"WHAT DOES THE MULTINOMIAL LOGIT MODEL REALLY MEASURE?"

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Printed at INSEAD, Fontainebleau, France

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Revised February 1993

* Professor of Marketing, INSEAD, Boulevard de Constance, 77305 Fontainebleau, France. The title as well as some of the content of the paper were inspired by Horowitz and Louviere (1991). Helpful comments on an earlier draft were provided by Luc Wathieu, Ph.D. student at INSEAD, and my junior colleagues at INSEAD.

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A B S T R A C T

The Multinomial Logit Model of choice has been used extensively in the literature. The traditional interpretation is that the model describes the probability of choosing a specific alternative out of given set of considered alternatives (the "consideration set"). This paper shows that when the decision maker experiences uncertainty in defining the consideration set, the choice model is still MNL under relatively weak assumptions. However, in such instances, one cannot disentangle in the actual MNL predictions what comes from real preferences and what comes from characteristics of the imperfectly carried out consideration set generation task. This observation has important practical implications, since implied marketing efforts differ substantially depending on whether they aim at adaptation to preferences or at manipulation of the consideration set generation.

1. INTRODUCTION

The multinomial logit (MNL) model of choice is one of the most widely used models of discrete choice (McFadden 1974,1986). Assuming that the utility of the choice alternatives consists of a strict utility component (or deterministic utility component) and a random utility component with the latter following a Type-1 Extreme Value distribution, the utility maximizing choice rule provides a closed-form probability model which is simple and easy to validate empirically. Applications have been diverse ranging from college choice (Punj and Staelin 1978), to travel mode choice (e.g., Ben-Akiva and Lerman 1985, Gensch and Recker 1979), to the study of brand choice (e.g., Cooper 1988, Currim, Meyer, and Lee 1988, Guadagni and Little 1983, Gupta 1988, Malhotra 1984, Lattin and Bucklin 1989, Chintagunta, Jain, and Vilcassim 1991, Fader, Lattin and Little 1992, Fader and Lattin 1992). In all of these instances, the model is shown to provide a good account of the relationship between characteristics of a set of alternatives, the consideration set, and the environment within which they are presented and the choices made from that set.[1]

As a representation of an individual's choice intentions from a set of options, the MNL model has been criticized for offering a rather restrictive view of the process which underlies choice. The main criticism has been the model's assumption that choice of an alternative is independent of the characteristics of the consideration set. This assumption gives rise to the "constant ratio rule" or the "independence of irrelevant alternatives (IIA)", which implies that if a new alternative is added to the consideration set, the choice shares of the existing alternatives will always decrease in direct proportion to the size of their original shares. Numerous counter-examples to this property have been given in the literature (Debreu 1960, Restle 1961, Rummelhart and Greene 1971, Tversky 1972). A number of generalizations of the MNL model were developed subsequently to provide a non-IIA account of choice without jeopardizing the model's simplicity (for a review, see e.g., Meyer and Kahn 1991). Most of these models are ad hoc adaptations which allow in one form or another the strict utility function to be dependent on the consideration set.

More recently, attention has shifted to consideration set generation (Shocker et al. 1991). This work has been motivated by behavioral decision theory as well as methodological concerns arising from consideration set misspecification. Work on similarity of alternatives in choice tasks and the related violations of IIA point to the importance of correctly identifying the consideration set (see, e.g., Payne 1982). Experimental research on agenda effects (see, e.g., Tversky and Sattath 1979) points to the importance of consideration set generation. Furthermore, behavioral evidence exists that choices are made after a set is formed (e.g., Bettman 1987, Payne 1982). Methodologically, misspecifying the consideration set has been

linked to poor predictions and changing properties of parameter estimates (see, e.g., Stopher 1980, Williams and Ortuzar 1982, Swait 1984, Swait and Ben-Akiva 1986). Particularly in the transportation literature, substantial work has been done in this area (Ben-Akiva 1977, Swait 1984, Pitschke 1980, Swait and Ben-Akiva 1987, Boccara 1989, Ben-Akiva and Boccara 1990).

