Estimating Availability Effects in Travel Choice Modeling: A Stated Choice Approach

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Existing stated preference models in the transportation literature focus principally on measuring preferences for travel alternatives. Choices are predicted by making ad hoc and possibly incorrect assumptions regarding the relationship between preference structures and choice behavior. In contrast, stated choice models are derived from choice data observed under hypothetical conditions. These models provide a powerful approach to testing simultaneously the assumed choice model and specification of the implied utility function. Nevertheless, conventional stated choice models are based on the rigorous assumption that the nonavailability of a particular travel alternative does not affect the utility and relative choice probability of any other travel alternative included in a choice set. How designs that permit the estimation of such availability effects can be constructed is indicated. A case study on mode choice behavior in the Eindhoven region, the Netherlands, suggests that choice models incorporating such availability effects can improve the predictive success of mode choice models. The results suggest that people's preferences for choosing the car to commute are only slightly influenced by the availability of modes of public transportation.

The continued demand for environmental quality coupled with growing car availability ratios has led many governments to design transport policies that aim at reducing car use by stimulating public transportation. This development increases the importance of obtaining defensible measures of the impact of such transport policies. To allocate resources efficiently and effectively, transport planners require information on the costs and the likely choices or changes in choices that might result from the implementation of various planning alternatives.

Over the years, various modeling approaches have been suggested in the literature and applied to real-world transport planning problems to provide the required information. One such approach that has gained increasing interest in the transportation literature over the last decade is the stated preference or decompositional preference approach (*1–8*). In contrast to conventional models that are based on actual travel choices, stated preference models are derived from experimental design data (*3,9,10*). Individuals are typically presented a series of hypothetical travel alternatives, constructed according to the principles of the design of statistical experiments, and asked to express their strength of preference for each alternative. The overall preference measurements are then decomposed into part-worth utilities associated with the attribute levels used to describe the hypothetical travel alternatives. Choice behavior is predicted by assuming some functional relationship between preferences and overt behavior (*11*).

Stated preference models have been applied successfully in a variety of transport contexts such as long-distance travel choice (*12*), competition between coach and rail (*13,14*), preferences for bus services (*14,15*), preferences for rail services (*16,17*), the effects of area licensing proposals (*18*), route choice (*19,20*), valuation of travel time (*21,22*), destination choice (*23–28*), and the effect of transport facilities on residential choice behavior (*29*).

Nevertheless, stated preference models have not escaped criticisms. A fundamental objection to stated preference models has been that it is not readily evident that individuals will act in hypothetical situations in a way that resembles how they would act in the real world. A related concern is that individuals may not be able to carry out the experimental task in a way corresponding to their actual decision making. These concerns have stimulated methodological research indicating that the assumption that conventional models based on actual behavior are inherently superior no longer goes unchallenged. Still, preference models rely typically on ad hoc assumptions to relate preferences to choice probabilities.

Recently Louviere and Woodworth (*30*) have therefore suggested that choices rather than preferences be measured in controlled experiments. One then observes choices directly and does not have to make ad hoc assumptions regarding the relationship between preferences and overt choice behavior. This is not to say that choices in laboratory settings may not differ from choices in the real world. Thus, even though the choice experiments have some potential methodological advantages over preference experiments, one still has to demonstrate that expressed choices are systematically related to observed choices. In these stated choice experiments individuals are not asked to rate or rank a series of hypothetical travel alternatives, but rather to choose among them. To estimate the choice model, the travel alternatives are placed into choice sets, usually using 2^N (N is the number of alternatives) or fractional factorial designs. Louviere and Woodworth (*30*) and Louviere and Hensher (*31*) have formalized the necessary and sufficient conditions that experimental designs must meet to satisfy the statistical requirements of the multinomial logit (MNL) model that is typically used in this

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modeling approach. Louviere and Hensher (*31*) present two examples of this approach to forecast mode choice behavior.

A problem common to all these decompositional preference and choice models is the rigorous assumption that preferences and choices are independent of context. That is, these models typically assume that individuals form preferences for alternatives or choose among alternatives independently of the composition of the choice set. In the MNL model, this problem stems from the independence from irrelevant alternatives (IIA) property, which states that the utility of a particular choice alternative is independent of the existence and the attribute values of any other choice alternative included in a choice set. Consequently, pairwise choice probabilities are independent of choice set composition. This assumption of context independence is rather rigorous because one might hypothesize that the availability or nonavailability of some transport mode will affect individuals' preferences/utilities or choices for the remaining available modes.

Louviere (*32*) indicates how to develop experimental designs that allow one to test for violations of the IIA property underlying MNL models and estimate generalized choice models, but applications of this approach in transportation are restricted to problems of destination choice (*33,34*) and have concentrated on substitution effects. One would like to be able to estimate the impact of varying choice set compositions on (pairwise) choice probabilities.

The purpose of this paper, therefore, is to extend conventional stated preference and choice models to allow the estimation of availability effects and illustrate this approach in the context of transportation mode choice.

STUDY DESIGN

In an attempt to reduce car use, the Dutch Ministry of Transport has created new planning authorities (transport regions) whose task is to coordinate transport plans. These planning bodies have to develop various kinds of plans to stimulate public transport and carpooling, thereby reducing the use of the car for all kinds of daily activities. These planning authorities need information on the likely impacts of such policy decisions on travel choice behavior. This study is an attempt to develop a sophisticated stated choice model that may serve this purpose.

To estimate a stated choice model, one first has to decide on the travel options and their attributes that are varied in the experiment. Five mode choice alternatives were identified: car, train, carpooling, bus, and bicycle. Bicycle was used as a base alternative in the experimental design, implying that all results obtained are relative to the estimated utilities and choice probabilities for using the bicycle. Using a literature search and interviews with planners, the attributes presented in Table 1 were selected because these attributes affect individual mode choice behavior most or are of planning interest. Commuting journeys were selected as the context of interest because these account for a high proportion of actual travel distances.

