Context effects and decompositional choice modeling

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CONTEXT EFFECTS AND DECOMPOSITIONAL CHOICE MODELING

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ABSTRACT This paper describes the application of the extended or universal logit model to decompositional or "stated" choice modeling in order to increase the scope and validity of such choice models. In this approach, choice experiments are designed that permit the estimation of utility functions that include the effects of context variables like choice set composition and decision background. The approach is illustrated with some simple calculated examples concerning consumer choice of shopping center, housing, and transportation mode.

1. INTRODUCTION

Decompositional multiattribute preference and choice models, also known as stated preference/choice models, have gained increasing popularity in regional science and related disciplines. A decade ago, this modeling approach had been applied in this discipline in a few cases, especially in the field of housing studies and shopping behavior (Timmermans 1984); 10 years later it has become an established approach in fields like transportation (see, e.g., special issue of *Journal of Transport Economics and Policy,* Vol. 22, 1988) and recreation research (see, e.g., special issue of *Leisure Sciences,* Vol. 12, 1990) as well, for predicting consumer preferences and (spatial) choice behavior.

The approach is based on the assumption that preferences or utilities can be uncovered by presenting subjects with profiles (i.e., descriptions in terms of relevant attributes) of hypothetical choice alternatives (transportation systems, housing situations, shopping centers, etc.) and asking them to express their preference for these profiles. To maximize statistical efficiency, these profiles are constructed according to the principles of the design of statistical experiments. A subject's preferences are then decomposed into so-called *part-worth utilities,* which represent the contribution to the subject's overall preference or utility of the attribute levels what were used to generate the profiles. Strictly speaking, this is a preference model. If one wishes to construct a choice model, for instance, the multinomial logit model, the attribute profiles have to be placed into choice sets. Subjects are then asked to choose one alternative from each choice set or, alternatively, to allocate some fixed budget among the choice alternatives (Louviere and Woodworth 1983). One can then estimate the param-

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eters of the preference/utility function and test the specification of the choice model simultaneously. The details of decompositional preference and choice modeling and its pros and cons are discussed at more length elsewhere (Green and Srinivasan 1978; Timmermans 1984; Louviere 1988a, 1988b; Bates 1988; Louviere and Timmermans 1990a, 1990b).

Most models estimated from decompositional preference or choice experiments involve utility functions with only main effects, that pertain to the attributes of alternatives. In these cases a compensatory decision process is assumed: a consumer's low evaluation of a particular attribute of some alternative may at least be partially compensated by a high evaluation of one or more of the remaining attributes of this alternative. Some applications involve the use of interaction effects among attributes; hence, such models are capable of approximating noncompensatory decision processes. Often, numerical attributes are varied to have more than two levels to permit the estimation of nonlinear utility functions. Though these kinds of model specifications are flexible and have proven to be quite robust in many applications (Louviere 1988b), they are limited in that the models all assume independence of context.

The *decision context* may affect the decision-making process in various ways. First, the *composition* of the choice set may influence the evaluation of an alternative. This may be either because (a) the size of the choice set brings consumers to use noncompensatory decision heuristics to screen and eliminate alternatives (e.g., Timmermans 1983, 1984), (b) some alternatives are perceived as being more similar and therefore more substitutable, or (c) the framing or presentation format of the choice task leads consumers to attribute-wise processing of information (Payne 1976; Recker and Golob 1979; Johnson and Meyer 1984). Such effects would violate the assumption of Independence of Irrelevant Alternatives (IIA), which underlies the multinomial logit (MNL) model and which states that the utility of a choice alternative is independent from the existence and attributes of all other alternatives in one's choice set. There have been many attempts to derive tractable models that relax this assumption. A review of such models can be found in Timmermans and Golledge (1990).

Second, preference or utility functions can only be assumed to be valid over a limited set of circumstances. This is because variables that describe the *background* of the choice situation may differentially affect the evaluations of the alternatives. For example, people's evaluations of housing attributes might be conditional upon factors such as mortgage costs and tax levels. Likewise, firms' investment strategies will be influenced by interest levels, economic prospects, and strategic planning of competitors, and choice of transportation mode will likely be dependent on trip purpose. Most applications do not explicitly account for such background effects in the specification of the utility function. Either one assumes that the model is independent of context and the model is applied directly to different conditions, or a new model is estimated for each condition separately.

Both kinds of context effects — composition effects and background effects — can, however, be incorporated to a large extent in the MNL framework by extending the specification of the utility function, as suggested and applied by McFadden, Train, and Tye (1977). These extensions come close to treating the logit model as a general statistical method for the analysis of categorical data, as described, e.g., in Wrigley (1985).

As will be demonstrated, the principles that apply to the design of choice experiments to estimate MNL models — such as fixed-size choice sets of orthogonal profiles, or choice sets of varying size constructed by way of a 2^N design (Louviere and Woodworth 1983) — also apply to the design of choice experiments to estimate and test such extended MNL models.

The inclusion of composition and background effects might substantially improve the validity and predictive success of decompositional models. Although the results of theoretical and statistical work are available, few researchers seem to have put these advances together into a general approach, let alone apply these principles in their experimental work. The purpose of this paper is therefore to present a general framework for developing such extended logit models from, and for, decompositional choice experiments. The paper will discuss some recent advances in this field of study and illustrate the principles with a series of examples. The discussion will be limited to decompositional choice experiments only, although most of these principles could be applied to decompositional preference models as well.

2. THE EXTENDED LOGIT MODEL

The extended model that is capable of estimating contextual effects may be expressed as a straightforward extension of the standard multinomial logit model. Therefore we will first recapitulate the MNL model and describe the design matrix for the estimation of this standard choice model from a choice experiment.

