PLANNING CONSTRAINED DESTINATION CHOICE MODELING IN THE ADAPTS ACTIVITY-BASED MODEL

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ABSTRACT

This paper describes a set of destination choice models estimated using a recent survey from the Chicago region and a previously developed model of the timing of activity planning decisions. The household travel survey data is used to estimate both a standard multinomial logit destination choice model, and a set of conditional choice models under certain assumptions about the activity planning process, where the choice set is constrained by what has already been planned in the schedule. Then, each model is applied to a set of destination choice data collected in a recent activity-travel survey The performance of each model is evaluated and the impacts of using the planning-constrained model in place of the standard model on the accuracy of the results estimated. The use of a model where the destination choices are conditioned on what has already been planned in the each individual's activity-travel schedule could improve the accuracy and policy sensitivity of the model results.

Keywords: Destination Choice, Activity Planning, Choice Set Formation

INTRODUCTION

Recent advances in activity-based analysis have provided new and innovative ways to model travel demand and allowed for significant improvements in the understanding and forecasting of travel behavior. The realism and explanatory power of activity based modeling, especially when developed into a full microsimulation modeling system continue to improve. However, it has been recognized that significant issues still exist in all activity-based microsimulation systems and that there are areas where theoretical and practical developments still need to be made (Litwin and Miller 2004), including in modeling the underlying decision processes behind activity scheduling, improving the representation of time and representing the interdependence between the various decisions underlying the activity scheduling process (Miller 2005). To address these issues, an activity-based model which explicitly addresses the dynamics of activity planning behavior, the ADAPTS model (Auld and Mohammadian 2009a). This model attempts to simulate the dynamics of activity planning behavior through the concept of planning horizons, which specify when the various decisions about each activity are made. This means, however, that for each attribute planning decision, such as mode choice, party composition, and in the case of this paper destination choice, the dynamics of planning must be explicitly incorporated, i.e. how does the destination choice for an impulsive activity differ from the choice for an activity planned two weeks ago? The models developed in this paper are, then, meant to represent destination choices which are constrained by the prior planning decisions of individuals so that the effects of planning dynamics on destination choice can be represented.

Many examples of disaggregate destination choice models exist in the literature. Early examples include Burnett (1973) and Ansah (1977) among many others. Destination choice formulations have been extended to more closely represent choice behavior with the development of the competing destinations model (Fotheringham 1983) and later extensions (Bernardin et al 2009, Schussler and Axhausen 2009) which attempt to account for systematic similarities and differences between destinations in various ways. Discrete choice models of destination choice have further been extended to include more advanced formulations including correlated errors in a workplace location choice model for physicians (Bolduc et al. 1996), and the development of a mixed generalized extreme value model for residential location choice (Sener et al 2009) which take into account the unobserved correlations between destinations. Others have looked at the constraints imposed by the daily activity patterns of individuals on destination choice. Arentze and Timmermans (2007) incorporated the concept of detour time derived from the daily activity pattern into the destination choice model to account for trip chaining effects. The constraints on activity patterns are also addressed from the perspective of time geography; in Miller (2004) for example. Finally, another important consideration in discrete choice modeling is how to handle choice set formation, i.e. the zones for each individual from which each discrete choice is made, which is not a straightforward topic when moving to more advanced models. Thill and Horowitz (1997) attempted to account for scheduling constraints and choice set formation by modeling the choice set formation process within the destination choice model as did Zheng and Guo (2008) through their spatial two-stage model. Reviews of research in choice set formation can be found in Thill (1992) and Pagliara and Timmermans (2009).

This paper builds on past work in destination choice modeling to develop a new set of destination choices models for the Chicago region using the recent Travel Tracker Survey data (CMAP 2007), under a variation of the competing destinations framework, for implementation in the ADAPTS activity-based model. The key concept of the model is the assignment of an available set of destination choices for each choice situation which represents all of the destinations that could theoretically be considered by an individual given their space-time and planning constraints. The remainder of the paper is organized as follows. First, a discussion of the modeling framework is provided. Next a discussion of the data utilized in the estimation of the model and the model application context is discussed. Results of the model estimation are then provided. A validation of the model results is then performed and discussions and conclusions are presented.

