Planning Constrained Destination Choice in the ADAPTS Activity-Based Model

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ABSTRACT

This paper describes a destination choice model estimated for Chicago using a recent survey and a previously developed model of activity planning decision timing. The travel survey data is used to estimate both a standard multinomial destination choice model and a model where the choice set is constrained by what has already been planned in the schedule. The performance of each model is evaluated and the impact of using the planning-constrained model in place of the standard model on the accuracy of the results is evaluated. The use of a model where the destination choices are conditioned on what has been previously planned improves the accuracy of the model. This is true in terms of correctly predicted location choices and especially in terms of overall trip length distributions where more realistic distributions are observed when decisions are constrained.

1. 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. However, it has been recognized that significant issues still exist in many activity-based microsimulation systems and that there are areas where improvements still need to be made (*1*), including in modeling the underlying decision processes behind activity scheduling and representing the interdependence between the various decisions underlying the activity scheduling process (*2*). An activity-based model which explicitly addresses the dynamics of activity planning behavior, the ADAPTS model (*3*), has been developed. 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.

Many disaggregate destination choice models exist in the literature. Early examples include Burnett (*4*) and Ansah (*5*) among others. Destination choice formulations have been extended to more closely represent choice behavior with the development of the competing destinations model (*6*) and later extensions (*7, 8*) 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 (*9*), and the development of a mixed generalized extreme value model for residential location choice (*10*) 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 (*11*) 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 (*12*) for example. Finally, another important consideration in discrete choice modeling is handling choice set formation, i.e. the zones for each individual from which each discrete choice is made. Thill and Horowitz (*13*) 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 (*14*) through their spatial two-stage model. In depth reviews of this topic can be found in Thill (*15*) and Pagliara and Timmermans (*16*).

This paper develops a new set of destination choices models for the Chicago region using the recent Travel Tracker Survey data (*17*), 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, dependent on what has previously been planned so that planning dynamics are explicitly incorporated into the model. 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.

2. 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 space-time prism constraint on the choice set formation. The basic multinomial logit model is well documented in the literature (*18*) 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} which is a function of observed data x_{in} and parameters β_i to be estimated and an unobservable random error 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:

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

This model 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.

2.1 Choice Set Formation

Before developing the model specification it is necessary to address the role that choice set formation plays. Choice set formation has long been recognized as a challenging aspect of destination choice modeling (*15*) 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 (*15*, *16*). The method proposed in this work is based on previous work in using space-time constraint on choice set formation within activity-based models (*19*, *20*), using the concept of the time-space prism (*21*). The current model utilizes new data sources regarding the underlying process of activity scheduling (*22*), 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 (*3*).

This procedure differs from previous instances of 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 (*20*), 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 determined using an *Activity Planning Horizon* model, which specifies how long an activity was planned before it was observed. The previously developed 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 (*23*). The procedure for specifying the choice set is then to specify when each non-fixed activity (i.e. not primary work, school, etc.) was planned through simulation using this plan horizon model. Then travel time constraints to each activity are set based on the simulated planning times of the surround activities.

This is illustrated in the diagram in Figure 1, which shows two example location choice situations in a 1-dimensional space. In each case the individual has a daily activity pattern of Home-Social-Shop-Work observed from travel survey data. The *Activity Planning Horizon* model, shown in Table 1, would then be applied to each activity in this pattern to determine the order in which the activities are planned, based on household, individual and activity-level characteristics. The two choice situations shown in Figure 1(a) and 1(b) differ only in the order in which the activities are planned. Note that in the example, only the location decision for the *Shop* activity will be discussed. In the first part of the figure, there is a preplanned shopping trip on the way to the fixed work activity, while the *Social* activity is estimated as *impulsive*, so it does not factor into this location choice. The space-time constraints are set based on the time leaving home, time arriving at work and the feasible travel speed. In contrast, Figure 1b shows a similar situation, but with the social visit being preplanned and the shop activity estimated to be impulsive. In this case the social activity location would be estimated first and its end-time/location would constrain the available choices for the shopping activity.

