A model of multi-purpose shopping trip behavior

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A MODEL OF MULTI-PURPOSE SHOPPING TRIP BEHAVIOR

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ABSTRACT Existing utility-based models of complex choice behavior do not adequately deal with the interdependencies of chained choices. In this paper, we introduce a model of multi-purpose shopping which is aimed at overcoming this shortcoming. In the proposed model, dependencies between choices within as well as between trips are covered by a recursive definition of trip utility. The standard log-likelihood estimation procedure is used to calibrate the model. Simulation experiments show that estimation results are satisfactorily accurate and robust. Comparison of the model to a conventional choice model using simulated data indicates that even low tendencies to make multi-purpose trips have a significant influence on predicted destination choice. Furthermore, it is shown that conventional models do not satisfactorily predict simulated multi-purpose behavior.

1. INTRODUCTION

Demand analysis continues to be a research area in geography and urban planning important for a broad range of issues pertaining to consumer behavior (Golledge and Timmermans 1990; Timmermans and Golledge 1990). The most widely used model in demand analysis is the multinomial logit model, which predicts the probability that consumers will choose a particular alternative, given its locational and non-locational attributes, the attributes of its competitors, and possibly a set of socio-economic characteristics of the consumers. The model is easy to use, is based on sound economic principles, and appears to be rather robust (Borgers and Timmermans 1987).

Recent research however has raised a number of reasons for doubting the ability of the multinomial logit model to predict consumer choice in complex situations involving interrelated choices. Although it is possible to use a proxy of the magnitude of multi-purpose shopping as a predictor, the multinomial logit model is typically a model of single-stop, single-purpose choice behavior: the effects of past or future choices on current choice, and the fact that a trip may involve different purposes are not explicitly taken into account. This suggests that the multinomial logit model may be a weak predictor of multi-stop, multi-purpose shopping behavior. Because empirical evidence suggests

that an increasing proportion of shopping trips involves multiple purposes, and especially in the United States also multiple stops, there is clearly a need to develop, test and apply more complicated choice models of multi-stop, multi-purpose shopping choice behavior.

In this paper, we introduce a new model that, at least to some extent, may fill this gap. More specifically, we suggest a recursive model of multi-purpose shopping behavior. Thus, the present model focuses on the multi-purpose aspect of shopping trips, and does not (yet) incorporate multi-stop behavior.

The paper is organized as follows. First, we will briefly discuss existing models of multi-stop, multi-purpose behavior to place the present model in a wider context. Then, we will outline the assumptions behind the model. This is followed by a discussion of the method used to estimate the parameters of the model. Next, we will discuss the degree to which multi-purpose shopping influences destination choice, and the extent to which conventional models are able to account for this influence. This discussion will be based on the results of simulation experiments. Finally, we will draw some conclusions and discuss some avenues for future research.

2. EXISTING APPROACHES

The topic of multi-purpose, multi-stop behavior is not new. It has received considerable attention in the past, in geography, urban planning and transportation science. To situate our model in the context of previous attempts, we will first briefly discuss existing models of multi-stop, multi-purpose trip behavior before introducing our model.

Thill and Thomas (1987) have presented an extensive review of studies on trip chaining. They distinguish between a theoretical and econometric line of research. The theoretical approach aims to obtain insight into the implications of trip chaining for properties of demand and supply related phenomena, while the econometric approach is primarily concerned with the simulation and prediction of choice behavior of consumers. In order to obtain insight into limited aspects of trip chaining, various sets of simplifying assumptions have been adopted in the theoretical approach. The simplifications consist of considering a two-commodity, two-firm world (e.g., Bacon 1984; Ghosh and McLafferty 1984; Thill 1985), of assuming cost-minimizing behavior (e.g., Kohsaka 1984; Ghosh and McLafferty 1984; Bacon 1984; Thill 1985), or of imposing a perfect hierarchically structured facility system (Ghosh and McLafferty 1984). Because of the simplifying assumptions, these models are less appropriate for predicting specific consumer choice behavior. Therefore, we will focus on the econometric line of research.

Markov chain models have been widely used in modeling the sequence of actions that compose trip chaining behavior. In these models, the probability of travel (transition) between each possible pair of destinations (states) is estimated. The estimation of transition probabilities may be obtained by means of random utility choice models (Ben-Akiva et al. 1978; Horowitz 1980) or entropy-maximizing models (Borgers and Timmermans 1986). However, a fundamental shortcoming of this approach stems from the unrealistic

assumption that transition probabilities do not depend on former or later choices in the chain.

In the model proposed by O'Kelly (1981), the assumption of independence between current and previous choices in trip chains is relaxed. As in Markov chain models, a trip chain is viewed as a sequence of transitions from one state to another, whereby a state consists of a stop-purpose combination. Given the probability distribution of initial stops, O'Kelly's model predicts the probability of any particular path by multiplying the conditional probabilities for each link of the chain. The probability distribution of initial stops may be obtained by using another spatial choice model. Unlike what holds for Markov chain models, the probabilities are not necessarily constant across stops or purposes. However, the dependency relationship between current and *future* choices is not covered by the model. This is clearly manifested by the fact that the distribution of initial stops is obtained separately from the distribution of subsequent stops.