Following Manski (1977), almost all modeling efforts considering consideration set formation have assumed the task to be carried out perfectly prior to choice. Accordingly, the decision maker experiences no uncertainty in the consideration set generation task. The probabilistic description of the consideration set adopted in these efforts merely reflects uncertainty on the part of the modeler as a result of the latent character of the consideration set. However, as discussed in this paper, there is reason to believe that uncertainty enters consideration set formation at the individual level. Alternatives are "considered" for choice (Simon 1955), but perhaps not all to the same extent which draws into question the traditional discrete consideration set definition treated as given or deterministically predictable (Shocker et. al. 1991). More importantly, this uncertainty makes it impossible to treat consideration set generation and choice as separate, independent tasks. Integrating uncertainty into consideration set generation alongside traditional random utility assumptions for the alternatives was studied in Fotheringham (1988) and Vanhonacker (1992).

The objective of this paper is to provide an alternative interpretation of the MNL model given the behavioral rationale underlying Fotheringham (1988) and Vanhonacker (1992). With the traditional utility assumptions and choice rule, experiencing consideration set uncertainty implies under relatively weak assumptions an MNL model with an inherent consideration set generation process . More importantly, that set generation process cannot be separated from the choice act itself. The MNL choice predictions cannot be disentangled as to identify the impact of real preferences underlying the choice task and the impact of the characteristics underlying the consideration set generation task. In the extreme, the MNL model predictions might capture only the imperfectness of the consideration set generation task of an otherwise perfectly loyal or captive individual. On the one hand, this observation lends credence to the result established recently by Horowitz and Louviere (1991) that, with fully specified utility functions, consideration set generation does not add anything to MNL model predictions. On the other hand, the observation has important practical implications since, for example, marketing efforts differ depending on whether they aim at modifying preferences or at manipulating consideration set generation.

2. THE MULTINOMIAL LOGIT (MNL) MODEL

Following the standard approach of random utility modeling, the utility of alternative i can be expressed as

$$U_i = V_i + \varepsilon_i \quad \text{for } i = 1, 2, ..., N \tag{1}$$

where V_i denotes the strict (or deterministic) utility component and ε_i denotes the random utility component. N denotes the number of alternatives contained in consideration set C. At this point, we consider C a discretely-defined subset of the "universal" set of all alternatives (Shocker et. al. 1991). The random component ε_i in (1) refers to the uncertainty in preference assessment for alternative i.

For the utility maximizing consumer, the probability of choosing alternative i out of set C equals

$$P_i = \text{Prob}\left[V_i + \varepsilon_i > V_k + \varepsilon_k \,;\, \forall\, k \in C, k \neq i\right]. \tag{2}$$

Assuming that the random components ε_i in (1) for i = 1, 2, ..., N are independently and identically distributed (i.i.d.) according to a Type-1 Extreme Value distribution, (2) results in the classic result (McFadden 1974)

$$P_i = \exp(V_i) / \sum_{k \in C} \exp(V_k) \tag{3}$$

which is the Multinomial Logit (MNL) model of choice. An overview of its use and relationship to other models is given in McFadden (1986). For subsequent discussion, it is interesting to note that Horowitz and Louviere (1991) call expression (3) the "marginal probability of choosing alternative i meaning that this probability does <u>not use any information contained in the consideration set</u>". It will be shown subsequently that if the individual decision maker experiences uncertainty surrounding the content of set C, expression (3) might contain only information about the consideration set.

The empirical work with the MNL model has focused on the specification of the strict utility component V_i in (1). In the transportation literature, survey-based research relies primarily on choice alternative characteristics or attributes. In marketing, characteristics of the choice alternatives as well as variables capturing characteristics of the choice environment are specified as part of the strict utility component. For subsequent discussion, it is interesting to

note that the preference measures can be categorized as either describing the physical nature of the choice alternative (e.g., the brand constants capturing the "intrinsic utility", Guadagni and Little 1983), the behavior of the individual making the choice (e.g., loyalty or inertia in shopping behavior), or the physical environment in which the choice was made (e.g., in-store environment such as special displays, shelf space, end-of-aisle placement, etc.). Mostly driven by availability, there is usually little reflection on the theoretical justification of the particular role those variables play in the decision process. Whether the variables capture real preference characteristics for the alternatives or perhaps characteristics of the consideration set generation, a central question in this paper, is not addressed.

