A COMPREHENSIVE, UNIFIED, FRAMEWORK FOR ANALYZING SPATIAL LOCATION CHOICE

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ABSTRACT
This paper develops a conceptual and econometric framework of non-work activity location choice that is comprehensive in its incorporation of spatial cognition, heterogeneity in preference behavior, and spatial interaction. The proposed framework subsumes a variety of restricted models including the multinomial logit, first-order state dependence logit, spatially correlated logit and mixed spatially correlated logit models. The applicability of the framework is demonstrated through an empirical analysis using the German Mobidrive data.

Keywords: Location choice, variety-seeking, spatial cognition, state dependence, activity-based analysis

1. INTRODUCTION

1.1 Background

The activity-based approach to travel analysis emphasizes the modeling of the activity-travel patterns of individuals, which may be characterized by six broad attributes: (a) Motivation or, equivalently, the purpose of each activity episode (such as work and shopping), (b) Location of participation of each activity episode (such as the work place or grocery store), (c) Sequencing of activity episodes and the time of day of each episode participation, (d) Mode used to travel to the episode location (for example, auto or transit), and (e) Solo or joint activity episode participation. Of these activity-travel attributes, the location of participation spatially pegs the daily activity-travel patterns of individuals. Thus, it is important to accommodate behavioral realism in models of activity location choice to produce accurate predictions of travel demand under changing land-use, demographic, and transportation system contexts. Moreover, an understanding of the factors that influence the choice of location can contribute to more effective land-use and zoning policies. For instance, a habit-persistent individual may be more likely to continue shopping at the same grocery store, rather than switching stores, in response to a new land-use policy that brings more shopping opportunities closer to home.

The choice of location of episode participation, and the factors that influence this choice, vary with activity purpose. Generally, the work location for most people is fixed in the short-term (except for teleworking individuals). Non-work activity participation, on the other hand, is typically (though not always) characterized by a higher degree of spatial flexibility. In particular, the choice of location for non-work activities can vary not only across individuals but also across choice occasions of an individual. Thus, non-work location modeling is a challenging problem. At the same time, non-work location modeling is of interest not only from a transportation and urban planning perspective, but also from the perspective of service, retail and real estate businesses. For instance, predictions of where people shop, and spend their recreational and leisure time, plays an important role in the location and marketing decisions of businesses and firms [see, for example, (*1*), (*2*), (*3*), (*4*), and (*5*)].

1.2 The Current Study

The development of behaviorally realistic models of non-work location choice requires a good understanding of the factors influencing the choice process. Accordingly, earlier research has emphasized the spatial cognitive processes/preference behavior, and spatial interaction considerations, underlying location choice decisions. In particular, there have been studies exploring the psychological aspects of spatial cognition/preference behavior issues at the decision-making agent level [see, for example, (*6*), (*7*), (*8*), (*3*), and (*2*)]. At the same time, there have been other studies directed toward understanding geographical interactions between spatial units, and their effects on choice behavior, but with limited to no consideration of spatial cognition/preference issues [see, for example, (*9*), (*10*), (*11*), (*12*), (*13*), provide a review of such studies]. Few earlier studies have comprehensively considered both cognitive/preference concepts at the decision maker level, as well as interactions between spatial choice units [but see (*14*) and (*15*); the reader is referred to Sivakumar (*16*) for a comprehensive survey of the literature on location choice modeling].

The above context frames the motivation for this study, which is to develop a behaviorally realistic location choice model for non-work activity participation that comprehensively incorporates spatial cognition/preference behavior (habit persistence, variety-seeking, cognitive learning, and spatial-temporal constraints) and spatial interaction effects [spatial heterogeneity and spatial autocorrelation; see (*13*)].

The rest of this paper is organized as follows. Section 2 describes a comprehensive conceptual framework of location choice decisions for non-work activity participation. Section 3 formulates a location choice model structure based on the conceptual framework presented in section 2, and discusses model estimation techniques. Section 4 presents an empirical analysis of location choice for non-work travel that demonstrates the applicability of the proposed location choice model structure. Section 5 concludes the paper with a brief discussion of policy implications and a summary of the findings.

2. CONCEPTUAL FRAMEWORK

The only observable characteristics of individual location choice behavior, as obtained from typical activity-travel surveys, are the actual (revealed) choice of location, the associated circumstances (such as mode used, time of day, and accompanying individuals), individual demographic characteristics, and the attributes of the alternative locations. In order to clearly understand the motivations behind the observed choice, however, it is important to recognize the underlying processes and factors manifesting themselves in the revealed choice behavior.

Figure 1 provides a conceptualization of this link between the underlying process and factors, and the revealed location choice. There are three types of broad elements in the figure: (1) Time-invariant factors that are common to the mental locational mapping preferences of the individual on every choice occasion over a certain period of time, (2) Time-variant factors that potentially influence the mental location map/preferences differently across different choice occasions of the individual, and (3) The spatial information processing rule, which may also vary across choice occasions of the individual. The second and third elements will be jointly referred to as time variant elements in this paper.

The time invariant factors (see box toward the bottom left corner of Figure 1) may be broadly categorized into time invariant individual preferences, time invariant attractiveness of alternatives, and time invariant spatial interactions. The *time invariant individual preferences* for locations can be attributed to observed factors such as race, age or income, and unobserved factors such as habit persistence or loyalty. The *time invariant attractiveness of alternative locations* may include attributes such as accessibility and parking availability, or the quality of goods available at a shopping location. The *time-invariant effects of spatial interactions* are associated with such characteristics as the proximity and spatial configuration of shopping locations.

The time variant factors that form a part of the time variant elements box in Figure 1 may be broadly categorized into time variant attractiveness of alternatives, effects of time-varying constraints, time variant individual preferences, and the presence of other decision-makers on the choice occasion. Examples of *time variant attractiveness of alternatives* include special sales at shopping malls, advertising campaigns by retailers, land-use and other attribute changes within and around the spatial alternatives, and temporal variations in accessibility due to traffic conditions. *Time variant constraints* can be attributed to the availability of time or mode, or trip-chaining decisions. The *time variant individual preferences* may be a result of variety-seeking, unfulfilled consumption desires, preference updating due to past experiences, or time-varying desires to travel. The degree of such time variant preferences can also vary, both across individuals and across choice occasions of an individual. Another time variant factor that could potentially influence location choice decisions is the *presence of one or more persons* traveling with the decision-maker, since this significantly alters the dynamics of the choice process.