MODEL FORMULATION

The destination choice model discussed in this work has been developed as a discrete choice model using the multinomial logit (MNL) framework, with several modifications to account for the influence of surrounding zones, and the addition of a new planned space-time prism constraint on the choice set formation. The basic conditional multinomial logit model is well documented in the literature (see Ben-Akiva and Lerman, 1985) and is derived from random utility maximization theory, which states that for each decision maker *n*, and zone *i*, there is a utility U_{in} associated with selecting zone *i* which is composed of both a component observable to the modeler V_{in} (systematic utility) composed of a linear combination of observed data x_{in} and parameters β_i to be estimated and an unobservable random error component ε_{in} where the error components are independent and identically distributed (IID) with a Type I extreme value (Gumbel) distribution for each zone. Under these assumptions the probability of selecting any zone *i* from a choice set of zones *C* can then be given by the formula:

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j \in C} e^{V_{jn}}} = \frac{e^{\sum \beta_i x_{in}}}{\sum_{j \in C} e^{\sum \beta_j x_{jn}}} \qquad (1)$$

This model, with the additions discussed above forms the basis for the destination choice models for the various activity types. A discussion of the planning constrained choice set formation procedure and MNL model formulation with competition and agglomeration effects follows.

Choice Set Formation

Before developing the model specification for the planning constrained destination choice model for discretionary activities, it is necessary to address the role that choice set formation plays in the model. Choice set formation has long been recognized as a challenging aspect of destination choice modeling (Thill 1992) for a variety of reasons chief among them the large number of alternatives in the *Universal Choice Set*, consisting of all potential activity locations in the modeled region. Many choice set formation methods have been previously proposed in the literature (see Thill 1992, Pagliari and Timmermans 2009 for an overview). The method proposed in this work is based on previous work in using space-time constraint on choice set formation within activity-based models, for example ALBATROSS (Arentze and Timmermans 2000), PCATS (Kitamura et al 1997) and others, based on Hagerstrand's (1970) concept of the time-space prism. The current model is operationalized with new data sources regarding the actual underlying process of activity scheduling (Frignani et al 2010), which allows the development of a *Planning Constrained* choice set formation procedure. The formation of the choice set and subsequent activity destination selection occurs within the context of an *Activity-Based Demand Model*, the ADAPTS model system (Auld and Mohammadian 2009a).

This procedure differs from previous instances of developing model using space time constraints, as the constraint on the travel time are based not on the travel times to the preceding and following activities surrounding the current activity (or on the preceding and following fixed activities as in PCATS (Kitamura et al 1997)), but rather on the constraints set by the preceding and following activities *which were planned before the current activity*, called the *prior planned activities*. The prior planned activities for any activity observation are found through the application of an *Activity Planning Horizon* model, which specifies how long an activity was planned before it was observed. The activity planning horizon model is an ordered probit model with four levels of planning horizon (impulsive, same day, same week, preplan) which uses individual, activity-type and schedule-level data as input. Details of the activity planning horizon model can be found in Auld and Mohammadian (2009b). The procedure for specifying the choice is then to specify when each non-fixed activity (i.e. not primary work, school, etc.) was planned according to the plan horizon model. Then travel time constraints to each activity were set based the planning times of the surround activities. This can be seen in the diagram in Figure 1, which shows example location choice situations in a 1-dimensional space. In the first part of the figure, there is an impulsive shopping trip planned on the way to the fixed work activity. The space-time constraints in this case are set based on the time leaving home and the time arriving at work, and the feasible. In contrast, Figure 1b shows a similar situation, but with a preplanned social visit on the way to work. The end time and location of the social visit severely limit the destination options for the impulsive shopping activity as seen in the figure.