3. CONSIDERATION SET GENERATION AND UNCERTAINTY

As described above, the MNL model describes choice as the outcome of a conjunctive process conditional on a consideration set. From (2), it is clear that all alternatives in the set are compared directly to one another in the utility domain. Hence, the outcome is very much dependent on which alternatives are contained in the set. Many authors have voiced concerns about the implications of an incorrect definition of consideration set (see, e.g., Meyer 1979, Hauser and Gaskin 1984, Swait 1984, Gensch 1987). Empirical as well as theoretical results on the impact of set misspecification on predictions and parameter estimates are discussed in Stopher (1980), Williams and Ortuzar (1982), Swait and Ben-Akiva (1986). Because of these concerns and documented implications, some attention has been given to consideration sets and their generation. In the transportation literature, the work is contained in Swait (1984), Swait and Ben-Akiva (1985, 1986, 1987), Ben-Akiva and Swait (1984), Ben-Akiva (1977). In marketing, recent attention to consideration set generation has given rise to a stream of research (e.g., Roberts 1989, Roberts and Lattin 1991, Hauser and Wernerfelt 1990, Nedungadi 1987, 1990, Shocker, et. al. 1991, Vanhonacker 1992).

Since Manski (1977), most authors in this literature have incorporated probabilistic descriptions of consideration sets recognizing their latent character. The assumption is made that consideration sets are either given or deterministically predictable. Hence, the decision maker is assumed not to experience any uncertainty in the set generation task. The probabilistic description merely reflects uncertainty in the mind of the model builder as he/she is unaware of the actual set used by the individual decision maker. From a model builder perspective, the uncertainty creates specification (and, hence, estimation) difficulties, as the number of possible consideration sets can be quite large. Some recent work has focused on modeling explicit constraints which drastically reduces the number of possible consideration sets (see, e.g., Swait and Ben-Akiva 1987). In all this work the assumption continues to be made that at the

individual level, the consideration set is deterministic. To the individual decision maker, what is in and what is not in is clear and, hence, there is no uncertainty experienced in consideration set generation. However, there are quite a number of behavioral reasons why the assumption might be untenable.

First of all, the random utility formulation underlying the MNL model implies the preference evaluations of the alternatives to have a random component. Too much doubt about tastes might lead the decision maker not to seriously consider an alternative. In this sense, it does not seem unreasonable to assume that preference uncertainty (captured in the random utility component) gives rise to uncertainty in consideration set generation. The argument used by some authors who use search theory to capture the generation process at the decision-maker level is fully consistent with this assertion. If the generation process is governed by a cost-benefit rule in the utility domain (see, e.g., Vanhonacker 1991, 1992) or an incremental utility rule (see, e.g., Hauser and Wernerfelt 1990), the random utility component will naturally give rise to a probabilistic definition of consideration set. Hence, the basic utility assumptions seem to be in contradiction with the long-standing assumption of deterministically predictable consideration sets. However, one does not need to rely solely on the random utility component to argue for an imperfectly carried out consideration set task.

Shocker et. al. (1991) and others have argued that usage or consumption occasion influence consideration set membership for frequently-purchased brands. If there is uncertainty about future usage or consumption occasions actually occurring, the probabilistic assessment of those future events will lead to probabilistic consideration of alternatives. Naturally, the decision maker experiences uncertainty in consideration set generation task which is totally independent of the preference uncertainty in the utility domain.

