A UNIFIED MODEL SYSTEM OF ACTIVITY TYPE CHOICE, ACTIVITY DURATION, ACTIVITY TIMING, MODE CHOICE, AND LOCATION CHOICE

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1. INTRODUCTION

Emerging policy issues of interest, including concerns regarding global climate change and the desire to better understand how pricing policies impact travel demand, have contributed to a new era in travel demand modeling and forecasting (Pendyala *et al*, 2005; Pinjari *et al*, 2006). This era is characterized by an increasing shift towards activity-based travel demand modeling approaches that explicitly recognize that travel is undertaken to fulfill activity needs and desires dispersed in space and time (Pinjari et al., 2009). The move towards microsimulation-based approaches facilitates the disaggregate representation of behavioral agents and their interactions, while simultaneously incorporating the ability to analyze policy impacts and address equity concerns at the level of the individual traveler or any sub-market segment of interest (Miller and Roorda, 2003).

Regardless of the specific model design adopted, it is found that activity and tour-based model systems universally strive to mimic and replicate activity-travel choice processes of individuals. These choice processes include such dimensions as activity type choice, time of day choice, trip chaining or linking choice, joint versus solo activity engagement choice, activity location choice, travel mode choice, activity sequencing decisions, and activity time allocation (duration) decisions. Many of these choice processes are discrete in nature (e.g., activity type choice, time of day period choice, mode and destination choices), while a few may be more continuous in nature (e.g., activity duration). Given the large number of choices that are involved in the behavioral process, many models, particularly the tour-based models in practice, resort to the adoption of deeply nested logit models (Ben-Akiva and Lerman, 1985) where one choice process is nested within another choice process and so on, forming a long chain of inter-connected nests to complete the representation of the behavioral process (Bowman, 1995; Bowman and Bradley, 2006; PB Consult, 2005). As it is virtually impossible to estimate such long chains of nested logit models simultaneously (i.e., in one single step), components of the nested logit model are usually estimated one step (or maybe two steps) at a time and the logsum from one level is carried up to the next higher level, resulting in a sequential estimation and model application approach. Although there are other behavioral model systems that attempt to move away from such deeply nested logit specifications, such as those based on computational process modeling and heuristic approaches (Arentze and Timmermans, 2005), most activity-based model systems do break down the behavioral decision process in some form or the other so that only one or two choice processes are modeled at any step in the system.

Although a sequential treatment of choice mechanisms is convenient from a practical model estimation and application standpoint, it is unclear whether such model systems truly replicate behavioral processes. While tour-based and activity-based models in practice can be lauded for their ability to model activity engagement patterns, consider interactions among activities and trips, and microsimulate activity-travel patterns at the level of the individual traveler, the issue arises as to whether these model systems can be challenged and questioned from a behavioral standpoint not unlike the limitations associated with the traditional four-step travel modeling process. Thus, there is growing interest in the ability to model multiple choice dimensions simultaneously, which motivates the research in current paper. Specifically, this paper presents a joint model system of five choice dimensions: (1) Activity type choice, (2) Activity time of day choice (treated as discrete time intervals), (3) Mode choice, (4) Destination choice and (5) Activity duration (continuous choice dimension). These five choice dimensions are of critical interest to any activity-based model system regardless of the model design adopted. The methodological emphasis in the paper is on specifying and estimating an econometric model system that jointly models the five choice dimensions identified above in a holistic unifying utility-maximization framework. From an empirical standpoint, the model system explicitly includes consideration of built environment attributes including level of service variables and spatial land use characteristics to capture the potential impacts of such variables on the activity generation process.

The next section presents a very brief description of the modeling methodology. This is followed by a description of the dataset and survey sample. The fourth section presents the empirical analysis, while the fifth and final section offers concluding remarks.

2. MODELING METHODOLOGY

The modeling methodology adopted in this paper builds on previous work by the authors and constitutes a joint multiple discrete continuous extreme value model and multinomial logit model system (Bhat 2005, Bhat et al., 2006, Bhat 2008). The multiple discrete continuous extreme value (MDCEV) model component is used to jointly analyze activity type choice, activity time of day choice, mode choice, and activity duration. Specifically, the MDCEV model is used to represent activity participation (discrete choice) and time use (continuous choice) for different types of activities at different time periods of the day by different travel modes. The activity location choice is modeled using a multinomial logit (MNL) model nested within the MDCEV framework. In the MNL component, to reduce the computation time, we only include a smaller sample of the location choice alternatives (with the chosen alternative in the sample) during estimation. According to McFadden (1978), random sampling of alternatives will not compromise the consistency of the location choice model parameters as long as a simple multinomial logit modeling framework is maintained for the location choice.

