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Choice Task Complexity and Decision Strategy Selection

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Abstract

The psychology, the marketing consumer behavior and, to a much smaller extent, the economics literature have long reported evidence that decision makers utilize different decision strategies depending upon many factors (person-specific, task-specific, etc.). Such observations have generally failed to affect the specification of choice models in commercial practice and academic research, both of which still tend to assume an utility maximizing, full information, indefatigable decision maker. This is true whether the models deal with Stated Preference (SP - from hypothetical elicitations) or Revealed Preference (RP - from actual market decisions) choice data. This paper, which deals only with SP data, addresses the following issues: (1) does task complexity affect decision strategy selection in experimental choice tasks? (2) does the cumulative cognitive burden created by multiple choice scenarios done in sequence affect the selection of decision strategy by respondents?

Our contribution is two-fold: (1) we introduce decision strategy selection as an explicit factor in aggregate choice models via the mechanism of latent classes, which are assumed to be a function of task complexity; (2) we demonstrate, for a particular set of data, that within the scope of an SP choice task, respondents did indeed make use of multiple decision strategies as choice set complexity changed and as the SP task progressed. We examine the import of our findings to current practice, model interpretation and future research needs.

INTRODUCTION

The judgment and decision making (JDM) literature has devoted much of its attention to the strategies used by human beings and organizations to make decisions (see, e.g., the review in Bettman, Johnson and Payne 1991). A number of researchers have concerned themselves with formulating descriptive and mathematical models of different decision strategies (e.g., Simon 1955, with the Satisficing decision rule; Dawes 1964, Einhorn 1970, 1971, who proposed and tested the Conjunctive decision rule, respectively; Dawes 1964, with the Disjunctive rule of choice; and Tversky 1972, with Elimination-by-Aspects); another stream of the JDM literature has concerned itself with finding evidence of the utilization of compensatory and (a plethora of) non-compensatory decision strategies by decision makers as task complexity (e.g. time pressure, alternative similarity) and context change (see, e.g., Bettman 1970; Payne 1976; Russo and Dosher 1983; Lynch 1981; Ball 1997).

While the JDM literature has satisfactorily established that people utilize multiple choice strategies depending upon a large number of factors (product, occasion, information presentation format, time pressure, alternative similarity, etc.), there has been little linkage to the literature on multi-attribute, multi-alternative experimental choice tasks (see Louviere and Woodworth 1983). This preference elicitation method (also known as Stated Preference, or SP, elicitation), while it can take many different forms, basically presents respondents with the task of choosing from among multiple product profiles, each described in terms of a generally common attribute set. In addition, respondents are usually presented with multiple decision scenarios in a short time span. Traditionally, these data are modeled through specifications such as the Multinomial Logit (MNL), Nested MNL and Probit models (Ben-Akiva and Lerman 1985). While some small number of non-compensatory models have been used with choice data (see Swait and Ben-Akiva

1987a,b; Roberts and Lattin 1991; Ben-Akiva and Boccara 1993; Andrews and Srinivasan 1995; Swait 1997; Horowitz and Louviere 1995; all these references, except the last two, deal with revealed, or market, choices, rather than stated choices), the models utilized are almost exclusively compensatory in nature.

There have also been few links between the JDM literature and the economics literature on the issue of decision strategy changes and stability. Econometric models of consumer choice, whether employing revealed preference or stated preference data, continue to focus on compensatory models of choice in which the consumer makes use of all available information in selecting the optimal choice.

Swait and Adamowicz (1997) have produced evidence that the complexity of experimental choice tasks (number of alternatives, number of attributes and utility similarity) affects not the taste weights in discrete choice models, but instead affects between-subjects variance components. They show that this result holds across a wide range of products (frozen orange juice, hunting site selection, mode choice, campground selection and a consumer loan product). In effect, complex choice scenarios induce less consistency across subjects (which translates into greater error variance). This can unwittingly be captured in choice models by between-subject taste differences as opposed to increased error variance.

In their work, Swait and Adamowicz (1997) utilize compensatory choice models (a variant of the MNL, in that case) to uncover the latent preference functions. In their closing paragraphs, they suggest that future research into the interaction between complexity and decision strategy selection is needed. Following up on that research, then, we address the following issues in this paper: (1) Does task complexity affect decision strategy selection in experimental choice tasks? (2) Does the cumulative cognitive burden created by multiple choice scenarios done in

sequence affect the selection of decision strategy by respondents?

We approach these questions differently than most previous researchers. Rather than use verbal protocols (Bettman 1970), eye-tracking techniques (Russo and Dosher 1983) or registering information search patterns (Ball 1997), we utilize a particular latent class structural choice model to infer likely decision strategies across a sample of respondents given SP choice tasks, as a function of complexity and cumulative cognitive burden. We are able to show that complexity and cumulative cognitive burden significantly affect preference patterns, and further, that these patterns appear to be changes in processing strategies in response to changes in context or task demands. The hypothesis of no change in preference structure in response to changes in complexity is clearly rejected in the data utilized. Furthermore, the resulting preference patterns support the notion of a movement toward a simplified choice heuristic as complexity increases. Though it is somewhat unusual to utilize econometric methods to analyze processing strategy, we have been preceded by Bockenholt and Hynan (1994), who apply a latent class model to information acquisition data (as compared to our use of holistic choice elicitations), to capture individual differences among respondents in information search strategy selection.

STRATEGY SELECTION FOR MULTI-ATTRIBUTE DECISIONS

Past Work in Strategy Identification

The usual explaination for the use of heuristics, or strategies, by decision makers is that there exists a tradeoff between decision cost and outcome benefit. This framework is formalized in Shugan's (1980) analysis, which demonstrates the theoretical basis for strategy selection as a compromise between making the right decision and reducing the effort needed to reach a decision. As reviewed by Bettman, Johnson and Payne (1991, 64), this research stream has demonstrated through simulation and experimental work that the cost-benefit viewpoint is able to explain

contingent decision making behavior. Particularly, the simulations performed in Johnson and Payne (1985), Payne, Bettman and Johnson (1988) and Bettman, Johnson and Payne (1990) were used to calculate decision effort and accuracy for different heuristics; experiments were then performed with human subjects to determine whether they would switch to effort-reducing strategies in contexts in which those strategies would maintain high decision accuracy levels, which they did do.

Russo and Dosher (1983) approach the identification of strategy selection differently, concentrating on observing the strategies rather than modeling their effect on behavior. For decisions involving choice between two alternatives, described by multiple attributes, they utilized a combination of eye-tracking and prompted verbal protocols to characterize the information processing strategies. They identified two classes of processing: holistic (processing alternatives first) and dimensional (processing attributes first), and find in their data that there is a slight predominance of use of the latter. Very interestingly, they also find that subjects adopted two simplification procedures: dimensional reduction (DR: ignoring attributes deemed of small importance) and majority of confirming dimensions (MCD: ignoring magnitudes and giving directional, but equal importance to all attributes). The use of these simplification procedures does not seem to have been tied to decision difficulty, which is somewhat indicative that they were part of a routine decision strategy. While these processing strategies (with or without simplifications) have different effort and accuracy implications for subjects, note that from the point of view of traditional compensatory choice models they are indistinguishable since the information is assumed combined for all alternatives and attributes to achieve an alternative-specific measure of object utility.

Ball (1997) examines the ability of single-step transition indices to discriminate between

different decision strategies used by subjects in information processing experiments. He finds strong support for his contention that multi-step indices are needed to adequately identify strategies. From the perspective of our paper, Ball's research is noteworthy because he utilizes cluster analysis of transition information to characterize decision strategies. He warns, however, that due to the nature of cluster analytic methods, "… caution should be expressed when interpreting the results of such cluster analyses as the final selection of clusters can not be supported statistically …" (Ball 1997, 203).