The Standard Model

Note that the standard multinomial logit model is based on the following assumption:

$$P(i \mid A) = \frac{\exp(U_i)}{\Sigma_{j \varepsilon A} \exp(U_j)},$$

$$U_i = V_i + e_i$$

$$= f_i\,(X_{ik}) + e_i, \qquad \forall\ i\ \varepsilon\ A, \text{ and } A \subseteq S,$$

where

$P(i \mid A)$ is the probability that choice alternative i is chosen from set A,

U_i is the utility of choice alternative i in choice set A, which is a subset of the global choice set S,

V_i is the explained part of the utility for i,

X_{ik} is the k^{th} attribute of alternative i, and

e_i is an error term.

Note that alternatives i in A can be either generic profiles or specific alternatives. The explained or deterministic part of the utility function is assumed to be a linear-in-the-parameters function of the K attributes X_{ik} ($k = 1 \ldots, K$) that describe alternative i. Choice probabilities depend on the assumptions regarding the error terms. The MNL model assumes the error terms to be identically and independently distributed according to the double exponential, or type I extreme value, distribution. This assumption leads to a random utility model that is compatible with Luce's Choice Axiom (Luce 1959) — a strict form of the Independence of Irrelevant Alternatives (IIA) property. The IIA assumption can be interpreted in terms of utility in that the utility of some alternative is a function of the attributes of that alternative only and is independent from attributes of other alternatives in the choice set.

Choice experiments can be designed that permit maximum statistical efficiency in the estimation of an MNL choice model. Details on how to design and analyze such experiments can be found in Louviere and Woodworth (1983) and Louviere (1988a, 1988b). For the present, let us assume a choice experiment has been administered to a sufficiently large number of respondents, in which a total set of choice sets, say G, was presented and where some set A within G contained I_A alternatives. One of these choice alternatives would typically be a base alternative that is present in all choice sets. A design matrix **Z** is required to estimate the choice model assumed to underlie the observed choices. Matrix **Z** consists of T rows, where $T = \Sigma_{A \epsilon G} I_A$. Each row of **Z** represents a choice alternative. The base alternative is represented by a row of zeroes only.

Suppose there are, in addition to the base, a total of B different *specific alternatives* (or modes or brands). Specific alternative b varies on K_b attributes. So, the total number of specific attributes in the experiment is equal to $\Sigma_{b=1}^{B} K_b$. Different coding schemes, such as dummy, effect, or orthogonal coding, may be used to represent the attribute effects. In all cases, the main effects of an attribute with L levels can be represented in $L - 1$ indicator variables. The total number of main-effects indicator variables for alternative b is then $M_b = \Sigma_{k=1}^{K} (L_{kb} - 1)$. The maximum number of two-way interactions between the attributes within specific alternatives can be specified as

$$N = \Sigma_{b=1}^{B}[M_b(M_b - 1)/2],$$

i.e., the number of possible pairs of indicator variables within specific alternatives. Then, the columns in **Z** appear in blocks:

$$\mathbf{Z} = [\mathbf{Z1} \,|\, \mathbf{Z2} \,|\, \mathbf{Z3}],$$

where

Z1 is a $T \times B$ indicator matrix that represents the alternative specific constants.

Z2 is a $T \times M$ matrix that represents the levels of the alternative specific attributes. Rows that refer to other specific alternatives contain only zeroes. Each column corresponds to an *attribute "own" main effect* in the utility function.

Z3 is a $T \times N$ matrix that represents all possible two-way attribute interactions within brands. Higher-order interactions can be included as well, provided the design allows the estimation of such effects.

Note that $B = 1$ if the experiment concerns only *generic* alternatives. This could drastically reduce the number of parameters.

Composition Effects

The standard utility model can be extended to include constants and attributes of other available alternatives in the utility function, as first applied by McFadden, Train, and Tye (1977) who called this extended model the Universal Logit model. Such additional terms, called *cross effects,* represent corrections on the utilities as predicted by the standard IIA-type model, to account for the composition effects mentioned previously. Significant cross effects indicate violations of the IIA property and so provide direct tests of IIA. To distinguish between utility derived from the standard IIA-type of model and utility that is corrected by cross effects, the corrected, non-IIA utility will be denoted as U''. Where IIA models predict choice probabilities to vary proportionally with the utilities (U_i), cross effects provide context-specific corrections to these utilities to derive corrected utilities U_i''.

For example, a negative cross effect indicates that the utility, and hence the market share, of an alternative is lower than predicted by the IIA model. Likewise a positive cross effect would indicate that an alternative's utility is underestimated by the IIA model and should be corrected upward. In the latter case, this could lead to a violation of regularity.

Design strategies for experiments that allow the estimation of composition effects are a little more complicated than those for experiments that assume IIA, but essentially the same principles can be applied. Common strategies are to construct choice sets of fixed size in which all attributes of all profiles are orthogonal, or to construct choice sets of varying size according to a 2^N design to vary the availability of alternatives in an orthogonal way.

Background Effects

The utility function can also be extended with terms that represent the effects of background variables on utility. Conventional decompositional preference and choice experiments typically manipulate only the attributes of choice alternatives. Background variables that affect the utilities of alternatives are specified in the task instructions but never vary as part of the experiment. One could, nonetheless, easily treat the background variables as additional factors in the factorial design to create treatments that vary the hypothetical background.

Such an approach could thus employ the same design principles that underlie standard decompositional choice experiments. There is, however, one exception: whereas in standard experiments the main focus is often on the main effects of the attributes, in stated background experiments all effects have to be specified as interactions with alternative specific constants and/or as interactions with alternative specific variables. This is necessary because if some background variable were specified as a generic effect, the variable's effect on each of the alternatives would be equal and cancel out.