Basically, the same criticism holds for the discrete choice model of trip chaining proposed by Horowitz (1980). In this model, the frequency, destination and travel mode of single-stop and multi-stop trips are predicted, based on the assumption of utility maximizing behavior. Although the decision to initiate trips is made dependent on past travel decisions and future travel plans, the destination choices within a trip chain are viewed as mutually independent.

Adler and Ben-Akiva (1979) and Timmermans (1988) have overcome the problem of interrelated choices by considering complex trip chains rather than individual destinations as choice alternatives. However, when applied to real world situations, the models soon become intractable, because of the numerous possible trip chain alternatives involved.

Another way to account for the dependence of current destination choices on subsequent choices (of next destinations) is based on the concept of prospective utility, introduced by Kitamura (1984). The prospective utility of a destination consists of its intrinsic utility and the expected utility of continuing the trip to a next destination. The recursive nature of the model is apparent, since the utility of a next destination is also defined as a prospective utility. Although Kitamura's model is general for chaining purposes and stops, multi-purpose trips are not adequately accounted for. This is manifested by the fact that factors influencing multi-purpose behavior, such as the relative frequency of visiting various facilities, and the tendency to chain specific combinations of purposes, are not included in the analysis.

Although the above review of approaches is far from complete, it illustrates the general conclusion that current models are either too restrictive or do not adequately account for the interdependence of chained choices. Thill and Thomas (1987) conclude that the most promising approach seems to consist of multinomial logit (MNL) models in which multi-purpose, multi-stop behavior is considered to be the outcome of a simultaneous decision process. The model presented in this paper is consistent with this suggestion.

In the model we propose, individuals initiate trips aimed at the purchase of a certain type of good. Optionally, other goods are bought in combination

with that good at the destination location (shopping center) of the trip. The set of purposes of a trip is determined by: (a) the relative frequency of purchasing the various types of goods; and (b) a tendency to utilize opportunities for multi-purpose shopping. Purchase frequencies are taken as exogenous constants, and the tendency to combine purposes is represented by a parameter specific to each good, which is estimated on the basis of observed consumer behavior. The choice between optional trip destinations is based on the utility of the alternatives. The utility of a destination depends on attributes of the supply of the type of good and also on opportunities for multi-purpose shopping. As in Kitamura's model, the expected utility derived from multi-purpose shopping adds to the utility of the destination. Decisions on trip destinations and purpose combinations are made simultaneously, i.e., the choice of a trip destination depends on subsequent choices of combined purchases at that location. Choices are not only interrelated at the level of trip stages, but also at the level of trips, since trip utilities are included in the expected utility of combined purchases during any trip. Therefore, destination choices of different trips are made conditional upon each other.

The model does not impose any restrictions on the number of commodities (goods) and firms, or on the structure of the shopping system. Furthermore, no strong assumptions are made with respect to consumer behavior, except that multi-stop trips are excluded in the current formulation of the model. However, the model can be generalized in a straightforward way to account for multi-stop trips as well.

The calibration of the model may yield insight into the degree to which opportunities for multi-purpose shopping affect destination choices, as reflected by the *tendency* parameter. Given the estimated values of parameters, the model can be used in urban planning to evaluate the impact of retail planning proposals. If consumers indeed display multi-purpose behavior, then the new model may improve the prediction of consumer choices.

3. THEORY

The Problem

The problem addressed in this paper may be formally stated as follows: suppose that individuals face a set of N shopping centers distributed over discrete points in space at certain distances from their home. Each shopping center contains a discrete set of stores that offer various goods which are known to the individual. Individuals wish to purchase a set of L goods with differing purchase frequencies over time. Individuals have the option of making a shopping trip for each purchase separately (single-purpose trip), or, alternatively, they may combine the purchase of different goods during a trip (multi-purpose trip) in order to reduce the costs of acquiring the goods. The problem then is to predict simultaneously (a) the number of multi-purpose trips made within a given finite time horizon, and (b) for each of the shopping centers, the probability it will be chosen, with the purchase frequencies for each of the goods given.

Assumptions

- (a) *For the sake of parsimony, we assume that the L goods may be categorized into G hierarchical orders based on their purchase frequencies.* Let $g = 1$ denote the good with the lowest purchase frequency, then $g = G$ represents the lowest hierarchical order with the highest purchase frequency.
- (b) *Individuals seek to reduce their transportation costs by combining purchases of different goods during a single shopping trip.* This tendency towards multi-purpose trips involves synchronizing purchase cycles. With synchronization we mean the planning of purchases in a given time period in such a way that the demand for different types of goods coincides in time. With respect to this, behavior can be considered to fall between two extremes. Synchronization is at its maximum when lower order goods are purchased each time a trip is made to purchase higher order goods. Hence, the number of multi-purpose trips is at its minimum. Synchronization is at its minimum when separate trips are made for each purchase. In fact, in this case the individual would only make single-purpose trips, and the number of multi-purpose trips would be equal to zero.
- (c) *The tendency to combine the purchase of different order goods is represented by a model parameter.* No assumptions are made regarding the degree to which individuals tend to make multi-purpose trips. Instead, this tendency is estimated based on observed choice behavior. If such a tendency is absent in observed choice behavior, the model would reduce to the conventional MNL model.
- (d) *Purchase frequencies for all individuals and goods are exogenously given.*
- (e) *Individuals only make single-stop trips.* This assumption is made in the present paper, primarily because we did not have the data required to estimate a model that incorporates multi-stop trips as well. However, the extension of the present model to the case of multi-stop, multi-purpose trips is relatively straightforward.
- (f) *Individuals are involved in utility-maximizing behavior when they choose shopping centers to purchase goods.*