The attributes used in the experiment were alternative-specific. Four attributes were selected to describe the car alternative: in-vehicle time, costs, in-vehicle delay, and walking distance. Each of these attributes was varied in terms of three attribute levels. The train alternative was described by seven attributes: in-vehicle time, fare, in-vehicle delay, walking distance, delay in departure time, comfort, and interchange. Six of these attributes were varied in terms of three levels; the remaining attribute (interchange) had two levels. Carpooling was represented by six three-level attributes: in-vehicle time, costs, in-vehicle delay, walking distance, delay in departure time, and driver. The bus alternative was described in terms of seven attributes: in-vehicle time, fare, in-vehicle delay, walking distance, delay in departure time, comfort, and interchange. In addition to these alternative-specific attributes, distance from home to place of work was selected as a generic background attribute. The levels of all numerical attributes were adjusted to distance traveled (see Table 1). Some of the attribute levels were made specific to distance to make the profiles more realistic. For the car and carpooling, walking distance included the walk from the parking lot to the job location; for the two other means of transportation, walking distance included the distance from home to the bus stop or railway station and from the railway station or bus stop to the job location.

The Eindhoven region in the Netherlands was chosen as the study area, primarily because the planning authorities indicated some interest in this research project and were willing to provide the funds required to distribute the questionnaires. In general, the region has a good supply of various kinds of public transport, but of course not every municipality has a train station, and the quality of bus service differs substantially among the municipalities. Also, carpooling schemes are not equally well developed in all parts of the region. Therefore, it seems that the Eindhoven region is perfect for examining availability effects.

The survey was undertaken in January 1991. Of the 2,150 questionnaires sent by mail to randomly selected households in the region who were asked to participate in this study provided they had a job, 347 usable questionnaires were returned after one follow-up attempt, a response rate of 16.1 percent. This may seem a low figure, but it should be remembered that unemployment rates and the proportion of retired people in the Netherlands are rather high. Although exact figures are not available, we believe that the response rate for the population of interest is roughly 30 to 40 percent. Unfortunately, the representatives of the sample could not be tested because of lack of relevant population statistics. The sample respondents account for 7,293 monthly commuter journeys, an average of 19.3 journeys per month per person. The average travel distance per trip is 16.22 km. Of these trips, 53.1 percent are made by car, 34.8 percent by bicycle, 4.0 percent by carpooling, 2.8 percent by bus, and 3.2 percent by train.

In addition to completing the stated choice task, the respondents were asked to provide information relating to their actual travel choices, their evaluation of features of the regional transport system, and the socioeconomic characteristics of their households. The results of analyses incorporating these variables are not reported in this paper. We focus on an illustration of the model specification and the design strategy.

DESIGN STRATEGY

When the IIA property is not satisfied, one approach is to introduce terms into the systematic component of the utility

TABLE 1 Names and Levels of Attributes

Attribute	distance	level 1	level 2	level 3
CAR:				
In-vehicle travel	8 km	7.5 min.	10.0 min.	12.5 min.
time in minutes	16 km	15.0 min.	20.0 min.	25.0 min.
	24 km	20.0 min.	30.0 min.	40.0 min.
In-vehicle delay	8 km	0.0 min.	2.0 min.	4.0 min.
in minutes	16 km	0.0 min.	4.0 min.	8.0 min.
	24 km	0.0 min.	6.0 min.	12.0 min.
Walking distance	8 km	1.0 min.	3.0 min.	5.0 min.
in minutes	16 km	1.0 min.	3.0 min.	5.0 min.
	24 km	1.0 min.	3.0 min.	5.0 min.
Costs	8 km	fl. 2.00	fl. 3.00	fl. 4.00
in guilders	16 km	fl. 3.00	fl. 5.10	fl. 7.20
	24 km	fl. 4.40	fl. 7.00	fl. 9.60
BUS:				
In-vehicle travel	8 km	10.0 min.	15.0 min.	20.0 min.
time in minutes	16 km	20.0 min.	30.0 min.	40.0 min.
	24 km	30.0 min.	45.0 min.	60.0 min.
Delay in depar-	8 km	0.0 min.	3.0 min.	6.0 min.
ture time in	16 km	0.0 min.	3.0 min.	6.0 min.
minutes	24 km	0.0 min.	3.0 min.	6.0 min.
In-vehicle delay	8 km	0.0 min.	2.0 min.	4.0 min.
in minutes	16 km	0.0 min.	4.0 min.	8.0 min.
	24 km	0.0 min.	6.0 min.	12.0 min.

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TABLE 1 *(continued)*

Attribute	distance	level 1	level 2	level 3
Walking distance	8 km	2.0 min.	5.0 min.	8.0 min.
in minutes	16 km	2.0 min.	5.0 min.	8.0 min.
	24 km	2.0 min.	5.0 min.	8.0 min.
Fare	8 km	fl. 1.00	fl. 1.50	fl. 2.00
in guilders	16 km	fl. 1.50	fl. 2.50	fl. 3.50
	24 km	fl. 2.00	fl. 3.00	fl. 4.00
Comfort	8 km	2.0	5.0	8.0
on a 0-10 scale	16 km	2.0	5.0	8.0
	24 km	2.0	5.0	8.0
Interchange	8 km	none	1	
	16 km	none	1	
	24 km	none	1	
CARPOOLING:				
In-vehicle travel	8 km	7.5 min.	10.0 min.	12.5 min.
time in minutes	16 km	15.0 min.	20.0 min.	25.0 min.
	24 km	20.0 min.	30.0 min.	40.0 min.
Delay in depar-	8 km	2.0 min.	5.0 min.	8.0 min.
ture time in	16 km	2.0 min.	5.0 min.	8.0 min.
minutes	24 km	2.0 min.	5.0 min.	8.0 min.
In-vehicle delay	8 km	0.0 min.	2.0 min.	4.0 min.
in minutes	16 km	0.0 min.	4.0 min.	8.0 min.
	24 km	0.0 min.	6.0 min.	12.0 min.
Walking distance	8 km	1.0 min.	3.0 min.	5.0 min.
in minutes	16 km	1.0 min.	3.0 min.	5.0 min.
	24 km	1.0 min.	3.0 min.	5.0 min.