All the above factors, representing the cognitive processes, and the effects of the social and spatial environments, are consolidated together in an *information processing rule* to generate the revealed choice of location [see (*16*) for a more detailed discussion]. The chosen alternative, in turn, influences future choices as individuals' preferences adapt to past experiences (see arrow between choice alternative (t) and individual preferences (t+1) in Figure 1). The time-variant elements on choice occasion t also influence the time-variant elements on choice occasion t+1, since past preferences and constraints (whether satisfied or not) are a part of an individual's memory and therefore cognition.

3. MODEL STRUCTURE

In this section, the conceptual framework of the previous section is translated into a random utility maximization-based model structure. Section 3.1 presents the model structure, while Section 3.2 discusses the estimation procedure.

3.1 Location Choice Model Structure

The location choice model expresses the utility that an individual i (i = 1, …, I) associates with an alternative j (j = 1, …, J_i) on choice occasion t (t = 1, …, T_i) as

$$\begin{aligned} U_{ijt} = {} & Z_j(\alpha_i + \eta_{it} + \delta_1 X_i + \delta_2 C_{it} + \delta_3 C_{it} X_i) + D_{ij}(\beta_i + \gamma_{it} + \omega_1 X_i + \omega_2 C_{it} + \omega_3 C_{it} X_i) + (\xi_i\ )L_{jt} \\ & + PREATT_{ijt}(\chi_{it}) + PRECHO_{ijt}(\zeta_{it}) \\ & + \lambda_0[\tilde{U}_{ij(t-1)} + \lambda_1 \tilde{U}_{ij(t-2)} + \lambda_1^2 \tilde{U}_{ij(t-3)} + \ldots \lambda_1^t \tilde{U}_{ij1}] + \varepsilon_{ijt} + \rho \sum_{j' \in J'} \varepsilon_{ij't} \end{aligned} \tag{1}$$

where, Z_j is a vector of observed time invariant attributes of zone j,

X_i is a vector of observed demographic attributes of individual i,

C_{it} is a vector of characteristics of choice occasion t for individual i (including constraints faced by the individual),

D_{ij} is a matrix of distance or time and cost measures associated with the home/school/work locations of individual i and zone j,

L_{jt} is a vector of special attraction variables associated with alternative j on choice occasion t,

$PREATT_{ijt}$ is a function of the attributes of spatial alternative j on choice occasions *t-1, t-2, …, 1*), and the similarities of these attributes with individual i's previously chosen alternatives,

$PRECHO_{ijt}$ is a function of the number of times individual i has chosen alternative j on choice occasions t-1, t-2, …, 1,

$\tilde{U}_{ij(t-1)}$, $\tilde{U}_{ij(t-2)}$,… are the utilities that individual *i* associated with alternative *j* on choice occasions prior to occasion *t*, excluding the effects of constraints, and

$\{\alpha_i, \eta_{it}, \delta_1, \delta_2, \delta_3, \beta_i, \gamma_{it}, \omega_1, \omega_2, \omega_3, \xi_i, \chi_i^0, \chi_{it}^1, \chi^2, \zeta_i^0, \zeta_{it}^1, \zeta^2, \lambda_0, \lambda_1, \rho\}$ are the parameters of the model that are explained in the following paragraphs.

The term $\alpha_i + \delta_1 X_i$ represents the vector of time invariant preferences of individual *i* for the attributes Z_j of the choice alternative. The vector of parameters δ_1 represents the extent of the preferences that can be captured by observed demographic characteristics of the individual, while α_i represents the unobserved preferences of the individual that makes her/his choice behavior different from that of an observationally identical individual. The vector of parameters α_i, therefore, accounts for inter-personal response heterogeneity due to such unobserved factors as variety-seeking and the desire for travel. The term, $\beta_i + \omega_1 X_i$, similarly, represents the vector of time invariant preferences of individual *i* for the time and costs (D_{ij}) associated with the choice alternative (the other parameters on Z_j and D_{ij} are discussed later).

The parameter ξ_i represents the time invariant preferences of individual *i* for the special attractions associated with alternative *j* on choice occasion *t*. For instance, if a shopping mall has a big sale, the individual might want to visit that mall on that particular occasion. Constraints might, however, bring the utility of the mall down despite the 'special attraction'. The vectors of parameters ($\delta_2, \delta_3, \omega_2, \omega_3$) represent the effects of constraints on individual *i*. This could include time budget, trip chaining, and mode availability constraints.

The terms χ_{it} and ζ_{it}, and the parameters (λ_0, λ_1), represent the time variant preferences of individual *i* that are a result of learning, variety seeking and unfulfilled desires, respectively. The term χ_{it} represents the preference of individual *i* for an alternative at choice occasion *t* that is the result of 'learning'. This 'learning' could be due to individuals updating their preferences for certain attributes based on experience from the past choice, so that alternatives that are perceived to have similar attributes to the attributes of the actually chosen alternative in the previous choice environment are assigned higher (or lower) utilities in the current choice (*i.e.*, preference learning). The 'learning' can also be due to delayed effects of land-use changes on the transportation system, because new spatial attributes take time to enter into the spatial perception map of individuals (*i.e.*, spatial learning). The term ζ_{it} represents the preference of individual *i* for an alternative at choice occasion *t* due to effects of previous choice occasions when that alternative was chosen. This captures variety seeking in the choice of alternatives. An individual who exhibits habit persistence is likely to have a higher preference for locations she has visited in the past, while one who exhibits variety seeking is likely to have a lower preference for locations he has visited in the past. The term $\lambda_0[\tilde{U}_{ij(t-1)} + \lambda_1 \tilde{U}_{ij(t-2)} + \lambda_1^2 \tilde{U}_{ij(t-3)} + ...\lambda_1^t \tilde{U}_{ij1}]$ represents the carryover effects and unfulfilled desires from past choice occasions on the utility individual *i* associates with alternative *j*. The terms $\tilde{U}_{ij(t-1)}, \tilde{U}_{ij(t-2)}, ..., \tilde{U}_{ij1}$ are the utilities that individual *i* associated with alternative *j* on choice occasions prior to occasion *t*, excluding the effects of constraints.