Specification

Given the ordering of G goods from low to high purchase frequency, we can distinguish between G orders of trips. A trip of order g , or, in short, a g -trip, is a trip aimed at purchasing good g , and optionally also one or more lower order goods, $h > g$. Whether or not the combinations of lower order goods are made depends on several factors, such as the degree to which the trip maker tends to synchronize his or her purchase cycles. From this definition, it follows that trips of the lowest trip order (order G) are necessarily single-purpose trips.

Following utility theory, we assume that the structural utility that individuals derive from making a (multi-purpose) trip of order g from their home located at i to the j -th shopping center, V_{ij}^g , equals the utility of the supply of goods of order g at the j -th shopping center plus the total expected utility

of the supply of all lower order goods ($h = g + 1, \dots, G$) at the j -th shopping center, less the disutility associated with traveling from i to j . Formally:

$$V_{ij}^g = W_j^g + \sum_h (p_{ij}^h W_j^h) - \theta^g d_{ij} \quad h = g + 1, \dots, G \quad j \in N_i^g, \quad (1)$$

where:

W_j^g is the attractiveness of the supply of order g at shopping center j ;

p_{ij}^h is the probability that lower order good h is purchased in shopping center j during a trip of higher order;

d_{ij} is the distance between location i and shopping center j ;

θ^g is a good-specific distance decay parameter;

N_i^g is the i -specific set of shopping centers that supply good g .

The second term on the right hand side of equation (1) expresses the expected utility derived from multi-purpose shopping. This formulation is analogous to Kitamura's model of prospective utility, which states that the expected utility of continuing a trip to a next destination adds to the attractiveness of the current destination. The chaining of next destinations in Kitamura's model corresponds to *chaining* of purposes of lower order in (1).

If good h is supplied at the destination center of a higher order trip, the trip maker is faced with the choice between either buying h at that location (multi-purpose shopping), or buying it at one of the optional destinations of h -trips. If individuals display optimal behavior, h will be bought during a higher order trip to center j if the attractiveness of h -supply in j exceeds the utility of an h -trip to each of the optional destinations of h -trips (including j). Therefore, the probability of purchasing h during a higher order trip to center j , by an individual located at i who demonstrates optimal behavior, q_{ij}^h , equals the probability that the attractiveness of h -supply in j is larger than the utility of each alternative. This probability is specified by using a logit model:

$$q_{ij}^h = \frac{\exp(W_j^h)}{\exp(W_j^h) + \sum_k \exp(V_{ik}^h)} \quad k \in N_i^h. \quad (2)$$

Note that the utility of an h -trip, V_{ik}^h , is defined by the same equation as that of a g -trip, i.e., equation (1). Hence, the utility of an h -trip includes the expected utility of buying (even) lower goods in an h -trip.

Equation (2) is based on the assumption that individuals display optimal behavior, in the sense that they utilize opportunities for multi-purpose shopping every time this adds to the total utility, summed across trips. We assume, however, that individuals do not necessarily behave in such an optimal manner, but rather that they have a *tendency* to make multi-purpose trips. This notion is incorporated into the model by including a parameter which rep-

resents this tendency. In the most general case, this parameter should be made specific to each individual and each order. However, for the sake of parsimony, we assume that the tendency to purchase good h in combination with higher order goods is only good-specific. The associated parameter is formally defined as the proportion of times multi-purpose shopping is chosen when this is beneficial from the point of view of utility maximization. Consequently, the actual probability that h is bought during a higher-order trip to j , p_{ij}^h , equals:

$$p_{ij}^h = \tau^h q_{ij}^h, \quad (3)$$

where the parameter τ ranges from zero to unity. A zero value for τ indicates the absence of utility maximization through multi-purpose shopping. In such an instance, the model reduces to a conventional choice model. On the other hand, a value for τ of one indicates optimal utilization of the opportunities for multi-purpose shopping.

The formulation of the probability of multi-purpose shopping, as defined by equation (3), is similar to the trip chaining component in Kitamura's model. In the same way, Kitamura defines a parameter to derive the actual probability of going to a next destination option, given the objective probability of this option, i.e., the probability under conditions of optimal behavior. The parameter is interpreted as a general propensity to make multi-stop trips and is based on observed choice behavior.