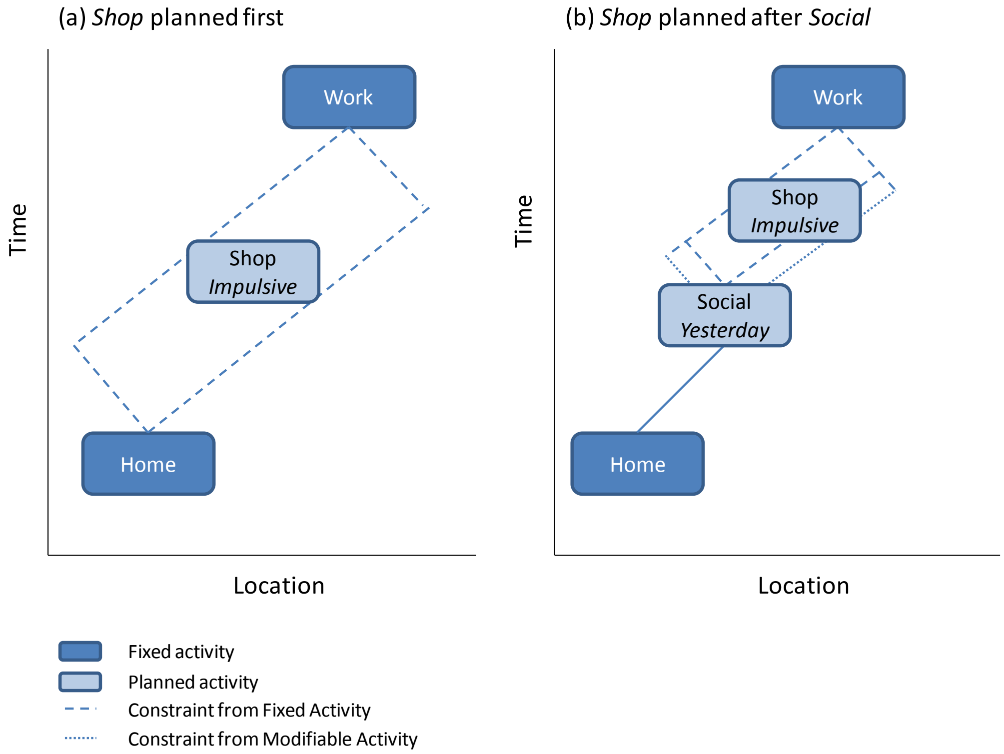

FIGURE 1 Planning Constraints on Choice Set Formation Example

The process described above is followed for all activities to develop what is called the *Available Set*. This set *A* is defined as the feasible choices from the universal set that can be reached given the space-time planning constraints imposed by the other activities in the schedule. The definition of the available set is then necessarily accomplished through simulation by applying the model described in Auld and Mohammadian (2009b) to all choice observations. This process, however, only defines the available set, which can still have quite a large number of alternatives depending on the constraints. As it is unlikely that all alternatives will be considered a separate *Choice Set* is derived from the alternative set through *Stratified Importance Sampling* (Li et al 2005), where a small stratified choice set is selected with N_c elements from the overall available set. In this work the available choices are stratified according to the *Deflected Travel Time*, which is defined as the travel time of the tour with the current activity included minus the travel time without the activity. So, for example, the deflected travel time for the shopping trip shown in Figure 1a would be the travel time from Home-Shop-Work minus the travel time from Home-Work, or the extra travel time imposed by the inclusion of the activity. A second stratification variable is a simple measure of attractiveness of each zone defined by the overall employment level in that zone. So the set *A* is split into subsets A_{ij} where *i* indexes the travel time strata from 1 to I and *j* indexes the employment strata from 1 to J, where an equal number of zones are selected into each strata. The probability of a zone *k* being selected into the choice set if it is in the available set can then be defined by:

$$p(k) = \frac{N_c}{I+J}\left(\sum_i \sum_j \delta_{ij} \left|A_{ij}\right|^{-1}\right),\ 0 < p(k) \leq 1 \tag{2}$$

Where,

$$\delta_{ij} = \begin{cases} 1, & k \in A_{ij} \\ 0 & \end{cases}$$

This process of importance sampling of the alternatives in the *Available Set* defined by the planning constraints to develop the choice set provides for a more realistic choice set as closer and more attractive zones are oversampled relative to more distant and unattractive zones, although the process does introduce sampling bias to the model (Ben-Akiva and Lerman 1985) which needs to be accounted for in the model specification.

Model Specification

The model for the choice of destinations for each activity type is specified as a standard multinomial logit (MNL) model, with the addition of several terms. These additions include the use of several competing destination terms as describe in Fotheringham et al (1983), which were originally intended to mimic the processing of zones from the universal choice set into those which zones which were actually considered. These terms represent an addition to the utility function which increase or decrease the utility of a zone based on its accessibility to nearby competing (or cooperating) destinations. Note that the competition terms in Equation 1 differ from the standard competing destinations model as they are not log-transformed in the utility function and also include a parameterized distance decay function which is explicitly solved for rather than assuming a linear distance decay as is commonly done. The model is similar to that developed by Bernardin et al (2009) in that it includes competition and agglomeration effects (depending on the sign of the q parameters) and explicit inclusion of the distance decay parameter although in this case alternatives are discretely categorized as complements/substitutes for each other. The formula for the systematic portion of the utility for zone *i* and decision-maker *n* is given in Equation 3.

$$V_{in} = \beta_T T_{in} + \beta_I ln(I_{in}) + \beta_R R_{in} + \sum_j^J \beta_j \log(A_{ij}) + \sum_k^K \beta_k E_{ik} + \sum_k^K \theta_k C_k + \ln\left(\frac{1}{p(i)}\right) \quad (3)$$

