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Comments on "On Conjoint Analysis and Quantal Choice Models"

In his paper, "On Conjoint Measurement and Quantal Choice Models," Albert Madansky (this issue) points out that conjoint analysis[1] usually deals with each respondent separately. It is an individual level analysis in the sense that the idiosyncratic parameters for each individual are estimated using only the preference judgments of that individual (for an illustration, see Parker and Srinivasan [1976, p. 1009]). On the other hand, quantal choice models are usually estimated at the aggregate level in the sense that a common set of parameters is estimated from the choice data of a sample of individuals (for an illustration, see McFadden [1976, p. 130]). Variation in the utility function across individuals is incorporated in such quantal choice models through a vector of measured characteristics of the individual. In this comment, we first discuss the rationale for the popular use of individual level analysis of preferences in marketing.

Although conjoint analysis is usually carried out at the individual level and quantal choice approach is usually carried out at the aggregate level, it is possible to use conjoint analysis at the aggregate level (e.g., see Srinivasan and Shocker 1973) and use quantal choice analysis at the individual level (e.g., see Jain et al. 1979). The second part of this comment discusses some of the limitations of a popular quantal choice approach, namely, the LOGIT model, in individual level analysis.

Individual versus Aggregate Analysis

Given the substantial amount of variations in consumer preferences from one person to another, it has become essential in marketing analysis to take adequate account of individual differences. As remarked earlier, quantal choice models are usually estimated at the aggregate level with individual differences incorporated only in the form of a vector of measured characteristics of the individual. Usually this is a vector of demographic and socioeconomic variables. But empirical evidence in marketing (Frank 1968) indicates that demo-

1. What Madansky refers to as "conjoint measurement" is more appropriately called "conjoint analysis" (for a distinction between these two terms, see Green and Srinivasan [1978]).

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graphic, socioeconomic, and psychographic variables are poor predictors of variations in behavior across consumers for grocery products. In empirical studies that have used componential segmentation (Green 1977), in which individual variations in preferences are incorporated through demographic and socioeconomic variables, it appears that the incremental variance explained by demographic and socioeconomic variables is usually quite modest.

The poor predictive ability of demographic and socioeconomic variables in explaining variations in consumer behavior should not be interpreted to imply that such variables are useless. They may still be of some value, and the usefulness may be greater for durable goods as well as in industrial marketing, two areas in which there has been very little empirical evidence one way or the other regarding the usefulness of demographic and socioeconomic variables. Aside from this caveat, we have to conclude that in quantal choice models much of the individual variation in preferences will not be measured systematically but will instead be treated as "error." This may be a satisfactory approach for economists who are concerned primarily with aggregate equilibrium behavior of markets, but it is certainly not adequate for a marketing manager. The marketer does not restrict his attention to the average preferences of the market (which may sometimes lead to the so-called majority fallacy [Kuehn and Day 1962], since there may be too many firms competing for this major segment of the market). Often, the marketer is looking for niches in the market, that is, segments which are not well served by the current offerings in the market place. Thus marketers tend to place a considerable emphasis on measuring differences in preferences and on tailoring their product offerings and marketing plans to segments of the market. Conjoint analysis at the individual level is thus likely to be a useful tool in product planning efforts. Based on the earlier arguments, we would expect that aggregate level quantal choice analysis is less likely to be useful.

Limitations of the Multivarite LOGIT Model in Individual Level Analysis

The quantal choice models, such as the popular multivariate LOGIT model (McFadden 1976), can also be used to estimate individual utility functions using the same data inputs as those collected for conjoint analysis approaches such as MONANOVA (Kruskal 1965) and LINMAP (Srinivasan and Shocker 1973). The input data consist of a set of prespecified hypothetical product descriptions (i.e., stimuli defined in terms of their levels on each of the product attributes) together with an individual's rank order of preferences for this set of stimuli. The output is the set of estimated parameters of the preference model for that individual.

The use of the LOGIT model involves the "independence of irrelevant alternatives" assumption, which is not a realistic assumption in many consumer behavior contexts (see McFadden [1976, p. 113] for a discussion of this assumption).

The LOGIT model also assumes that the input paired comparisons are probabilistically independent. If the data are obtained directly as paired comparisons, this may be a realistic assumption. However, this is an inefficient way of collecting individual level preference data. If the data are obtained more efficiently as a rank order of n stimuli and then converted to the equivalent $n(n-1)/2$ paired comparisons, the independence assumption is not realistic.

Finally, in public sector applications of preference measurement, it is useful to express the utility function in monetary terms so that incremental utilities resulting from a change in the public system can be aggregated across individuals and compared against incremental cost (e.g., Parker and Srinivasan 1978). Assume that the utility function is linear, that is,

$$U_{ij} = \sum_{p=1}^{t} w_{ip}\, y_{jp},$$

where U_{ij} is the estimated utility of the ith consumer for the jth object, w_{ip} is the estimated weight of the ith consumer for the pth attribute ($p = 1, 2, \ldots, t$), and y_{jp} is the value of the jth stimulus along the pth attribute. Then defining $p = 1$ to be a monetary attribute (price) and multiplying the equation throughout by $(-1/w_{i1})$ gives

$$U'_{ij} = -y_{j1} + \sum_{p=2}^{t} \left(\frac{-w_{ip}}{w_{i1}} \right) y_{jp},$$

with U'_{ij} denoting the utility in monetary terms. (Since greater price would be related to smaller monetary utility, *ceteris paribus*, the weight for y_{j1} has been made equal to -1.) For this transformation to be valid, the estimation procedure should have the property that the multiplication of all the estimated parameters $\{w_{ip}\}$ by a positive constant should not alter the goodness (poorness) of fit that is maximized (minimized) in the estimation procedure. (Note that since $w_{i1} < 0$, the multiplicative constant $(-1/w_{i1})$ used in the transformation above is positive.) The estimation procedures such as LINMAP have this property, while LOGIT does not. Consequently the use of LOGIT is limited for such public sector applications.

Conjoint analysis procedures such as MONANOVA and LINMAP have limitations of a different kind. In such procedures, the standard errors of the estimated parameters are not known, as against LOGIT where asymptotic approximations to standard errors are available.

Although the small number of hypothetical stimuli typically used and the dependence of the paired comparisons obtained through the rank order task make the use of such asymptotic standard errors questionable, they may still provide rough estimates of the standard errors of estimation. An additional problem with the use of procedures such as MONANOVA and LINMAP is that they result only in estimates of preferences so that another modeling step is needed to link the preferences to choice probabilities. The LOGIT model, however, links input data to choice probabilities in a single step.

To summarize, individual differences in preferences are not well captured by aggregate level quantal choice analysis, so that at least for marketing analysis, it makes more sense to estimate individual utility functions. Even at the individual level, quantal choice procedures such as LOGIT have a number of deficiencies which limit their applicability to the modeling of consumer preferences.

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