The proposed two-level MDCEV-MNL model is an attractive alternative to the deeply nested logit modeling approach used in the literature, where accessibility measures have to propagate up to the activity generation level through multiple levels of a deeply nested logit model. Further, the MDCEV-MNL model provides a seamless way of incorporating time-use (and the impact of accessibility on time-use) into the framework. Specifically, the modeling framework explicitly accommodates the concept that individual's activity time-use (*i.e.,* time allocation) decisions are important and influential components of their activity-travel decision-making (Bhat and Koppelman, 1999). On the other hand, it is not that straightforward to incorporate activity time-allocation choices into the deeply nested logit analysis approach. Another appealing feature is that the model recognizes the simultaneity of the activity time-use, timing, mode choice, and location choice decisions within a unified utility maximization framework. Details of the econometric structure are suppressed here due to space considerations.

3. DATA AND SURVEY SAMPLE

The data set used in this paper is derived from the 2000 San Francisco Bay Area Travel Survey (BATS), designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC). The data includes information on: (1) Individual and household socio-demographics for over 15,000 households in the Bay Area, and (2) All activity episodes (including activity type, start and end times of the activity, geo-referenced location of activity participation, and mode of travel to the activity) undertaken by the individuals in all surveyed households for a two-day period. The travel survey records were augmented extensively with several secondary data items, including land-use characteristics, transportation network level-of-service data, and Census population and housing data. In addition, geo-referenced data on businesses, bicycle facilities, highways and local roads were used to derive spatial variables characterizing the activity-travel environment (ATE) in and around the household locations of the individuals in the data set. Details regarding the data preparation and augmentation processes can be found in Guo and Bhat (2004) and Pinjari et al., (2009).

As mentioned in the previous section, the activity choice dimensions modeled in this paper include activity type choice, activity time of day choice, travel mode choice, activity location (destination) choice, and activity time use allocation (duration). The MDCEV model component alternatives are formed as combinations of activity type, time of day, and travel mode, while the duration of each activity episode constitutes the continuous dependent variable. The MDCEV alternatives include the following: (a) maintenance activity type, (b) in-home discretionary activity type, and (c) five out-of-home discretionary activity types, six time periods, and two travel modes, yielding a total of 62 possible MDCEV choice alternatives (2 + 5x6x2 = 62). Finally, the MNL module accommodates the activity location choice dimension.

To control for fundamental differences between workers and non-workers in their activity engagement patterns and choice processes, and in the interest of brevity, the analysis in this paper is restricted to the sample of 5,360 non-working individuals aged 16 years or above. Descriptive statistics for this sample of individuals are presented in Table 1. All 5,360 individuals participate in in-home maintenance for an average duration of nearly 11 hours. Forty percent engage in in-home discretionary activities for an average duration of about 5.5 hours. Note that the average durations are computed over those who actually participate in the activity type. A little over one-half of the sample participate in OH discretionary activities, for an average duration of about 2.5 hours. The automobile mode is the preferred and dominant mode of travel accounting for nearly 90 percent of all out-of-home discretionary activity engagement. Non-maintenance shopping shows a relatively high participation rate, but lower time allocation (regardless of mode), while activities such as meals, socializing, and recreation show lower participation rates but higher time allocation. The top of the table (in the grey shaded row) indicates that only a very small percent of individuals participate in OH discretionary activities in the early morning, and the percentage steadily rises into the afternoon, and then shows a decline towards the night hours. Activities undertaken in the morning and early morning, however, show the longest average durations relative to those in the afternoon and evening, potentially indicating the effect of time constraints that might get tighter towards the latter half of the day. Overall, this table shows the interplay among the dimensions of activity-travel participation that merit a unified approach towards modeling these behavioral characteristics.

4. EMPIRICAL ANALYSIS

A variety of variables were included in the model specification including household and personal socio-economic and demographic variables, contextual variables such as day of week and season of the year, and a host of spatial variables characterizing the activity-travel environment (ATE) around the household locations, not to mention several transportation network level of service variables. The spatial ATE variables included density measures, activity opportunity and accessibility measures, and population and housing data for the neighborhood (traffic analysis zone). The ATE measures were considered at the level of the traffic analysis zone and at finer spatial resolutions, including within 0.25 mile, 1 mile, and 5 mile radii buffers of the household location (see Guo and Bhat, 2004 and Pinjari *et al*, 2009 for complete details).