Therefore, the designs with only main effects, which are often used in standard experiments, are not sufficient, and larger designs have to be used that permit the independent estimation of these types of interactions. Such larger designs can easily be constructed by nesting a standard design that varies the attributes of alternatives under a design that specifies the levels of the background variables. This process comes down to the completion of a series of standard choice experiments, one for each of the conditions of the background design. The advantage of employing a background design is that the separate experiments can be integrated into one choice model that includes parameters for the utility effects of the background variables. Note that this specification, in contrast to composition effects, does not lead to violations of the IIA property.

Specification

The total extended model now could be described as follows:

$$U_i'' = V_i'' + e_i$$
$$= f_i\,(X_{ik}, X_{jk}, Y_s) + e_i, \qquad \forall\ i, j \in A, \text{ and } j \neq i,$$

where

X_{jk} is the k-th attribute (which may be a constant, or intercept dummy) pertaining to the other alternatives j ($j \neq i$) in choice set A, and

Y_A are the background characteristics that apply to choice set A.

All other terms are defined as above.

Given the well-known assumptions regarding the error terms, a logit model can be estimated, using the same estimation techniques, from a design matrix **Z**:

$$\mathbf{Z} = [\mathbf{Z1} \,|\, \mathbf{Z2} \,|\, \mathbf{Z3} \,|\, \mathbf{Z4} \,|\, \mathbf{Z5} \,|\, \mathbf{Z6} \,|\, \mathbf{Z7}],$$

where

Z1, **Z2**, and **Z3** are as defined previously.

Z4 is a $T \times P$ matrix, P representing the number of *attribute cross main effects.* P is maximally equal to $(B - 1) \times M$ because each attribute main effect can have an effect on each of the other specific alternatives and because these effects are not necessarily symmetrical. **Z4** is a block matrix; each block pertaining to alternative j that represents the cross effects of i on j is identical to the corresponding block in **Z2** describing the attributes of alternative i. All other blocks are equal to 0. In addition to these attribute cross main effects, attribute cross interaction effects can be included in **Z4** in a similar fashion. Of course this increases the number of columns.

Z5 is a $T \times Q$ indicator matrix that represents potential *availability,* or *constant cross effects.* Each specific alternative's availability can have a constant, or main, effect on each other alternative's utility. In addition the joint availability of alternatives can have separate effects on utility. The estimation of all availability cross main effects would require that $Q = B(B - 1)$.

Z6 is a matrix that represents the *alternative-specific constant background effects.* As with the attributes, the background factors can be coded by $L - 1$ main effects. **Z6** contains the products of background main effects with columns from **Z1**. In a similar fashion, interactions between background factors could be multiplied with columns from **Z1** to represent their constant effect on some alternative. Then, **Z6** could be defined as $\mathbf{Z6} = [\mathbf{Z1'Z2} \,|\, \mathbf{Z1'Z3}]$.

Z7 is a matrix that contains the *alternative-specific variable background effects.*

Z7 contains the products of background main effects with columns from **Z2**. Again, in a similar fashion interactions between background factors could be multiplied with columns from **Z2** to represent the differential effects of these interactions on the slopes of the utility functions of the alternatives.

Note again that, if $B = 1$, the experiment concerns only *generic* alternatives. Specifying parameters as generic is a way to reduce the number of parameters. As will be demonstrated, Elrod, Louviere, and Kumar (1989) used a choice task with pairs of generic profiles together with a base alternative. They argue that in this case the cross effects should be symmetrical. Therefore in their study the **Z4** matrix is identical to **Z2** except that rows are switched within each set.

Note also that, in principle, *additional blocks* could be added that contain cross products from the blocks **Z1**, . . . **Z5**. An example of this is provided by the multiattribute extension of the Batsell and Polking (1985) model that is presented by Jain and Bass (1989). Their model, which directly scales ratios of market shares, contains availability cross effects that are conditional on (multiplied by) the "own" attribute effects. This model therefore could be estimated from a matrix that consists of the column products of **Z2** with **Z5**. A model, however, that contains all blocks **Z1** . . . **Z7** and all possible cross products would be completely saturated and not of any practical use. The complete extended model should be seen as a general formulation of the complete set of possible specifications of utility functions. Each experiment will only focus on a subset of columns from the complete model, which should be selected in advance of designing the experiment. The experimental design that is chosen determines the range of different specifications that can be tested after administering the experiment. These specifications can be tested using the likelihood ratio test (as, e.g., described in Ben-Akiva and Lerman 1985). Several techniques, such as maximum likelihood or generalized least squares, are available to estimate the different models. These techniques can be employed in standard software and are described in detail elsewhere (Louviere and Woodworth 1983; Ben-Akiva and Lerman 1985; Bunch and Batsell 1989; Louviere and Timmermans 1990b).

3. SOME ILLUSTRATIVE EXAMPLES

The previous sections indicate that different kinds of context effects can be included in the conventional decompositional choice (MNL) model by appropriate design construction and straightforward extension of the design matrix used to estimate the parameters of the choice model. A number of illustrative examples, some referring to completed research and others to hypothetical problems only, will now be given to demonstrate possible design strategies, estimation principles, and interpretations.