The effects of any other factors (that have not already been accounted for) that cause intra-personal heterogeneity in observed choices are captured in the utility function by η_{it} (the time variant preferences of the individual for the attributes of the alternative) and γ_{it} (the time variant preferences of the individual for the travel time and costs associated with the alternative).

The term ε_{ijt} is the random error component of the utility individual *i* attributes to alternative *j* on choice occasion *t*. The inclusion of the term $\rho \sum_{j' \in J'} \varepsilon_{ij't}$ captures the spatial correlation of alternative *j* with other choice alternatives that are adjacent to *j* (represented by the set *J'*), with the parameter ρ capturing the degree of spatial correlation.

The proposed location choice model is a mixed logit (MxL) model that accommodates spatial interaction effects, and response heterogeneity due to various observed and unobserved factors (including state dependent effects such as variety seeking, habit persistence, carryover effects and spatial learning). Different assumptions imposed on this model will, therefore, result in simpler (restricted) models that represent specific behavioral circumstances. Some of the restricted models nested within the proposed model structure include the multinomial logit (MNL) model, the first order state dependence multinomial logit model, the spatially correlated logit model (SCL) of Bhat and Guo (*15*), the mixed spatially correlated logit model (MSCL), and a bi-level mixed logit model to introduce intra-individual heterogeneity [see (*16*)].

3.2 Model Estimation

The vector of parameters to be estimated in the model structure is $\{\alpha_i, \eta_{it}, \delta_1, \delta_2, \delta_3, \beta_i, \gamma_{it}, \omega_1, \omega_2, \omega_3, \xi_i, \chi_{it}, \zeta_{it}, \lambda_0, \lambda_1, \rho\}$. Of these parameters, $\{\alpha_i, \beta_i, \xi_i\}$ vary across individuals and capture unobserved inter-individual response heterogeneity, while $\{\eta_{it}, \gamma_{it}, \chi_{it}, \zeta_{it}\}$ vary across choice occasions of an individual and capture unobserved intra-individual response heterogeneity. For convenience, let $\Psi = \{\alpha_i, \beta_i, \xi_i,\}$, $\Omega = \{\eta_{it}, \gamma_{it}, \chi_{it}, \zeta_{it}\}$ and μ represent the rest of the fixed response parameters $\{\delta_1, \delta_2, \delta_3, \omega_1, \omega_2, \omega_3, \lambda_0, \lambda_1\}$. ρ is the dissimilarity parameter that captures the degree of spatial correlation (absorbed into μ where appropriate, for ease of presentation). Let the distribution of unobserved inter- and intra-individual heterogeneities be multivariate normal, so that the elements of Ψ and Ω are realizations of the random multivariate normally distributed variables that comprise $\tilde{\Psi}$ and $\tilde{\Omega}$ respectively. Let θ be a vector of true parameters characterizing the mean and variance-covariance matrix of $\tilde{\Psi}$, and let σ be a vector of true parameters characterizing the mean and variance-covariance matrix of $\tilde{\Omega}$.

In its most general form, the utility associated by individual *i* with zone *j* on choice occasion *t* is given by $U_{ijt} = V_{ijt} + \varepsilon_{ijt}$, where

$$\begin{aligned} V_{ijt} = {} & Z_j(\alpha_i + \eta_{it} + \delta_1 X_i + \delta_2 C_{it} + \delta_3 C_{it} X_i) + D_{ij}(\beta_i + \gamma_{it} + \omega_1 X_i + \omega_2 C_{it} + \omega_3 C_{it} X_i) + (\xi_i\ )L_{jt} \\ & + PREATT_{ijt}(\chi_{it}) + PRECHO_{ijt}(\zeta_{it}) \\ & + \lambda_0[\tilde{U}_{ij(t-1)} + \lambda_1 \tilde{U}_{ij(t-2)} + \lambda_1^2 \tilde{U}_{ij(t-3)} + \ldots \lambda_1^t \tilde{U}_{ij1}] + \rho \sum_{j' \in J'} \varepsilon_{ij't} \end{aligned} \tag{2}$$

As per the notations, the parameters $\{\alpha_i, \beta_i, \xi_i\}$ and $\{\eta_{it}, \gamma_{it}, \chi_{it}, \zeta_{it}\}$ in the above expression are drawn from the random variables that comprise $\tilde{\Psi}$ and $\tilde{\Omega}$. V_{ijt} may therefore be represented as $V_{ijt}(\tilde{\Psi}, \tilde{\Omega}, \mu)$.

Under the assumption of no spatial correlation, the probability that individual i will choose alternative j at the t^{th} choice occasion, conditional on $\tilde{\Psi}$, $\tilde{\Omega}$ and μ, is the usual multinomial logit form [see (*17*)]:

$$P_{ijt} \mid (\tilde{\Psi}, \tilde{\Omega}, \mu) = \frac{e^{V_{ijt}(\tilde{\Psi}, \tilde{\Omega}, \mu)}}{\sum_{k=1}^{J} e^{V_{ikt}(\tilde{\Psi}, \tilde{\Omega}, \mu)}} \tag{3}$$

The assumption of spatial correlation, on the other hand, combined with a GEV-based structure to accommodate this correlation, leads to the following expression for the conditional probability [see (*15*)]:

$$P_{ijt} \mid (\tilde{\Psi}, \tilde{\Omega}, \mu) = \frac{\sum_{m \neq j} (\alpha_{j,jm} e^{V_{ijt}(\tilde{\Psi}, \tilde{\Omega}, \mu)})^{1/\rho} [(\alpha_{j,jm} e^{V_{ijt}(\tilde{\Psi}, \tilde{\Omega}, \mu)})^{1/\rho} + (\alpha_{m,jm} e^{V_{imt}(\tilde{\Psi}, \tilde{\Omega}, \mu)})^{1/\rho}]^{\rho-1}}{\sum_{k=1}^{J-1} \sum_{l=j+1}^{J} [(\alpha_{k,kl} e^{V_{ikt}(\tilde{\Psi}, \tilde{\Omega}, \mu)})^{1/\rho} + (\alpha_{l,kl} e^{V_{ilt}(\tilde{\Psi}, \tilde{\Omega}, \mu)})^{1/\rho}]^{\rho}}, \tag{4}$$

where $\alpha_{i,ij}$ is an allocation parameter.