Payne (1982) has argued that decision makers exhibit probabilistic attention to and use of information. It is not unreasonable to assume that this probabilistic attention results in a probabilistic assessment of consideration set composition. Furthermore, even if information about alternatives is not attended to probabilistically, there is likely to be some heterogeneity in the depth of knowledge the decision maker has about the alternatives. This heterogeneity can give rise to uncertainty in the mind of the decision maker about the appropriateness of the various alternatives for a specific future usage or consumption occasion. Hence, uncertainty in the consideration set generation task could be linked to imperfect information or knowledge (perhaps because of lack of experience) or the probabilistic attention to the information.

The uncertainty in the consideration set generation task can also arise from the decision maker's inability to guarantee availability of the alternatives. If, for example, brand choices are

made prior to the shopping trip (e.g., at the time of generating a shopping list), uncertainty about actual availability will enter the consideration set generation task.

From these behavioral arguments already, there is reason to believe there is uncertainty implicit in the consideration set generation process. No doubt further behavioral justification could be accumulated to argue the case. Alternatives are "considered" for choice (Simon 1955), but not all to the same extent which draws into question the traditional discrete consideration set definition (Shocker et. al. 1991) with 0/1 membership treated as given or deterministically predictable. This uncertainty experienced by the decision maker versus the model-builder's uncertainty about what was considered leads to a different structure of the choice problem, which is discussed next.

4. CONSIDERATION SET UNCERTAINTY: DECISION MAKER BEHAVIOR VERSUS MODELER BEHAVIOR

Attributing consideration set uncertainty either to its latent nature or fuzziness experienced by the individual decision maker leads to a fundamentally different problem formulation. Stated simply, if uncertainty exists in the mind of the decision maker, then the choice decision needs to be modeled as a maximum expected utility problem. If, however, the decision maker is perfectly clear about consideration set membership but there is uncertainty in the mind of the modeler about which alternatives were actually in the set, then the choice decision needs to be modeled as an expected maximum utility problem. It is important to be clear about this as to formulate the problem (Lindley 1986) and to interpret the results accurately. Let us investigate both formulations in some detail.

Figure 1-A structures the choice decision among three alternatives for an individual who is uncertain about consideration set membership. The decision maker will take into account both the utility of the alternatives as well as the likelihood of the alternatives being included in the consideration set. Hence, the uncertainty experienced in the consideration set generation task becomes an integral part of the choice task (i.e., the consideration set generation task and the choice task are inseparable). As shown in Figure 1-A, the individual will select an alternative knowing that there is some probability of it not being part of the consideration set. For example, for alternative 1, there is a probability $P(1 \notin C)$ that it is not considered as an alternative; hence, its utility U_1 is only relevant if it is considered (which is measured with a likelihood of $P(1 \in C)$). Accordingly, the individual will select that alternative which has the highest expected utility. The choice problem is a maximum expected utility