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TABLE 1 (*continued*)

Attribute	distance	level 1	level 2	level 3
Costs	8 km	fl. 1.00	fl. 1.50	fl. 2.00
in guilders	16 km	fl. 1.50	fl. 2.50	fl. 3.50
	24 km	fl. 2.20	fl. 3.50	fl. 4.80
Who drives	8 km	self-drive;	passenger;	flexible
	16 km	self-drive;	passenger;	flexible
	24 km	self-drive;	passenger;	flexible
TRAIN:				
In-vehicle travel	8 km	7.5 min.	10.0 min.	12.5 min.
time in minutes	16 km	10.0 min.	15.0 min.	20.0 min.
	24 km	15.0 min.	20.0 min.	25.0 min.
Delay in depar-	8 km	0.0 min.	3.0 min.	6.0 min.
ture time in	16 km	0.0 min.	3.0 min.	6.0 min.
minutes	24 km	0.0 min.	3.0 min.	6.0 min.
In-vehicle delay	8 km	0.0 min.	1.0 min.	2.0 min.
in minutes	16 km	0.0 min.	2.0 min.	4.0 min.
	24 km	0.0 min.	3.0 min.	6.0 min.
Walking distance	8 km	2.0 min.	5.0 min.	8.0 min.
in minutes	16 km	2.0 min.	5.0 min.	8.0 min.
	24 km	2.0 min.	5.0 min.	8.0 min.
Fare	8 km	fl. 1.60	fl. 2.00	fl. 2.40
in guilders	16 km	fl. 2.00	fl. 3.00	fl. 4.00
	24 km	fl. 2.40	fl. 4.00	fl. 5.60

(*continued on next page*)

TABLE 1 (*continued*)

Attribute	distance	level 1	level 2	level 3
Comfort	8 km	2.0	5.0	8.0
on a 0-10 scale	16 km	2.0	5.0	8.0
	24 km	2.0	5.0	8.0
Interchange	8 km	none	1	
	16 km	none	1	
	24 km	none	1	

functions to represent the violations. If these terms are the levels of the attributes of the competing transportation modes, they are called attribute cross effects. If the terms represent the presence or absence of competing modes, they are called availability cross effects.

The general problem of optimal design for such discrete choice experiments is unsolved. Anderson and Wiley (*35*) have constructed locally optimal designs for the case in which alternatives are characterized by name only, and hence only availability cross effects need to be estimated. Lazari (*36*) and Lazari and Anderson (*37*) have considered the discrete choice set problem, in which both availability and attribute cross effects are present and there is only one attribute for each alternative. They provide an extensive catalog of designs for practical numbers of choice sets. General solutions are not available when the number of attributes for each alternative is large, except along the lines of this study.

For this study, the underlying design consisted of orthogonal fractional factorial designs arranged in a balanced incomplete block structure plus another orthogonal design with all modes present. The resulting design allows for estimation of mode-specific models including all mode-specific main effects, attribute cross effects, and availability cross effects. For the purpose of this paper only the mode-specific main effects and the availability cross effects have been estimated.

The following strategy was used to develop the experimental design that allows the estimation of availability effects. Remember that we have four travel modes (car, train, carpooling, and bus) with respectively four, seven, six, and seven attributes, and the bicycle as a base alternative. In addition, we have distance as a background variable. All of the attributes were assigned three levels, except the number of interchanges for bus and train, which only have two levels. First, a 54 treatment combination orthogonal fraction of the resulting $3^{23} * 2^2$ full factorial design was used to create choice sets of fixed size. These choice sets varied in terms of the descriptions of the four travel alternatives. Next, for each of the six pairs of travel alternatives [$6 = (4 \times 3)/2$], an orthogonal fraction consisting of 36 treatment combinations was selected from the corresponding full factorial designs to allow the estimation of availability effects. The full factorial design representing all possible profiles for the car is a 3^4 design; the bus and train profiles both involve a $2 * 3^6$ design; and the carpooling profiles imply a 3^6 design. Thus, for example, the full factorial design for the car versus bus option involves a $(3^4 + 2 * 3^6) = 2 * 3^{10}$ design. Likewise, the bus versus train option involves a $(2 * 3^6 + 2 * 3^6) = 2^2 * 3^{12}$ design. For all pairs of travel modes, a 36 treatment combination orthogonal fraction describing the two travel modes was selected from the corresponding full factorial design. The two designs were combined to create an overall design. Thus, in total, $54 + (6 * 36) = 270$ choice sets were created. Although this design strategy does not generate a perfectly orthogonal design as a result of the merging of the separate designs, the overall correlations are generally very low. The highest correlation that we observed was only -0.0022.

Each respondent was presented three randomly selected choice sets from the 54 treatment combinations design and two randomly selected choice sets from each of the paired comparison, 36 treatment designs. Thus, in total, each respondent was presented $3 + (6 * 2) = 15$ choice sets. Respondents were told to assume that only the travel modes described in a choice set were available for commuting. They were also informed that the travel modes described in the various choice sets differ in terms of the attribute levels as indicated previously. The descriptions of the available travel modes were displayed on a single sheet. Respondents were asked to allocate 20 trips among the travel alternatives included in each choice set given that only the ones listed in a particular choice set are available. This task was repeated twice: once for the summer situation and once for the winter situation. Care was taken that respondents fully understood the experimental task and that they were familiar with the attributes and their levels used in the experiment. Before presenting the experimental task, respondents were asked to evaluate separately the attribute levels. Moreover, the task was explained in detail using an example, and respondents were asked to make sure they understood their task before completing the questionnaire.

The questionnaire was extensively pretested; the version that was finally used was the third version that was pretested.

