RURAL ECONOMY

The Effect of Choice Environment and Task Demands on Consumer Behavior: Discriminating Between Contribution and Confusion

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Staff Paper 96-09

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1. INTRODUCTION

Choices, whether they are made in actual markets (revealed preference or RP) or in surveys (stated preference or SP), provide information about the preferences of individuals. These choices also contain what researchers interpret as "noise" or unexplained variation; a variety of techniques (e.g. statistical design theory, econometric specifications, and the combination of stated and revealed preference data) have been used to understand preferences and separate the signal from noise. However, in applying these tools we have tended to focus on the information provided by the choices themselves, to the detriment of understanding the effect of the *choice environment* or the *task demands* on the observed choice behavior, the quality of the information provided, and noise levels.

Task demands (or the choice environment)[1] can be characterized by such factors as choice set size (the number of alternatives the individual is choosing from), the number of attributes under consideration within alternatives in a choice set, the correlation structure of the attributes of the alternatives in the choice set, the number of and sequence of choices the individual is asked to make during the "task", as well as a variety of other factors. While the definition of the choice set, and the implications of choice set definitions on empirical results (Swait and Ben-Akiva, 1987a,b), has received some attention in the literature, there has been little attention paid to the characterization of the choice set or other dimensions of task demands.

Task complexity is illustrated by Figure 1, in which an individual is presented with alternatives (A,B, and C) in attribute space (X1,X2). One of the individual's indifference curves is depicted as I. If

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[1]The term *task demand* is often associated with SP data while the *choice environment* is often used to describe RP choice contexts. However, there are many common characteristics between RP and SP environments. Recently, there has been a movement to exploit the advantages of each form of data. The fusion of RP and SP data has many desirable characteristics such as the controlled nature of the design matrix from the SP data and wider ranges of attribute levels (Ben-Akiva et al. 1994). However, this fusion creates an additional set of issues: RP and SP data are typically based on very different data structures, with different levels of complexity, and in fact, different sources for decision complexity. RP choice sets may be quite large, individual specific, and display a large variation in the attributes of each alternative. SP choice data, on the other hand, generally arise from researcher-defined choice sets. Thus, the complexity involved in stated preference choice tasks can be quite different than the environmental characteristics of revealed preference data. Hence, we must ask: will the different task demands of SP and RP data affect their pooling and potentially offset the benefits associated with fusion? We assess this issue using a case study involving RP and SP recreational site choice data.

the individual is asked to choose between A and B it is clear that A dominates B and the demands on the individual, in terms of choice complexity, are relatively low. Situations that force consumers to make tradeoffs, like choosing between A and C, are more challenging and reveal more information about preferences, albeit imposing greater cognitive demands on the individual. Will the variance or noise associated with choice be increased in this case? Will the respondent use different strategies when choosing from the set {A,B} versus the set {A,C}?

Consider the case illustrated in Figure 2 in which preferences, illustrated as the shaded indifference area, are depicted as being "uncertain." In this case the impact of task demands may be even greater. The uncertainty about preferences can be exacerbated by task demands and may result in less consistency in choice, leading to higher variance in statistical models. Characterizing complexity or task demand and incorporating it into statistical models may aid in our understanding of choice and help us design tasks that provide more information and less noise.

This paper presents an analysis of context effects on choice in the same tradition as Heiner (1983), who investigated the processing capacity of consumers. We characterize task demands and incorporate them into random utility models of choice. We describe task demands using entropy, a well-known information theoretic measure which provides a summary measure of the uncertainty inherent in the choice environment. We model choice as a function of attributes in a traditional compensatory model but include our summary measure of task complexity in the variance term of the model. Both entropy and cumulative entropy are included in the model to account for the fact that task demands are partly defined by the current choice set, and partly by prior effort expended (which we term "cumulative cognitive burden"). We use this model to examine choice data from a number of contexts. It is worth noting that in such a model elasticities are now made up of two components: a direct effect through the impact on utility and an indirect effect through the impact on complexity.

Our results indicate that task complexity significantly affects the variance of choice in a fashion that is consistent with notions of limited consumer processing capacity and cognitive budgets. Employing six case studies that examine choice within very different product classes, we find that complexity affects variance in a non-linear fashion with both very difficult and very easy choices resulting in near random

choice behavior. Furthermore, we find that pooling across the six cases, we cannot reject the null

hypothesis that complexity affects these very different choice processes in a similar fashion. This is an

interesting finding suggesting a generalizability of our formulation over a variety of product classes. We

also find some evidence of fatigue and learning effects in the different case studies, although the cumulative

effects are not as systematic as the direct impacts of complexity on choice.