Bockenholt and Hynan (1994), in contrast, utilize a latent class model to cluster transition patterns. They apply the model to information acquisition data gathered in a trinary choice situation, each alternative described by three attributes. They argue that the latent classes are needed as a parsimonious representation of individual differences between subjects. Because their approach is model-based, they are able to determine the statistical significance of the clusters they find in their data, which Ball (1997) admits to not being able to do with his adopted approach. Bockenholt and Hynan (1994) differ from what we do in that (1) they concentrate on the information acquisition strategy itself, whereas we seek to infer the strategy by the choices made; and (2) their specific model form is, therefore, quite different from the one proposed herein.

Relating Decision Strategy Selection to Task Complexity and Cognitive Burden in SP Choice Tasks

We propose to take, then, a model-based route to identify strategy selection during SP choice tasks involving repeated choices between multiple alternatives described by multiple attributes. We hypothesize that two effects, decision complexity and cumulative cognitive burden, contribute to the strategy selection process. The basic reasoning behind our hypotheses is that a common sequence of events for a respondent in an SP choice task may be something like this: (1)

learning about the task and the effort necessary to accomplish it by trying out different decision strategies for some number of replications, followed by (2) the *application* of the learned behavior during another number of replications, and finally, (3) *fatigue* sets in, leading to the use of simplified decision strategies. Note how this reasonable sequence conflicts with the usual assumption of full information, compensatory behavior throughout the entire task that is assumed in the traditional model forms used to analyze SP choice data. But this is not simply a modeling issue: the very notion that complexity affects decision making conflicts with the traditional notion of value maximization used in economics, in which individuals are assumed to be able to assign values to alternatives, and choose the alternatives with the highest value, independent of context, learning, fatigue, etc.

Nonetheless, some authors in the economics literature have discussed the limitations of an individual's ability to process information and the implications of these limitations on choice behavior. For example, Heiner (1983) argues that agents cannot grasp the full complexity of the situations they face and thus make decisions that appear sub-optimal. He argues that the complexity and uncertainty surrounding a choice situation often leads consumers to adopt simplified strategies. A more formal examination of the processing limitation argument is presented by de Palma et al. (1994), who theoretically model consumers with different abilities to choose such that an individual with lower ability to choose will make more errors in comparisons of marginal utilities. They outline the implications of limited processing capability on choice and discover that heterogeneity in the ability to choose over a sample of individuals produces widely different choices, even if in all other aspects the individuals are identical. In our context, we suggest that the complexity of the decision problem will affect the ability to choose, and thus for any given individual, ability to choose will differ depending on the task demands. Similar

conclusions arise from the literature on “bounded rationality” (March, 1978; Simon, 1955).

In the JDM literature, Shugan (1980) suggests that the costs of decision making to the individual are associated with his or her limited processing capability, the complexity of the choice, time pressure and other factors. He constructs a conceptual “confusion index” which attempts to measure the effort required by the individual to make the choice. In a similar vein, Bettman et al. (1993) examine the impact of task complexity, measured as the degree of negative correlation between attributes, on the decision making strategy chosen by the consumer. These researchers suggest that providing more difficult choices may lead to richer information on preferences as respondent processing effort increases with complexity.

Alternatively, it has been suggested that individuals may attempt to avoid conflict when choices are complex, leading to the use of simpler choice heuristics when attributes are negatively correlated. Keller and Staelin (1987) suggest that complexity may have an inverted U-shaped relationship with decision effectiveness. That is, as the situation becomes more complex, individuals initially exert additional effort and become more effective, until a point is reached where their effectiveness begins to deteriorate. Tversky and Shafir (1992) show that when the choice environment is made complex (by adding alternatives or making the choice alternatives similar, but not identical), some individuals opt to delay choice, seek new alternatives, or even revert to a default (or status quo) option. Similar findings by Olshavsky (1979), Payne (1976), Payne et al. (1988) and Simonson and Tversky (1992) suggest that the context and complexity of the decision, as described by the number of attributes, correlation between attributes, number of alternatives, time pressure and various other factors, significantly influence decisions.

The concept of complexity affecting choice also applies to repeated choice situations, wherein additional choices may increase cumulative cognitive burden. In SP choice tasks,

individuals are generally asked to face repeated choice decisions (say, R≥1 replications) to decrease data collection costs. There is some evidence of fatigue effects in SP choice experiments (Bradley and Daly, 1994, Swait and Adamowicz 1997) although there is also some counterevidence suggesting this fatigue effect may be minimal (Brazell et al. 1995). In some cases respondents may actually become more proficient at the choice task as they are exposed to more replications (i.e. learning occurs).

Swait and Adamowicz (1997) studied how complexity and cumulative cognitive burden affect the variance of the latent utility construct estimated from choice models. We concentrate our attention on how these effects impact strategy selection. To outline our approach in more detail, we proceed first to describe how complexity and cognitive burden can be quantitatively represented; we then present the specific model form we apply to our data to accomplish our goals.

Quantifying the Complexity and Cumulative Cognitive Burden of Multiple SP Choice Tasks

Our objective in this section is to present and justify the use of a specific mathematical representation of choice environment complexity. Some dimensions of such a measure have already been discussed above (the number of attributes, the number of alternatives, negative correlation of attributes, etc.). Note, however, that each of these quantities is a component of complexity rather than an overall measure.

Distance between alternatives in attribute space, which is related to the correlation structure of the attributes, is a candidate for capturing the degree of overall complexity involved in a choice context. Suppose we wish to examine choice sets with 3 alternatives, described by K-vectors of attributes x_A, x_B and x_C. These distance measures can generally be constructed as sums

of distance norms (e.g. absolute value distance or Euclidean distance) for vectors x_i and x_j, $i,j \in \{A,B,C\}$. While such measures would reflect the distance between alternatives in attribute space, they may not capture the number of alternatives in the measure of complexity. These measures also require that all attributes be commensurable, a requirement that usually is not met.

In order to design a more complete and formally defined measure of complexity, we turn to information theory to provide a measure of information content or uncertainty. Information theory refers to an approach taken to characterize or quantify the amount of information contained in an experiment or phenomenon (Soofi, 1994; Shannon, 1948). Given a set of outcomes (or *alternatives*, in our context) $\{x_j,\ j = 1,\ldots,J\}$ that are described by a probability distribution $\pi(x)$, the entropy (or uncertainty) of the choice situation is defined as

$$H(X) \;=\; H(\pi_x) \;=\; -\sum_j \pi(x_j)\log\pi(x_j) \;\geq\; 0\,. \tag{1}$$

In a case with J alternatives in a choice set, entropy reaches its maximum if each of the J are equally likely. If the number of equally likely alternatives increases, entropy also increases. Thus, the number of alternatives in the choice set directly affects the level of complexity, making this measure a useful mechanism for testing hypotheses regarding the impact of the number of alternatives on different components of the choice process (e.g. decision rule, choice set composition, tastes, variance). Entropy is minimized if there is one dominant alternative in the choice set. For example, if one alternative has a probability of one and the others have probabilities of zero, entropy achieves its minimum of zero. The degree of attribute correlation and number of attributes also play a role since these elements will affect the assignments of probabilities.