ANALYSIS

Attribute Effects

The allocation data were aggregated across respondents to relative frequencies. Iterative reweighted least squares analysis was used to estimate the choice model. The following model was estimated:

$$p_{j|S} = \exp(V_{j|S}) / \sum_{j' \in S} \exp(V_{j'|S}) \tag{1}$$

$$V_{j|S} = \alpha_j + \sum_{j' \in S \setminus \{j\}} \gamma_{j'j} + \sum_{k=1} \beta_{jk} X_{jk} \tag{2}$$

where

$p_{j|S}$ = probability that travel alternative j in choice set S will be chosen,
$V_{j|S}$ = deterministic part of the utility of j in choice set S,
α_j = alternative-specific constant for alternative j,
$\gamma_{j'j}$ = availability effect of alternative j' on alternative j,
β_{jk} = parameter for the kth attribute of the jth travel alternative, and
X_{jk} = value of attribute k of travel alternative j.

Dummy coding was used to represent the availability effects and alternative-specific constants. To obtain a parsimonious model, the actual values rather than the categorical levels were used in estimating the choice model. Moreover, to reduce interattribute correlations, deviations from the mean were used in the analysis. Finally, both linear and quadratic effects were estimated to allow for nonlinear effects.

The parameter estimates are presented in Table 2, and the part-worth utility functions are shown in Figure 1. Note that

TABLE 2 Parameter Estimates of the Choice Model

	parameter estimate	standard error	t-value
CAR:			
constant	1.04	0.022	47.66
in vehicle time			
-linear	-0.02	0.002	-10.64
-quadratic	-0.10	0.008	-13.34
In-vehicle delay			
-linear	-0.05	0.002	-26.87
-quadratic	-0.06	0.046	-1.40
walking distance			
-linear	-0.00	0.004	-0.87
-quadratic	-1.88	0.341	-5.50
costs			
-linear	-0.14	0.004	-30.62
-quadratic	-0.83	0.138	-5.99
distance	0.20	0.002	80.74

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TABLE 2 (*continued*)

	parameter estimate	standard error	t-value
TRAIN:			
constant	0.79	0.026	30.59
in vehicle time			
-linear	-0.08	0.002	-35.71
-quadratic	0.21	0.027	7.63
delay in departure			
-linear	-0.08	0.003	-27.64
-quadratic	0.26	0.163	1.58
in-vehicle delay			
-linear	-0.05	0.004	-10.88
-quadratic	3.17	0.193	16.41
walking distance			
-linear	-0.09	0.003	-31.25
-quadratic	-1.24	0.161	-7.74
costs			
-linear	-0.22	0.010	-21.76
-quadratic	-1.67	0.476	-3.50
comfort			
-linear	0.06	0.003	21.68
-quadratic	-1.17	0.163	-7.18
interchange	-0.06	0.007	-8.05
distance	0.28	0.002	121.15
CARPOOL:			
constant	0.91	0.023	38.63
in vehicle time			
-linear	-0.05	0.002	-27.58
-quadratic	-0.02	0.008	-2.90

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TABLE 2 (*continued*)

	parameter estimate	standard error	t-value
waiting time			
-linear	-0.06	0.003	-21.18
-quadratic	-0.07	0.156	-0.44
in-vehicle delay			
-linear	-0.05	0.002	-22.36
-quadratic	0.07	0.048	1.51
walking distance			
-linear	-0.00	0.004	-0.88
-quadratic	1.37	0.367	3.74
costs			
-linear	-0.21	0.010	-22.01
-quadratic	6.65	0.591	11.25
driver	-0.02	0.008	-2.64
distance	0.24	0.003	94.54
BUS:			
constant	0.03	0.036	0.92
in vehicle time			
-linear	-0.06	0.001	-44.95
-quadratic	-0.04	0.006	-8.01
delay in departure			
-linear	-0.03	0.004	-6.47
-quadratic	-0.84	0.218	-3.86
in-vehicle delay			
-linear	-0.01	0.003	-3.55
-quadratic	-0.02	0.068	-0.35
walking distance			
-linear	-0.06	0.004	-15.77

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TABLE 2 (*continued*)

	parameter estimate	standard error	t-value
-quadratic	1.80	0.227	7.91
costs			
-linear	-0.39	0.014	-28.12
-quadratic	7.17	1.053	6.81
comfort			
-linear	0.11	0.004	28.02
-quadratic	-1.85	0.218	-8.49
interchange	-0.18	0.010	-19.01
distance	0.26	0.003	84.64

for ease of interpretation of Figure 1, the parameter estimates were rescaled, setting the origin of each part-worth utility scale to zero.

The results obtained for in-vehicle travel time indicate that utility decreases with increasing in-vehicle time, as expected. Apparently, respondents are less concerned about in-vehicle travel time while driving their cars; they are much more sensitive to in-vehicle travel time with respect to the bus and carpooling, and especially with respect to the train.

The parameter estimates for fare/costs indicate that, as expected, respondents are less sensitive to increasing costs with respect to car and carpooling compared with means of public transport. For all these part-worth utilities both the linear and the quadratic terms are significant at conventional probability levels.

The parameters obtained for in-vehicle delay clearly demonstrate that utility for the car and carpooling drops dramatically with increasing delays. Respondents' utility is much less influenced by increasing delays for train and bus. Apparently, delays are already associated with means of public transport, implying that increasing delays affect utility much less. Again, both the linear and the quadratic effects are significant. The utility function for the train is unexpected in that utility increases with substantial delays. It is not readily evident why this effect occurs.

The effects of walking distance indicate that the part-worth utility functions of the two means of public transport decrease with increasing walking distance. The effects are less clear for car and carpooling. This finding suggests that the probability that respondents will choose a means of public transport is affected adversely with increasing walking distance. The slope of the utility function suggests that these effects might be dramatic.