In the current research effort, a comparison was undertaken between the joint MDCEV-MNL model that integrates destination choice with activity choices and an independent MDCEV-MNL model that does not incorporate the log-sum parameters in the MDCEV component. The goodness of fit measures of the two models were compared using the Bayesian Information Criterion (BIC), which is given by the following expression : $-2 \times \ln(L) + number\ of\ parameters \times \ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence and Q is the number of observations. The model that results in the lower BIC value is the preferred model. The BIC value for the MDCEV-MNL model (with 103 model parameters) was 150514.2, which is substantially lower than that for the independent MDCEV-MNL model (152334.2 with 102 model parameters). Thus, the BIC clearly favors the MDCEV-MNL model of integrated activity choices and destination choice. A detailed description of the MDCEV-MNL model results is not provided here due to space considerations. Instead, we demonstrate the capabilities of the model system presented in this paper by predicting the impact of a variety of policy scenarios on activity and time use behavior.

4. 1. Policy Simulation

The major objective of this paper was to develop a unified model of activity-travel and location choices and time use that would allow one to examine the influence of level of service measures and activity-travel environment (ATE) attributes on these choice dimensions in an integrated manner. Specifically, the model was used to examine the impacts of the following scenarios on activity and time use behavior:

- Doubling travel cost across all time periods
- Doubling travel cost during peak periods
- Doubling travel cost for auto mode
- Doubling travel time across all time periods
- Doubling travel time during peak periods
- Doubling travel time by auto mode

Logsum variables computed using the activity location choice MNL model were used as explanatory variables in the MDCEV model to predict individual's participation in and time allocation to activities by activity purpose, timing, and mode. For each policy scenario, logsum variables were computed for all 60 OH discretionary activity purpose, timing, and mode combinations (for use in the base case prediction), and then updated for the specific timing or travel mode categories for which the policy applied (for the policy case prediction). The prediction using MDCEV was carried out for all individuals in the sample using 1000 replications of the error term draws for each individual. Additional details about the forecasting procedure using the MDCEV model are provided in Pinjari and Bhat (2009). The forecasts under alternative scenarios are presented in Table 2. Specifically, the influence of each policy is reported as an aggregate percent change in the amount of time invested in maintenance activities, in-home discretionary activities, and out-of-home discretionary activities by purpose, time of day, and mode (relative to the base case).

In general, the results provide indications along expected lines. Increases in travel cost lead to reduced out-of-home activity engagement and slight increases in in-home activity engagement. Increases in travel cost during the peak period impact volunteer, eat-meal, and recreation activities more than others, and reduce peak period activity engagement while increasing off-peak activity engagement. Increases in auto travel costs and times reduce the use of auto mode for activity engagement and contribute to enhanced mode shares for non-auto modes. In general, travel time increases appear to have larger impacts than travel costs, suggesting that individuals are more time-sensitive when making activity-travel choices. In terms of the modal impact, it appears that all day travel cost or time increases have a greater impact than a time-specific peak-period travel cost or time increase. It appears that individuals are more likely to respond to price and time signals that cover an entire day as opposed to those that are narrower in the time band of influence. Overall, the policy simulation results clearly show that the model is effective in capturing the responses of individuals to system changes in a unifying framework.

5. CONCLUSIONS

This study aims to present a comprehensive unified model system of activity-travel choices that is consistent with microeconomic utility maximization behavior theory. The activity-travel choice dimensions analyzed in this paper include activity type choice, time of day choice, mode choice, location choice, and activity time allocation or duration. Model estimation results and the policy simulation analysis showed that the joint model system has merit, offers behaviorally intuitive interpretation, and offers a goodness of fit statistically superior to that offered by an independent model system that treats various choice dimensions separately and sequentially. The model specifications included built environment and transportation network level of service attributes demonstrating the impact of these variables on activity-travel dimensions. The model system is presented for a non-worker sample drawn from the 2000 San Francisco Bay Area Travel Survey (BATS). One of the key empirical findings of this analysis is that the built environment and transportation network level of service attributes of the destinations significantly impact activity time use allocation, an aspect that is often overlooked in the literature.

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Table 1 Descriptive Statistics of Activity participation and Time-Use by Activity Purpose, Activity Timing and Travel mode[1]