The unconditional probability can be obtained thereafter as:

$$P_{ijt} = \int_{\tilde{\beta}=-\infty}^{\infty} \int_{\tilde{\Omega}=-\infty}^{\infty} (P_{ijt} \mid \tilde{\Psi}, \tilde{\Omega}, \mu) dF(\tilde{\Omega} / \sigma) dF(\tilde{\Psi} / \theta) \tag{5}$$

where F is the multivariate cumulative normal distribution. The dimensionality of the above integration is dependent on the number of elements in the Ψ and Ω vectors.

The parameters to be estimated under the assumption of zero spatial correlation are the σ, θ and μ vectors corresponding to Equations (3) and (5). The parameter to be estimated under the assumption of spatial correlation include the scalar ρ, and the σ, θ and μ vectors, corresponding to Equations (4) and (5). To develop the likelihood function for parameter estimation, we need the probability of each sample individual i's sequence of observed choices on choice occasions *1*, …T_i. Conditional on $\tilde{\Psi}$, the likelihood function for individual i's observed sequence of choices is:

$$L_i\left(\tilde{\Psi}, \sigma, \mu\right) = \prod_{t=1}^{T_i} \left[\int_{\tilde{\Omega}=-\infty}^{+\infty} \left\{ \prod_{j=1}^{J} P_{ijt}\left(\tilde{\Psi}, \tilde{\Omega}, \mu\right)^{Y_{ijt}} \right\} f(\tilde{\Omega} \mid \sigma) d\tilde{\Omega} \right], \tag{6}$$

where, Y_{ijt} takes the value 1 if individual i chose alternative j on choice occasion t, and 0 otherwise.

The unconditional likelihood function of the choice sequence is:

$$L_i(\theta,\sigma,\mu) = \int L_i(\tilde{\Psi},\sigma,\mu) f(\tilde{\Psi} \mid \theta) d\tilde{\Psi}$$

$$= \int_{\tilde{\Psi}=-\infty}^{+\infty} \left\{ \prod_{t=1}^{T_i} \left[\int_{\tilde{\Omega}=-\infty}^{+\infty} \left\{ \prod_{j=1}^{J} P_{ijt}\left(\tilde{\Psi},\tilde{\Omega},\mu\right) Y_{ijt} \right\} f(\tilde{\Omega} \mid \sigma) d\tilde{\Omega} \right] \right\} f(\tilde{\Psi} \mid \theta) d\tilde{\Psi} \qquad (7)$$

The log-likelihood function is $L(\theta,\sigma,\mu) = \sum_i \ln L_i(\theta,\sigma,\mu)$.

The likelihood function in Equation (7) is quite different from those in previous applications of the mixed logit model. In particular, there are two levels of integration rather than one. This arises because, from an estimation standpoint, the random coefficients formulation that accommodates taste variations within individuals across choice occasions operates at the choice level, while the random coefficients formulation that accommodates taste variation across individuals operates at the individual level.

Quasi-Monte Carlo (QMC) simulation techniques are applied to approximate the integrals in the likelihood function and maximize the logarithm of the resulting simulated likelihood function across all individuals with respect to θ, σ and μ. The procedure to simulate each individual's likelihood function $L_i(\theta,\sigma,\mu)$, is as follows: (a) For a given value of the parameter vector θ, draw a particular realization of $\tilde{\Psi}$ from its distribution, (b) For a given value of the σ vector, draw several sets of realizations of $\tilde{\Omega}$ from its distribution, each set corresponding to a choice occasion of the individual, (c) compute the probability of the chosen alternative for each choice occasion (*i.e.*, the likelihood function of that choice occasion) at that choice occasion's set of $\tilde{\Omega}$ realizations, and for the current $\tilde{\Psi}$ realization, (d) Average the likelihood functions across the various realizations of $\tilde{\Omega}$ for each choice occasion, (e) Compute the individual likelihood function as the product of the averaged likelihood functions across all choice occasions of the individual, (f) Repeat steps a through e several times with fresh realizations of $\tilde{\Psi}$ and new sets of draws of $\tilde{\Omega}$, and (g) Compute the average across all individual likelihood function evaluations. Mathematically, the individual likelihood function is approximated as:

$$SL_i(\theta,\sigma,\mu) = \frac{1}{N}\sum_{n=1}^{N}\left[\prod_{t=1}^{T_i}\left\{\frac{1}{M}\sum_{g_n=1}^{M}\left(\prod_{j=1}^{J} P_{ijt}(\tilde{\Psi}^n \mid \theta, \tilde{\Omega}^{g_n} \mid \sigma,\mu)^{Y_{ijt}}\right)\right\}\right], \qquad (8)$$

where $SL_i(\theta,\sigma,\mu)$ is the simulated likelihood function for the i^{th} individual's sequence of choices given the parameter vectors θ, σ and μ, $\tilde{\Psi}^n \mid \theta$ is the n^{th} draw (n = 1, 2, …, N) from $f(\tilde{\Psi} \mid \theta), \tilde{\Omega}^{g_n} \mid \sigma$ is the g_n^{th} draw (g_n = 1, 2, …, M) from $f(\tilde{\Omega} \mid \sigma)$ at the n^{th} draw of $\tilde{\Psi}$, and other variables are as defined earlier. $SL_i(\theta,\sigma,\mu)$ is an unbiased estimator of the actual likelihood function $L_i(\theta,\sigma,\mu)$. Its variance decreases as N and M increase. It also has the appealing properties of being smooth (*i.e.*, twice differentiable) and being strictly positive for any realization of the draws.