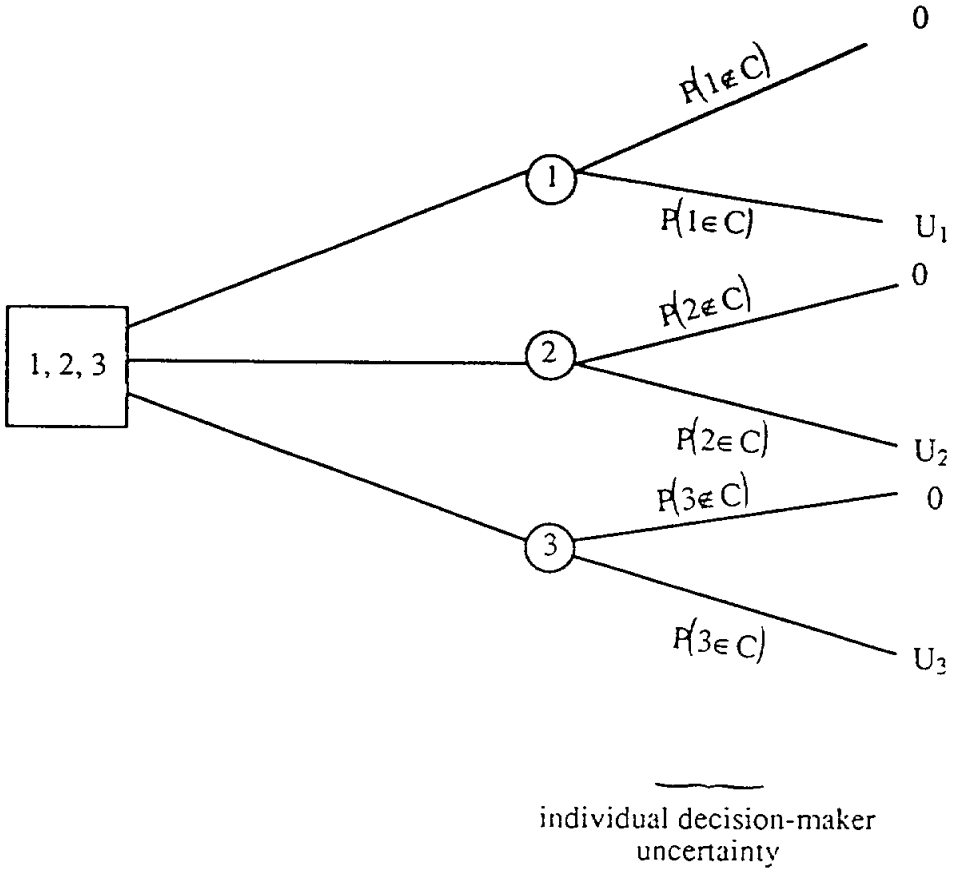

Figure 1-A. - Structuring the Choice Decision:
Endogenous Uncertainty

problem in the tradition of decision making under uncertainty, and the probability that the individual selects alternative j equals

$$P_j = \text{Prob}\left[P(j \in C).\ U_j > P(k \in C).\ U_k\ ;\ \forall k \neq j\right]$$

where $P(j \in C)$ is the likelihood of alternative j belonging to consideration set C. Using the same utility functions as in (1), it can be shown that (Fotheringham 1988, Vanhonacker 1992)

$$P_j = \frac{P(j \in C).\ \exp(V_j)}{\sum_{k \in J} P(k \in C).\ \exp(V_k)} \tag{4}$$

where J denotes the universal set of all alternatives (i.e., set {1,2,3} in the example). Note that if $P(j \in C) = 1$ for all $j \in J$, (4) reduces to the standard MNL model over the universal set.

If there is no uncertainty in the mind of the decision maker about the composition of the consideration set, the choice decision for that individual is a simple utility maximization problem over the alternatives contained in the set. However, because of its latent character to the modeler, the choice problem is structured as in Figure 1-B. Here, the probabilities describe the likelihood of the individual having a specific consideration set. Hence, those probabilities are in the mind of the modeler, and the combination of that uncertainty together with the individual's behavior gives rise to an expected maximum utility formulation. With the above utility functions, we obtain

$$P_j = \sum_{R} \text{Prob.}\ (C_r) \frac{\exp(V_j)}{\sum_{l \in C_r} \exp(V_l)} \tag{5}$$

where R denotes the set of all possible consideration sets C_r. Note that the choice probabilities in (5) are described as weighted averages of standard MNL choice probabilities as shown in (3).[2] Starting with Manski (1977), all theoretical and empirical work on choice modeling incorporating consideration set formation has been done with (5) except for Fotheringham (1988) and Vanhonacker (1992). As is evident from expression (5), the difficulty in empirical work is the size of R. Swait and Ben-Akiva (1987) provide a way to reduce its size using external constraints. They suggest the use of stochastic constraints defined by the modeler.