An additional aspect associated with the use of entropy as a measure of task complexity is the fact that cumulative entropy can be used to assess the impact of cumulative complexity of

multiple choice tasks (i.e. cumulative cognitive burden). *Cumulative entropy* provides a measure of the amount of uncertainty faced by individuals as they make *sequences* of choices.[1]

Our measure of task complexity and cumulative cognitive burden is incorporated into a latent class discrete choice econometric model. Details on the model and the incorporation of the complexity factor to identify decision strategy selection are given in the next section.

Justification and Formulation of Proposed Model

Suppose that a population of respondents will be in one of S latent (i.e., unknown to the analyst) states during an SP choice task. Thus, in one task the same individual might be in one state (say, s), while in the next choice task, either due to the complexity of that task and/or to cumulative effort expended, the same person might be in another state (say, s'). Each state has associated with it a taste parameter vector β_s, s=1,...,S, which is the basis for the individual's evaluation of the attractiveness of product offerings in the current choice set. If, in a particular state k, β_k contains all zero elements corresponding to attribute values and nonzero elements corresponding to brand intercepts, one might surmise that the state corresponds to a purely brand-based decision strategy (since attributes are being ignored); on the other hand, if all tastes are nonzero, one might cogently argue that a fully compensatory decision strategy is used in that state. Thus, the configuration of the taste vector in latent state s is directly reflective of the decision strategy used by individuals when in that state. The literature has noted before the capacity of compensatory models to represent non-compensatory processes through functional form nonlinearity and parameter vectors. This literature goes back some time to Einhorn (1970, 1971); more recent examples are Johnson and Meyer (1984), Elrod, Johnson and White (1992) and Swait (1997).

Thus, conditional on being in state s, we assume that the utility $U_{i|s}^{r}$ of the i-th product

offering in replication r is given by

$$U_{i|s}^{r} = \beta_s X_i^r + \varepsilon_{i|s}^{r}, \tag{2}$$

where X_i^r is the vector of product attributes and context characteristics, and $\varepsilon_{i|s}^{r}$ is an error term. (We suppress here and henceforth the subscript for the individual respondent, for purposes of clarity.) If we assume that the joint distribution of the error terms, conditional on the decision state, is IID Gumbel with unit scale factor, then the conditional choice probability of choosing alternative i is the familiar Multinomial Logit (MNL) model:

$$P_{i|s}^{r} = \exp(\beta_s X_i^r) \Big/ \sum_{j \in C^r} \exp(\beta_s X_j^r) \tag{3}$$

where C^r is the set of alternatives from among which choice is exercised in the rth replication.

As observers, we are unable to classify a randomly selected individual from the population into a particular decision state s for a particular replication r. Instead, we postulate that there exists a certain latent stochastic cost-benefit strategy selection factor Y^r, defined as follows:

$$Y^r = \alpha_1 H^r + \alpha_2 (H^r)^2 + \alpha_3 \psi^r + \alpha_4 (\psi^r)^2 + \alpha_5 H^r \psi^r + \nu^r, \tag{4}$$

where $\alpha_1, \ldots, \alpha_5$ are parameters, H^r is the entropy of the rth choice set seen by a respondent, ψ^r is the cumulative entropy encountered by the respondent up to the rth replication, and ν^r is an error term with zero mean. ψ^r is defined as

$$\psi^r = \begin{cases} 0 & for\ r = 1 \\ \sum_{r'=1}^{r-1} H^{r'} & for\ r = 2, \ldots, R \end{cases}. \tag{5}$$

Through (4), we assume that as the cumulative cognitive burden increases and the complexity of the current task increases, the latent selection factor Y^r also increases. In addition, we include an interaction term between current entropy and cumulative entropy to permit a nonlinear response

in the factor as fatigue sets in: as cumulative cognitive burden increases, sensitivity to current complexity level increases.

We must now relate the factor Y^r to the decision state entered by the individual. Define a latent state indicator I^r, which takes on values in the set {1,...,*S*}. It is related to Y^r as follows:

$$I^r = \begin{cases} 1 & \mathrm{Y}^{\mathrm{r}} \le \tau_1 \\ 2 & \tau_1 \le \mathrm{Y}^{\mathrm{r}} \le \tau_2 \\ \vdots & \vdots \\ \mathrm{S} & \tau_{S-1} \le \mathrm{Y}^{\mathrm{r}} \end{cases} \tag{6}$$

where τ_s, s=1,...,S-1, are cutoff parameters to be estimated that define the ranges of Y^r that lead to classification into each latent decision state. (Note that only S-1 cutoff parameters are needed to construct S states.)

Note that expression (6) imposes an ordinal relationship among the latent segments: membership in higher order segments implies higher values of Y^r, and vice-versa. Figure 1 depicts this relationship graphically. Each range (as defined by the cutoffs) on the latent factor corresponds to a different decision strategy, as defined by the configuration of relative attribute importances contained in the associated taste vector β_s, s=1,...,S.

--- Figure 1 about here. ---

Since Y^r is a random variable, we must assume some distribution law to describe v^r; we can then calculate probabilities $W_s^r = \Pr(I^r = s)$, s=1,...,S. For our model development, we shall assume that v^r is independently logistic distributed across individuals and decision states, so that the cumulative density function is

$$G(v^r) = [1 + \exp(-v^r)]^{-1}, \; -\infty < v^r < \infty \; . \tag{7}$$

Therefore,

$$W_s^r = \Pr(I^r = s) = \begin{cases} G(\tau_1 - \overline{Y}^r) & s=1 \\ G(\tau_2 - \overline{Y}^r) - G(\tau_1 - \overline{Y}^r) & s=2 \\ \vdots & \vdots \\ 1 - G(\tau_{S-1} - \overline{Y}^r) & s=S \end{cases} \tag{8}$$

where $\overline{Y}^r = E_v(Y^r)$ (see expression 4).

We can now express the unconditional probability that a consumer will choose alternative $i \in C^r$ as

$$P_i^r = \sum_{s=1}^{S} P_{i|s}^r W^r \quad . \tag{9}$$

The structural model proposed above is termed the *ordered logistic latent class MNL choice model*. It has been previously used by Swait and Sweeney (1996) to study the impact of value perception on consumers' retail outlet choice behavior. Gopinath and Ben-Akiva (1995) also use an ordered latent segment model (though not an MNL model for the conditional choice); their application context is transport mode choice and models the implicit ordering among consumers due to their value of time. Swait (1994) develops a similar model to this, but does not permit ordered segments. Both these models are inspired by McFadden's (1986) concept of combining psychographic and choice data. At another level, all these models can also be seen as examples of Dayton and Macready's (1988) use of concomitant variables to explain latent segment membership.

Certain parameter identification conditions are applicable to the model above. Only (S-2) of the cutoff parameters τ_s, s=1,...,S-1, are actually identifiable, so one of them must be arbitrarily fixed (say, $\tau_1 \equiv 0$). Other identification conditions common to choice models also apply here: for example, constants can only be estimated for (J-1) of J brands. The reader is referred to Ben-Akiva and Lerman (1985) for further details on identification conditions for choice models.

For a fixed value of *S*, parameter estimation is accomplished via maximum likelihood techniques using specialized code. To estimate *S*, which is a parameter taking on discrete values, it is necessary to estimate the model over a range of interest that is problem-specific. Parsimony and interpretability should dictate a reasonably small number of segments in the final solution, however.

Before proceeding to the case study, we present next our operationalization of the entropy measure.