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 estimated through simulation by applying the model described in Auld and Mohammadian (*23*) to all choice observations to determine the ordering in which the activities were planned as described above. The model is an ordered probit model with four plan horizon levels, including “impulsive”, “same day”, “same week”, and “preplanned”. The model parameters are shown in Table 1 below.

This process, however, only defines the available set which can still have many alternatives depending on the constraints. Therefore a separate *Choice Set* is derived from the alternative set through *Stratified Importance Sampling* (*24*), 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 activity minus the travel time without the activity, i.e. 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:

$$p(k) = \frac{N_c}{I+J}\left(\sum_i \sum_j \delta_{ij} \Big/ \left|A_{ij}\right|\right), 0 < p(k) \le 1 \qquad (2)$$

Where,
N_C = size of choice set
$|A_{ij}|$ = number of zones in subset A_{ij}
$$\delta_{ij} = \begin{cases} 1, k \in A_{ij} \\ 0 \end{cases}$$

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 (*18*) which needs to be accounted for in the model specification. Additionally, other important factors for consideration in choice set formation are the final size of the choice set (and each strata within the choice set) and the consistency of the parameter estimates obtained using the reduced choice set. These issues are investigated next.

2.2 Choice Set Size and Parameter Consistency

An important consideration in the development of the model is the size of the choice set from which individuals make their decisions. Smaller choice sets are easier simulate but too-small choice sets produce inconsistent parameter estimates. Therefore it was necessary to determine the smallest possible choice set size which produced consistent parameter estimates. An analysis was performed using the model described in the following sections to determine the optimal choice set size. The results of this analysis are shown in Figure 2 below. In the analysis, the root mean squared error and average absolute percent error for the parameter estimates obtained from model runs using a range of choice set sizes (from 20 to 600 maximum choice set size) are calculated against parameter values obtained from using the full "available set" as the choice set for each choice observation. Each observation is shown as the average and +/- one standard deviation of a number of model runs to account for the variance from the stochastic choice set selection. The analysis is only shown for the "Shopping" activity although other activity types follow a similar pattern.

The results of the analysis show that initially there is large error in the parameter estimates when the choice set size is small. However the error decreases rapidly as the maximum choice set size increases and levels off somewhere around 100 zones. The table below the figures shows some statistics regarding each maximum choice set size. Note that the average realized choice set size is never as large as the maximum due to the stratification scheme used, i.e. for a choice set size of 100 there are 4 strata with a maximum of 25 zones in each. However, as the maximum size increases some strata become harder to fill (i.e. low travel times) so the choice set size never reaches the maximum. At a maximum size of 100 the average choice set consists of 59 zones. At this size, the average choice set comprises approximately 46% of the available choice set. Based on these results a choice set size of 100 zones was selected. Next, the specification for the model used in the above analysis is described.

2.3 Model Specification

The destination choice model for each activity type is specified as a standard multinomial logit (MNL) model with several additions. These additions include the use of competing destination terms as describe in Fotheringham et al (*6*), 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. 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 linear distance decay. The model is similar to that developed by Bernardin et al (*7*) in that it includes competition and agglomeration effects (depending on the sign of the θ parameters) and explicit inclusion of the distance decay parameter. The zonal size variables, including the land-use and employment by various categories, enter the utility function as a log-sum with an additional parameter (*26*, *27*). The diverted travel time described previously is also included. The formula for the systematic portion of utility, for zone *i* and decision-maker *n*, is given in Equation 3.

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

Where,

β_T = travel time parameter
T_{in} = diverted travel time to reach zone *i* for 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*
γ = logsum parameter for zonal size variables
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 competition/agglomeration factor for each employment category is defined as shown in Equation 4.

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

Where,

N_z = number of zones in region
t_{il} = distance between zone *i* and another zone *l*
α = 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 E_{ik} in the other zones. This factor is 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 combined with the choice set formation procedure to estimate a destination choice model for seven discretionary activity types in the Chicago region as described in the next section.