The probability that individuals will choose shopping center j to make a multi-purpose trip of order g then equals the probability that the utility of visiting center j exceeds the utility of visiting all other shopping centers in their choice set. If we assume that the error terms of the utility function are independently and identically double exponentially distributed, then the probability that an individual located at i will choose shopping center j to make a multi-purpose trip of order g equals:

$$a_{ij}^g = \frac{\exp(V_{ij}^g)}{\sum_k \exp(V_{ik}^g)} \quad j, k \in N_i^g.$$

The above equations for calculating the a and p variables can be solved only from lower to higher order goods, because the utility of higher order trips depends on the probability of combined purchases of lower order goods. Hence, the utility of lower order trips must be known to determine the utility of higher order trips.

Given the a and p probabilities and the frequency of purchasing different goods, the distribution of visits across centers can be determined. The number of g -trips to j , T_{ij}^g , equals the purchase frequency for g , f_i^g , less the number of times that good g is purchased during higher order shopping trips. Formally:

$$T_{ij}^g = a_{ij}^g \left(f_i^g - \sum_k p_{ik}^g \sum_h T_{ik}^h \right) \quad j \in N_i^g \quad k \in N_i^h \quad h = 1, \dots, g-1.$$

Given the trip pattern, T_{ij}^g , the frequency pattern can be determined. The frequency of purchasing good g in shopping center j is equal to the number of g -trips to shopping center j plus the frequency of purchasing good g during shopping trips of higher order to j . Thus:

$$F_{ij}^g = T_{ij}^g + p_{ij}^g \sum_h T_{ij}^h \quad j \in N_i^g \quad k \in N_i^h \quad h = 1, \dots, g-1.$$

These equations can be solved only from higher to lower order, because the pattern of lower order trips depends on the pattern of higher order trips (multi-purpose shopping reduces the number of trips of lower order).

4. MODEL ESTIMATION

Estimation Procedure

In order to make the choice model operational, the attractiveness term of the utility functions needs to be specified first. Following most of the existing literature in retailing, we assume the utilities to be linear additive functions of shopping center attributes. The utilities are thus expressed as:

$$W_j^g = \sum_s (\beta_s^g X_{js}^g)$$

where:

β_s^g is the weight of the s -th attribute of g -supply;

X_{js}^g is the s -th attribute of g -supply in center j .

Thus, we have three types of parameters that must be estimated: (a) the attribute coefficients that represent the contribution of the shopping centers' attributes to the attractiveness component of the utility functions; (b) the distance parameters; and (c) the parameters that reflect the propensity of multi-purpose trips.

Given the values of these parameters, the model gives as output the distribution of frequencies across the alternatives j for the choice set of each good g , F_{ij}^g . The log-likelihood of the model can be calculated provided that these frequencies are converted to probabilities. By using a gradient search method and/or a sequential linear search method, the parameter values that optimize the log-likelihood function can be found. For this, we used the computer package CALDIS (Borgers 1985), in which the model is calibrated by using a standard log-likelihood estimation procedure that includes the extra step of converting frequencies to probabilities. The solution is a set of parameter values that maximizes the chosen goodness-of-fit criterion.

Effectiveness of the Estimation Procedure

The search procedure used to estimate the parameter values guarantees that the optimal solution is found provided that the log-likelihood function is regularly shaped, in the sense that local optima are absent. Since it is not possible to prove analytically whether the log-likelihood function meets this

requirement, we carried out a series of simulation experiments to test the effectiveness of the estimation procedure.

For this purpose, various data sets are generated by assuming different sets of (fictitious) parameter values. These data sets are used as inputs into the procedure outlined above in order to obtain estimates of the (known) parameters. The effectiveness of the procedure can then be evaluated by comparing estimated to *real* parameter values.

The model is based on data on attributes, X_{js}^g , distances, d_{ij} , purchase frequencies, f_i^g , and choice sets, N_i^g . Given this input, the model generates the distribution of visits across the alternatives of the choice sets, F_{ij}^g . The attribute data, X_{js}^g , are obtained from the shopping system of Maastricht, a middle-sized city in the Netherlands. This shopping system consists of thirty spatially distributed shopping centers, in which three sectors (categories of goods) are distinguished. From high to low order the three sectors are: appliances goods, clothes and food. For all three, the size and variety of supply of the outlets are included as attributes in the analysis, and for the cloth and food sector the general price level is considered as well. Consequently, the model includes 8 attribute parameters. The distance data, d_{ij} , and choice set data, N_i^g , are obtained from a sample of 428 respondents who are using the shopping system of Maastricht. Distance parameters are supposed to be sector specific, resulting in three distance parameters. The frequency of purchasing the different types of goods in a given time period is held constant across individuals, and set to the average values 3, 4 and 25 respectively. In other words, we assumed that appliance goods are bought three times, clothes four and food twenty-five times in a given time period. In the context of multi-purpose shopping, lower order goods may be bought in combination with a higher order good. Consequently, two tendency parameters are involved, which reflect the tendency to buy clothes and food during a higher order trip. In all, eight attribute parameters, β_s^g , three distance parameters, θ^g , and two tendency parameters, τ^g , are involved in the model.