Empirical Calculation of Entropy and Cumulative Entropy

A measure of the probability of selection of the alternatives is required to operationalize entropy as a complexity measure (see expression 1). Here, we follow Swait and Adamowicz (1997) and construct an *a priori* estimate that will sufficiently characterize the choice context to allow discrimination between decision strategies. We assume that a measure of probability of choice can be obtained from an MNL model with the following form:

$$\tilde{\pi}_i^r(X) = \frac{\exp[\omega X_i^r]}{\sum_{j \in C^r} \exp[\omega X_j^r]} \qquad , \tag{10}$$

where ω is a set of unknown attribute weights, other quantities as previously defined. Thus, obtaining an approximate choice probability reduces to specifying the weights ω. Several approaches could be taken to specify ω in the absence of knowledge of the true parameters: (1) if there is no prior knowledge of relative attribute importance, one could give equal weight to all attributes (Dawes 1979); (2) the analyst might venture to specify ω on the basis of his or her experience with similar choice problems, perhaps with the support of economic theory, where possible; (3) one could "borrow" estimates from another study considered similar to the one being conducted; or (4) one might conduct an initial data collection effort to estimate ω, and use this

estimate in the second stage of data collection. These options roughly span the spectrum of one's willingness to inject exogenous information into the estimation of the choice probabilities.

In the empirical work reported subsequently, we have specified a simplified choice model (10) in which the principal effect of attributes are given the sign expected by theory or the analyst's experience (e.g. high price is worse than low price, high quality is more attractive than low quality) and *equal weight* is assigned to all attributes. We term this estimate of ω a "flat prior." Dawes (1979) shows that using equal weights in the General Linear model applied to predicting numerical standardized responses from numerical standardized predictors yields results that compare quite favorably with use of the optimal weights (see his Table 1). Earlier work by Dawes and Corrigan (1974) is supportive of Dawes' later finding.

We have also limited ourselves to attributing weights to the main effects of attributes (e.g., price, quality feature 1, …), leaving interactions (e.g. between two quality features) with zero weight. Thus, the level of uncertainty about a choice set is described using a measure of similarity of alternatives, where similarity is based on an attractiveness metric calculated using a set of equal prior weights. The resulting approximate entropy measure is, therefore,

$$\tilde{H}^r = -\sum_{i \in C_n} \tilde{\pi}_i^r(X^r) \ln[\tilde{\pi}_i^r(X^r)] \qquad , \tag{11}$$

where $\tilde{\pi}_i^r(X^r)$ is given by (10) using equal weights. Based on this entropy approximation, we also define our proxy for cumulative cognitive burden, namely, cumulative entropy:

$$\tilde{\psi}^r = \begin{cases} 0 & for\ r = 1 \\ \sum_{r'=1}^{r-1} \tilde{H}^{r'} & for\ r = 2, \ldots, R \end{cases} \tag{12}$$

where r refers to replication index, R is the total number of replications seen by each respondent and $\tilde{H}^r$ is the entropy of the rth replication (given by equation 11) seen by a respondent.

Our use of the flat prior can be considered an *approximation* to the true level of information since we have not included interaction effects and we have not constructed individual-specific priors. However, it is important to note that we do not wish to make behavioral assumptions about the consumer. Rather, we are constructing an index that characterizes the task demands on the respondent. Thus, while more accurate information about the consumer might help us construct a more precise measure of the task demands or complexity the consumer faces, it may be that the benefit of such additional refinement is marginal. Swait and Adamowicz (1997) conducted some limited testing of the relative performance of the flat prior versus an improved estimate of ω. Specifically, they used the flat prior to estimate taste parameters, which then became the estimate of ω, and so forth till convergence. They did this for two of the six data sets they report upon; it was found that iterative improvement of the prior estimate of ω resulted in *very small* improvements in goodness-of-fit: log likelihood improvements were a mere 0.1% and 0.2%, respectively, in the two studies examined. Thus, on the basis of their (admittedly) limited experience indicating an insensitivity of their conclusions to more informative priors, we adopt the conceptually straightforward flat prior in our reported empirical work.

Summary

We have presented a conceptual and modeling framework within which to detect and characterize the selection of different decision strategies by subjects in experimental, or SP, choice tasks. Our approach departs fundamentally from previous work in the JDM literature because we utilize a structural econometric model to *a posteriori* identify classes of decision strategies utilized by a group of respondents at different points in an SP task. The advantage of this approach, of course, is that it is non-intrusive and does not generate some sort of Heisenberg uncertainty. Extant methods (i.e. process-tracing through verbal protocols, eye-tracking or computer registration of respondent actions, chronometric methods) are subject to the observation that the very act of measurement can change the state of the thing measured (see the discussion in Bettman, Payne and Johnson 1991, 73).

The method utilizes a latent class model that associates decision strategy states with unique taste parameter vectors, which can then be examined *a posteriori* to characterize the decision strategies. The basis for classifying an individual subject into a decision state is a function defined in terms of decision task complexity and cumulative cognitive burden; the former is represented in the model through an empirical entropy measure, which is then summed up to capture the latter.

EMPIRICAL EVIDENCE OF MULTIPLE DECISION STRATEGY SELECTION

In this section we report upon the estimation of an ordered logistic latent class MNL choice model. The data originate from a SP choice experiment about frozen concentrate orange juice. We next describe the data utilized, then present model estimation results. The more substantial part of this section interprets the results from the strategy selection viewpoint.

Data Collection

The variables manipulated in this experiment to describe the orange juice available to the respondents are (1) brand (McCain's, Old South, Minute Maid and Generic), (2) grade (A vs. C), (3) sweetness (sweetened vs. unsweetened), (4) package size (unit vs. package of 4), and (5) price per unit ($1.30 vs. $1.60/unit). A one-half fractional factorial design was used to create 32 orange juice profiles that permit the independent estimation of all main-effects and two-way interactions. These profiles were presented with two other orange juice profiles. The first of these was created by randomly assigning profiles created by the fold-over (Louviere 1987) of the original design described above. The second was a fixed alternative, described as grade C, sweetened orange juice, sold by the unit at $1.00 per unit. It should be noted that none of the levels of attributes are out of the ordinary; these are the levels found in a typical purchase situation faced by respondents. Furthermore, the fixed alternative used in all of the sets is a commonly seen promotion in area supermarkets. To complete the choice set, a non-purchase alternative was sometimes added, sometimes not, according to a design variable. Thus, the total size of each choice set varied between three and four alternatives, three of which are described by four attributes.

To enable evaluation of the experimental design underlying the SP tasks shown to respondents, we present Figure 2. This graph presents the cumulative entropy (our proxy for cumulative cognitive burden) for each of eight blocks used in the original study (not pertinent to the issues at hand; see Olsen and Swait 1997), as a function of choice task order (1 through 16). It is apparent that all blocks had approximately equal total cognitive loads at all points during the course of the entire SP exercise for each respondent, though some tasks were somewhat more demanding than others.

--- Figure 2 about here. ---

Individuals were recruited by telephone and provided with a general description of the study (i.e., that they would be required to fill out a short survey about concentrated orange juice), and were then asked how frequently they went grocery shopping for a major grocery purchase. Only those people who went grocery shopping two or more times per month were given the option to participate. Two incentives were given to take part in the study. First, $2 was offered to the respondent if they agreed to do the survey, and second, $2 was given to a charity of the respondent's choice. Those people agreeing to participate were randomly assigned to one of the eight blocks described above.

The final sample has 280 respondents. Since each individual provided choices for 16 sets, we observed 3,942 choice decisions, somewhat less than the potential of 4,480 (=280x16) due to missing data. This large number of choices is interesting because the highly nonlinear latent class model requires much data to be numerically (and, therefore, statistically) stable.