Three observations are in order here. First, it seems reasonable to assume that such "constraints" also play a role at the decision-maker level when he/she "considers" alternatives; such stochastic constraints by themselves would generate uncertainty in the consideration task,

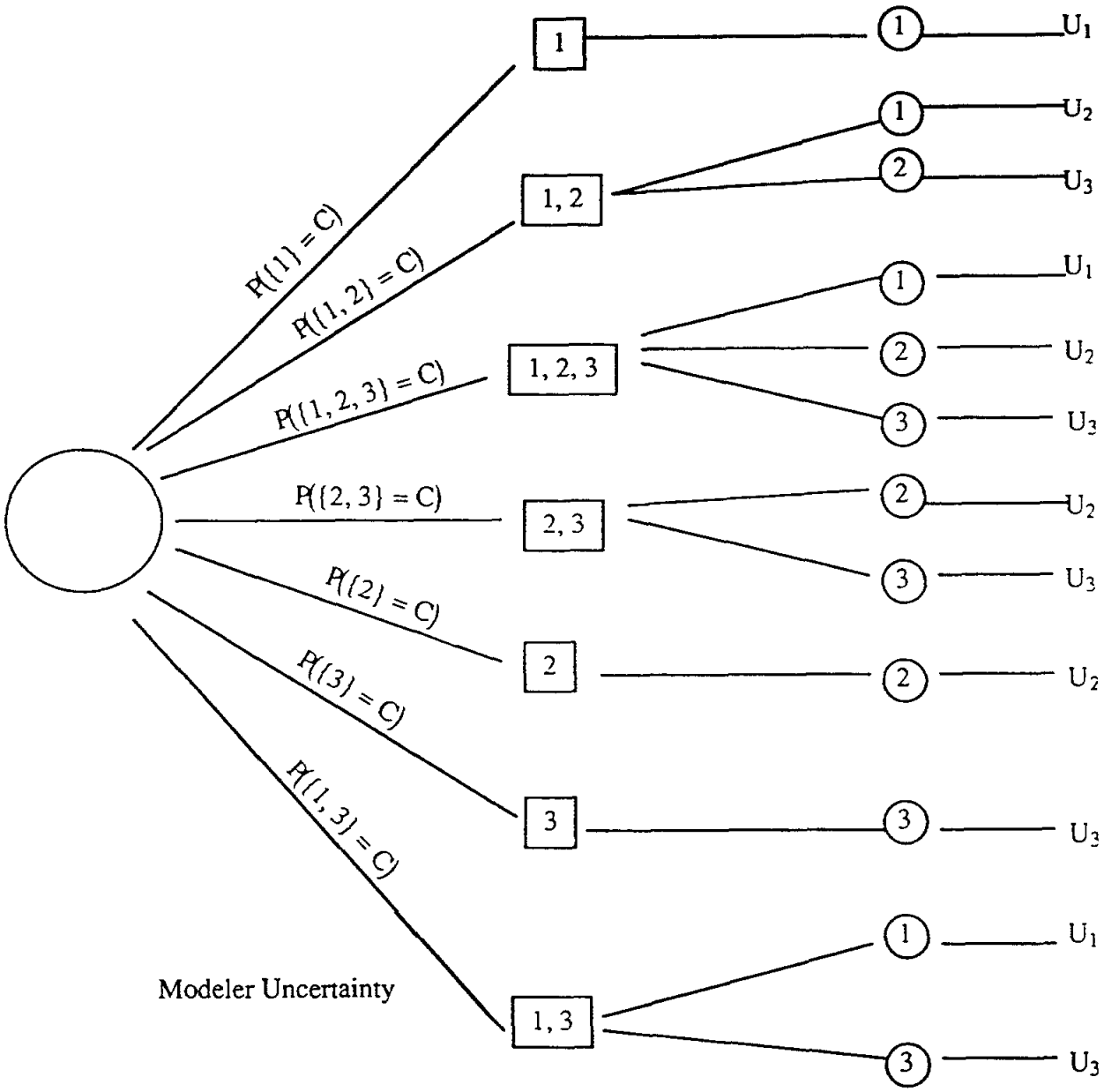

Figure 1-B - Structuring the Choice Decision:
Exogenous Uncertainty

and hence provide another ground for rejecting the traditional treatment of consideration sets as either given or deterministically predictable. Second, with respect to the structure underlying (5), there is not much sense in talking about consideration set generation as an "independent, cognitive construct" (see, e.g., Horowitz and Louviere 1991), as the process which gives rise to C_T at the individual level is ignored entirely. Third, it is interesting to note that the Elimination-by-Aspects Model of Tversky (1972), can be expressed in a form similar to (4). This model implies a hierarchical process in feature space which can be expressed as (adopting the notation of Meyer and Kahn 1991)