Where,

β_T = travel time parameter
T_{in} = travel time to zone *i* from home location of decision-maker *n*
β_I = income difference parameter
I_{in} = absolute value of average zonal income for *i* minus income for decision-maker *n*
β_R = race difference parameter
R_{in} = 1-R_i, where R_i is the percentage of residents of zone *i* of a different race than decision-maker *n*
β_j = parameter for the *j*=1…*J*, land use variables
A_{ij} = values of the *j*=1…*J*, land use area variables for zone *i*
β_k = parameter for the *k*=1…*K*, employment sector variables
E_{ik} = values of the *k*=1…*K*, employment sector variables for zone *i*
θ_k = competition/clustering parameter for employment variable *k*
C_k = Competition/Agglomeration factor, see Equation 4
p(i) = probability of selecting zone *i* into the current choice set, from Equation 2

The completion/agglomeration factor for each employment category is defined as shown in Equation 4 below.

$$C_k = \left(\frac{1}{N_z - 1}\sum_{l \neq i}^{N_z} E_{lk} e^{\gamma d_{il}}\right) \quad (4)$$

Where,

N_z = number of zones in region
d_{il} = distance between zone *i* and another zone *l*
γ = distance decay parameter

This factor is approximately equivalent to the average accessibility of all other zones to the current zone weighted by the employment variable k in the other zones. So, this factor will be higher for zones which are more accessible to surrounding employment categories, and measures, in effect, how clustered the current zone is with different surrounding employment types.

This utility specification was then combined with the choice set formation procedure described previously to estimate a destination choice model for seven discretionary activity types in the Chicago region as described in the next section.

DATA SOURCES

The destination choice model describe above has been developed for the Chicago region using the 2007 Travel Tracker Survey collected by the Chicago Metropolitan Agency for Planning (2007), which was an activity-travel survey of 10,552 households over one or two days, producing data on 61,267 non-mandatory activities. This has been combined with land use data (CMAP 2010) overlaid onto the regional traffic analysis zone system. This analysis focused on seven major classes of non-mandatory activities including Major Shopping, Minor/Grocery Shopping, Eating Out, Recreation/Entertainment, Social, Services/Healthcare and Religious/Civic Engagement.

MODEL RESULTS

The destination choice models for each activity type have been estimated using the Chicago Travel Tracker data as described in the previous sections. In addition to the planning constrained destination choice models a second set of destination choice models have been estimated for comparison purposes. The second set of models is estimated using choice sets formed only with routine, fixed activity constraints without considering any activities in the schedule which may have been preplanned but are not routine. This model will be referred to as the “Non-planning constrained” model through the remainder of the paper. Parameter estimates for each model are shown in Tables 2 and 3 below.

These tables show how the major independent variables impact the destination choice decisions for each activity type. The travel time, income and race difference parameters are always negative, showing that these variables have a negative impact on choice probabilities as expected. The attraction variables all have positive impacts for both models. The competition/agglomeration parameters, meanwhile, have a more varied impact, sometimes showing agglomeration effects and sometimes competition effects, and the results are often different between the plan constrained and unconstrained models. Finally the gamma parameters from the distance decay in the accessibility equations have also been estimated. Note that a common gamma parameter is estimated for all competition equations for each activity type to simplify the model estimation.

TABLE 2 Planning Constrained Destination Choice Model Results

Parameter	Services	Minor Shop	Major Shop	Eat Out	Rel/Civic	Rec/Entertain	Social
Travel Time	-0.068	-0.085	-0.060	-0.064	-0.068	-0.067	-0.059
Log (d_Income)	0.016	–	-0.113	-0.110	-0.096	-0.073	-0.101
d_Race	-1.190	-0.405	-1.020	-0.857	-2.020	-1.040	-1.530
Ln (Area_resid)	–	–	–	–	–	–	0.106
Ln (Area_rec)	0.045	–	–	0.020	–	0.109	0.051
Ln (Area_retail)	0.022	0.058	0.045	0.036	0.013	–	0.019
Ln (Area_ent)	–	–	–	–	0.011	0.024	–
Ln (Area_inst)	0.023	0.032	0.062	0.027	0.073	0.035	0.038
Ln (Area_office)	0.013	–	–	–	–	–	–
Ln (Area_mix)	0.033	0.038	–	0.055	0.027	0.041	–
Ln (Area_school)	0.036	–	–	–	0.098	0.033	–
Other Emp. (000s)	–	0.301	–	–	–	–	0.439
Government Emp. (000s)	0.111	–	–	–	–	–	0.089
Service Emp. (000s)	0.091	–	–	0.036	0.122	0.016	0.023
Retail Emp. (000s)	0.129	0.272	0.576	0.269	–	0.290	0.119
θ gov	–	-0.053	0.332	–	–	–	0.068
θ manufacture	–	-0.024	–	–	–	–	–
θ retail	–	-0.028	0.342	-0.085	-0.118	-0.117	-0.131
θ service	–	–	-0.127	–	–	0.026	–
θ industrial	–	-0.108	–	–	–	-0.092	-0.096
θ other	-0.079	0.147	–	–	–	–	–
Gamma	-0.29	-0.40	-0.18	-0.25	-0.18	-0.40	-0.33