Estimation Method and Results

As described before, the estimation procedure is made somewhat more complex by the fact that the optimal number of decision states (S) must be determined simultaneously with the taste and cutoff parameters. Traditionally, this is done by varying S until an appropriate criterion is optimized. For a given value of S, the log likelihood of the sample is given by

$$L(\beta, \tau | S) = \sum_{n} \sum_{r=1}^{R} \sum_{i \in C^r} \delta_{inr} \ln(P_{in}^r) \tag{13}$$

where δ_{inr}=1 if individual n chose alternative i in replication r, =0 otherwise; P_{in}^r is given by expression (9); all other quantities as previously defined. Because maximum likelihood estimation theory requires continuity in the parameter space, maximization of (13) does not apply to the

discrete parameter S. Several alternative measures have been suggested, but we shall utilize both the Akaike Information Criterion (AIC) and the Consistent AIC as the basis for selection of S (see Bozdogan 1987). Multiple measures are often used to guide selection of S since there is neither irrefutable theory nor unanimous researcher agreement on the basis for selection. The AIC is calculated as $[-2(L_S+K_S)]$, where L_S is the log likelihood at convergence in expression (13) and K_S is the number of free parameters, for a model with S latent segments. The CAIC is similarly defined but considers sample size rather than the number of parameters: $[-2L_S+(S-1)\{\ln(2N)-1\}]$. (Actually, the CAIC implicitly assumes that the number of parameters per additional segment is constant, which holds in our model.) The model with smallest AIC and/or CAIC is selected. Using these criteria, model selection is affected by goodness-of-fit *and* parsimony.

Below are the values of the AIC for S equal to 1, 2, 3 and 4 decision states:

S	AIC	CAIC
1	7472.8	7462.7
2	7385.4	7365.2
3	7289.6	7267.3
4	7301.8	7277.4

Though this need not be the case in general, in this example both the AIC and CAIC measures are minimized with three latent segments. On the basis of these results, we select three segments as our best estimate of S. The corresponding taste and cutoff parameter estimates are presented in Table 1. We now discuss these parameter estimates in relation to our study objectives.

--- Table 1 about here. ---

Discussion of Results

In the discussion below, we use the terms “segment” and “decision state” interchangeably. We also abbreviate the latter as DS.

The linear and quadratic terms of the latent cost-benefit strategy selection function are all statistically significant, indicating that these factors significantly influence segment membership. However, interpreting this expression is difficult without provision of the base levels of entropy and cumulative entropy. Figure 3 provides a graphical representation of this function over entropy, holding cumulative entropy constant at two different levels At zero cumulative entropy level (CE=0 in the graph), that is, at the beginning of a set of tasks, increasing entropy first reduces the probability that an individual falls into segment 1 and then, as the entropy level increases, the probability of being in segment 1 increases. Hence, the greater the entropy of the first SP task the more likely it becomes that the respondent is in decision state 1 (i.e. using the strategy implied by the corresponding taste vector in Table 1; more about this later). The opposite effect occurs in the case of segment 3. Increasing entropy initially increases the probability that a respondent is in this state, but after an entropy level of approximately 0.6 the individual's chances of falling into DS 3 decrease. The probability of being in DS 2 is almost entirely unaffected by changing entropy levels.

--- Figure 3 about here. ---

These general relationships also hold for cumulative entropy levels of 8 (CE=8, that is, essentially half way through the sequence of tasks in the average block of choice questions; see Figure 2). The difference in this case is that as entropy increases beyond a level of 0.6, the probability of being in DS 1 is considerably higher (as entropy increases) and the probability of being in segment 3 is considerably smaller than in the CE=0 case.

A different perspective on these results is presented in Figure 4. For a fixed cumulative entropy, as the entropy of the next task changes from 0.6 to 1.0, the probability of being in segment 1 increases, the probability of being in segment 3 decreases, but the probability of being

in segment 2 remains approximately the same. This arises because segments 1 and 3 form the ends of the distribution categorizing segment probabilities. The model still implies that individuals move in an "ordered" fashion (e.g. from decision state 3 to state 2, and finally to state 1) as described by the latent classification function. However, 3→2 transitions must be approximately equal to 2→1 transitions.

--- Figure 4 about here. ---

The selection function parameters associated with cumulative entropy are illustrated in Figure 5. Holding the entropy for each task constant (at two different levels implying increasing difficulty) reveals the general pattern that as cumulative entropy increases, the probability of being in DS 1 increases, while the probability of being in DS 3 decreases. Once again, however, this must be interpreted in light of the ordered nature of the model: as cumulative entropy increases, individuals will move from DS 3, through DS 2, thence to DS 1.

--- Figure 5 about here. ---

The latent classification function describes the likelihood of being in each segment and shows that segment membership is significantly associated with the degree of complexity and cumulative complexity faced by the individual. However, from these results not much can be said about the behavioral responses to complexity that arise when moving from decision state to decision state. It is to this topic which we now turn.

The taste parameter estimates in Table 1 for the three decision states show the differences in the structure of the three segments. In DS 1 many taste parameters are significant, although there appears to be a considerable amount of weight on brand-specific constants and the sweetness attribute. In DS 2, however, the brand constants are all not significant, as also are many of the attribute parameters. In this segment there appears to be no statistically significant

use of the information for the McCain's and Old South brands, only package size for the Minute Maid brand, and all but one of the attributes of the generic brand (grade is not utilized). This appears to reflect individuals who are not following a compensatory strategy at a certain level of entropy and cumulative entropy; rather, they focus on certain brand/attribute combinations, then base their decision entirely on this subset. DS 3 illustrates yet another processing strategy: the generic brand has the only significant brand constant (quite negative); in contrast to segments 1 and 2, however, several attribute parameters are significant and relatively large in all the brands.

The decision strategies being reflected in the three segments are more clearly depicted in Figure 6 using "radar plots." These radar plots graph the absolute value of those taste coefficients in each segment that are statistically significant at the 90% level. If all attributes in a segment are significant and all are equally important to the consumer, the radar plot will be circular in shape. If only 1 or 2 parameters are significant, the radar plot will show 1 or 2 "spikes" emanating from the center of the plot. For decision state 1, the radar plot contains three distinct spikes associated with sweetness (for all brands except McCain's), as well as a range of brand coefficients (the North-East quadrant of the plot) that are considered in the choice process. In DS 2, only 3 spikes appear in the plot, indicating the simplified strategy associated with this state, in which most of the characteristics of the generic product and the package size of Minute Maid are used; all other information seems to be unimportant to preference evaluation in this state. In DS 3, the generic brand parameter provides one large spike (indicating, as said before, a strong dislike of generic products, all other things equal) in the radar plot; a set of other attributes is also displayed in the plot but at what appear to be lesser importance relative to the generic brand constant. Nonetheless, more information is used in DS 3 than in either DS 1 or 2.

--- Figure 6 about here. ---

Thus, it would seem that the following summary characterization of these decision states, loosely based on Russo and Dosher's (1983) nomenclature, is possible:

Decision State	Name	Statistically Significant Information Utilization				
		Brand	Grade	Sweetness	Package Size	Price
1	Brand Dimensional Reduction	✓		✓		
2	Attribute Dimensional Reduction			✓	✓	
3	Compensatory	✓	✓	✓	✓	✓

Figure 7 shows stylized decision state classification probabilities over the course of an SP task. Initially, the probability of being in DS 3 (Compensatory) is likely to be highest; as respondents progress through their tasks, this probability will tend to decrease (see Figure 5 also). DS 1 (Brand DR) begins with a lower probability, which increases towards the end of the task. Throughout, the likelihood of using an Attribute DR strategy (DS 2) remains relatively constant. Thus, a high likelihood pattern of movement between decision states is starting out in DS 3, switching to DS 2, then switching to DS 1; this corresponds to moving from a more complex to a simpler decision strategy. (Note, however, that we did not model decision state transitions *per se*; instead, we have modeled the marginal probability of being in each state directly. Thus, our results suggest the DS switching pattern rather than directly supporting it.)