$$P(i/C) = \frac{\sum_{\alpha \in i'} u(\alpha).\ P(i/C_\alpha)}{\sum_{j \in C} \left(\sum_{\alpha \in j'} u(\alpha).\ P(j/C_\alpha) \right)}$$

where P(i/C) denotes the probability of selecting alternative i out of consideration set C, $u(\alpha)$ is the utility (or weight) associated with feature α , i' denotes a set of features of i (i.e., i' = $\{\alpha, \beta, \ldots\}$) and C_α is that subset of alternatives of C which share this feature. Furthermore, we can express P(i/C) as (see, Meyer and Kahn 1991, p. 99)

$$P(i/C) = \frac{u_i.K_i}{\sum_{j \in C} u_j.K_j} \tag{6}$$

with $K_j = \frac{\Sigma_{\alpha \in j'} u(\alpha).\ P(j/C_i)}{\Sigma_{\alpha \in j'} u(\alpha)}$, and $u_i = \sum_{\alpha \in i'} u(\alpha)$. Expression (6) is structurally similar to (4), which implies a hierarchy in consideration set generation and, hence, choice as modeled in (4). In contrast, the MNL model incorporated in (5) is usually not considered to be a hierarchical choice model. In terms of behavioral story, both (4) and (5) are very different. It will be shown now that the basic MNL model as shown in (3) can be reduced to (4). The good news is that, under some relatively weak assumptions the MNL model does implicitly recognize imperfectness in the consideration set generation task. The bad news is that its choice predictions become difficult to interpret.

5. UTILITY SPECIFICATION AND THE MNL MODEL

Consider a utility function where the strict utility component can be separated into two parts, or

$$V_j = V_{1j} + V_{2j} \qquad \text{for all } j \in J. \tag{7}$$

Hereafter, we will consider this the "full" specification; i.e., the utility functions include all deterministic elements which could influence the value (or evaluation) of an alternative. Hence, in line with Ben-Akiva and Boccara (1990), both the availability effect as well as the substitution effect are included. Accordingly, given (3), we have the MNL model

$$P_j = \frac{\exp(V_{1j} + V_{2j})}{\sum_{k \in J} \exp(V_{1k} + V_{2k})}.$$

Following derivations identical to the incremental MNL model (see, e.g., Ben-Akiva and Lerman 1985, p. 114), it can be shown that the choice probability P_j can be expressed as

$$P_j = \frac{\overline{P}_j . \exp(V_{2j})}{\sum_{k \in J} \overline{P}_k . \exp(V_{2k})} \tag{8}$$

with $\overline{P}_j = \exp(V_{1j}) / \sum_{k \in J} \exp(V_{1k})$. This expression is exactly identical to (4) assuming an MNL-type consideration set generation process based on a strict utility component. In other words, under certain conditions, the MNL model implies a consideration set generation process. Given the representation of Tversky's (1972) hierarchical model in (6), the MNL model would under these conditions not be that structurally different from the Elimination-By-Aspects model and imply a sense of hierarchy not usually associated with it.

In the extreme case then, when $V_{2k} = 0$, we obtain

$$P_j = \frac{\overline{P}_j}{\sum_{j \in J} \overline{P}_k} \tag{9}$$

which would mean that the MNL model only describes the consideration set generation task. Specifically, the P_j probability is the relative likelihood of j alternative being considered. The model would no longer describe choice in the traditional MNL sense, but the "fuzziness" of the consideration set experienced by the decision maker. The particular (and appropriate) interpretation of the results would then depend on the origin of that fuzziness.