Example 1: Attribute Cross Effects in the Context of Consumer Choice of Shopping Center

Timmermans, Borgers, and Van der Waerden (1990) provide an illustration of the use of attribute cross effects in the context of choice of shopping centers. Their choice experiment was developed as follows. A fixed choice set design consisting of three shopping centers (Veldhoven city-center [VH], Eindhoven city-center [EH], and Veldhoven–Burgermeester van Hoofflaan [VB]) was developed. For each shopping center a set of possible actions was envisaged. The actions for VH were (a) a 10 percent increase of total floor space and (b) a 10 percent extension of the number of parking spaces. Possible actions for EH were (a) a new, major, in-town hypermarket located close to the market square, (b) a 15 percent increase of parking costs, (c) 600 additional underground parking spaces, and (d) a 10 percent increase in floor space for shops. The actions for VB consisted of (a) a diversification of shop types, (b) pedestrianization of a shopping street, and (c) the opening of a major appliance store.

Because there were nine actions and each could be either implemented or not, a fraction of the full 2^9 factorial design was used to create different combinations of actions. Sixteen choice sets were constructed, each consisting of one of the three shopping centers described by a different combination of actions. A base alternative ("any other shopping center") was added to each choice set. Respondents were shown each of the 16 choice sets, 1 at a time. They were asked how they would allocate their shopping trips among the three shopping centers and the base alternative if the actions described in the experimental tasks would be effectuated. Aggregated choice data were analyzed using iteratively reweighted least-squares analysis. The utility function was parameterized as follows: first, it was assumed that the utility function was alternative specific. Each of the three shopping centers has a specific intercept. Second, an additive main-effects model with some selected interaction effects was assumed for EH; the utility of the other two shopping centers was represented by a main-effects-only utility function. Third, all 18 (9×2) possible cross main effects were tested.

The design matrix is given in Table 1. Columns labeled EH, VH, and VB allow the estimation of each center's constant utility, and the utility of the base is scaled to be zero. The next nine columns represent the main effects of each of the alternative-specific attributes, i.e., the effects of the nine actions that were described. For the Eindhoven alternative (EH), the design also permitted the estimation of the interactions between "own" attributes; these are represented in the next six columns. The cross main effects are estimated from the rightmost set of columns. In these columns, for each set, the values of the main-effects columns reappear once again in each of the rows that pertain to one of the remaining alternatives in the choice set.

Estimation results are presented in Table 2. The estimated model fits very well (ρ^2 = .99, adjusted ρ^2 = .99). We will concentrate our discussion on the interpretation of the cross effects. Table 2 lists only the cross effects that are significant at the .05 α level. These data demonstrate that the simple MNL model should be rejected, implying that the IIA property is not supported by the data of the present study. The IIA property is violated by three cross effects. A diversification policy in VB would draw customers less than proportionally (positive cross effect) from EH, but more than proportionally (negative cross effect) from VH. Likewise, the opening of a major appliances store in VB decreases the relative attractiveness of VH (cross effect is negative). Hence, the

TABLE 1. 2^9 Design Matrix Creating 16 Sets of Shopping Centers, in Which Each of Nine Possible Actions Was Either Implemented or Not

					Main Effects									EH Interaction Effects						Cross Main Effects																	
		Constants																		On EH					On VH							On VB					
					EH				VH		VB									VH		VB			EH				HB			EH				VH	
Set	Alt.	EH	VH	VB	1	2	3	4	1	2	1	2	3	1×2	1×3	1×4	2×3	2×4	3×4	1	2	1	2	3	1	2	3	4	1	2	3	1	2	3	4	1	2
1	1	1	0	0	−1	−1	−1	−1	0	0	0	0	0	1	1	1	1	1	1	−1	−1	−1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	2	0	1	0	0	0	0	0	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	−1	−1	−1	−1	−1	0	0	0	0	0	0
1	3	0	0	1	0	0	0	0	0	0	−1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	−1	−1	−1	−1
1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	0	−1	−1	−1	1	0	0	0	0	0	1	1	−1	1	−1	−1	1	1	1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	2	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	−1	1	1	1	−1	0	0	0	0	0	0
2	3	0	0	1	0	0	0	0	0	0	1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	−1	1	1	1
2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	0	−1	−1	1	−1	0	0	0	0	0	1	−1	1	−1	1	−1	1	1	−1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3	2	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	1	−1	−1	1	1	0	0	0	0	0	0
3	3	0	0	1	0	0	0	0	0	0	−1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	1	−1	1	1
3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	1	0	0	−1	−1	1	1	0	0	0	0	0	1	−1	−1	−1	−1	1	−1	−1	1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
4	2	0	1	0	0	0	0	0	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	1	1	1	−1	1	0	0	0	0	0	0
4	3	0	0	1	0	0	0	0	0	0	1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	−1	1	1	−1	−1
4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	0	0	−1	1	−1	−1	0	0	0	0	0	−1	1	1	−1	−1	1	1	−1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	2	0	1	0	0	0	0	0	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	−1	−1	1	1	1	0	0	0	0	0	0
5	3	0	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	−1	−1	1	−1
5	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	1	1	0	0	−1	1	−1	1	0	0	0	0	0	−1	1	−1	−1	1	−1	−1	1	−1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
6	2	0	1	0	0	0	0	0	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	−1	1	−1	−1	1	0	0	0	0	0	0
6	3	0	0	1	0	0	0	0	0	0	−1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	−1	1	−1	1
6	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	1	1	0	0	−1	1	1	−1	0	0	0	0	0	−1	−1	1	1	−1	−1	−1	1	1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
7	2	0	1	0	0	0	0	0	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	1	−1	1	−1	−1	0	0	0	0	0	0
7	3	0	0	1	0	0	0	0	0	0	1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	1	−1	−1	1
7	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	1	1	0	0	−1	1	1	1	0	0	0	0	0	−1	−1	−1	1	1	1	1	−1	−1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
8	2	0	1	0	0	0	0	0	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	1	1	−1	1	−1	0	0	0	0	0	0
8	3	0	0	1	0	0	0	0	0	0	−1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	1	1	1	1	−1
8	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 1 — *Continued*