We begin the paper with a brief review of the literature on task complexity and choice, then outline

several possible measures of complexity. We next expound on our chosen measure of complexity, entropy,

as a form of characterizing task demands. A statistical modeling approach, that includes entropy in the

variance function, is presented in Section 3. Examples using choice data from different situations are then

examined in Section 4. The paper concludes with a discussion of the implications of our findings and

future research topics.

2. COMPLEXITY AND CHOICE

2.1 Task Environment, Respondent Processing Ability and Choice Outcomes

A variety of 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. Much of this

literature relates to choices under uncertainty (e.g. difficulty in evaluating risks, ambiguity or lack of

information about the risks, and difficulty in decision making under risk). Uncertainty about the attributes

of options often plays a role in explaining limitations of human processing capability. For example, Heiner

(1983) argues that agents cannot decipher the complexity of the situations they face and thus make

decisions that appear to be sub-optimal. He argues that the complexity and uncertainty surrounding a

choice situation often leads consumers to adopt simplified strategies. Heiner suggests that more effort

should be expended to understand the role that complexity plays in choice behavior.

A more formal examination of the processing limitation argument is presented by de Palma et al

(1994). They 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).

There are relatively few empirical applications of the literature on processing limitations. A notable exception is Mazzotta and Opaluch (1995), whose objective is to empirically test the validity of Heiner's (1983) hypothesis concerning complexity and choice behavior. Mazzota and Opaluch relate complexity in a contingent behavior choice task to variance in an econometric choice model, which is a restricted form of the model we shall present later. They find support for the hypothesis of imperfect cognitive ability and for the notion that increasing complexity increases the "noise" associated with choice.

Literature in Human Decision Theory examines the notion that individuals change their decision making "heuristics" as task complexity changes. The selection of choice strategy is hypothesized to depend on the trade off between costs of effort in making the attribute comparisons versus the benefits of making an accurate choice (essentially, it is assumed that respondents make a cognitive effort versus outcome accuracy tradeoff). Shugan (1980), for example, 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.

However, alternatives to the effort-accuracy tradeoff have also been advanced. It has been suggested that individuals may attempt to avoid conflict in situations where choices are complex, leading to the use of simpler choice heuristics when attributes are negatively correlated. For example, 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

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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 the cumulative cognitive burden. In SP choice tasks, individuals are generally asked to face repeated choice decisions (say $\geq R$ replications) to decrease data collection costs. There is some evidence of fatigue effects in SP choice experiments (Bradley and Daly, 1994) 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).

The notion that complexity affects decision making conflicts with the traditional notion of value maximization used in economics: individuals are assumed to be able to assign values to alternatives, and choose the alternatives with the highest value, independent of context. To address this issue, we design a mechanism that reflects the degree of complexity associated with a task. We incorporate this measure into statistical models of choice in a fashion consistent with the notion of context-based decision making. We assume that the basic mechanism whereby choice complexity affects our ability to infer taste parameters in a sample of respondents is through the distributions of choice alternative utilities; specifically, we assume that complexity impacts the variance of the utility distributions.[2]

Given the research previously reviewed, we present and discuss two hypotheses for subsequent investigation.

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[2]This is particularly important in the case of pooling SP and RP data, in which the very different choice contexts may have significant effects on the parameters and the variance terms. Pooling without accounting for context differences may produce inefficient estimators and predictions.

H1: The variances of the latent utilities will be convex in the level of complexity.

As individuals face increasing complexity they will respond with increasing information about their tradeoffs (decreasing variance) but, beyond some point of complexity, greater inconsistency across individuals will be found, and so variance increases. This hypothesis is based on a blend of the literature described above in which increasing complexity has been shown to result in improved performance up to a point. After this point individuals may avoid conflict or use simple heuristics to make choices.

H2: The variance of utility is a convex function of cumulative cognitive burden.

A common sequence of events for a respondent in an SP choice task may be (1) *learning* 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 less consistent choice behavior. This would lead us in general to expect a U-shaped (convex) relationship between variance and cumulative cognitive burden. However, the dominance of the fatigue or learning effect in any given task (perhaps due to the number of replications, the number of attributes, or lack of familiarity with the choice) may produce a strictly increasing or decreasing relationship between cognitive burden and variance in any given empirical data set.

2.2 Representing The Effect of Complexity and Cumulative Cognitive Burden in Choice Models

In this section the objective is to characterize the complexity of choice environments through a measure that can capture its various dimensions. 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, $i,j \in \{A,B,C\}$. In Figure 1, for example, the calculation of the difference in attribute levels would represent as a large positive value the dominance of

alternative A over B. If two alternatives were very similar, these metrics would produce a small value. 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 cannot be met.