The simulated log-likelihood function is constructed as:

$$SL(\theta,\sigma,\mu)=\sum_i \ln\left[SL_i(\theta,\sigma,\mu)\right] \tag{9}$$

The parameter vectors θ, σ and μ are estimated as the values that maximize the above simulated function. Under rather weak regularity conditions, the simulated maximum likelihood estimator is consistent, asymptotically efficient, and asymptotically normal [see (*18*), (*19*)].

Depending on the number of parameters in θ and σ, and the number of draws *N* and *M*, however, the simulated maximum likelihood estimation of this bi-level model can be very time consuming. Most applications of mixed logit models in the literature use QMC sequences, such as the Halton sequence, to draw realizations for $\tilde{\Psi}$ and $\tilde{\Omega}$ from their normal population distributions. Although Halton sequences are a vast improvement over pseudo-Monte Carlo (PMC) methods in the efficiency of the simulated estimation process, there are several other QMC sequences that are potentially superior to the Halton sequences. In the empirical analysis presented in the following section, we have used the random linear scrambled Faure sequence, which was identified in Sivakumar *et al.* (*20*) for its superior performance over the standard and scrambled Halton sequences in simulated maximum likelihood estimation.

4. EMPIRICAL RESULTS

This section presents an empirical analysis that applies the location choice model structure of the previous section. All model estimations were undertaken using the GAUSS matrix programming language.[1]

4.1 Data Sources

A multi-day data is needed to estimate a location choice model that captures the effects of past choices (state dependence), and accommodates inter- and intra-individual heterogeneity. The current study uses the Mobidrive data, which is a multi-day (6-week) travel survey conducted in the Fall of 1999 in the cities of Karlsruhe (West Germany) and Halle (East Germany). The survey collected information on 361 individuals from 162 households.

In addition to the Mobidrive data, several secondary data sources were also used in the analysis. These included Geographic Information Systems (GIS) files of the transportation network and zonal land-use for the core-city of Karlsruhe.

In our empirical analysis, we confined our attention to shopping for non-daily consumption goods (*i.e.*, non-maintenance shopping). Further, due to data limitations, we restricted the analysis to the core city of Karlsruhe, which consists of 69 transportation analysis zones (TAZs). The final estimation sample comprises 903 non-maintenance shopping activity occasions undertaken by 158 individuals belonging to 81 households. The number of shopping occasions per individual varies from 2 to 29 during the survey period, and the number of unique zones (shopping locations) per individual varies from 1 to 10.

4.2 Variable Specifications

The variables considered in the analysis may be categorized into six groups, each of which is discussed in turn in the following sections.

[1] The GAUSS code is available on request from the authors.

4.2.1 Zonal Size Attributes

There are several zonal *size* attributes that capture the attractiveness of a zone, such as area, population, and number of shopping opportunities. In this study, a non-linear composite size measure is used, which is defined as follows:

$$Composite\ Size_j = \ln(x_{1j} + \delta_1 x_{2j} + \delta_2 x_{3j} + \delta_3 x_{4j} + \ldots), \tag{10}$$

where (x_{1j}, x_{2j}, x_{3j}, x_{4j}, …) are zonal *size* attributes, and $(\delta_1, \delta_2, \delta_3, ...)$ are parameters to be estimated. Based on specification trials, four variables representing zonal size were included: (1) zonal area (in square feet), (2) number of shopping opportunities, (3) number of recreational opportunities, and (4) zonal area (in square feet) covered by mixed development. The coefficients on the number of shopping opportunities, number of recreational opportunities, and mixed development area were estimated to be 0.638, 2.588, and 89.8, respectively, based on simple specifications with a distance impedance measure [the coefficient on the total zonal area variable is normalized to one for identification purposes; see (*21*)]. The estimates above were used to construct the composite size measure for each zone. The unit of the composite size measure is square feet.

4.2.2 Zonal Non-Size Attributes

The zonal non-size attributes available in the data include population density (in population per 1000 square feet), central business district (CBD) (dummy variable) and presence of daycare (dummy variable that takes a value of 1 if there is a daycare facility available in the zone). These variables, along with the composite size variable, are introduced in the location choice model as measures of zonal attractiveness.

4.2.3 Zonal Impedance Measures

The distance of each candidate activity location zone from the home zone of an individual is treated as the impedance associated with that candidate zone, since zones which are farther away from an individual's home zone will be less preferred. In addition, several studies have shown that people tend to visit locations that are around their school/work place [see (*22*)]. Thus, the distance of zones from the work/school zone of an individual is introduced as another impedance measure. The distances are measured in miles in the current study.

4.2.4 Demographic Variables

The zonal composite size and non-size attributes, and impedance measures, are interacted with individual demographic characteristics to capture observed sources of heterogeneity across individuals in their response to the zonal attributes and impedance. For instance, distance interacted with gender captures the difference in sensitivities to impedance between males and females.

The Mobidrive data contains a number of individual and household level demographic attributes, such as gender, marital status, employment status, household income, household size, and number of public transportation season tickets held.[2] All the demographic variables were tested in the model estimations, and the statistically significant ones were retained.

4.2.5 Attributes of Choice Occasion

The zonal attributes and impedance measures (discussed in Sections 4.2.1, 4.2.2, and 4.2.3) were also interacted with attributes of the choice occasion to capture time-variant effects and constraints on the response to zonal attributes and impedances. For example, distance interacted with time of day captures the time-varying effects of time-budget constraints on the sensitivity to impedance.

The attributes of the choice occasion available in the data include time-of-day, day of week, whether or not the shopping episode was chained with other episodes (dummy variable), number of accompanying household members, number of accompanying non-household members, and activity duration.