3. DATA SOURCES

The destination choice model has been developed for the Chicago region using the 2007 Travel Tracker Survey *(17)*, 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 (*25*) 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. The average of the model variables for the selected zones by each activity type is shown in Table 2.

4. MODEL RESULTS

The planning-constrained destination choice models for each activity type have been estimated using the data described above. Additionally, a second set of unconstrained models have been estimated for comparison purposes. The second set of models is estimated using choice sets formed only with routine, fixed activity constraints. This model will be referred to as the "Non-planning constrained" model through the remainder of the paper. Parameter estimates for the constrained model are shown in Table 3.

The table shows how the major independent variables impact the destination choice decisions for each activity type. The travel time and income / race difference parameters are always negative showing these variables have a negative impact on choice probabilities as expected. Conversely, the attraction variables all have positive impacts. The competition/agglomeration parameters, meanwhile, have a more varied impact, sometimes showing agglomeration effects and sometimes competition effects. Generally, being surrounded by more industrial/manufacturing employment reduces zonal attraction, while retail/service employment increases attraction although not usually together.

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, such as scale differences between different activity types, etc. Therefore to compare the impact of the model variables the direct elasticities for the variables are used. Unfortunately, determining variable elasticities in destination choice models is not particularly straightforward as there is no definition of an average choice set at which to evaluate the elasticities since every chooser faces a different set of zones. So in reality, the actual elasticities 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, due to 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 20 identical copies of this zone is created for purposes of elasticity calculations. Because the choices are identical this gives a base probability of 5%, which falls on the lower end of the logit curve. For this reason the elasticities presented will likely be underestimates of true elasticities for clearly dominant zones, however they should be fairly representative. The point elasticities are calculated using the formula in Equation 5 for the linear terms and Equation 6 for the size-variables. Arc elasticities can be calculated using Equation 7 for various Δx values, which converge to the values given by (5) and (6) as Δx goes to 0.

$$E_{i,j} = \beta_j x_{ij}(1 - P_i) \tag{5}$$

$$E_{i,j} = \gamma \frac{\beta_j}{\sum_k \beta_k x_{ik}} x_{ij}(1 - P_i) \tag{6}$$

$$E_{i,j} = \left(P(i \mid x_{ij} + \Delta x) / P(i \mid x_{ij}) - 1\right) / \left(\Delta x / x_{ij}\right) \tag{7}$$

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. 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 arc elasticity curves for several variables, including travel time, race and income difference, retail employment, retail area and retail accessibility, are shown in Figure 3 from a decrease of 20% to an increase of 20% of each independent variable. The figures show the elasticities for the variables for each type of discretionary activity which gives a clearer picture of how each variable impacts each model than the parameter values alone. For example, it is clear from Figure 3a that shopping activities are far less sensitive to travel time than are social and civic/religious activities with elasticities of -1.2 and -1.7 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 1.2% for a shopping activity but 1.7% for a social or religious activity. This, however, would not be immediately clear from the parameter estimates as major shopping and social have the approximately the same value, as do minor shopping and social. The result is meaningful as it seems likely that individuals would be willing to absorb more travel time increase when travelling to make purchases (and spending money) than when traveling for social or religious reasons.

The elasticity estimates for the variables all show reasonable results. All activities show a highly elastic negative response to changes in travel time, while most of the activities show slightly inelastic negative responses to differences in income, especially for the civic/religious activity. The stronger negative response of the civic/religious activity to income difference makes sense as these tend to be activities done locally. 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 activities like recreational, entertainment and 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 eating out and to a lesser extent other activities such as services and socializing 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 area the other activity types have. Interestingly, retail employment for a zone does not have much impact on the shopping activities, but does impact through the accessibility term, suggesting when choosing zones for these types of activities individuals tend to look for shopping districts where retail zones have clustered around one another, such as shopping malls, downtown shopping districts, etc.. The retail employment competition term also has a strong positive impact on social activity location choice and a strong negative impact on eating out location choice. This last result is interesting when contrasted with the positive impact of zonal retail employment for eating out activity, suggesting that these activities, as expected are attracted to commercial/mixed use areas where restaurants can be expected to be found, but are not attracted generally to large shopping centers.