The conclusion is that what we traditionally interpret as choice governed by real preferences is an MNL model might not be correct. The model might only (or partially) describe consideration set generation. The conditions under which this would happen are not that stringent. To reiterate, three assumptions gave rise to the observation: first, there is uncertainty experienced by the decision maker about consideration set membership. Second, the utility functions are "fully" specified, which essentially means containing both the "dominance" component as well as the "portfolio" component as defined in Vanhonacker (1992). Third, the consideration set generation task follows an MNL-type process (and, hence, is characterized by IIA). These assumptions are relatively weak. As discussed above, there is reason to believe that the decision maker experiences uncertainty in considering alternatives. Although it would be difficult to argue that utility functions are fully specified, the discussion above about the specification of the strict utility component in applied work (certainly in marketing) exemplifies the use of variables which might be more explanatory of the consideration set generation task than the preference evaluation in the choice task. Whether the set generation task is adequately described by an MNL is questionable.[3] However, the recognized robustness of the model would indirectly support the assumption. Some authors have implicitly made that assumption without really questioning it (see, e.g., Horowitz and Louviere 1991).

6. CONCLUSION AND IMPLICATIONS

This paper questioned the traditional interpretation of the MNL model as a model of choice. Under relatively weak assumptions, an alternative interpretation arises when recognizing that the decision maker experiences uncertainty when performing the consideration set generation task. In this instance, one cannot separate the effect of real preferences in the choice task from the effect of the consideration set generation task characteristics on the MNL predictions. This observation has important practical implications as marketing efforts, for example, differ depending on whether they aim at preference adaptation or at manipulation of the consideration set generation.

The origin of the problem is the uncertainty in the consideration set generation task experienced by the decision maker. A behavioral rationale does exist for it, and to the extent that we are driven by the behavioral richness of the decision we attempt to model, we need to recognize and incorporate it into our choice models. Merely relying on a random utility assumption and, hence, recognizing preference uncertainty does not implicitly account for consideration set generation uncertainty. Assuming that the sets are given or deterministically predictable does not do justice to the phenomenon either. The existence of uncertainty in the consideration set generation task makes it impossible for us to realistically separate it from the preference-driven choice task. Therein lies a challenge, but a potentially rewarding one as the practical implications are conditional on the origin of the uncertainty.

Consider the brand choice situation at the time of constructing a shopping list. As the decision maker cannot guarantee availability, some uncertainty will enter into the consideration set generation task. As availability is linked to where the shopping will occur, the characteristics of the generation task will reflect more store choice than brand choice. For example, in the convoluted MNL model, significant in-store consumer promotions could indicate that store choice is dependent on those promotional activities rather than affecting actual preferences as is currently inferred. Although clearly not independent, the promotional effect is at the trade level and not the brand level. Although perhaps not important for the manufacturer, the implications for the retailer are rather evident. Because the traditional MNL model predications do not allow us to disentangle these effects, we need to go beyond it to gain full insight into important managerial implications.

If the uncertainty surrounding the consideration set arises from not exactly being able to establish the appropriateness of alternatives for a particular future usage or consumption occasion, then the MNL model predications could capture how fitting each alternative is to the anticipated usage/consumption occasion. Here, the variables specified in the strict utility component would describe the decision maker's assessment of that alternative's suitability for future usage or consumption. Advertising, which in copy explicitly links an alternative to that occasion, would be rather effective here. Not discriminating purchases on the basis of usage might lead to insignificant advertising effectiveness in a traditional MNL model (even if it is estimated at the individual level). Hence, a potentially effective campaign might not be recognized.

The observation raised in this paper with respect to the MNL model has important implications. It points to the need to incorporate the consideration set generation task into our choice models recognizing the decision maker's uncertainty experienced in the task and the conditional nature of the interpretation of the task characteristics (and, hence, their impact on choice predictions) based on the origin of the uncertainty.

FOOTNOTES

1. "Consideration set", following Simon (1955), is defined as the set of alternatives considered for choice. Some authors use the term "choice set" to describe the same set.

2. As shown in Vanhonacker (1992), the predictor variable elasticities are quite different between the MNL model and (4), indicating the potential for erroneous managerial conclusions.

3. Note that forcing an MNL-type process would constitute a misspecification.

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