																			Cross Main Effects																		
					Main Effects									EH Interaction Effects						On EH					On VH							On VB					
		Constants			EH				VH		VB									VH		VB			EH				HB			EH				VH	
Set	Alt.	EH	VH	VB	1	2	3	4	1	2	1	2	3	1×2	1×3	1×4	2×3	2×4	3×4	1	2	1	2	3	1	2	3	4	1	2	3	1	2	3	4	1	2
9	1	1	0	0	1	−1	−1	−1	0	0	0	0	0	−1	−1	−1	1	1	1	1	1	1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
9	2	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	−1	−1	1	−1	1	0	0	0	0	0	0
9	3	0	0	1	0	0	0	0	0	0	1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	−1	−1	1	1
9	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	1	1	0	0	1	−1	−1	1	0	0	0	0	0	−1	−1	1	1	−1	−1	−1	−1	−1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
10	2	0	1	0	0	0	0	0	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	−1	1	−1	1	1	0	0	0	0	0	0
10	3	0	0	1	0	0	0	0	0	0	−1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	−1	1	−1	−1
10	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	1	1	0	0	1	−1	1	−1	0	0	0	0	0	−1	1	−1	−1	1	−1	−1	−1	1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
11	2	0	1	0	0	0	0	0	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	1	−1	1	1	−1	0	0	0	0	0	0
11	3	0	0	1	0	0	0	0	0	0	1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	1	−1	−1	−1
11	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	1	0	0	1	−1	1	1	0	0	0	0	0	−1	1	1	−1	−1	1	1	1	−1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
12	2	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	1	1	−1	−1	−1	0	0	0	0	0	0
12	3	0	0	1	0	0	0	0	0	0	−1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	1	1	1	1
12	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	1	1	0	0	1	1	−1	−1	0	0	0	0	0	1	−1	−1	−1	−1	1	−1	1	−1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
13	2	0	1	0	0	0	0	0	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	−1	−1	−1	1	−1	0	0	0	0	0	0
13	3	0	0	1	0	0	0	0	0	0	−1	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	−1	−1	−1	1
13	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	1	1	0	0	1	1	−1	1	0	0	0	0	0	1	−1	1	−1	1	−1	1	−1	1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0
14	2	0	1	0	0	0	0	0	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	−1	1	1	−1	−1	0	0	0	0	0	0
14	3	0	0	1	0	0	0	0	0	0	1	−1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	−1	1	1	−1
14	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	1	1	0	0	1	1	1	−1	0	0	0	0	0	1	1	−1	1	−1	−1	1	−1	−1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
15	2	0	1	0	0	0	0	0	1	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	−1	−1	−1	1	0	0	0	0	0	0
15	3	0	0	1	0	0	0	0	0	0	−1	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	−1	1	−1
15	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	1	1	0	0	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	−1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
16	2	0	1	0	0	0	0	0	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0
16	3	0	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	−1	1
16	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Source: Timmermans, Borgers, and Van der Waerden 1991.
Note: See Table 2 and text for further explanation of column labels.

TABLE 2. Parameter Estimates and t-Values of the Extended Logit Model Estimated from Table 1

	Estimate	t-Value
Eindhoven City-Center (EH)		
Alt.-Specific Constant	−1.3433	−251.1309
Main Effects		
1. Opening Magnet Store	0.0335	5.3705
2. 15% Increase Parking Costs	−0.0300	−4.8108
3. 600 Additional Parking Spaces	0.0193	3.0858
4. 10% Increase Retail Floor Space	0.0159	2.5406
Interaction Effects		
1 × 2	−0.0040	−0.7063
1 × 3	0.0051	0.8946
1 × 4	−0.0118	−2.0739
2 × 3	0.0041	0.7202
2 × 4	−0.0042	−0.7419
3 × 4	0.0119	2.0914
Veldhoven City-Center (VH)		
Alt.-Specific Constant	0.7904	230.7770
Main Effects		
1. 10% Increase Floor Space	0.0241	7.0239
2. 10% More Parking Spaces	0.0037	1.0693
Veldhoven-Burgermeester van Hoofflaan (VB)		
Alt.-Specific Constant	0.9623	288.0714
Main Effects		
1. Diversification of Shops	0.1388	41.5503
2. Pedestrianization	−0.0054	−1.6108
3. Opening Appliances Store	0.0401	12.0019
Cross Effects (Significant)		
VB Diversification on EH	0.0275	4.4109
VB Diversification on VH	−0.0233	−6.8106
VB Appliance Store on VH	−0.0190	−5.5610
Log Likelihood Values		
L(0) = −172812.5		
L(c) = −2883.7		
L(β) = −352.4		

cross effects provide useful information regarding substitution and competition among shopping centers.

Example 2: Generic Attribute Cross Effects in the Context of Apartment Choice

In the previous example, it was assumed that the attribute cross effects are alternative specific. That is to say, it is assumed that departures from proportionality due to attributes of competing choice alternatives may differ between choice alternatives. A more general idea would be to assume that such effects would *not* be alternative specific.

An example of such generic attribute cross effects can be found in Elrod, Louviere, and Kumar (1989), who studied apartment choices. As mentioned previously, they used a choice task with pairs of generic profiles together with a base alternative. They argued that in this case, in the absence of order effects, the cross effects should be symmetrical. Hypothetical apartments were described by four attributes: rent level ($330, $450, or $570 per month), number of bedrooms (one or two), distance (0.5, 1.5, or 2.5 miles), and neighborhood safety (fairly safe or very safe). Rent and distance were allowed to vary slightly around the design value for each level, using the approach suggested in Louviere and Hensher (1983).