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. 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. It is important to note here that “percent correctly predicted” statistic is only useful for relative comparisons, i.e. how well the constrained model performs compared to the unconstrained and null model results, rather than as an absolute measure of model performance, as the percentage of correct predictions can be increased arbitrarily by reducing the choice set size. An aggregate-level comparison then, was also performed, where the destination choices for each activity were aggregated to the zone level and compared against the observed zone level counts using R^2 measure.

In both comparisons 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 correctly predicts 8.3% (σ = 0.04%) of destination choice TAZs, while the unconstrained model only correctly predicts 6.0% (σ = 0.02%) of choices, averaged over 10 model runs, and both are significantly higher than the null model expectation of 2.7% correct predictions. For the aggregate zone level counts, there is a R^2 of 0.602 (σ = 0.005) for the plan constrained model results to the actual counts compared against a value of 0.518 (σ = 0.003) for the unconstrained model. The planning constrained model significantly outperforms the unconstrained model in both measures.

A final validation was the comparison of trip length distributions obtained from the planning-constrained and non-constrained models to the observed trip length distributions in the CMAP survey. The results can be seen in Figure 4. It is clear from the figure that the planning-constrained model fits 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 results show that not considering constraints imposed by activity planning can bias aggregate results.

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 (*3*). 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 (8.3% 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.

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 et al (*9*). 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 (*28*). 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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LIST OF TABLES AND FIGURES

TABLE 1 Activity Planning Horizon Ordered Probit Model

	Variable	β	t-stat		Variable	β	t-stat
	Constant	0.088	0.62				
Person	Employed	0.717	4.23	**Activity**	Inflexible Location	0.617	4.93
	Frequent ICT usage	0.549	2.4		Inflexible Start Time	-0.663	-5.47
	Teleworker	-0.612	-4.38		Inflexible Duration	-1.416	-5.34
Activity Type	ACT1 (Work/School)	1.061	2.47	**Activity Type**	ACT4 (Discretionary)		
	x *Employed*	-1.223	-2.09		x *Student*	0.833	2.74
	x *Student*	1.809	2.25		x *Senior*	0.717	3.63
	x *Inflexible Location*	-0.805	-1.92		x *Male*	-0.787	-3.99
	x *Inflexible Duration*	2.081	5.03		x *ICT User*	-0.425	-1.67
	x *Average Gen. Cost*	0.101	2.08		x *Inflexible Duration*	1.317	4.22
	x *Average Frequency*	-0.459	-2.48		x *Average Frequency*	0.563	2.59
	ACT2 (Personal)				x *Average Duration*	2.409	1.95
	x *ICT User*	-0.897	-2.09		ACT5 (Shopping)		
	x *Inflexible Duration*	1.459	4.11		x *Employed*	-0.653	-2.55
	x *Average Gen. Cost*	0.133	2.7		x *Senior*	0.456	2.22
	x *Average Duration*	13.816	4.73		x *ICT User*	-0.809	-2.89
	ACT3 (Maintenance)				x *Inflexible Duration*	1.0009	3.55
	x *Employed*	-0.659	-2.52		x *Average Gen. Cost*	0.051	2.11
	x *Student*	-1.103	-2.21		x *Average Frequency*	0.293	3.49
	x *Senior*	1.045	3.42				
	x *Male*	-0.59	-1.92				
	x *Inflexible Duration*	0.554	1.69				
	x *Average Frequency*	1.586	2.59				
Limits	α_{week}	1.66	27.23				
	$\alpha_{preplan}$	3.53	36.52				