--- Figure 7 about here. ---

Instead of viewing the taste weights by segment one can simulate the "total" parameter vector as entropy or cumulative entropy increases. Figure 8 presents a series of radar plots that present weighted parameter vectors over cumulative entropy levels.[2] Note that as cumulative

entropy increases beyond 4, the degree of reliance on the brand constant for generic products tends to dissipate and the parameters for sweetness become more refined.

--- Figure 8 about here. ---

The movement from the apparently rich, brand- and attribute-based strategy at low levels of complexity, to the simpler strategies at higher levels of cumulative complexity suggests that decision makers are trading off the benefits of expending processing effort against the costs of making "incorrect" or unpalatable decisions. Avoiding the generic brand and avoiding alternatives which are sweetened becomes a frequently applied heuristic choice rule. This may mean that individuals had a minimum threshold level (unsweetened and not generic) below which they are not willing to accept any choice (see Swait 1997). When the choice task is complex, individuals may resort to this rule. This appears to be a form of a criterion-dependent choice model (e.g. Bockenholt et al, 1991) in which the individual examines a selected set of attributes and when the difference across this selected set has reached some specified level, the decision is made. In our case, it appears that as complexity increases the individual is led to reduce the size of the set of alternatives over which the attribute difference analysis is made. This can also be viewed as a movement toward a less compensatory decision making strategy, as increasing complexity results in fewer attributes being considered.

CONCLUSIONS AND FUTURE RESEARCH

The fact that consumers appear to change their decision making strategies in response to choice context and particularly in response to choice environment *complexity* has been well documented in the literature on human decision processing (e.g. Payne et al, 1988). However, these findings have seldom been incorporated into aggregate econometric models of choice behavior. There are likely several reasons for this. First, a consistent method for reflecting choice

context and complexity within aggregate econometric models of choice has not been available. Second, a method which allows aggregate econometric models to test for changes in decision making strategy over ranges of task complexity (or other context factors) has not been developed. In this paper we provide potential solutions to both of these issues. We employ entropy as a measure of choice task complexity, and cumulative entropy as a measure of cumulative cognitive burden, within an aggregate model of choice. Furthermore, we use these measures of complexity in a model which allows for changes in decision making strategies over ranges of task complexity. This latent classification scheme provides the link between the choice environment and the potential for the selection of different processing strategies by the respondent.

In the particular case we examine, decision makers appear to fall into three segments, depending significantly on the level of complexity of a particular choice task and on the amount of complexity (i.e. cumulative cognitive burden, as we have termed it) already faced in previous tasks. The hypothesis that preference parameters depend on the degree of complexity is strongly supported. Furthermore, the empirical analysis illustrates that a distinct processing strategy arises in cases with high levels of task complexity (or after significant expenditure of processing effort, through cumulative entropy). This processing strategy appears to focus on two characteristics of the task, greatly simplifying the choice task for respondents.

While our empirical analysis supports the notion that increasing complexity generates changes in choice behavior towards non-compensatory strategies, this may not always be the case, of course. Previous research has shown that task complexity appears to affect different types of tasks in different ways (Swait and Adamowicz 1997). However, models such as those developed here will be able to test the hypothesis of whether task complexity results in changes in processing strategy as well as whether changes in complexity drive consumers toward non-compensatory

choice heuristics. Furthermore, these models could be used to simulate at what point decision making strategies begin to change and what the implications of increasing complexity are for the choice of specific alternatives. Such information can be used to better understand how to present information to decision makers and it can be used to better forecast the response of individuals to changes in complexity arising from the introduction of new goods or from changing attribute levels within actual markets.

One of the directions that this stream of research must take in the future is to investigate how the decision strategies used in SP choice tasks relate to those used by consumers in real markets. Experience with aggregate SP choice models has shown that well designed choice tasks result in models that can predict well to real markets (see, e.g., Horowitz and Louviere 1990, Louviere 1996, Louviere and Swait 1996). However, it is unclear what relationship exists between decision strategies adopted in hypothetical tasks (not to speak of *variation* in decision strategies during the course of a task!) and market decisions. A better understanding of this matter will certainly aid in designing SP choice tasks that better reflect market decision making, hence improve the external validity of SP choice models.

ENDNOTES

[1]It should be noted that cumulative entropy corresponds to a measure of the joint uncertainty level over choice sets if the replications are assumed to be independent. This suggests that cumulative entropy is measuring the response to the uncertainty generated by the entire task or group of choice sets in an SP survey.

[2] The parameters are weighted by a factor of 1 minus the p-value of the coefficient. This weights the parameter by the significant level, or if a parameter is highly statistically significant, it is given a weight of 1 while if a parameter is only significant at the 0.80 level, it is assigned a weight of .8.

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Figure 1 - Decision Strategy Cost-Benefit Factor

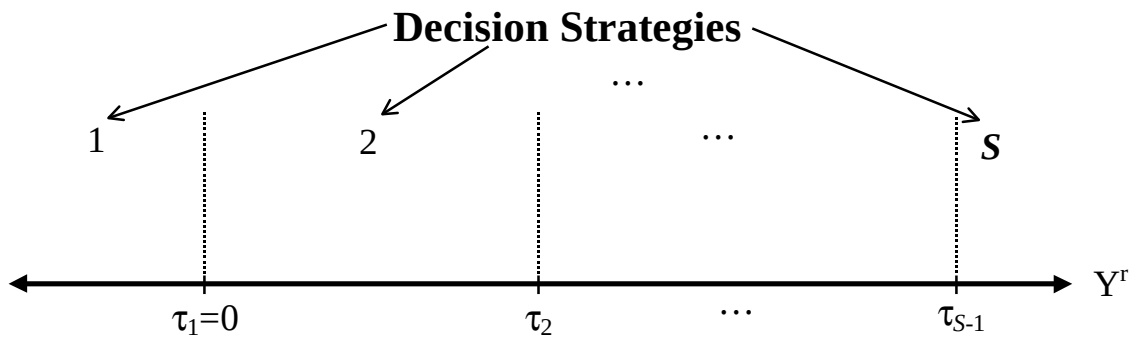


Figure 2 - Cumulative Cognitive Burden of Experimental Design, Over Eight Conditions