Two series of simulation analyses are performed. The first series is conducted to test the effectiveness of the estimation procedure with respect to sample size. For this purpose, five subsets of varying size are selected from the total set of 428 respondents. Based on these subsets and an arbitrary set of parameter values the model is used to generate frequency data, resulting in five data sets. These simulated data are then used as input into the procedure to estimate (unknown) model parameters. The second series of simulations aims to test the robustness of the estimation procedure with respect to variations in the settings for the initial parameter. These simulations involve only one data set, which is generated by the model based on the total set of 428 respondents and an arbitrary set of parameter values. The estimation procedure is executed various times using these data and a representative series of sixteen mutually independent sets of lower and upper extreme initial parameter values.

TABLE 1. Estimated Values and t-Values of Model Parameters: Simulation Results^a

Variable ^b	N = 85	N = 169	N = 252	N = 337	N = 428
Appliance Size	0.099 (1.782)	0.101 (1.172)	0.099 (2.262)	0.101 (2.631)	0.097 (3.432)
Appliance Variety	0.100 (1.789)	0.102 (1.913)	0.103 (2.586)	0.103 (3.567)	0.103 (3.821)
Clothes Size	0.101 (2.412)	0.101 (2.284)	0.097 (3.209)	0.095 (4.230)	0.096 (4.203)
Clothes Variety	0.093 (1.566)	0.097 (1.584)	0.095 (2.885)	0.095 (3.300)	0.101 (4.084)
Clothes Price	0.109 (1.435)	0.103 (0.873)	0.113 (3.160)	0.116 (4.278)	0.113 (3.826)
Food Size	0.101 (8.421)	0.101 (12.07)	0.101 (14.89)	0.099 (18.11)	0.101 (21.43)
Food Variety	0.101 (7.194)	0.101 (10.08)	0.101 (13.06)	0.101 (15.31)	0.099 (17.47)
Food Price	0.099 (3.673)	0.099 (5.454)	0.099 (6.394)	0.101 (7.594)	0.099 (9.241)
Distance Appliance	-0.010 (-1.887)	-0.010 (-2.466)	-0.010 (-3.189)	-0.010 (-3.861)	-0.010 (-4.274)
Distance Clothes	-0.010 (-1.890)	-0.010 (-2.337)	-0.011 (-3.173)	-0.010 (-3.659)	-0.010 (-4.092)
Distance Food	-0.010 (-7.891)	-0.010 (-11.11)	-0.010 (-13.65)	-0.010 (-15.78)	-0.010 (-17.35)
Tendency Clothes	0.901 (28.83)	0.803 (34.08)	0.777 (73.76)	0.790 (86.14)	0.788 (49.85)
Tendency Food	0.794 (18.57)	0.795 (14.28)	0.793 (84.49)	0.792 (123.0)	0.806 (101.0)

a. t-values in parentheses below estimates.

b. true parameter values are -0.01 for distance variables, 0.8 for tendency variables, and 0.1 for all others.

Results of Simulation Experiments

Table 1 summarizes the real and estimated parameter values for data sets of different sizes. The true values of the parameters used to generate the data were chosen arbitrarily. The differences between estimated and real parameter values are small, and the t-values are highly significant over the whole range of data set sizes. This indicates that the results of the procedure are satisfactorily adequate as well as reliable even when small sample sizes are involved. Table 2 shows the estimation results when different sets of initial parameters are used as input into the estimation procedure. Again, the true parameter values used to generate the data are set to arbitrary levels. The small standard deviation and range of parameter estimates implies that the procedure is robust for variations in the specification of initial parameter values. This finding indicates that local optima are absent in the log-likelihood function of the model.

TABLE 2. Summary of Estimated Values (16 runs):
Simulation Results

Variable ^a	Average	St.Dev.	Min.	Max.	Range
Appliance Size (0.09)	0.0907	0.0016	0.0887	0.0932	0.0046
Appliance Variety (0.11)	0.1104	0.0019	0.1076	0.1132	0.0055
Clothes Size (0.11)	0.1081	0.0040	0.1005	0.1138	0.0133
Clothes Variety (0.08)	0.0788	0.0069	0.0682	0.0932	0.0251
Clothes Price (0.07)	0.0760	0.0109	0.0540	0.0932	0.0392
Food Size (0.07)	0.0705	0.0014	0.0695	0.0718	0.0023
Food Variety (0.09)	0.0899	0.0018	0.0888	0.0910	0.0023
Food Price (0.12)	0.1196	0.0023	0.1161	0.1230	0.0059
Distance Appliance (0.005)	0.0049	0.0000	0.0049	0.0049	0.0000
Distance Clothes (0.005)	0.0074	0.0005	0.0063	0.0076	0.0014
Distance Food (0.015)	0.0156	0.0000	0.0156	0.0156	0.0000
Tendency Clothes (0.8)	0.7932	0.0245	0.7549	0.8399	0.0850
Tendency Food (0.6)	0.6006	0.0121	0.5838	0.6213	0.0375

a. true parameter values (chosen arbitrarily) are given in parentheses below variable name.