TABLE 2. Average Values of Variables For Selected Zones

Variable	Services	Minor Shop	Major Shop	Eat Out	Rel / Civic	Rec / Entertain	Social
Travel Time	26.97	17.17	20.98	21.67	24.14	26.85	30.03
Log (Income diff.)	10.22	10.21	10.23	10.24	10.24	10.28	10.21
Race diff.	0.28	0.28	0.26	0.27	0.25	0.27	0.26
Resid. Area (mm sf)	21.4	21.2	23.2	20.2	21.4	21.9	22.5
Rec. area (mm sf)	6.1	5.6	7.3	5.8	5.8	6.6	6.9
Retail area (mm sf)	0.4	0.7	1.0	0.5	0.2	0.4	0.3
Entertain area (mm sf)	0.3	0.3	0.3	0.3	0.3	0.4	0.3
Institutional area (mm sf)	1.4	1.1	1.1	1.1	1.2	1.2	1.2
Office area (mm sf)	0.5	0.6	0.9	0.6	0.2	0.5	0.4
Mixed use area (mm sf)	2.2	2.4	2.6	2.3	2.1	2.2	2.0
School area (mm sf)	1.2	1.0	1.1	1.0	1.3	1.2	1.2
Government Emp. (000s)	0.64	0.36	0.34	0.53	0.45	0.49	0.46
Service Emp. (000s)	2.25	1.68	1.77	2.30	1.52	2.13	1.54
Retail Emp. (000s)	0.67	0.82	0.96	0.79	0.50	0.74	0.54
Other Emp. (000s)	0.40	0.37	0.40	0.42	0.31	0.38	0.32
θ gov	1.69	1.26	1.31	2.28	1.12	1.72	0.99
θ manufacture	0.91	0.82	0.83	1.08	0.73	0.91	0.71
θ retail	1.21	1.06	1.13	1.50	0.89	1.25	0.85
θ service	6.58	4.95	5.34	9.11	4.08	6.97	3.64
θ industrial	0.94	0.78	0.83	1.17	0.68	0.93	0.64
θ other	0.97	0.80	0.84	1.26	0.68	1.00	0.63

TABLE 3. Destination Choice Model Results for Constrained Model

Parameter	Civ/Relig	Eat out	Maj. Shop	Min. Shop	Rec/Ent.	Service	Social
Travel Time	-0.076	-0.067	-0.062	-0.075	-0.062	-0.060	-0.059
Income diff.	-0.092	-0.056	–	-0.027	-0.046	-0.070	-0.058
Race diff.	-2.009	-1.139	–	-0.844	-1.325	-1.027	-0.969
Resid. Area	0.108 *	–	–	–	–	–	0.091
Rec. area	–	–	–	0.011	0.017	0.016	0.043
Retail area	–	4.241	4.475	4.140	0.621	0.466	0.491 *
Entertain area	–	–	–	–	2.285	–	–
Institutional area	0.028 *	–	–	0.033	0.035	0.061	0.150
Mixed use area	–	–	–	0.075	0.712	0.341	0.717
School area	0.986 *	–	–	–	1.000 †	0.348	0.305
Gov. Emp.	1.547 *	–	–	–	0.066	0.527 *	1.403
Service Emp.	1.000 †	–	–	–	–	0.966	1.000 †
Retail Emp.	–	2.815	1.085	1.000 †	–	1.000 †	0.942
Other Emp.	–	1.000 †	1.000 †	–	–	–	–
θ gov	0.201	–	–	–	–	–	0.190
θ manufacture	–	-0.296	–	-0.326	-0.420	-0.407	–
θ retail	–	-0.223	0.355	0.191	–	–	0.285
θ service	–	0.056	-0.055	-0.032	0.093	0.029	0.051
θ industrial	-0.711	-0.255	–	-0.385	-0.619	-0.126 *	–
θ other	–	–	–	0.400	–	–	-1.228
Logsum	0.648	0.274	0.381	0.434	0.582	0.635	0.979
Dist. decay	-0.18	-0.25	-0.18	-0.40	-0.40	-0.29	-0.33
LL_o	-12965.6	-36028.0	-4649.1	-59479.5	-34718.7	-46626.0	-26548.3
LL_f	-8713.0	-28257.5	-3774.4	-44835.0	-26334.8	-35761.9	-20355.5
ρ^2	0.328	0.216	0.188	0.246	0.241	0.233	0.233

Note: All parameter estimates significant at 0.05 level, except for:
* Significant at 0.10 level.
† Fixed parameter.