The comfort attribute was used only in connection with the train and the bus. Because it is a multidimensional construct, several indicator variables were used to measure the comfort dimension. Therefore, we first analyzed the contribution of these indicator variables to the overall evaluation of comfort using multiple regression analysis. Next, the effect of comfort on choice probabilities was analyzed. The following equations were estimated:

$$E_{\text{bus}} = 5.12 + 0.71X_{1,\text{bus}} + 0.95X_{2,\text{bus}} + 0.65X_{3,\text{bus}} + \varepsilon_{\text{bus}} \quad (3)$$

and

$$E_{\text{train}} = 6.18 + 0.67X_{1,\text{train}} + 0.63X_{2,\text{train}} + 0.81X_{3,\text{train}} + 0.46X_{4,\text{train}} + \varepsilon_{\text{train}} \quad (4)$$

where

E_{bus} = evaluation of the comfort of the bus;
$X_{1,\text{bus}}$ = -1 if old equipment, 1 if new equipment;
$X_{2,\text{bus}}$ = -1 if no shelter is available at the bus stop, 1 otherwise;
$X_{3,\text{bus}}$ = -1 if there is a 75 percent chance of seat availability, 1 if a seat is available for certain for the entire trip;
ε_{bus} = an error term;
E_{train} = the evaluation of the comfort of the train;
$X_{1,\text{train}}$ = -1 if old equipment, 1 if new equipment;
$X_{2,\text{train}}$ = -1 if no shelter is available at the railway station, 1 otherwise;
$X_{3,\text{train}}$ = -1 if there is a 75 percent chance of seat availability, 1 if a seat is available for certain for the entire trip;
$X_{4,\text{train}}$ = -1 if no refreshments are available on train, 1 otherwise; and
$\varepsilon_{\text{train}}$ = an error term.

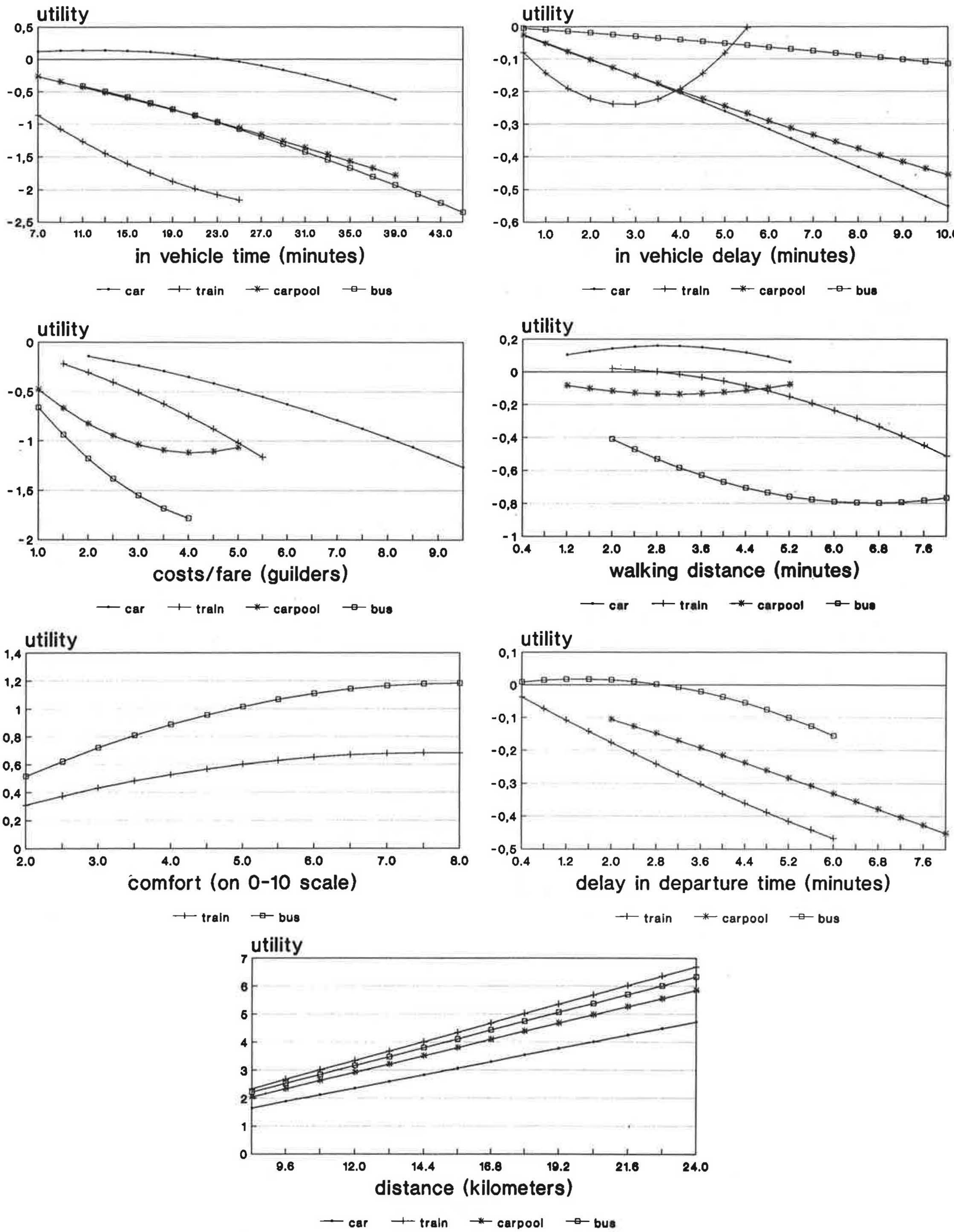

FIGURE 1 Part-worth utility functions.

The explained variances were respectively 98 and 99 percent. For the bus, the evaluation of comfort is determined mostly by shelter provision, followed by new equipment and the chance of obtaining a seat. For the train, seat availability is the most important attribute contributing to comfort, followed by new equipment, shelter provision, and refreshments, respectively. The parameters for both the bus and the train were highly significant.