4.2.6 Feedback Effects

In this application, a simple form of the $PRECHO_{ijt}$ function, $SAME_{ijt}$ (first-order Markov process, first order state dependence, or lagged choice indicator), is used, which is defined as follows [a similar approach is used by Miller and O'Kelly (*23*)].

$$SAME_{ijt} = \begin{cases} 1, \text{ if zone } j \text{ was chosen by individual } i \text{ on choice occasion } t-1 \\ 0, \qquad\qquad \text{otherwise} \end{cases}$$

The introduction of feedback in a model must be accompanied by a specification of the initial conditions. This study makes two assumptions regarding the initial conditions. First, it assumes that the survey respondents have reached a state of equilibrium in their activity-travel patterns, so that the survey period will be representative of their choice behavior. Second, the first non-maintenance shopping episode of each survey respondent is assumed to be exogenous to the estimation. This condition can be relaxed in several ways [for example, see Degeratu, (*24*)]. However, the consideration of endogenous initial conditions is beyond the scope of this paper. Also, due to the limited information on, and the lack of adequate temporal variation in, the spatial attributes of alternatives in the Mobidrive data, it was not possible to explore learning effects [captured by the $PREATT_{ijt}$ term in Equation (1)] and carryover effects [captured by the sequence of previous utility values in Equation (1)].

4.3 Empirical Results

A basic MNL model of location choice labeled (MNL-1), with the variable specifications described above, was estimated as the benchmark against which all other models were compared. An MNL model with state dependence (MNL-2) was also estimated to assess the impacts of introducing feedback. The MNL-1 model was then extended to incorporate unobserved inter-individual response heterogeneity (mixed logit model, MxL-1). Finally, the MNL-2 was extended to accommodate state dependence in addition to unobserved inter-individual response heterogeneity (mixed logit model, MxL-2).

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[2] There are several different public transportation agencies serving the Karlsruhe area, such as the Karlsruhe/Halle public transit network and the Deutsche Bahn (German rail). Thus, an individual may hold more than one public transportation season ticket.

Several other models, including the spatially correlated logit (SCL), mixed spatially correlated logit (MSCL), and a bi-level mixed logit model to introduce intra-individual heterogeneity in addition to inter-individual heterogeneity, were also estimated as part of this study. However, the estimation results indicated the absence of spatial correlation effects and unobserved intra-individual heterogeneity in the current empirical context. The remaining part of this section discusses the model results in greater detail.

4.3.1 Likelihood-Based Measures of Fit

The log-likelihood value at convergence for the MNL-1 model with 26 parameters is -2862.4 ($\bar{\rho}^2$ = 0.248), while the corresponding value for the MNL feedback model (MNL-2) with 27 parameters is -2250.9 ($\bar{\rho}^2$ = 0.282). Although the two models cannot be directly compared (MNL-2 is estimated on a smaller sample than MNL-1 in order to accommodate the initial conditions for feedback), their $\bar{\rho}^2$ measures indicate that the model with state dependence is a substantially better fit for the data. Also, the MxL-1 model provides a better fit (log-likelihood at convergence = -2786.9, $\bar{\rho}^2$ = 0.267) for the data compared to the MNL-1 model, indicating that the incorporation of unobserved inter-individual heterogeneity captures choice behavior more accurately. The MxL-1 and MNL-1 models are directly comparable using a nested likelihood ratio test. This test value is 151, which is much larger than the chi-squared table value with 6 degrees of freedom (corresponding to 6 unobserved heterogeneity terms) at any reasonable level of significance. The MxL-2 model that incorporates both unobserved heterogeneity as well as state dependence effects is the best fit for the data, with a convergent log-likelihood value of -2223.5 ($\bar{\rho}^2$ of 0.290). A nested likelihood ratio test comparison with MNL-2 provides a test value of 54.8, which is again much larger than the chi-squared table value with 6 degrees of freedom at any reasonable level of significance.

Table 1 presents the results of the MxL-2 model, which are discussed in detail in the following sections. We do not present the results for the other models because the substantive interpretations from these other models were similar to the MxL-2 model.

4.3.2 Zonal Size and Interactions

The composite zonal size measure has a positive mean coefficient, indicating that larger composite size zones, in general, are preferred more than zones of smaller composite size. This is to be expected, since larger composite size zones contain more elemental units of attraction.

The interactions of composite size with demographic/other attributes suggest that individuals in low income households (less than an annual income of 3000 Deutsche Marks or DM) have a significantly higher preference for shopping at large size zones. Also, individuals who own several season tickets for public transport show a higher preference for large composite size zones, perhaps because large zones are typically better connected by public transport.

The interaction of the composite size measure with choice occasion-specific constraints yielded only one significant term, corresponding to whether the shopping stop is chained with other shopping episodes. The parameter on this term in Table 1 indicates that large composite size zones are less preferred when a non-maintenance shopping activity is chained with other shopping activities. Finally, there is also significant unobserved heterogeneity in the sensitivity to zonal size. The mean effect and the standard deviation coefficient imply that, in the group of middle/high income individuals who do not own public transportation season tickets, a larger zone is preferred 94% of the time when the shopping episode is not chained with other episodes.

4.3.3 Zonal Non-Size Attributes and Interactions

The results in Table 1 for the zonal non-size attributes suggest that a central business district (CBD) zone is, on average, preferred more for non-maintenance shopping activity participation than non-CBD zones. The observed sources of heterogeneity in this effect relate to individual gender and age. Specifically, women prefer CBD zones more than men, and older individuals prefer CBD zones less than younger individuals. In addition, there are several choice occasion-specific constraints that also influence the utility of a CBD zone. For instance, a CBD zone is more attractive if the shopping stop is part of a chained tour, presumably because of the variety of activity opportunities in CBD areas. A CBD zone is also less preferred when an individual has company in participating in non-maintenance shopping episodes. This result is not immediately intuitive, but may be capturing a host of constraints and group dynamics. The remaining CBD interaction terms indicate the higher likelihood of choosing CBD zones for long shopping duration episodes, and the lower propensity to shop at CBD zones in the morning (7:00AM to 9:00AM). There is also a very high level of unobserved sensitivity variation across individuals to the CBD variable.

The coefficient on the "presence of daycare" dummy variable indicates, in general, a lower preference for zones with daycare. Although the reason for this is not readily apparent, it may be the result of high correlation between residential zones (with few shopping opportunities) and the presence of daycare. Married people with children less than 16 years of age prefer zones with daycare for non-maintenance shopping, presumably because of a conscious effort to seek shopping locations close to the children's daycare to maximize the use of time without children. Again, the results also indicate substantial unobserved heterogeneity in the daycare presence effect.