In order to design a more complete, and a more formally defined, measure of complexity, we turn to information theory to provide a measure of information or uncertainty. Information theory refers to an approach taken to characterize or quantify the amount of information contained in an experiment or phenomenon[3] (Soofi, 1994; Shannon, 1948). Given a set of outcomes (*alternatives*, in our context) $\{x_j, \ j=1,\ldots,J\}$ that are described by a probability distribution (x), the entropy (or uncertainty) of the choice situation is defined as

$$H(X) \ = \ H(\ _x) \ = \ -\sum_j \ (x_j)\log \ (x_j) \ \geq \ 0. \tag{1}$$

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 choice 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.[4]

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[3] Information theory and entropy are used in other contexts in economics but these typically involve the use of the maximum entropy principle as an estimator in a statistical context (see Sengupta, 1993).

[4] 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.

Our measure of task complexity is incorporated into a discrete choice econometric model as a parametrization of the variance (or scale) of the stochastic error term of the utility function. Details on the econometric model and the incorporation of the complexity factor in the variance term are described below.

3.0 THE STATISTICAL MODEL

3.1 Model Derivation

Suppose that certain task demands or environmental conditions E_n apply to all the alternatives of the n-th choice set C_n (where n is the index of an individual decision-maker, in the case of RP data, or the index of a decision-maker/replication combination in the case of SP data). Suppose further that the utility function for the i-th alternative in C_n is additive, as below:

$$U_{in} = V_{in} + \varepsilon_{in} \qquad , \qquad (2)$$

where V_{in} is the systematic component and ε_{in} is the stochastic component. As postulated in the previous section, we assume that E_n affects the utilities only through the stochastic component. More precisely, we shall assume that differences in environments generate differential consistency levels in observed behavior across individuals, which will be reflected in (2) by affecting the variances of the assumed distribution for the disturbances.

The probability that individual n chooses alternative $i \in C_n$ is given by

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\begin{aligned}
P_{in} &= \Pr\{U_{in} > U_{jn}, \ \forall j \neq i, \ i, j \in C_n\} \\
&= \Pr\{V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}, \ \forall j \neq i, \ i, j \in C_n\}
\end{aligned}
\qquad (3)
$$

If we were to assume that the ε_{in}'s are IID Gumbel with a common scale factor μ, we would derive the very familiar Multinomial Logit (MNL) model from (3) (see Ben-Akiva and Lerman, 1985, chapter 5).

We shall suppose, however, that the ε_{in}'s are Gumbel distributed, independent across n and $i \in C_n$, with scale factors $\mu_{in} = \mu_n(E_n)$, $\forall i \in C_n$, where it is required that $\mu_{in} > 0$. That is to say, the error terms are independent, but *not* identically distributed. The density functions for the individual error terms are given by (see, e.g., Ben-Akiva and Lerman, 1985)

$$f(\varepsilon_{in}) = \exp[-\exp(-\mu_n(E_n) \cdot \varepsilon_{in})], \quad -\infty < \varepsilon_{in} < \infty, \qquad (4)$$

so that the variances are $\sigma_{in}^2 = \pi^2 / 6\mu_n^2(E_n)$. Our derivation is somewhat, but not unduly, complicated

by the assumption that the scale factors vary by individual observation, specifically, as a function of the

individual's environmental or task conditions E_n. Multiply (1) by the scale factor $\mu_n(E_n)$ to obtain

$$\mu_n(E_n) \cdot U_{in} = \mu_n(E_n) \cdot V_{in} + \mu_n(E_n) \cdot \varepsilon_{in} \qquad . \qquad (5)$$

Say that the random variable η is Gumbel distributed with scale factor μ. Then it is a property of

the Gumbel distribution (see Ben-Akiva and Lerman 1985, 105) that, for any scalar $\alpha > 0$, $\alpha\eta$ is also

Gumbel distributed, but with scale factor μ / α. Therefore in (5) the random variables $\mu_n(E_n)\varepsilon_{in}$, all n

and $i \in C_n$, are IID Gumbel with *unit* scale factors. Thus, if we multiply both sides of the probabilistic

event in (3) by $\mu_n(E_n) > 0$, we leave the probability statement unchanged:

$$\begin{aligned}P_{in} &= \Pr\{\mu_n(E_n) \cdot V_{in} + \mu_n(E_n) \cdot \varepsilon_{in} > \\ &\quad \mu_n(E_n) \cdot V_{jn} + \mu_n(E_n) \cdot \varepsilon_{jn}, \ \forall j \neq i, \ i, j \in C_n\} \\ &= \Pr\{\mu_n(E_n)[V_{in} - V_{jn}] > \mu_n(E_n)[\varepsilon_{jn} - \varepsilon_{in}], \ \forall j \neq i, \ i, j \in C_n\}\end{aligned} \qquad (6)$$