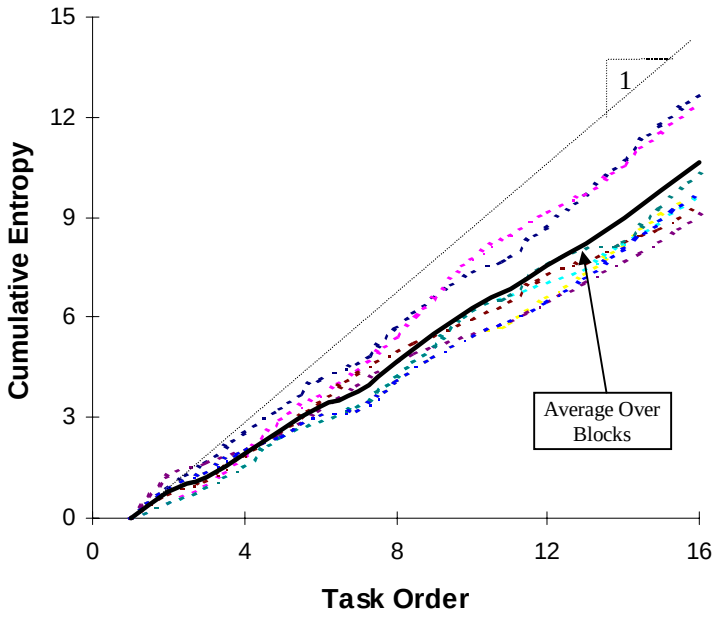


Figure 3 - Decision State Classification Probabilities by Entropy

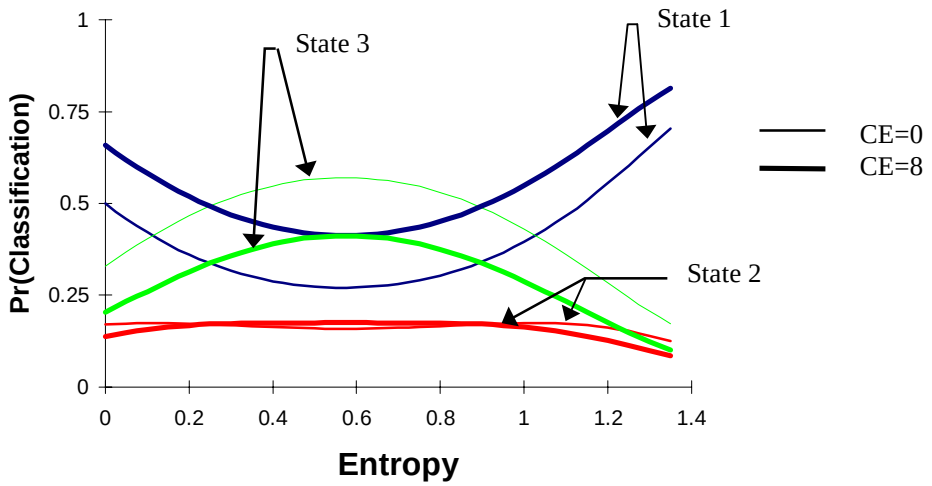


Figure 4 - An Example of Decision State Classification Probabilities for Two Entropy Levels

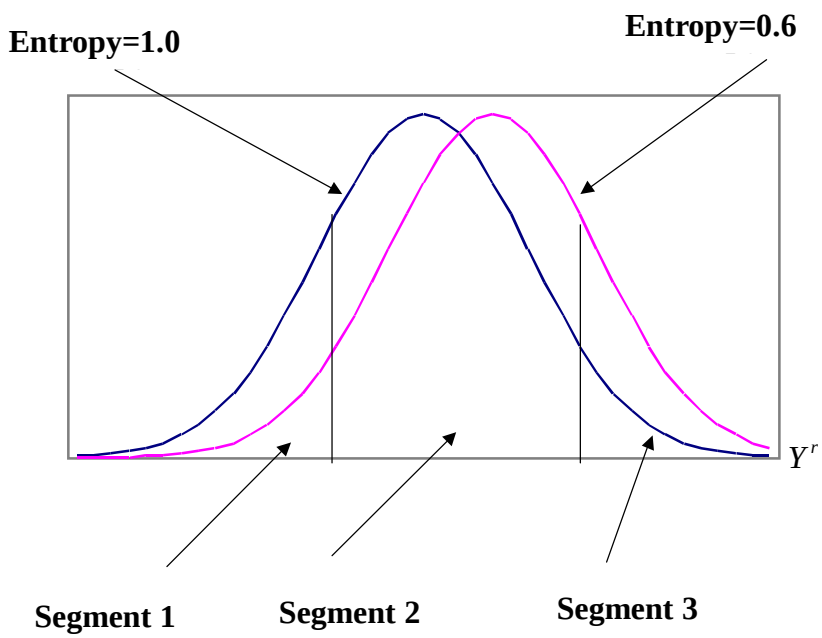


Figure 5 - Decision State Classification Probabilities as a Function of Cumulative Entropy

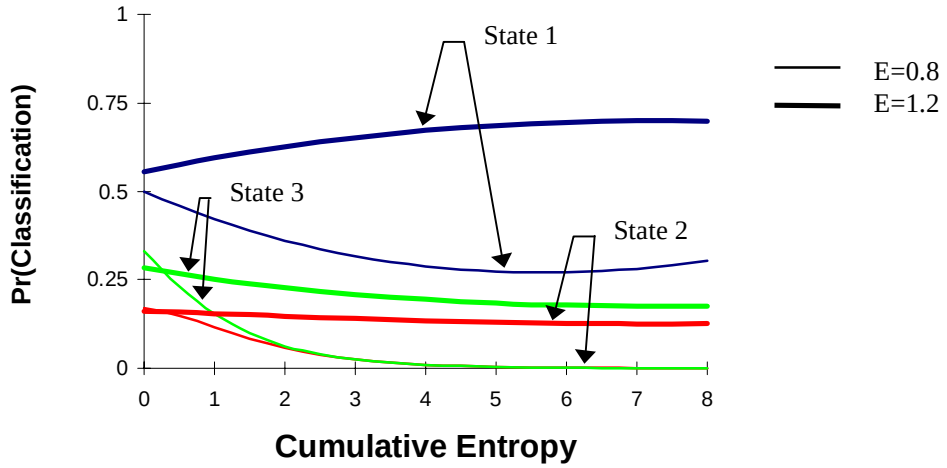
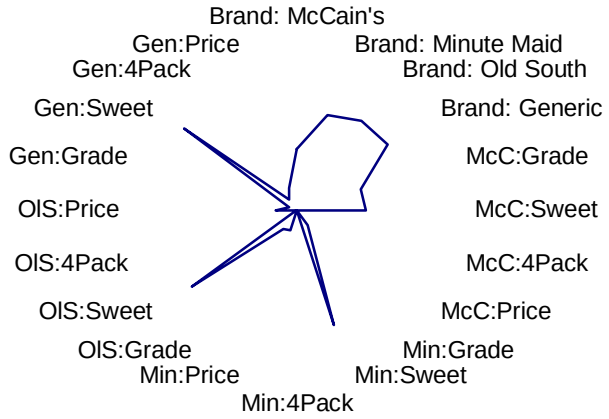
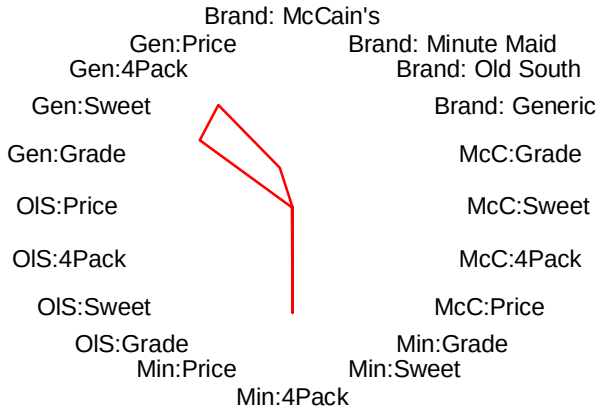


Figure 6 - Absolute Values of Statistically Significant (α=90%) Parameter Estimates for Each Decision State