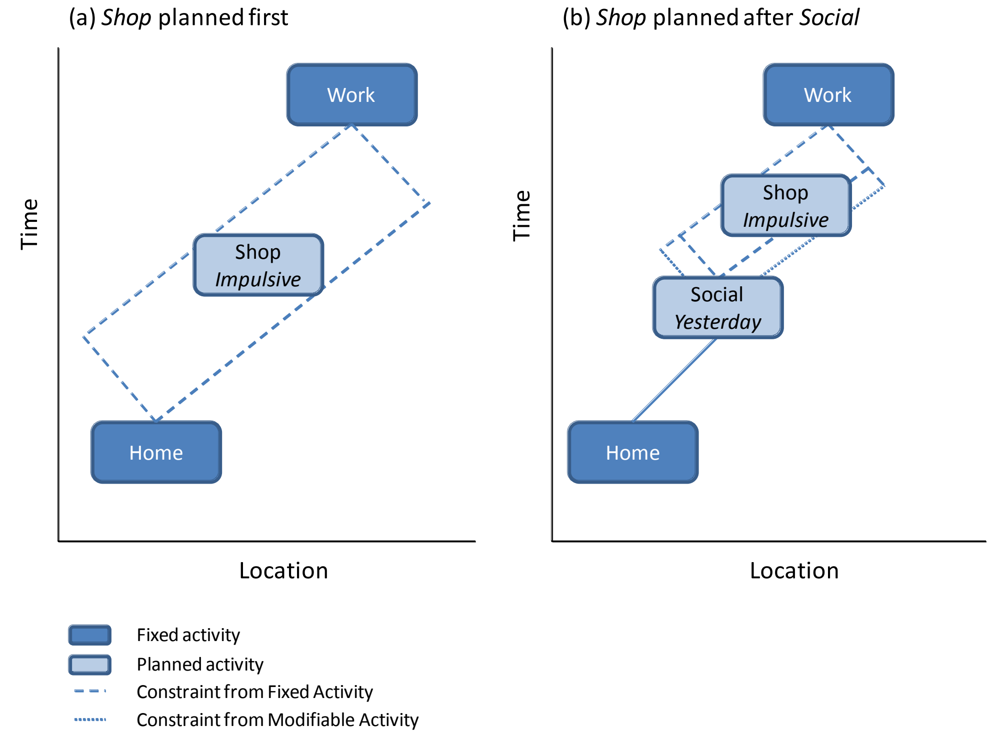
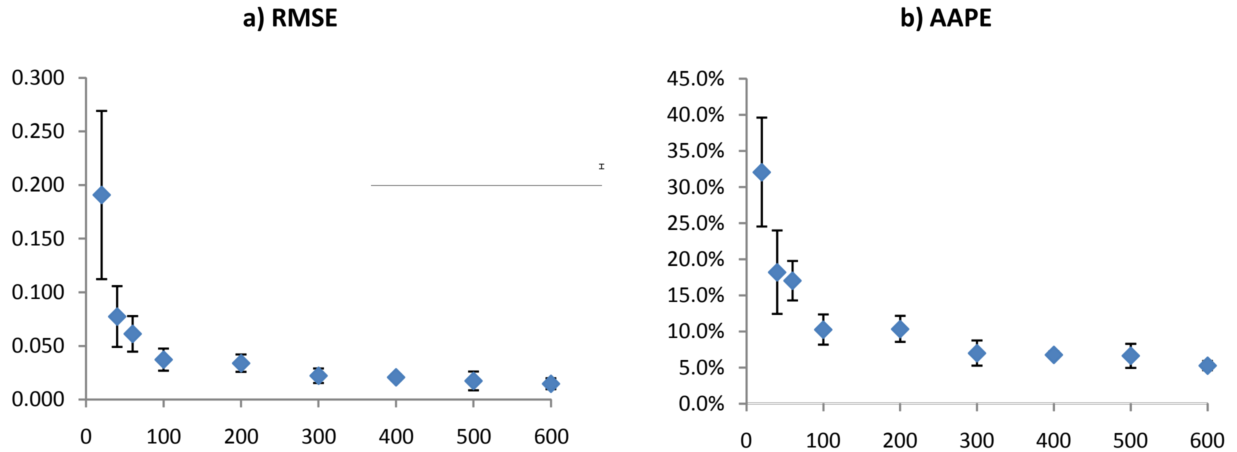