With respect to its accuracy, reliability and robustness, we conclude that the estimation procedure performs satisfactorily.

5. MULTI-PURPOSE SHOPPING AND DESTINATION CHOICE

Theoretically, multi-purpose shopping affects destination choice in two ways. First, a destination location which is intrinsically not the most attractive option may be chosen because of provided opportunities for multi-purpose shopping. Second, a lower order good may be bought at the destination location of a higher order trip which differs from the destination location of the corresponding lower order trips.

The magnitude of the effect of multi-purpose shopping on destination choice can be assessed by fitting a conventional MNL model for a Single-Purpose-Trip (SPT) model to data generated by the Multi-Purpose-Trip (MPT) model. The smaller the effect of (hypothetical) multi-purpose behavior, the better the fit of the SPT model will be, and vice versa. The fit of the MPT model with the same data indicates the maximum fit that can be obtained. Therefore, we will consider the performance of the SPT model relative to that

TABLE 3. Correlation between Predicted and Simulated Frequencies for Different Tendencies of Multi-Purpose Shopping (MP)

MP Tendency	Appliances	Clothes	Food
0.8	0.845	0.875	0.998
0.6	0.881	0.921	0.999
0.4	0.926	0.961	0.999
0.2	0.974	0.989	1.000

of the MPT model. Obviously, the magnitude of the effect of multi-purpose shopping is proportional to the extent to which individuals tend to behave in this manner. Therefore, we will simulate choice behavior assuming various degrees to which individuals tend to make multi-purpose trips. To generate the data sets, we used the attribute, distance and choice-set data of the Maastricht case (see Section 4). The simulated data thus describe the destination choice of 428 hypothetical individuals who behave perfectly in agreement with the MPT model. Based on these data we estimate both the MPT and SPT model. In principle, the difference in fit between the models indicates the degree to which destination choice is affected by multi-purpose behavior.

The SPT model consists of three separate models, i.e., one conventional MNL model for each of the distinguished goods. Before comparing the SPT and MPT model, we consider the goodness-of-fit of each of the separate models in relation to the assumed tendency of multi-purpose behavior, as indicated by the Pearson correlation coefficients shown in Table 3. As expected, the fit increases when the value of the tendency parameter decreases. Furthermore, the models for the higher-order sectors perform poorly. This suggests that the destination choice for higher order goods in particular is influenced by multi-purpose behavior. Probably, this is caused by the uneven distribution of purchase frequencies across sectors (3, 4 and 25). Consequently, the share of combined food purchases is low even when opportunities for multi-purpose shopping are at their maximum.

Table 4 shows a measure for the goodness-of-fit of the MPT and the SPT models, when the different data sets are used. As a measure of fit we used the likelihood ratio, adjusted for differences in the number of parameters (see Ben-Akiva and Lerman 1985, 167). This measure is defined as:

$$\bar{\rho} = 1 - \frac{L(\beta) - K}{L(0)}$$

where:

- $\bar{\rho}$ is the adjusted likelihood ratio index;
- $L(\beta)$ is the log likelihood of the model with optimal parameter estimates;
- $L(0)$ is the minimum log likelihood;
- K is the number of parameters,

TABLE 4. Adjusted Log-Likelihood Ratio for MPT and SPT Models for Different Tendencies of Multi-Purpose Shopping (MP)

MP Tendency	MPT	SPT	SPT(dummy) ^a	SPT(utility) ^b
0.8	0.12465	0.11745	0.11755	0.11825
0.6	0.11979	0.11494	0.11503	0.11577
0.4	0.11538	0.11250	0.11260	0.11303
0.2	0.11163	0.11011	0.11021	0.11040

a. defined in equation (4).

b. defined in equation (5).

TABLE 5. Difference in Adjusted Likelihood Ratio Between MPT and SPT Models for Different Tendencies of Multi-Purpose Shopping (MP)

MP Tendency	SPT	SPT (dummy)	SPT (utility)
0.8	0.0072	0.0071	0.0064
0.6	0.0049	0.0048	0.0040
0.4	0.0029	0.0029	0.0024
0.2	0.0015	0.0014	0.0012
critical level ^a	0.000035	0.000083	0.00013

a. critical level of difference in adjusted likelihood ratio at the 0.95 level.

The measure $\bar{\rho}$ can be used in a fashion similar to R^2 in regression analysis. The differences in $\bar{\rho}$ between the MPT and the SPT model can be seen in Table 5. Obviously, the difference in fit decreases when the value of the tendency parameters decreases.