State 1



State 2



State 3

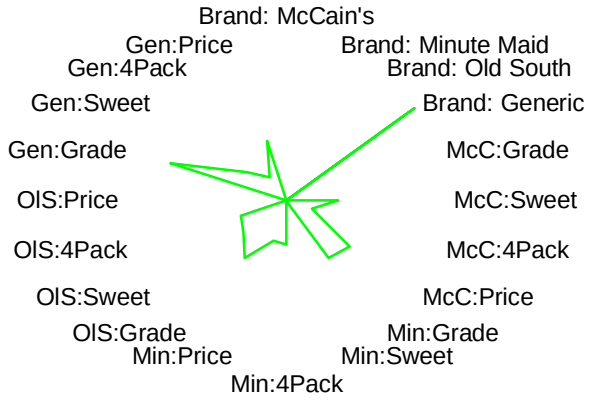


Figure 7 - Stylized Decision State Classification Probabilities

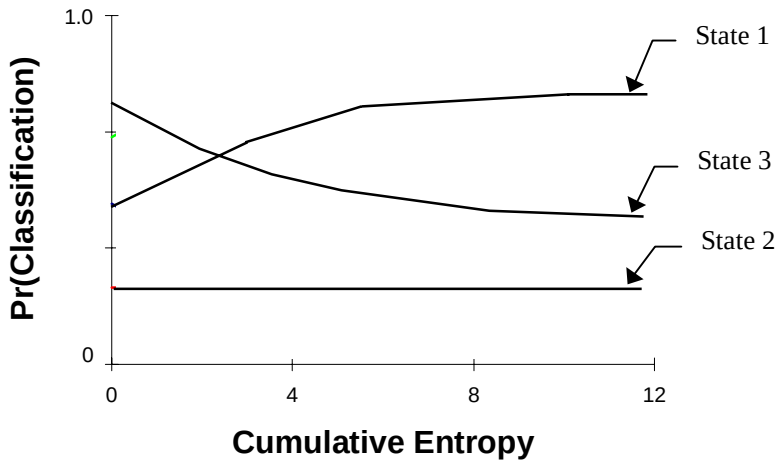
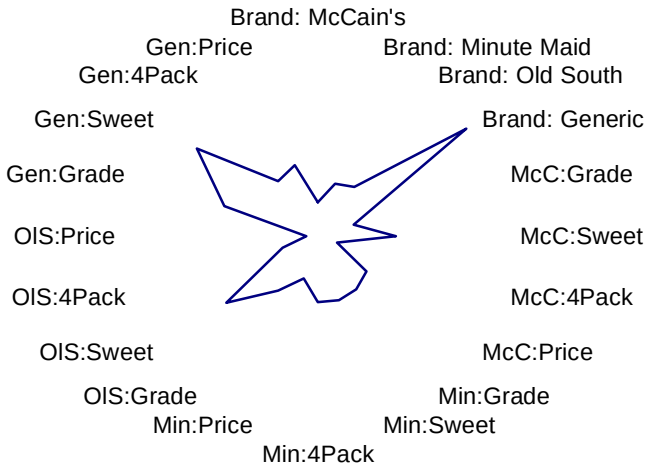
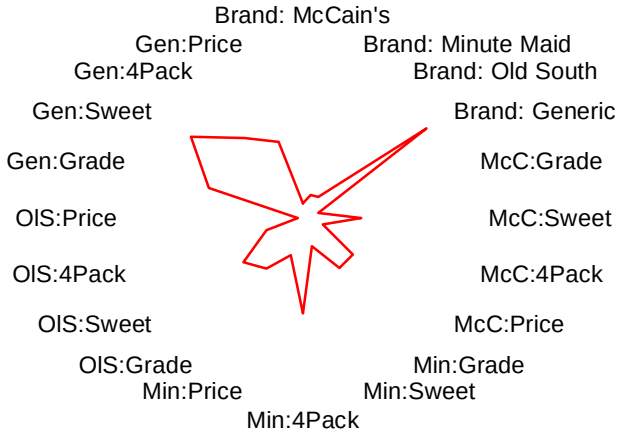


Figure 8 - Weighted Parameter Estimates at Four Levels of Cumulative Entropy

Cumulative Entropy=0



Cumulative Entropy=4



Cumulative Entropy=8

Figure 8 - (cont.)

Cumulative Entropy=12

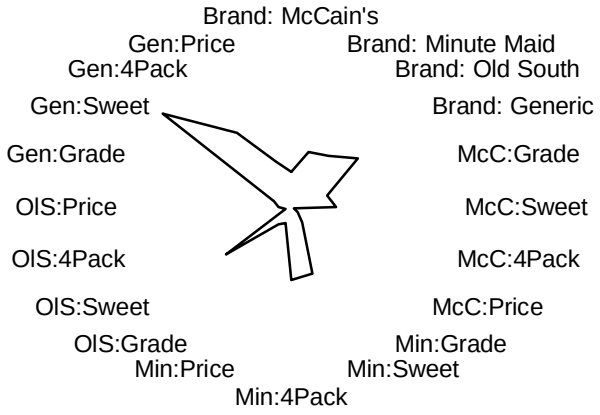


Table 1 - Estimation Results for Ordered Logistic Latent Class MNL Choice Model

	Parameter Estimates (t-statistics in parentheses)		
	Decision State 1	**Decision State 2**	**Decision State 3**
Utility Functions			
Brand Constants			
McCain's	-2.896 (-1.7)	3.873 (0.0)	-0.391 (-1.5)
Minute Maid	-4.718 (-1.8)	8.208 (0.0)	0.007 (0.0)
Old South	-5.210 (-2.0)	-10.685 (0.0)	0.469 (1.3)
Generic	-5.308 (-2.0)	6.615 (0.0)	-2.962 (-5.2)
McCain's Attributes			
Grade (=1 if A,=-1 o.w.)	3.168 (1.8)	1.892 (1.5)	0.081 (0.4)
Sweetness (=1 if sweet,=-1 o.w.)	-3.270 (-1.9)	3.379 (0.1)	-0.969 (-4.5)
Package Size (=1 if 4-pack,=-1 o.w.)	-1.646 (-1.6)	-4.504 (-0.1)	0.489 (2.2)
Price=(x-1.45)/0.15	0.896 (1.0)	2.911 (0.0)	-1.467 (-5.5)
Minute Maid Attributes			
Grade	0.868 (3.0)	-0.681 (-1.6)	1.348 (5.0)
Sweetness	-5.708 (-2.1)	-0.283 (-0.8)	-0.136 (-0.7)
Package Size	-0.315 (-0.9)	1.448 (2.9)	-0.826 (-2.9)
Price	-1.004 (-2.5)	0.500 (1.4)	-0.792 (-3.0)
Old South Attributes			
Grade	1.083 (4.0)	-5.496 (0.0)	1.325 (6.2)
Sweetness	-6.13 (-2.3)	-11.031 (0.0)	1.008 (2.9)
Package Size	0.434 (1.0)	6.177 (0.0)	-0.904 (-2.5)
Price	-1.000 (-2.1)	-7.862 (0.0)	-0.311 (-1.2)
Generic Attributes			
Grade	0.394 (1.7)	0.140 (0.3)	2.286 (4.7)
Sweetness	-6.585 (-2.5)	-1.576 (-2.8)	0.914 (2.3)
Package Size	0.630 (2.5)	-1.738 (-2.7)	0.538 (2.1)
Price	-1.122 (-4.8)	-0.572 (-2.2)	-1.183 (-4.6)
Latent Cost-Benefit Strategy Selection Factor Y^r		**Cutoff Parameters**	
Entropy H^r	-3.479 (-4.6)	τ_1	-0-
Entropy Squared $(H^r)^2$	3.052 (3.9)	τ_2	0.708 (7.7)
Cumulative Entropy ψ^r	0.176 (2.4)		
Cumulative Entropy Squared $(\psi^r)^2$	-0.012 (-2.5)		
H^r x ψ^r	-0.004 (-0.1)		
Summary Statistics			
Log Likelihood (random choice)	-4713.1		
Log Likelihood at Convergence	-3578.8		
$\rho^2 = 1 - LL(Conv) / LL(0)$	0.241		