Finally, in the group of zonal non-size attributes, high population density zones are, in general, preferred less than other zones. This is reasonable, since high population density zones are primarily residential and may offer fewer, and lesser variety in, shopping opportunities. However, there is substantial unobserved heterogeneity, with about 12% of individuals preferring high population density zones.

4.3.4 Impedance Measures and Interactions

Two impedance measures, distance from home and distance from work/school, were introduced in the model specifications and both of these measures turned out to be significant determinants of shopping location choice. The estimated parameters indicate that almost all individuals have a strong preference to visit locations in the vicinity of their homes, schools, and work places.

The 'distance from home' variable was interacted with several demographic variables that turned out to be statistically significant (however, no significant interaction effects were found for 'distance from work place'). Specifically, women, retired individuals, German citizens, and individuals who own several public transportation season tickets are more sensitive to distance (*i.e.*, are more inclined to shop close to home) than men, non-retired, non-German citizens, and individuals who own few public transportation season tickets, respectively. On the other hand, individuals in households that own several cars are less sensitive to distance, presumably due to less mobility constraints.

Choice occasion-specific constraints also significantly influence the disutility associated with distance. The results show that individuals are less inclined to shop at locations that are far away from home for non-maintenance shopping activities during the weekend relative to a weekday. This is a little surprising, though the statistical significance of this effect is also rather marginal. The results of the other interaction terms are more intuitive. Individuals are more willing to participate at locations farther away from their home when (a) accompanied by other people, (b) chaining shopping activity with other activities, (c) planning shopping activities of longer durations, and (d) considering large-sized zones. The latter result reflects the trade-off between travel distance and availability of shopping opportunities.

Finally, the results also reveal differences in distance sensitivity across individuals due to unobserved factors, though these unobserved heterogeneity effects are only marginally significant.

4.3.5 Feedback Effects

The model results in Table 1 (under "Feedback Effect") indicate that the effect of past choices on the utility of a zone is highly significant and positive. Therefore, on a specific choice occasion, all else being equal, zones visited in the previous choice occasion are preferred over other zones. This implies habit persistence and/or loyalty behavior. There is variation in the feedback sensitivity across individuals, as indicated by the statistically significant standard deviation parameter on the feedback variable.

Overall, it is important to include feedback effects in location choice models not only to capture habit persistence/loyalty behavior, but also to ensure that all the other parameters are correctly estimated (a comparison of the models with and without feedback indicated that several variable effects were over-estimated when feedback was ignored).

4.3.6 Spatial Correlation

The spatially correlated logit (SCL) and mixed spatially correlated logit (MSCL) models estimated as part of this analysis indicated that there are no significant spatial correlation effects in the study area (Karlsruhe core city). In other words, there is no correlation between the unobserved errors in the utilities associated by individual i with zones that are adjacent. While the absence of spatial correlation is rare for spatial data, it is possible under certain conditions, such as for Karlsruhe. In particular, the core city of Karlsruhe is a fairly small region approximately 15.6 sq.km with a mature transportation system and tight land-use control. It is therefore conceivable that the zonal configuration creates clear boundaries between different land-use parcels. Also, the goods on offer in the various zones in Karlsruhe are rather distinct. The non-maintenance shopping opportunities in Karlsruhe are focused in the CBD, which primarily sells fashion and expensive goods, and two minor centers in the east and the west (Durlach and Mühlburg, respectively), which sell goods in the middle price range. Under these conditions it is not unreasonable that the model estimations suggest the absence of spatial correlation in the study area.

5. POLICY APPLICATION AND CONCLUSIONS

In this section, we demonstrate the use of the estimated model to assess the effect of the application of a land use policy that increases shopping/recreation opportunities in the non-CBD zones, so that the composite size of non-CBD zones increases by 25%. Each of the MNL-1 model (no unobserved heterogeneity and no state dependence), MNL-2 model (no unobserved heterogeneity, but state dependence included), and MxL-2 model (both unobserved heterogeneity and state dependence included) was applied to predict the chosen location for each individual in the base case and the policy scenario. The predicted fraction of non-maintenance shopping travel to the central districts (or CBD) forms the basis for the comparison of the models. The MNL-1 model predicts an 11% drop in travel to the CBD zones. The MNL-2 model, however, takes loyalty and inertial behavior into account and predicts only a 3% drop in the travel to CBD zones. The MxL-2 model, not only accounts for loyalty and inertia but also for unobserved heterogeneity effects, and predicts a 7% drop in the travel to CBD zones. These results highlight the potentially inaccurate results from using models that do not adequately capture the behavioral considerations in location choice decisions.[3]

In conclusion, the focus of this research was to develop a comprehensive, unified, framework for spatial location choice that is behaviorally realistic, and that can be practically applied by planners and policy makers in the estimation of travel demand. Toward this objective, a conceptual framework of location choice decision-making for non-work activity participation is developed that incorporates all the observed and unobserved factors that potentially influence the decision-maker. The proposed conceptual framework is then translated into a general econometric model of location choice for non-work activity participation. The model structure thus developed is comprehensive in its incorporation of the different sources of heterogeneity, such as spatial cognition, preference behavior and spatial interaction. Finally, the applicability of the proposed model structure is demonstrated through an empirical application using the German Mobidrive multi-day activity survey. The results of the empirical analysis indicate the important effects of spatial attributes and impedance measures, and emphasize the sensitivity variation across individuals to these spatial attributes and impedance measures.

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[3] Several other policy scenarios, including aging of the population with a correspondingly larger retired community, increase in auto-ownership, increased access to public transport, and a reduction in trip chaining, were also tested with the estimated models. These are not presented here due to space considerations, but are available from the authors.