		ACTIVITY TIMING					
		Early Morning (3am-7am)	Morning (7am-9am)	Late Morning (9am-12pm)	Afternoon (12pm-4pm)	Evening (4pm-7pm)	Night (7pm-3am)
ACTIVITY PURPOSE and TRAVEL MODE	Number (%) of non-workers participating, and mean duration of participation among those participating	63 (2.3%)[2] 140 min	382 (13.9%) 169 min	1131 (41.1%) 121 min	1257 (45.7%) 97 min	720 (26.2%) 103 min	371 (13.5%) 111 min
Maintenance	5360 (100%) 651 min	--	--	--	--	--	--
IH Discretionary	2133 (39.8%) 341 min	--	--	--	--	--	--
OH Discretionary	2752 (51.3%) 163 min	--	--	--	--	--	--
OH Discretionary Auto mode	2473 (89.9%) 158 min						
Volunteering	396 (14.4%)[3] 149 min	4 (1.0%)[4]	81 (20.5%)	137 (34.6%)	89 (22.5%)	72 (18.2%)	63 (15.9%)
Socializing	508 (18.5%) 128 min	6 (1.2%)	20 (3.9%)	125 (24.6%)	159 (31.3%)	97 (19.1%)	77 (15.2%)
Meals	809 (29.4%) 115 min	13 (1.6%)	90 (11.1%)	206 (25.5%)	270 (33.4%)	223 (27.6%)	84 (10.4%)
Non-Maintenance Shopping	1092 (39.7%) 60 min	4 (0.4%)	46 (4.2%)	372 (34.1%)	571 (52.3%)	175 (16.0%)	53 (4.9%)
Recreation	7 38 (26.8%) 145 min	33 (4.5 %)	116 (15.7%)	256 (34.7%)	200 (27.1%)	115 (15.6%)	88 (11.9%)
OH Discretionary Non Auto mode	432 (15.7%) 134 min						
Volunteering	37 (1.3%) 170 min	2 (5.4%)	9 (24.3%)	10 (27.0%)	8 (21.6%)	3 (8.1%)	6 (16.2%)
Socializing	72 (2.6%) 140 min	0 (0.0%)	3 (4.2%)	19 (4.2%)	27 (37.5%)	21 (29.2%)	4 (5.6%)
Meals	135 (4.9%) 119 min	1 (0.7%)	9 (6.7%)	35 (25.9%)	54 (40.0%)	25 (18.5%)	18 (13.3%)
Non-Maintenance Shopping	132 (4.8%) 59 min	0 (0.0%)	4 (3.0%)	50 (37.9%)	62 (47.0%)	12 (9.1%)	6 (4.5%)
Recreation	131 (4.8%) 136 min	1 (0.8%)	14 (10.7%)	52 (39.7%)	33 (25.2%)	32 (24.4%)	6 (4.6%)

[1] The reader will note here that the average time investments reported in this table are for only those who participated in the corresponding activity purpose or for those who participated in OH discretionary activities during the corresponding time period. Also, the activity participation percentages across all activity purposes (or across all time periods, or modes) may sum to more than 100% because of multiple discreteness (*i.e.,* participation in multiple activity purposes and/or during multiple time periods and/or travel by multiple modes over a day). For example, a non-worker can undertake both OH recreation and OH meal activities on a day.

[2] Percentages in this row are out of the 2752 non-workers who participated in at least one OH discretionary activity during the day.

[3] Percentages in this column, from this row onward, are out of the 2473 non-workers who traveled by auto mode for at least one OH discretionary activity during the day.

[4] Percentages from this row and column onward (within this block of rows) are based on total number of non-workers participating in row activity purpose [(4/396)×100=1.0%].

Table 2 Policy Simulation Results

Alternatives	**Activity Purpose**							**Activity Timing**						**Travel Mode**	
Scenario details	Maintenance	IH Discretionary	OH Volunteer	OH Social	OH Meals	OH Shopping	OH Recreation	Early Morning	Morning	Late Morning	Afternoon	Evening	Night	Auto	Non-auto
Travel cost measure increased by 100% for all time periods	0.01	0.02	-0.99	-1.00	-0.84	-0.91	-0.93	-0.92	-0.90	-0.92	-0.96	-0.92	-0.87	-1.00	-0.75
Travel cost measure increased by 100% for peak periods	0.00	0.00	-0.58	-0.05	-0.46	0.07	-0.29	1.34	-3.89	1.30	1.26	-3.93	1.34	-0.30	-0.19
Travel cost measure increased by 100% for auto mode	0.01	0.01	-1.16	-1.21	-0.27	-0.31	-0.83	-0.77	-0.75	-0.69	-0.64	-0.68	-0.76	-2.10	2.48
Travel time measure increased by 100% for all time periods	0.04	0.06	-3.36	-3.40	-2.86	-3.09	-3.18	-3.11	-3.07	-3.13	-3.26	-3.13	-2.95	-3.39	-2.57
Travel time measure increased by 100% for peak periods	0.01	0.02	-1.88	-0.15	-1.53	0.22	-0.95	4.41	-12.70	4.22	4.12	-12.83	4.37	-0.99	-0.64
Travel time measure increased by 100% for auto mode	0.03	0.04	-3.85	-3.99	-0.95	-1.05	-2.73	-2.54	-2.51	-2.30	-2.12	-2.27	-2.54	-7.03	8.34