To test the significance of the difference in fit, we used the log-likelihood ratio test (Theil 1971, 396). This statistic indicates the improvement in fit that results from extending a given base model. Since the MPT model is an extension of the SPT model, the log-likelihood ratio test is useful for our purpose. The test statistic is:

$$-2 [L(\beta_{SPT}) - L(\beta_{MPT})],$$

where β_l denotes the estimated coefficients of the l -th model. This statistic is distributed as χ^2 with $(K_{MPT} - K_{SPT})$ degrees of freedom, where K_l is the number of parameters of the l -th model. The test statistic equals 146.35, 97.34, 56.11 and 27.72 when the multi-purpose tendency is set to 0.8, 0.6, 0.4 and 0.2 respectively. Since the critical χ^2 at the 0.95 level is 5.991 (df = 2), we conclude that the difference in fit is highly significant, even when the tendency to make multi-purpose trips is as low as 0.2 (combined purchases are made in only 20% of the cases in which it is beneficial). This finding suggests that multi-purpose shopping influences destination choice substantially, even if low tendencies of displaying this behavior are assumed. Consequently, the accuracy of predicting shopping behavior will be improved when the multi-purpose factor is incorporated in the model.

6. THE PERFORMANCE OF ALTERNATIVE MODELS

The significant effect of multi-purpose shopping on destination choice in the hypothetical examples raises the question whether extended forms of the SPT model are able to account for these effects. The SPT model may be extended by incorporating a proxy for the magnitude of multi-purpose shopping as an extra independent variable in the model. This can be done in various ways. First, a dummy variable that encodes the presence of lower-order supply can be built into the model as follows:

$$V_{ij}^g = W_j^g + \sum_h \tau^h \delta_j^h - \theta^g d_{ij} \quad h = g+1, \dots, G, \quad (4)$$

where:

V_{ij}^g is the structural utility of a g -trip from i to center j ;

W_j^g is the attractiveness of supply of good g at center j ;

τ^h is the weight of lower-order supply h ;

δ_j^h is a dummy variable, equal to one if lower-order supply h is present in center j , and equal to zero otherwise;

θ^g is a good-specific distance decay effect;

d_{ij} is an index for the cost of traveling from i to j .

A more sophisticated model results when the utility of lower-order supply is used as an additional independent variable:

$$V_{ij}^g = W_j^g + \sum_h \tau^h W_j^h - \theta^g d_{ij} \quad h = g+1, \dots, G, \quad (5)$$

where:

W_j^h is the attractiveness of lower-order supply h in center j

τ^h is the weight of lower-order supply h ;

and other elements are defined as above. In order to calculate the g -th model of this type, the parameter values of the attributes of lower-order supply h must be known (with $h > g$). Therefore, the G models are estimated from low to high order goods. The estimation results of lower order estimations are used to calculate the utility of lower-order supply, W_j^h , as a predictor in the g -th model ($g < h$).

The models (4) and (5) can be seen as the two extremes that cover the whole range of sophistication in extending the SPT model. In order to test if these extended SPT models are able to successfully predict the simulated multi-purpose behavior, we will compare the goodness-of-fit of these extended SPT models to the goodness-of-fit of the MPT model.

Table 4 shows the adjusted log-likelihood ratios of the four models, for simulated data sets that differ in the assumed tendency of multi-purpose shop-

ping. The inclusion of the dummy variable in the SPT model results in only a very small improvement of the fit. A stronger improvement is achieved by incorporating the utility of lower-order supply in the model. However, the MPT model still outperforms this more sophisticated model, even when low tendencies of multi-purpose shopping are assumed.

Since the extended SPT models cannot be derived as special cases of the MPT model (or vice versa), the log-likelihood ratio test is not appropriate to test the significance of difference in fit between the models. However, the models are related in the sense that they are all extensions of the same base model, i.e., the simple SPT model. Models that are related in this way can be compared by using the test on non-nested hypotheses developed by Horowitz (1983). The test shows the maximum probability that the adjusted likelihood ratio of the best fitting model (model 2) is greater by some $z > 0$ than that of the other model (model 1), under the null hypothesis that the latter is the true specification (see Ben-Akiva and Lerman 1985, 172):

$$\text{Prob}(\bar{\rho}_1 - \bar{\rho}_2 > z) \leq \Phi \{-[-2zL(0) + (K_2 - K_1)]^{1/2}\} \quad z > 0,$$

where:

$\bar{\rho}_l$ is the adjusted likelihood ratio index for model $l = 1, 2$;

K_l is the number of parameters in model l ;

Φ is the standard normal cumulative distribution function.

By means of this test we can determine the maximum probability that the MPT model is erroneously chosen as the true model, given the difference z in the adjusted likelihood ratio between the MPT model (model 2) and a SPT model (model 1).

Table 5 shows the differences in the adjusted log-likelihood ratio between the MPT model on the one hand and the SPT models on the other hand. As expected, the relative performance of the SPT models increases with increasing sophistication of the extended form, and with decreasing tendencies of multi-purpose shopping. Even for the most sophisticated SPT model and with the smallest tendency of multi-purpose shopping, the difference found is still considerably larger than the z -value at the 0.95 probability level. This means that it is highly unlikely that the MPT is chosen while the best SPT model is the true model, even when the assumed tendency rate is as low as 0.2.

This finding suggests that the extended forms of the SPT model do not satisfactorily predict the simulated multi-purpose behavior, even when low tendencies of multi-purpose behavior are assumed. Of course, this conclusion does not necessarily imply that the MPT model, when compared to alternative models, improves the prediction of *actual* consumer behavior. Instead, it implies that the MPT model *can* improve the prediction, so that it is not a priori pointless to perform an empirical test.

