	1.8
Can change start time of fixed activities							-0.103	-3.1							-0.099	-3.0
Household income less than 40k per year							-0.066	-2.2							-0.066	-2.2
	Log-likelihood at convergence = -13141.4								Log-likelihood at convergence = -13151.8; *γ_{1N}=-0.040(-0.6); γ_{2N} = 0.120(0.7); γ_{3N}=-0.057(-0.7); γ_{4N}= 0(-); σ'_N= 0.925 (40.2)*							

TABLE 4 Estimation results for the model specification where vehicle type choice affects tour length

	Independent Vehicle Type Choice Model						Independent Tour Length Model		Joint Vehicle Type Choice Model						Joint Tour Length Model	
	Car		Van		SUV				Car		Van		SUV			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	1.876	22.2	2.045	14.5	2.091	22.3	1.853	30.8	1.491	23.3	1.625	14.2	1.674	23.2	1.794	24.2
Tour Attributes																
Vehicle Type is Car							0.079	2.3							0.143	2.1
Vehicle Type is Van							0.042	1.0							0.174	2.5
Vehicle Type is SUV							0.044	1.2							0.099	1.6
More than one stop			0.200	1.9			0.793	32.4			0.186	2.1			0.792	32.4
Solo tour	-0.400	-4.8	-0.917	-7.2	-0.684	-7.0	-0.061	-1.7	-0.290	-4.2	-0.728	-6.9	-0.533	-6.6	-0.055	-1.5
Joint tour							0.234	6.7							0.234	6.7
Socio-economic Attributes																
Ratio of household to number of vehicles							-0.058	-1.7							-0.064	-1.9
Male	-1.821	-21.1	-2.289	-18.3	-1.905	-18.9	0.060	2.4	-1.474	-21.4	-1.858	-18.2	-1.537	-18.9	0.077	2.8
Age 65 years or older			0.231	1.7			-0.061	-2.1			0.185	1.6			-0.064	-2.2
Number of children	-0.092	-2.8	0.146	3.0			-0.058	-3.3	-0.077	-2.8	0.125	3.1			-0.061	-3.5
Household in non-urban area			-0.227	-2.0	-0.214	-2.6	0.456	17.9			-0.179	-1.9	-0.190	-2.7	0.461	18.0
Education level (atleast college)							0.047	1.8							0.045	1.8
Can change start time of fixed activities							-0.105	-3.1							-0.108	-3.2
Household income less than $40k per year							-0.066	-2.2							-0.064	-2.1
	Log-likelihood at convergence = -13140.5								Log-likelihood at convergence = -13148.3; γ_{1N}=-0.068(-1.1); γ_{2N} = -0.180(-2.6); γ_{3N}=-0.051(-0.8); γ_{4N}= 0(-); σ'_N= 0.914 (46.9)							