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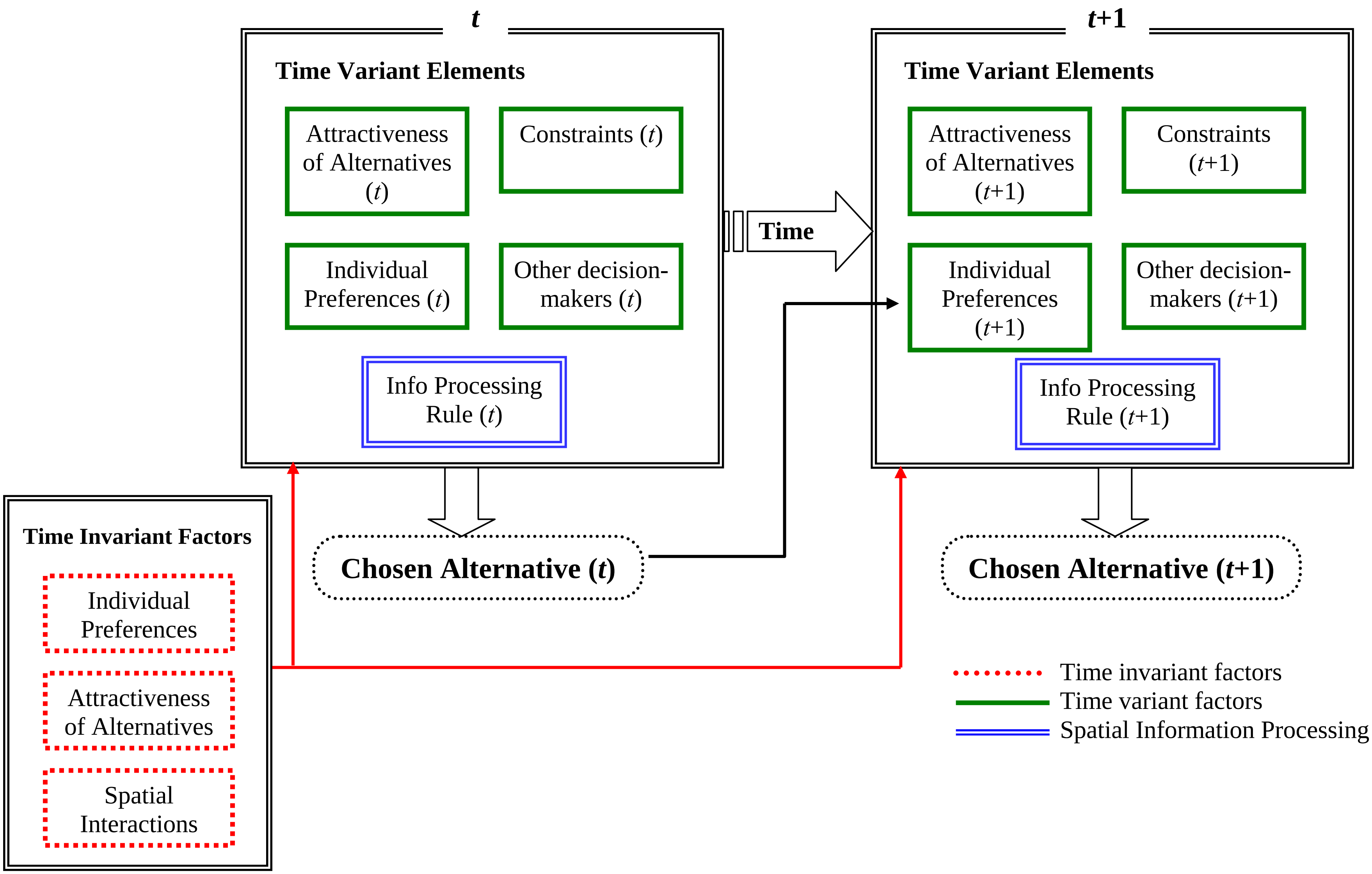

FIGURE 1 Conceptual framework of the location choice for non-work activity participation.

TABLE 1 Best Specification Mixed Logit Model of Location Choice

Variables	MxL-2	
	Param.	**t-stat.**
Zonal Size and Interactions		
Composite size of zone - Mean Effect	0.283	3.439
Composite size of zone x Low income (dummy variable for annual income < 3000 DM)	0.212	1.604
Composite size of zone x Number of public transport season tickets held	0.151	1.514
Composite size of zone x Stop chained with other shopping episodes (dummy variable)	-0.145	-1.744
Composite size of zone - Standard Deviation	0.174	2.257
Zonal Non-Size Attributes and Interactions		
CBD (dummy variable) - Mean Effect	0.820	1.395
CBD x Female (dummy variable)	0.113	0.413
CBD x Age	-0.008	-1.028
CBD x Stop chained with other episodes (dummy variable)	0.316	1.411
CBD x Number of accompanying adults	-0.403	-2.148
CBD x Activity duration (7:00AM to 9:00AM)	0.006	3.786
CBD x Morning hours	-0.280	-0.969
CBD - Standard Deviation	0.648	3.191
Presence of daycare (dummy variable) - Mean Effect	-0.332	-1.897
Presence of daycare x Married (dummy variable) x Number of Children < 16 years	0.665	0.878
Presence of daycare - Standard Deviation	0.647	2.452
Population density of zone - Mean Effect	-0.012	-6.532
Population density of zone - Standard Deviation	0.010	3.112
Impedance Measures and Interactions		
Distance of zone from home - Mean Effect	-3.002	-2.797
Distance of zone from work/school - Mean Effect	-0.975	-4.628
Distance of zone from home x Female (dummy variable)	-0.021	-0.078
Distance of zone from home x Retired (dummy variable)	-0.815	-2.297
Distance of zone from home x German citizen (dummy variable)	-0.602	-0.800
Distance of zone from home x Number of public transport season tickets held	-0.160	-0.534
Distance of zone from home x Number of cars owned	0.077	0.322
Distance of zone from home x Weekend (dummy variable)	-0.511	-1.710
Distance of zone from home x Number of accompanying adults (dummy variable)	0.409	2.146
Distance of zone from home x Stop chained with other shopping episodes (dummy variable)	0.398	1.595
Distance of zone from home x Activity duration	0.003	1.171
Composite size of zone x Distance of zone from home	0.195	2.484
Distance of zone from home - Standard Deviation	0.506	1.846
Distance of zone from work/school - Standard Deviation	0.377	1.040
Feedback Effect		
First order feedback of chosen zone - Mean Effect	1.361	10.531
First order feedback of chosen zone - Standard Deviation	0.549	3.335
Number of observations	903	
Log-likelihood at convergence	-2223.456	
Log-likelihood at equal shares	-3154.409	