The effect of comfort on utilities demonstrates that the probability of choosing the train or the bus increases with increased evaluation of the comfort dimension. This effect is larger for the bus.

Delay in departure time was incorporated into the utility function of the train, bus, and carpooling only. All three part-worth utility functions decrease with increasing waiting time. Respondents are most sensitive to increasing waiting times for the train, followed by carpooling and bus, respectively.

The utilities for the distance attribute indicate that the utility of all other transport modes via-à-vis the bicycle increases with increasing distance. This effect is largest, as expected, for the train, followed by bus, carpooling, and car.

Interchange was included in the utility function of the two selected means of public transport. Consistent with a priori expectations, both parameter estimates were negative, suggesting that choice probabilities decrease if an interchange is involved. The parameter estimate is higher for the bus. This suggests that respondents are more concerned about an interchange when choosing the bus than when choosing the train.

Finally, a "who drives" variable was included to describe the carpooling alternative. The estimated parameter estimate was −0.022, which reflects that respondents prefer to be a passenger rather than the driver when carpooling.

Availability Effects

These analyses are not different from those typically conducted in stated choice experiments in a transportation context. However, in this study we also estimated availability effects to examine whether the composition of the choice set has any effect on the utility of the travel alternatives. These availability effects depict any departures from the choice probability implied by the IIA-MNL model. The availability effects are presented in Table 3. The diagonal elements are the mode constants, and the other values in each row are the availability effects on the transportation mode as described by the row labels. The availability effects represent changes in the alternative-specific utility functions and are a result of the composition of a choice set. If the MNL holds, implying that the IIA property holds as well, the ratio of choosing a particular travel alternative relative to any other alternative would be independent of choice set composition. Consequently, the availability effects would all be equal to zero (or at least would statistically not be significantly different from zero). Likewise, significant availability effects depict departures from IIA that arise as a result of differences in choice set composition. Except for the relatively small effect of bus on car and the nonsignificant effect of bus on train, all the availability effects are negative and highly significant. This indicates that the transportation modes are to some extent substitutes for each other, but the effects are not symmetric. For example, the availability cross effects of each mode on car are significantly smaller than the corresponding effect of car on each mode. Only the effects of train and carpool are similar in magnitude.

Since we have assumed for practical reasons that the availability by attribute interactions is negligible, the availability cross effects influence only the mode constants in this model. The column ALL PRESENT in Table 3 is just the row sum, and it represents the mode constants in choice sets that have all four modes available. To get the constants in reduced sets, one simply has to sum across columns for those present. There are significant changes in these constants for different subsets.

One way to interpret the availability cross effects is to examine the (relative) changes in mode share and odds ratios for different patterns of availability. Table 4 presents some of these shares and odds assuming that the total contribution to the utility of each mode from the attributes is zero. Table 4 also presents the odds ratios for the MNL model that does not incorporate the effects of differences in choice set composition. Note that Table 4 only displays a few examples of varying choice set composition. The rows in Table 4 represent different choice set compositions, "----" indicating the nonavailability of that transport mode. The first five columns represent the market share of each transport mode as predicted by the non-IIA model that includes the estimated availability effects. Thus, the market share of the car is predicted to be equal to 40 percent if all five transport modes are available. The market share of the car increases to 47.5 percent

TABLE 3 Availability Effects (Off-Diagonal Elements) and Mode Constants (Diagonal Elements)

	CAR	TRAIN	CARPOOL	BUS	ALL PRESENT
CAR	1.040	-.114	-.271	.075	.730
TRAIN	-.295	.792	-.427	.005	.075
CARPOOL	-.527	-.412	.909	-.179	-.209
BUS	-.500	-.571	-.463	.033	-1.501

TABLE 4 Mode Shares and Odds Ratios (All Else = Zero)

	NON-IIA-MODEL								MNL-MODEL		
	MODE-SHARES					ODDS-RATIOS			ODDS-RATIOS		
SET	CAR	TRAIN	CPOOL	BUS	BIKE	C/TR	C/CP	TR/CP	C/TR	C/CP	TR/CP
1	.400	.208	.156	.043	.193	1.92	2.56	1.33	1.56	1.68	1.08
2	.388	.216	.195	----[1]	.201	1.80	1.99	1.11	1.56	1.68	1.08
3	.475	.288	----	.062	.175	1.65	----	----	1.56	----	----
4	.470	----	.248	.080	.202	----	1.89	----	----	1.68	----
5	----	.346	.328	.088	.239	----	----	1.05	----	----	1.08
6	.488	.318	----	----	----	1.53	----	----	1.56	----	----
7	.467	----	.317	----	.216	----	1.47	----	----	1.68	----
8	.652	----	----	.134	.214	----	----	----	----	----	----
9	----	.353	.402	----	----	----	----	0.88	----	----	1.08
10	----	.583	----	.154	.263	----	----	----	----	----	----
11	----	----	.557	.175	.268	----	----	----	----	----	----

[1]non-available transport mode

if the carpooling option is not available (Choice Set 3). Columns 6 to 8 represent the odds ratio for, respectively, car-train, car-carpooling, and train-carpooling as predicted by the model that includes the availability effects. Columns 9 to 11 present the corresponding odds ratios for the conventional MNL model. Note that these odds ratios are not influenced by the composition of the choice set (IIA property).

Examination of Table 4 then indicates that the odds ratio for share of car to train changes from 1.92 to 1.53, and car to carpool changes from 2.56 to 1.47 as the availability pattern changes. The odds ratio of train to carpool changes from 1.33 to 0.88. The differential mode shifts in changing availability are thus captured by the cross effects included in the choice model.

The MNL model predicts these odds ratios to be constant, independent of the availability of particular transport modes. A comparison of the ratios for the two models thus provides useful information about mode shifts. For example, the conventional MNL model indicates a slight preference for the train relative to carpooling (odds ratio = 1.08). The ratios obtained for the model that includes the availability effects indicates that this ratio is higher (1.33) if all transport modes are available, but drops to 1.05 if the car is not available. Apparently, therefore, a substantial proportion of commuters says it will switch from car to carpooling rather than choose the train if the car is not available. This ratio drops further to 0.88 if both the car and the bus are not available.