TABLE 3 Non-Planning Constrained (Fixed Activity Constraints Only) Model Results

PARAM	Services	Minor Shop	Major Shop	Eat Out	Rel/Civic	Rec/Entertain	Social
Travel Time	-0.057	-0.065	-0.047	-0.048	-0.062	-0.057	-0.046
Log (d_Income)	-0.005	–	-0.121	-0.092	-0.045	-0.077	-0.101
d_Race	-1.180	-0.493	-1.270	-1.310	-1.710	-1.120	-1.650
Ln (Area_resid)	–	–	–	–	–	–	0.119
Ln (Area_rec)	0.046	–	–	0.026	–	0.090	0.054
Ln (Area_retail)	0.025	0.068	0.043	0.043	0.006	–	0.015
Ln (Area_ent)	–	–	–	–	0.022	0.023	–
Ln (Area_inst)	0.022	0.034	0.063	0.029	0.077	0.035	0.039
Ln (Area_office)	0.018	–	–	–	–	–	–
Ln (Area_mix)	0.040	0.039	–	0.064	0.011	0.046	–
Ln (Area_school)	0.041	–	–	–	0.097	0.034	–
Other Emp. (000s)	–	0.317	–	–	–	–	0.526
Government Emp. (000s)	0.125	–	–	–	–	–	0.090
Service Emp. (000s)	0.072	–	–	0.034	0.087	0.007	-0.009
Retail Emp. (000s)	0.060	0.270	0.692	0.278	–	0.299	0.155
θ gov	–	-0.051	0.230	–	–	–	0.065
θ manufacture	–	0.026	–	–	–	–	–
θ retail	–	0.026	0.249	-0.065	-0.098	-0.152	-0.075
θ service	–	–	-0.094	–	–	0.028	–
θ industrial	–	-0.148	–	–	–	-0.063	-0.119
θ other	-0.057	0.086	–	–	–	–	–
Gamma	-0.29	-0.40	-0.18	-0.25	-0.18	-0.40	-0.33

Response Elasticities for Selected Variables

Direct comparisons of parameter impacts on each destination choice model are difficult to make simply by comparing the estimated parameter values between models for a variety of reasons, mostly relating to potential scale differences between the different activity types. Therefore, to compare the impact different model variables have on different activity types, the direct elasticity for the variables are instead compared for the planning constrained model.

Unfortunately, determining an average elasticity of destination choice models for given variables is not particularly straightforward for a number of reasons, the most important of which is that there is no definition of an average choice set at which to evaluate the elasticities, as every chooser faces a different set of zones. So in reality, the actual elasticities for a chooser are highly dependent on the choice set composition, and even for which choice within the choice set the elasticity is calculated for. If a zone is a clearly dominant or clearly inferior choice in the choice set the elasticities will be much smaller than if the zone falls somewhere in between, a well documented property of the logit formulation. Therefore, to get around these issues, for each activity type the average properties of all the selected zones for that type are calculated and a choice set composed of twenty identical copies of this zone is created for purposes of elasticity calculations. Because all of the choices are identical this gives a base probability of 5%, which falls on the lower end of the logit curve so in fact some of the elasticities presented above will likely be underestimates of true elasticities for clearly dominant zones, however they should be fairly representative. With this choice set specification the elasticities are then calculated using the formula in Equation 5 for the linear in terms and Equation 6 for the log-transformed terms

$$E_{i,x} = \beta_x x_i \left(1 - p_i\right) \tag{5}$$

$$E_{i,x} = \beta_x \left(1 - p_i\right) \tag{6}$$

One simplification in this procedure, however, involves the competition terms, as in reality a change in the competition term for one choice will almost always involve changes in competition terms for the other choices. This would mean that Equation 5 cannot be used to calculate the utility with respect to the competition terms. Therefore an assumption is made in this analysis that the competition increase for the choice of interest occurs without impacting the other choices, in which case Equation 5 can be used. While this result may seem to overstate the value of elasticity with respect to the competition term, the model is applied to a fairly small random selection from the total set of zones and these random selections are not necessarily near each other so that in many cases an increase in accessibility for one zone may not mean an increase for the other zones in the set, which may mitigate this issue to a degree.