Violations of IIA were tested by taking a fraction from the full factorial $2^4 3^4$ design, resulting in 27 different pairs of apartments that had the property that attributes are orthogonal within and between the profiles in a choice set. Subjects were asked to choose one of the two profiles or to choose the *base* alternative, which was added to each choice set and was described as "rent a residence very similar to where I live now."

Table 3 describes the design that was used in this study. Attribute profiles are effect coded. The design matrix used to estimate the parameters of the choice model is presented in Table 4. Note that the design matrix has 27 blocks, 1 block for each choice set, consisting of three rows — one for apartment A, one for B, and one for the base alternative. The constant is used to estimate the difference in utility between the base and the apartments. The first row pertains to apartment A in choice set 1. Note that the generic main effects are identical to columns 3 to 6 of the first row described in Table 3. Cross effects are represented by columns 7 to 10. Note that for the first row these columns are identical to columns 3 to 6 of the second row, which describe the attribute profile of apartment B. The same principles pertain to row 2. Columns 3 to 6 describe main effects; columns 7 to 10 represent cross effects and they are identical to columns 3 to 6 in row 1, which depict the attribute profile of apartment A.

To illustrate the general principles of the estimation of a model with generic attribute cross effects, we recoded both "miles" and "rent" as linear polynomial effects. For each of these, a second column could have been added that represents its quadratic effects. However, Elrod, Louviere, and Kumar included the absolute levels of miles and rent directly in their design matrix as can be noted from their parameter estimates, given in Table 5.

The estimates were derived with maximum likelihood techniques, assuming a linear additive utility function. The model is reported to fit well. The discussion will again be concentrated on the interpretation of the cross effects. Two main cross effects are significant: as rent for one apartment increases (and its own utility decreases), the utility of the other apartment slightly increases; as the number of bedrooms for one apartment increases (and its own utility increases), the utility of the other apartment decreases.

In this way, the cross effects provide corrections on the utilities that were derived assuming IIA, and they indicate which attributes contribute to the violation of the IIA property. If a newly added alternative is more similar in its attribute values to some alternative than to other alternatives that were already available, the utilities of the similar alternatives are corrected downward. This reflects the fact that these alternatives are competing more with each other than with other alternatives.

Example 3: Availability Cross Effects in the Context of Transportation Mode Choice

Because we are unaware of any empirical study, we present a hypothetical example of the use of availability cross effects. More specifically, we suppose a

TABLE 3. A Fraction of a $2^4 3^4$ Factorial Design Creating 27 Orthogonal Pairs of Apartments, Each Described by Four Attributes

	Apartment A				Apartment B			
Set	Rooms[a]	Miles[b]	Safety[c]	Rent[d]	Rooms[a]	Miles[b]	Safety[c]	Rent[d]
1	−1	1	1	0	1	−1	−1	1
2	1	−1	1	1	1	−1	−1	−1
3	−1	1	1	1	1	1	−1	0
4	−1	−1	1	−1	−1	1	−1	1
5	1	1	1	1	−1	0	−1	1
6	1	0	1	0	1	1	1	−1
7	1	1	−1	0	−1	0	1	0
8	−1	1	1	0	1	1	−1	−1
9	−1	1	1	−1	1	−1	−1	0
10	−1	0	1	1	1	0	1	1
11	−1	−1	−1	1	1	0	−1	1
12	−1	−1	−1	0	−1	1	−1	−1
13	1	−1	1	0	1	−1	1	1
14	−1	0	1	1	−1	−1	−1	−1
15	−1	0	1	−1	−1	−1	1	0
16	1	0	1	−1	1	1	−1	1
17	−1	1	−1	−1	1	1	1	1
18	1	−1	−1	−1	1	−1	−1	0
19	1	0	−1	1	1	1	−1	0
20	−1	0	−1	−1	1	0	−1	−1
21	−1	−1	1	1	−1	1	1	0
22	1	1	1	−1	−1	0	−1	−1
23	−1	1	−1	1	1	−1	1	−1
24	−1	0	1	0	1	0	−1	0
25	−1	−1	1	0	1	0	−1	0
26	−1	−1	1	−1	1	0	1	−1
27	−1	0	−1	0	−1	−1	−1	1

Note: Attribute design as used in Elrod, Louviere, and Kumar (1989), recoded for current use.
[a] Rooms: −1 = one bedroom, 1 = two bedrooms.
[b] Miles: −1 = 0.5, 0 = 1.5, 1 = 2.5.
[c] Safety: −1 = fairly safe, 1 = very safe.
[d] Rent: −1 = \$330/month, 0 = \$450/month, 1 = \$570/month.

TABLE 4. Design Matrix Corresponding to Design Described in Table 3

		Generic Main Effects				Generic Cross Effects			
Set	Const.	Rooms	Miles	Safety	Rent	Rooms	Miles	Safety	Rent
1	1	−1	1	1	0	1	−1	−1	1
1	1	1	−1	−1	1	−1	1	1	0
1	0	0	0	0	0	0	0	0	0
2	1	1	−1	1	1	1	−1	−1	−1
2	1	1	−1	−1	−1	1	−1	1	1
2	0	0	0	0	0	0	0	0	0
3	1	−1	1	1	1	1	1	−1	0
3	1	1	1	−1	0	−1	1	1	1
3	0	0	0	0	0	0	0	0	0
4	1	−1	−1	1	−1	−1	1	−1	1
4	1	−1	1	−1	1	−1	−1	1	−1
4	0	0	0	0	0	0	0	0	0
.									
.									
.									
27	1	−1	1	−1	0	−1	−1	−1	1
27	1	−1	−1	−1	1	−1	1	−1	0
27	0	0	0	0	0	0	0	0	0