Similar patterns are observed for the odds ratio car-train. If all transport modes are available, this ratio is equal to 1.92. The ratio drops to 1.80 and 1.65 if the bus and carpooling, respectively, are not available. This result indicates that a larger proportion of commuters is predicted to switch to the train rather than to the car if the bus or carpooling are not available. Thus, these odds ratios provide useful information about the competitive structure among the transport modes.

Goodness-of-Fit

The goodness-of-fit of the model was satisfactory. The log likelihood for the null model was −250,716.781; the log likelihood for the estimated model was −204,074.141. The chi-square statistic for the likelihood ratio test was 93,285.28 with 130 degrees of freedom. Thus, the estimated model significantly improves the null model.

The choice model was also estimated without the availability effects. The log likelihood for this case is −205,782.141.

The chi-square statistic for the likelihood ratio test was 3,416.00 with 24 degrees of freedom. Thus, it can be concluded that the inclusion of availability effects significantly improves the performance of the choice model.

CONCLUSION AND DISCUSSION

This paper has focused on the extension of stated choice models in transportation analyses. It has been shown how the MNL model can be extended to include availability effects that represent the effect of the availability or nonavailability of some travel alternative on the utility of remaining alternatives in the choice set. The results of this study suggest that the inclusion of such effects in models of mode choice may considerably improve the predictive success of the choice model. Such effects may account for departures from the IIA property underlying the MNL model.

The ease of including availability effects in a choice model constitutes another advantage of using choice experiments rather than preference experiments typically used in stated preference studies in transportation contexts. As Louviere and Gaeth (*38*) have advocated, the major advantage of choice tasks over rating or ranking tasks is that they focus on choice and hence are probably closer to actual decision making. Moreover, one does not require ad hoc assumptions to relate preferences to choices. Also, choice tasks make it easy to examine much more of the statistical response surface than is usually possible with traditional full-profile stated preference tasks. Finally, as has been illustrated by the present paper, choice experiments can be designed to accommodate a much wider variety of choice models and utility specifications.

The approach outlined in this paper produces models that are compatible with existing discrete choice models. Hence, no specific abilities are required to implement these "availability effects" models. One only needs to know how to design choice experiments that allow availability effects to be estimated. Especially for small-scale problems involving a limited set of attributes, such designs are easy to develop and administer, although choice experiments are more difficult to design than preference designs commonly applied in transportation.

From a substantive viewpoint, the results of this analysis indicate that people's habits to use the car for commuting will be difficult to change. People's preferences for the car only slightly decrease when its attributes deteriorate. Moreover, preferences for modes of public transport drop dramatically with less favorable attribute levels. It implies that the objectives of the transportation planners may be difficult to achieve fully. The values and signs of the availability effects indicate the degree of substitution between transportation modes. These parameters reiterate the strength of the position of the car compared with other transport modes.

We believe that transport mode models incorporating availability effects provide improved information to transportation planners. First, if the results of this application can be replicated in other contexts, models that include availability effects provide better predictions of transport mode share. Second, and perhaps more important, these non-IIA models provide transportation planners with the necessary information that allows them to identify the competitive structure among the transport modes. For example, in the present case the results of the model indicate that policies that aim at substantially reducing the market share of the car by introducing, stimulating, or expanding carpooling schemes or public transportation are not likely to be very successful, because these modes primarily compete among one another rather than with the car. Such additional information would not be provided by conventional MNL or other IIA models, simply because these models are based on the assumption that the utilities and market shares of transport modes are not influenced by the availability of any other transport mode in individuals' choice sets.

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REFERENCES

1. J. J. Louviere and K. L. Norman. Applications of Information-Processing Theory to the Analysis of Urban Travel Demand. *Environment and Behavior*, Vol. 9, 1977, pp. 91–106.
2. J. J. Bates and M. Roberts. Recent Experience with Models Fitted to Stated Preference Data. *Proc., PTRC 11th Summer Annual Meeting*, University of Sussex, Brighton, Vol. P243, 1983, pp. 61–82.
3. J. J. Louviere. Conjoint Analysis Modeling of Stated Preferences. *Journal of Transport Economics and Policy*, Vol. 22, 1988, pp. 93–119.
4. E. P. Kroes and R. J. Sheldon. Stated Preference Methods. *Journal of Transport Economics and Policy*, Vol. 22, 1988, pp. 11–25.
5. J. J. Bates. Econometric Issues in Stated Preference Analysis. *Journal of Transport Economics and Policy*, Vol. 22, 1988, pp. 59–71.
6. D. A. Hensher, P. O. Barnard, and T. P. Truong. The Role of Stated Preference Methods in Studies of Travel Choice. *Journal of Transport Economics and Policy*, Vol. 22, 1988, pp. 45–59.
7. M. Wardman. A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. *Journal of Transport Economics and Policy*, Vol. 22, 1988, pp. 71–91.
8. M. Wardman. Stated Preference Methods and Travel Demand Forecasting: An Examination of the Scale Factor Problem. *Transportation Research A*, Vol. 25, 1991, pp. 79–89.
9. H. J. P. Timmermans. Decompositional Multiattribute Preference Models in Spatial Choice Analysis: A Review of Some Recent Trends. *Progress in Human Geography*, Vol. 8, 1984, pp. 189–221.
10. T. Fowkes and T. Wardman. The Design of Stated Preference Travel Choice Experiments. *Journal of Transport Economics and Policy*, Vol. 22, 1988, pp. 27–45.
11. E. P. Kroes, R. J. Sheldon, and R. Swanson. Developing Choice Models Using Stated Preference Research. *Proc., PTRC 15th Summer Annual Meeting*, Bath, Vol. P290, 1987, pp. 131–153.
12. J. J. Bates. Stated Preference Techniques for the Analysis of Transport Behaviour. *Proc., World Conference on Transport Research*, Vol. 1, 1983, pp. 252–265.
13. J. J. Louviere, D. H. Henley, G. Woodworth, R. J. Meyer, I. P. Levin, J. W. Stoner, D. Curry, and D. A. Anderson. Laboratory Simulation Versus Revealed Preference Methods for Estimating Travel Demand Models. In *Transportation Research Record 794*, TRB, National Research Council, Washington, D.C., 1981, pp. 42–51.