The elasticity estimates for several significant model variables, including the travel time, race and income difference, retail employment, retail area and retail accessibility (competition), are shown in Figure 2 from a decrease of 20% to an increase of 20% of each independent variable.

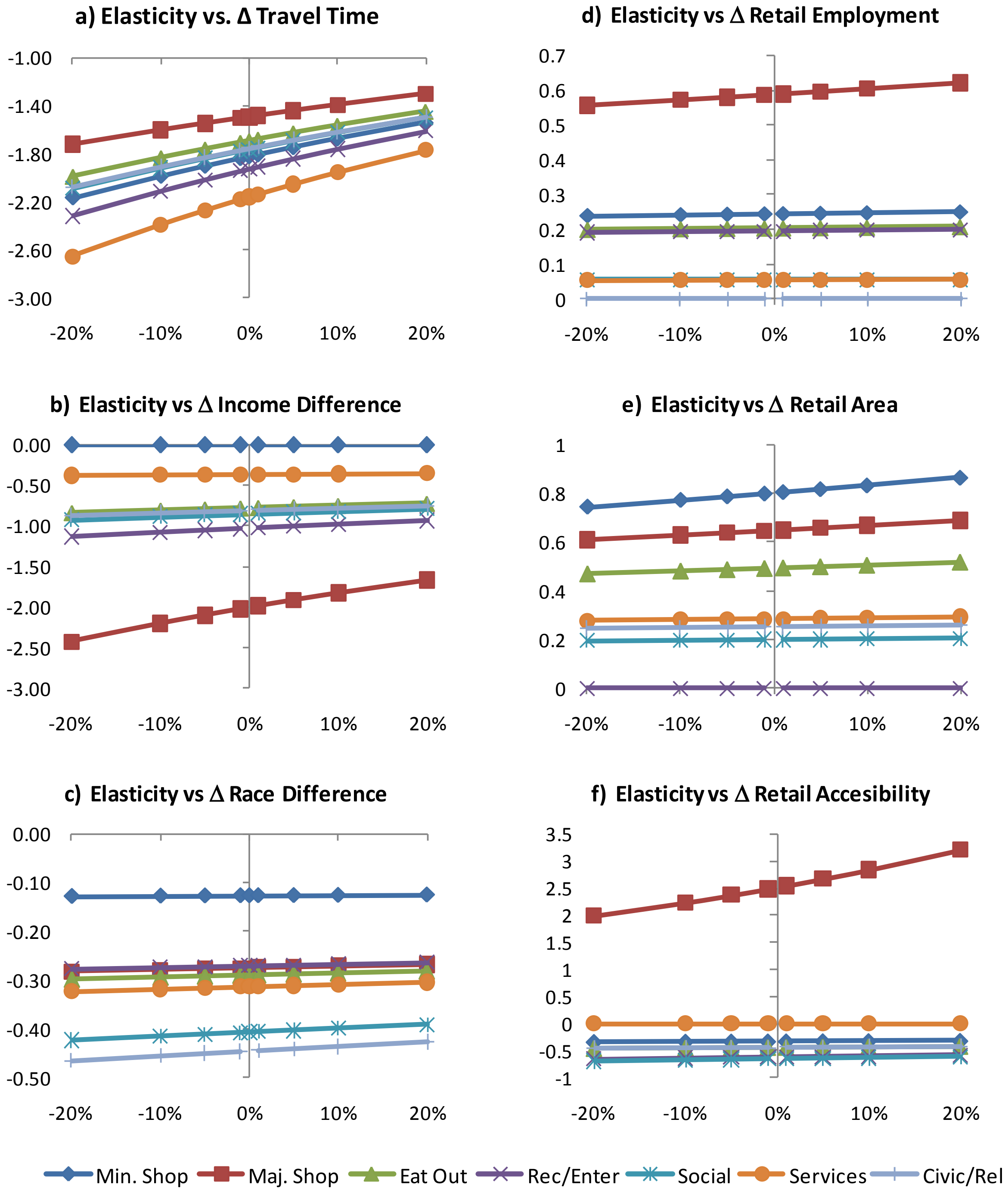

FIGURE 2 Elasticity versus percentage change in (a) Deflected Travel Time (b) Income Difference (c) Race Difference (d) Retail Employment (e) Retail Area (f) Retail Accessibility

The figures show the elasticities with respect to the selected independent variables for the seven main categories of discretionary activities which gives a clearer picture of how each variable impacts each model than a comparison of the parameter values alone. For example, it is clear from Figure 2a that Major Shopping activities are far less sensitive to travel time than are Recreation/Entertainment activities with elasticities of -1.5 and -2.0 respectively, meaning that an increase in travel time to a zone of 1% would be expected to cause a decrease in probability of choosing that zone of 1.5% for a major shopping activity but 2.0% for a recreational activity. This, however, would not be immediately clear from the parameter estimates of -0.06 and -0.068 respectively. The result is meaningful as it seems likely that individuals would be willing to absorb more travel time increase when travelling to make a major purchase (and spend a lot of money) than when traveling for recreation.