TABLE 5. Estimation Results for Elrod, Louviere, and Kumar (1989)

	Main Own Effects		Main Cross Effects	
	Estimate	t-Value	Estimate	t-Value
Constant	−2.524	−34.574	—	—
Bedrooms	1.135	24.149	−0.146	3.174
Miles	−0.298	5.960	0.040	.769
Safety	0.554	12.591	−0.007	.159
Rent	−0.013	13.000	0.002	5.000

simple choice experiment that focuses on the effects of the introduction of a new railway station on choice of transportation mode for commuting. Let us assume that four modes are available: car, bus, rail, and bike/walk, and let us assume a homogeneous population of commuters. However, not all modes are considered by all commuters — for example, because persons have no railway station in their vicinity or do not have a car. To model the potential differential competition between the different modes and to test the assumption of IIA underlying the MNL model, the main interest in this experiment would be on the availability or constant cross effects; therefore, a 2^3 design could be used to create eight sets of different size and composition, treating the bike/walk mode as a constant base (Table 6). One of these sets, however, is an empty set and should be dropped. In the experiment, each respondent is asked to choose, from each of the seven choice sets, the mode considered to be the most likely candidate used for commuting, given that only the modes described in the set are available. The design matrix to analyze this experiment would contain submatrices of type **Z1** and **Z5** only, as described in Table 7. Note that only availability main effects are included; inclusion of all three possible joint-availability, or interaction, effects would have led to a completely saturated model.

Suppose there are 100 commuters each responding to all choice sets, leading to choice frequencies as described in Table 8. If rail and bus are more "similar" than rail and bike/walk, or bus and bike/walk, it would be expected that the rail alternative would compete more with bus than with bike/walk, and vice versa. This means a negative availability cross effect of bus on rail and/or a negative availability cross effect of rail on bus would be expected. On the other hand, if people that go by foot or bike switch more easily to train than car users do, a positive availability cross effect of rail on car and/or a positive availability cross effect of car on rail would be expected. This hypothetical data set was deliberately constructed to contain these effects. Iteratively reweighted least-squares analysis was used to estimate the model; as can be seen from Table 9, the model fits quite well (ρ^2 = .59, adjusted ρ^2 = .49), and the parameter estimates are as expected. This hypothetical study would lead to the prediction that an extension of the rail system, which would result in more commuters having the rail alternative in their choice set, competes most with bus, next with the alternative to go by bike or to walk, and least with car.

Example 4: Background Variables in the Context of Transportation Mode Choice

Let the inclusion of background variables as factors in a choice experiment be illustrated by an extension of the above hypothetical study on transportation

TABLE 6. Attribute Design That Underlies the Construction of Choice Sets in Mock-Up Experiment on Choice of Transportation Mode

Set	Bus	Car	Rail
1	1	1	1
2	1	1	0
3	1	0	1
4	1	0	0
5	0	1	1
6	0	1	0
7	0	0	1
(8	0	0	0)

TABLE 7. Design Matrix to Estimate the Mock-Up Experiment with Choice Sets as Described in Table 6

	Constants			Availability Cross Main Effects					
Set	Bus	Car	Rail	Car-on-Bus	Rail-on-Bus	Bus-on-Car	Rail-on-Car	Bus-on-Rail	Car-on-Rail
1	1	0	0	1	1	0	0	0	0
1	0	1	0	0	0	1	1	0	0
1	0	0	1	0	0	0	0	1	1
1	0	0	0	0	0	0	0	0	0
2	1	0	0	1	0	0	0	0	0
2	0	1	0	0	0	1	0	0	0
2	0	0	0	0	0	0	0	0	0
3	1	0	0	0	1	0	0	0	0
3	0	0	1	0	0	0	0	1	0
3	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	1	0	0	0	0	1	0	0
5	0	0	1	0	0	0	0	0	1
5	0	0	0	0	0	0	0	0	0
6	0	1	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0

TABLE 8. Data Set Deliberately Constructed for Illustration of Availability Cross Effects

Set	Bus	Car	Rail	Bike/Walk	Σ
1	20	50	20	10	100
2	30	60	—	10	100
3	30	—	30	40	100
4	60	—	—	40	100
5	—	50	40	10	100
6	—	50	—	50	100
7	—	—	70	30	100
Σ	140	210	160	190	700

mode choice. Suppose we wish to include the effects of trip purpose (two levels: going to the work place and going shopping) and time of day (two levels: peak hour and off peak) on mode choice in the model in a statistically efficient way. Then, trip purpose and time of day should be varied as part of the experiment, and people should be asked to indicate for each set the mode they are most likely to choose, considering the condition that the trip purpose and time of day was as specified in the choice task.

The choice sets employed in the previous example could be employed in each of the four possible *stated backgrounds;* the total design would thus contain $7 \times 4 = 28$ treatments. However, this paper will focus only on the background variables and attribute main effects and use the main-effects fraction of the 2^3 in 4 treatments to create choice sets; next, this design is nested under the background design to create $4 \times 4 = 16$ treatments, as indicated in Table 10.