FIGURE 1 Planning Constraints on Choice Set Formation Example



Max Choice Set Size	20	40	60	100	200	300	400	500	600
Avg Choice Set Size	16.0	28.8	40.3	59.3	97.5	129.7	159.4	187.2	210.767
Avg of (Choice / Available)	26.9%	34.5%	39.6%	45.8%	54.5%	59.7%	63.8%	67.1%	81.7%
Avg Choice / Avg Available	2.3%	4.2%	5.9%	8.7%	14.3%	19.0%	23.4%	27.5%	30.9%

FIGURE 2. Choice Set Size Analysis

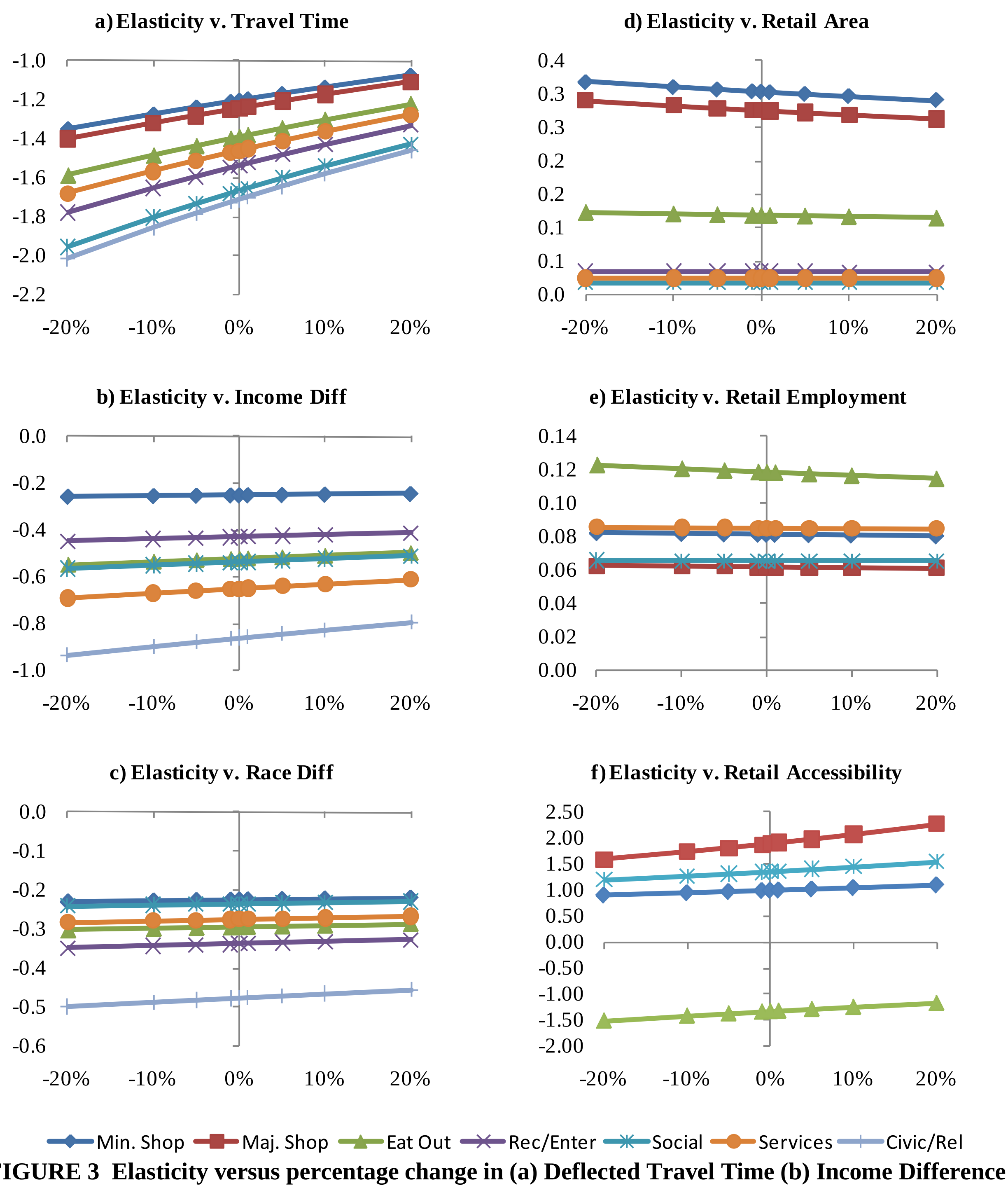


FIGURE 3 Elasticity versus percentage change in (a) Deflected Travel Time (b) Income Difference (c) Race Difference (d) Retail Area (e) Retail Employment (f) Retail Accessibility

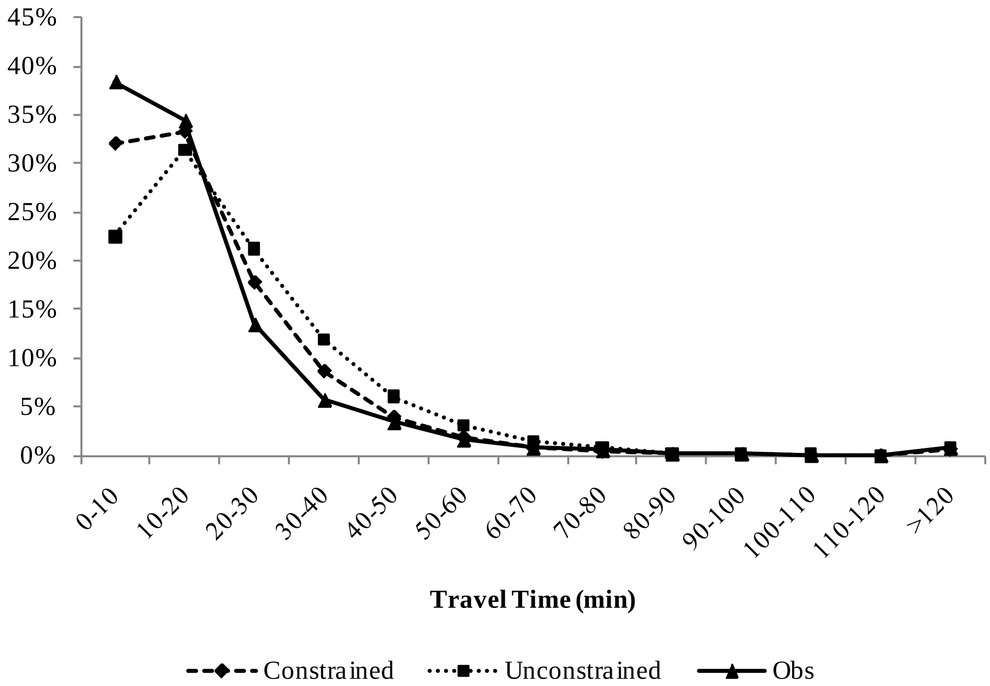


FIGURE 4. Observed and simulated trip time distributions with and without planning constraints