The elasticity estimates for the variables all show meaningful and theoretically sound results. All activities show a highly elastic negative response to changes in travel time, while most of the activities show slightly inelastic to highly elastic responses to differences in income, especially for the major shopping activity. The highly elastic response of the major shopping activity to income difference makes sense as individuals are less likely to make major purchases in zones which generally serve residents in different economic strata. Most activities are less sensitive to differences in zonal racial composition from the decision maker's race, but those activities which are most sensitive to this term are the social activities, such as socializing, religious and civic engagement. The remaining three variables all relate to measures of retail attractiveness and as expected they mainly impact the shopping activities, and to a lesser extent other activities such as eating out and services which can to some degree overlap with retail employment/land use. The shopping trips have stronger, though still inelastic, positive responses to increase in retail employment and area than the other activity types have. Finally, the retail employment competition term has little impact on all of the activity types except for the major shopping activity where it has a positive strongly elastic impact. This shows that individuals tend to look for shopping districts where retail zones have clustered around one another when making major purchases, such as shopping malls, downtown shopping districts, etc.

MODEL VALIDATION

In order to validate the use of activity planning constraints in the estimation of the destination choice model, the results of the planning constrained model were compared against results from the non-planning constrained model described previously in a number or ways. However evaluating the validity of models of this type is difficult as the traditional means of comparison – evaluating and comparing the respective increase in log likelihood, or the likelihood ratio, for each model – is uninformative as the differences between the models lies only in how the choice set is formed. In fact in terms of the likelihood ratios, the non-planning constrained models generally show better performance as it has a less restricted choice set formation which can include more random zones which do not compare as favorably with the actual choice, thereby leading to higher likelihood ratios. For this reason, different comparison metrics are needed.

The first comparison used to evaluate the performance of the planning-constraints in destination modeling was to look at the overall model accuracy, or percent correctly predicted, at the disaggregate level. In order to perform this comparison, both the planning-constrained and non-constrained models were applied to the CMAP survey data. Destination choices were estimated for each activity observation and compared to the actual choices. The correct predictions for each model were then compared and also compared against the expected null model results obtained through assuming equal likelihood of all zones within the available set for each situation. This comparison represents an estimate of the disaggregate accuracy of the model, which due to the nature of destination choice and the large number of choices, is naturally somewhat low. An aggregate-level comparison then, was also performed, where the destination choice for each activity were aggregated to the zone level and compared against the observed zone level counts. An R^2 measure between the simulated and observed counts for each model was then estimated for comparison. The results of both analyses are shown in Table 4.

TABLE 4. Disaggregate and Aggregate Measures of Accuracy

	Planning	No Planning	Null
% correct	7.12%	5.77%	2.71%
Adj R^2	0.602	0.571	–

In both comparisons shown in the table the planning constrained model outperforms the unconstrained model, and well outperforms the null model expectation (calculated from the available set size for each choice situation). The planning constrained model outperforms the unconstrained model in both aggregate and disaggregate measures as expected. A final validation performed was the comparison of the trip length distributions resulting from the application of the planning-constrained and non-planning constrained models to the CMAP survey data to the observed trip length distributions. The results can be seen in Figure 3 which shows each distribution. It is clear from the figure that the planning-constrained model fits much more closely to the observed data than does the non-constrained distribution. The non-constrained model greatly underestimates the number of short distance trips and overestimates the number of trips in the 20 – 60 minute range. The constrained model, meanwhile, exhibits these tendencies to a much less pronounced degree. The results show that not considering constraints imposed by activity planning can bias aggregate results.