Table 11 presents the design matrix to analyze this experiment, again assuming a linear additive utility function. In addition, the last column in Table 11 presents choice frequencies that are deliberately made up for the illustration of background effects. The data were constructed in an intuitive way to represent positive effects of both time of day and trip purpose on car attractiveness. Table 12 presents the results from this hypothetical experiment, analyzed with iteratively reweighted least squares. The total fit of the model is quite good (ρ^2 = .77, adjusted ρ^2 = .75). It appears that, relative to trips during peak hours, the utility of car increases with .74 units in the case of off-peak hours. The utilities

TABLE 9. Estimation Results for Data from Table 8 and Design Matrix from Table 7

	Estimate	t-Value
Bus	.2543	1.3686
Car	.3638	1.9823
Rail	.6455	3.3561
Car-on-Bus	.5332	1.9419
Rail-on-Bus	−.2008	−.7938
Bus-on-Car	.8388	3.3086
Rail-on-Car	.6689	2.6214
Bus-on-Rail	−.5709	−2.2445
Car-on-Rail	.4667	1.7003

Log Likelihood Values
$L(0) = -91.2$
$L(c) = -56.2$
$L(\beta) = -31.3$

TABLE 10. Attribute Design Underlying the Construction of Choice Sets That Vary Both in Composition and Background

Set	Purpose[a]	Time[b]	Bus[c]	Car[c]	Rail[c]
1	1	1	1	1	1
2	1	1	1	0	0
3	1	1	0	1	0
4	1	1	0	0	1
5	1	0	1	1	1
6	1	0	1	0	0
7	1	0	0	1	0
8	1	0	0	0	1
9	0	1	1	1	1
10	0	1	1	0	0
11	0	1	0	1	0
12	0	1	0	0	1
13	0	0	1	1	1
14	0	0	1	0	0
15	0	0	0	1	0
16	0	0	0	0	1

[a] Purpose: 0 = going to the work place, 1 = going shopping.
[b] Time: 0 = peak hour, 1 = off peak.
[c] Bus, Car, and Rail: 1 = mode is available, 0 = not available.

TABLE 11. Design Matrix to Estimate the Background Effects from the Experiment as Described in Table 10

	Constants			Background Effects: Purpose on			Background Effects: Time on			
Set	Bus	Car	Rail	Bus	Car	Rail	Bus	Car	Rail	Frequency[a]
1	1	0	0	1	0	0	1	0	0	5
1	0	1	0	0	1	0	0	1	0	80
1	0	0	1	0	0	1	0	0	1	5
1	0	0	0	0	0	0	0	0	0	10
2	1	0	0	1	0	0	1	0	0	20
2	0	0	0	0	0	0	0	0	0	80
3	0	1	0	0	1	0	0	1	0	85
3	0	0	0	0	0	0	0	0	0	15
4	0	0	1	0	0	1	0	0	1	15
4	0	0	0	0	0	0	0	0	0	85
5	1	0	0	1	0	0	0	0	0	10
5	0	1	0	0	1	0	0	0	0	70
5	0	0	1	0	0	1	0	0	0	10
5	0	0	0	0	0	0	0	0	0	10
6	1	0	0	1	0	0	0	0	0	10
6	0	0	0	0	0	0	0	0	0	90
7	0	1	0	0	1	0	0	0	0	70
7	0	0	0	0	0	0	0	0	0	30
8	0	0	1	0	0	1	0	0	0	15
8	0	0	0	0	0	0	0	0	0	85
9	1	0	0	0	0	0	1	0	0	10
9	0	1	0	0	0	0	0	1	0	60
9	0	0	1	0	0	0	0	0	1	20
9	0	0	0	0	0	0	0	0	0	10
10	1	0	0	0	0	0	1	0	0	65
10	0	0	0	0	0	0	0	0	0	35
11	0	1	0	0	0	0	0	1	0	70
11	0	0	0	0	0	0	0	0	0	30
12	0	0	1	0	0	0	0	0	1	70
12	0	0	0	0	0	0	0	0	0	30
13	1	0	0	0	0	0	0	0	0	20
13	0	1	0	0	0	0	0	0	0	50
13	0	0	1	0	0	0	0	0	0	20
13	0	0	0	0	0	0	0	0	0	10
14	1	0	0	0	0	0	0	0	0	60
14	0	0	0	0	0	0	0	0	0	40
15	0	1	0	0	0	0	0	0	0	50
15	0	0	0	0	0	0	0	0	0	50
16	0	0	1	0	0	0	0	0	0	70
16	0	0	0	0	0	0	0	0	0	30

[a] This column contains data deliberately constructed for illustrative purposes only.

TABLE 12. Estimation Results for Data from Table 11

	Estimate	t-Value
Bus	.2568	1.7489
Car	.7014	5.0471
Rail	.5536	3.8258
Purpose-on-Bus	−1.8226	−9.0885
Purpose-on-Car	.3239	1.9391
Purpose-on-Rail	−2.0936	−10.4798
Time-on-Bus	.1451	.7703
Time-on-Car	.7390	4.4016
Time-on-Rail	.0926	.4965

Log Likelihood Values

$L(0) = -388.0$

$L(c) = -217.6$

$L(\beta) = -87.7$

of bus and rail decrease with 1.82 and 2.09 points, respectively, in the case of a trip for shopping purposes relative to a trip to the work place.

4. CONCLUSION

The validity and scope of decompositional preference and choice models may be improved by incorporating context effects in the specification of these models. The aim of the present paper has been to distinguish various kinds of context effects, to discuss how these may be incorporated in decompositional modeling strategies, and to provide (hypothetical) examples. The paper demonstrates that context effects can be included by using design strategies that allow one to vary the contextual variables independently from the profiles, and by extending the conventional design matrix underlying choice and preference models in an appropriate fashion. It should be noted, however, that standard design selections are not yet available for some of the problems (Anderson 1990) and that the properties of some design strategies are not yet fully understood. Nevertheless, these developments make progress toward actual empirical tests of whether context effects are important in studies of choice behavior in regional science.

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