7. CONCLUSIONS AND DISCUSSION

Existing approaches to modeling multi-purpose and multi-stop behavior do not adequately deal with the interdependencies between current and later

choices in a trip chain. The model presented in this paper aims at overcoming this shortcoming. In the model, the choice of a shopping center for the purchase of a certain type of good depends on chained choices of buying goods of lower order in combination, in addition to the intrinsic utility of supply of that good. The choice of buying lower order goods in combination with some higher order good depends on the utility associated with the supply of the concerned lower order good relative to the utility of optional home-based trips to buy these goods. Consequently, the choice of a trip destination depends on subsequent choices during the trip and also on choices made during trips of lower order. The complex interdependencies of choices between and within trips are reflected in the model by a recursive definition of trip utility.

A standard log-likelihood estimation procedure is used to estimate the parameters of the model. In order to test the effectiveness of this procedure for this application, a series of simulation experiments were conducted. The results suggest that the procedure is satisfactorily accurate and robust for variations in initial parameter specifications.

Further simulation experiments show that, at least in theory, destination choice is significantly influenced by multi-purpose shopping, even when low tendencies to display this behavior are assumed. The conventional MNL model, compared with the multi-purpose trip model, does not satisfactorily account for these simulated effects. This conclusion holds even when extended forms of the MNL model are considered, which include a proxy of the magnitude of multi-purpose shopping as an independent variable. If consumers indeed tend to engage in multi-purpose shopping, then this finding means that the incorporation of multi-purpose trips in choice models may significantly improve the accuracy of the prediction.

In an ongoing study the multi-purpose model is being empirically tested. The estimation of the tendency parameter allows conclusions to be drawn on the actual importance of multi-purpose shopping for destination choice in relation to different lower-order goods. The comparison with the performance of a single-purpose choice model will reveal the degree to which the prediction of shopping behavior is improved by including the multi-purpose factor in the analysis.

A shortcoming of the present model is that it does not account for the contribution of nearby shopping opportunities to the utility of a destination. The addition of a multi-stop component will be the focus of a next study. Furthermore, it must be noted that the model imposes restrictions on the distribution of purchase frequencies across good categories (sectors). It is assumed that lower order goods are needed each time some higher order trip is made. Consequently, the purchase frequency of any lower order good must exceed the sum of the frequencies of all higher order goods in order to cover (extreme) cases wherein tendencies and beneficial opportunities for multi-purpose shopping are at their maximum. Furthermore, the adequacy of the model depends to some degree on the adequacy of the subdivision of goods into categories. A refined categorization may be in conflict with the restriction imposed on the frequency distribution mentioned above. One way out would

be to take purchase frequencies as a function of opportunities for multi-purpose shopping rather than as exogenous constants as in the present model. Modeling purchase frequencies seems to be a promising way of extending the present model.

Finally, we note that the model may be used as an analytic tool for measuring some aspects of multi-purpose behavior. If combination-specific tendency parameters are assumed, then the results of model calibration provide information on the degree to which good combinations are compatible. For example, a high tendency to buy lower-order good h during g -trips means that h is highly compatible with g . Note that estimates of tendency parameters are independent of the spatial structure of the specific case used for calibration, since this is covered by the structure of the model. Therefore, analyses like this may yield generally useful information for planning the composition of shopping centers.

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APPENDIX

Proof that the total of visits summed across j equals the purchase frequency of a given good g :

$$\sum_j F_{ij}^g = f_i^g \quad j \in N_i^g$$

Proof

$$\begin{aligned} \sum_j F_{ij}^g &= \sum_j \left\{ a_{ij}^g \left(f_i^g - \sum_k \left(p_{ik}^g \sum_h T_{ik}^h \right) \right) + p_{ij}^g \sum_h T_{ij}^h \right\} \\ &= f_i^g - \sum_k \left(p_{ik}^g \sum_h T_{ik}^h \right) \sum_j a_{ij}^g + \sum_j \left(p_{ij}^g \sum_h T_{ij}^h \right) \end{aligned}$$

$$\sum_j a_{ij}^g = 1, \text{ from which follows that:}$$

$$\sum_j F_{ij}^g = f_i^g - \sum_k \left(p_{ik}^g \sum_h T_{ik}^h \right) + \sum_j \left(p_{ij}^g \sum_h T_{ij}^h \right).$$

k and j belong to the same choice set, N_i^h , hence:

$$\sum_j F_{ij}^g = f_i^g,$$

where:

F_{ij}^g is the frequency of buying good g in center j by consumer i ;

T_{ij}^g is the number of g -trips made by consumer i to center j ;

a_{ij}^g is the probability of making a g -trip to center j by consumer i ;

p_{ij}^g is the probability of buying good g during a higher order trip to center j by consumer i ;

f_i^g is the frequency of purchasing good g by consumer i ;

N_i^g is the g -th choice set of consumer i .