14. H. J. P. Timmermans and Th. Overduin. Information Integration and Mode Choice Behaviour: Theory and Application (in Dutch). *Verkeerskunde*, Vol. 31, 1980, pp. 321–325.
15. M. Bradley, E. Kroes, R. Sheldon, S. Widlert, T. Gärling, and S. Uhlin. Preferences for Bus and Underground Services in Stockholm. Presented at the Fifth World Conference on Transport Research, Yokohama, Japan, July 10–14, 1989.
16. P. B. Anderson, J. Møeller, and R. J. Sheldon. Marketing DSB Rail Service Using a Stated Preference Approach. *Proc., PTRC 14th Summer Annual Meeting*, University of Sussex, Brighton, Vol. P282, 1986, pp. 263–270.
17. J. Dinwoodie. A Stated Preference Approach to Forecasting Suburban Rail Demand in Eastern Plymouth. *Proc., PTRC 17th Annual Meeting*, University of Sussex, Brighton, Vol. P318, 1989, pp. 169–180.
18. D. A. Hensher and J. J. Louviere. Behavioural Intentions as Predictors of Very Specific Behaviour. *Transportation*, Vol. 8, 1979, pp. 167–182.
19. M. Bradley and P. H. L. Bovy. A Stated Preference Analysis of Bicyclist Route Choice. *Proc., PTRC 12th Summer Annual Meeting*, University of Sussex, Brighton, Vol. P257, 1984, pp. 39–53.
20. P. H. L. Bovy and M. Bradley. Route Choice Analyzed with Stated Preference Approaches. Presented at the 64th Annual Meeting of the Transportation Research Board, Washington, D.C., 1985.
21. J. J. Bates. Values of Time from Stated Preference Data. *Proc., PTRC 12th Summer Annual Meeting*, University of Sussex, Brighton, Vol. P257, 1984, pp. 15–37.
22. D. A. Hensher and T. P. Truong. Valuation of Travel Time Savings. *Journal of Transport Economics and Policy*, Vol. 9, 1985, pp. 237–261.
23. H. J. Schuler. A Disaggregate Store-Choice Model of Spatial Decision-Making. *Professional Geographer*, Vol. 31, 1979, pp. 146–156.
24. H. J. P. Timmermans. Consumer Choice of Shopping Centre: An Information Integration Approach. *Regional Studies*, Vol. 16, 1982, pp. 171–182.
25. S. R. Lieber and D. R. Fesenmaier. Modeling Recreation Choice: A Case Study of Management Alternatives in Chicago. *Regional Studies*, Vol. 18, 1984, pp. 31–43.
26. H. Timmermans, R. van der Heijden, and H. Westerveld. Decision-Making Experiments and Real-World Choice Behaviour. *Geografiska Annaler*, Vol. 66B, 1984, pp. 39–48.
27. J. J. Louviere and H. J. P. Timmermans. Using Hierarchical Information Integration To Model Consumer Response to Possible Planning Actions: Recreation Destination Choice Illustration. *Environment and Planning A*, Vol. 22, 1990, pp. 291–309.
28. J. J. Louviere and H. J. P. Timmermans. Preference Analysis Choice Modeling and Demand Forecasting. In *Proc., National Outdoor Recreation Trends Symposium III* (J. T. O'Leary, D. R. Fesenmaier, T. Brown, D. Stynes, and B. Driver, eds.), Vol. I, Purdue University, West Lafayette, Ind., 1991, pp. 52–66.
29. A. Borgers and H. J. P. Timmermans. Transport Facilities and Residential Choice Behaviour. Forthcoming in *Papers in Regional Science*.
30. J. J. Louviere and G. G. Woodworth. Design and Analysis of Simulated Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research*, Vol. 20, 1983, pp. 350–367.
31. J. J. Louviere and D. A. Hensher. Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modeling. In *Transportation Research Record 890*, TRB, National Research Council, Washington, D.C., 1982, pp. 11–17.
32. J. J. Louviere. A Conjoint Model for Analyzing New Product Positions in a Differentiated Market with Price Competition. *Advances in Consumer Research*, Vol. 13, 1986, pp. 375–380.
33. H. J. P. Timmermans, A. W. J. Borgers, and P. J. H. J. van der Waerden. Mother Logit Analysis of Consumer Shopping Destination Choice. *Journal of Business Research*, Vol. 23, 1991, pp. 311–323.
34. H. Oppewal and H. J. P. Timmermans. Context Effects and Decompositional Choice Modeling. *Papers in Regional Science*, Vol. 70, 1991, pp. 113–131.
35. D. A. Anderson and J. B. Wiley. Optimal and Near Optimal Designs for Estimating Cross Effects Models. Forthcoming in *Journal of Marketing Research*.
36. A. Lazari. *Designs for Discrete Choice Experiments Including Availability and Attribute Cross Effects*. Ph.D. dissertation. University of Wyoming, Laramie, 1991.
37. A. Lazari and D. A. Anderson. *Availability and Attribute Cross Effects Models: Determinant Optimal Designs*. Technical Report. University of Wyoming (submitted for publication).
38. J. J. Louviere and G. J. Gaeth. A Comparison of Rating and Choice Responses in Conjoint Tasks. In *Sawtooth Software Conference on Perceptual Mapping, Conjoint Analysis and Computer Interviewing* (R. M. Johnson, ed.), Sawtooth Software, Inc., Ketchum, Idaho, 1988, pp. 59–74.

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