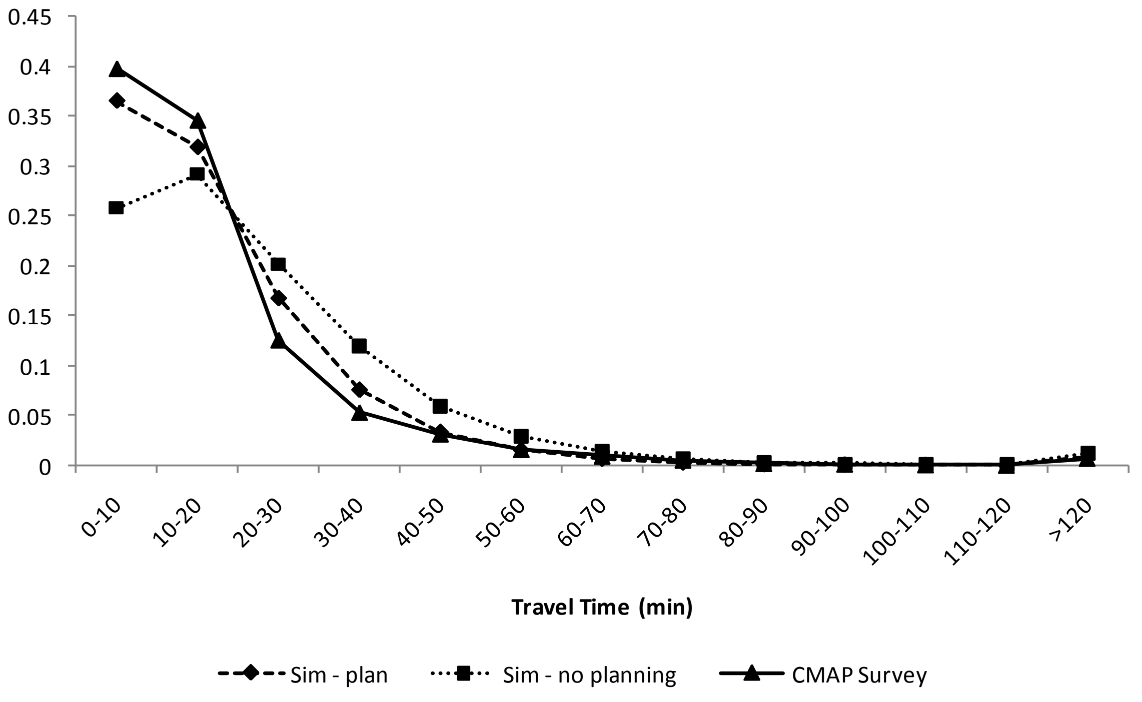

FIGURE 3. Observed and simulated trip time distributions with and without planning constraints

CONCLUSION

The destination choices of individuals represent perhaps the most significant influence on their overall travel demand making destination choice models critical component of all advanced disaggregate travel demand models. As activity-based travel demand models grow more advanced, especially in regard to representing the dynamics of activity-travel planning and scheduling, destination choice models will need to adapt. This issue arose in the development of the ADAPTS activity-based model which attempts to represent the dynamics of activity planning in an activity scheduling model (Auld and Mohammadian 2009). To address the issue of dynamics in destination choice, this paper presented a disaggregate choice model for non-mandatory activities where the choices are constrained by previously planned activities. A variant of the competing-destinations multinomial logit model formulation was used to estimate the impact of the travel time, the land use characteristics of the location, the attractiveness in terms of different employment types, socio-economic differences, and a competing destinations term meant to represent the behavioral influence of clustering/agglomeration on destination choices.

The destination choice model for non-mandatory activities was estimated using the recently collected 2007 CMAP Travel Tracker Survey data, combined with the results of a previously estimated activity planning model estimated through the use of the 2009 UTRACS activity planning survey. The results of the model estimation show that the model performs well, with an acceptable improvement in percent correct predictions over null model expectation (7.1% against 2.7%), which was also an improvement over the non-planning-constrained version of the model which did not consider preplanned activities in the formation of the choice set. The estimated model was then applied to a synthetically generated population for the region created to match known population characteristics. The results of the application to the synthetic population were then used to validate the model in terms of trip length distributions and final zonal attraction counts. The results show that the model works well in replicating the trip length distributions observed in the travel tracker survey. The model also replicates the aggregate measure of the expected attraction counts by zone to a high degree of accuracy, demonstrating the usefulness of the model.

Future work on the destination choice model will focus on improving the model formulation to account for the effects of individual heterogeneity and the correlations between zones which naturally arise in spatial contexts and occur in addition to the systematic correlations already addressed through the competition factors. These issues can both be addressed by transitioning from a MNL framework to a mixed-logit (ML) formulation. The mixed-logit model involves making different distributional assumptions regarding the random component of utility than for the simple MNL model. For example, to account for the correlation between zones (spatial autocorrelation), the error can be considered a combination of the IID random term and another random term arising from a Spatial Autoregressive (SAR) process as in Bolduc (1996). In a similar manner, individual parameters in the model can vary randomly over individuals rather than having a single fixed value by adding random error component to the parameters which results in the Random Parameters formulation of the ML model (Ben-Akiva et al. 2001). In any case, extensions of the basic model developed here to address these issues should result in a more accurate and meaningful representation of the destination choices of individuals.

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