Because of the IID property of the error differences $\mu_n(E_n)(\varepsilon_{jn} - \varepsilon_{in}), \ \forall j \neq i, \ i, j \in C_n$, it then follows

that choice probability (6) is simply a MNL model, but with systematic utilities $\mu_n(E_n) \cdot V_{in}$:

$$P_{in} = \frac{\exp[\mu_n(E_n|\theta) \cdot V_{in}(X_{in}|\beta)]}{\sum_{j \in C_n} \exp[\mu_n(E_n|\theta) \cdot V_{jn}(X_{jn}|\beta)]} \qquad , \qquad (7)$$

where we have made explicit the role of parameter vectors β and θ, and X_{in} is a K-vector of attributes for

alternative i and person n. Ben-Akiva and Lerman (1985, 204-207) make mention of this model for the

purpose of treating heteroscedasticity within the context of the MNL model.[5,6]

The Heteroscedastic MNL model has basically the same properties as the MNL model, notably

Independence of Irrelevant Alternatives (IIA) and uniform cross-elasticities. However, when a variable is

common to the mean of the utility and its variance, the elasticity contains two components: a direct effect

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[5]The parallel between this derivation and that used to derive heteroscedasticity corrections for the general linear model should be apparent.

[6]Note that the derivation of (7) assumes that the scale factors vary only by individual and not by alternative. If the scale factors vary by alternative, then probabilities (3) and (6) will not be equal. Swait and Stacey (1996) show, however, that it is possible to derive an expression similar to (7) for the more general case of the scale factors varying by alternative. They do so by deriving a MNL-like model with alternative-specific scale factors as a special case of a Tree Extreme Value model (McFadden 1981, Daly 1987). For the purpose of this paper, however, we shall use the slightly less general model form (7), with person-specific scale factors.

arising from changes in the means and an indirect effect from changes in variance. For example, if price is in the utility function and also is a component of a complexity index in the variance, a price increase for one alternative will have a direct effect reducing the attractiveness of this alternative. However, if this price increase makes the products more similar, it will increase the difficulty associated with choice in the marketplace. This may increase variance and could lead to an additional loss. If the attribute change leads to complexity reductions the indirect effect could offset the direct effect. Thus, market share elasticity depends not only the attributes of the alternatives but also on market conditions or the positioning of available alternatives.

3.2 Incorporating the Effect of Choice Complexity in a Choice Model

As stated in Section 2, we propose to summarize the effects of the complexity of the decision environment on choice via the information theoretic measure *entropy*, defined as

$$H_n = -\sum_{i \in C_n} P_{in} \ln(P_{in}) \quad , \tag{8}$$

where P_{in} is the probability of the outcome $i \in C_n$.

A measure of the probability of selection of the alternatives is required to operationalize entropy as a complexity measure. Obviously, if we knew the true values of the choice probabilities the entire choice modeling exercise (including all this complexity!) would be unnecessary. However, we do not know the true choice probabilities, so we must construct an *a priori* estimate that will sufficiently characterize the choice context to allow us to better separate information from "noise" in the choice data. In this paper we construct a measure of the probability of choice based on a "flat prior" over attribute levels. That is, we assign equal weights within a normalized attribute space to the main effects of all attributes in the choice set. This provides us with a measure of probability of choice as derived from an assumed MNL model:

$$\tilde{\pi}_{in}(X_n) = \frac{\exp[\omega X_{in}]}{\sum_{j \in C_n} \exp[\omega X_{jn}]} \quad . \tag{9}$$

Here, is the set of flat prior weights (a vector of 1's, perhaps scaled to account for differences in attribute units). Thus, the level of uncertainty about a choice set is described using a measure of similarity

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of alternatives, where similarity is based on an attractiveness metric calculated using a set of equal prior weights. The resulting approximate entropy measure is, thus,

$$\tilde{H}_n = -\sum_{i \in C_n} \tilde{\pi}_{in}(X_n) \ln[\tilde{\pi}_{in}(X_n)] \qquad . \qquad (10)$$

Based on this entropy approximation, we also define our proxy for cumulative cognitive burden, namely, cumulative entropy:

$$\tilde{\psi}_n^r = \begin{cases} 0 & \text{for } r = 1 \\ \sum_{r'=1}^{r-1} \tilde{H}_n^{r'} & \text{for } r = 2, \ldots, R \end{cases} \qquad (11)$$

where r refers to replication index, R is the total number of replications seen by each respondent and $\tilde{H}_n^r$ is the entropy of the r-th replication (given by equation 10) for individual n.

The definition of the prior and the use of main effects only (rather than main effects and interaction effects) may be modified based upon available information. For example, if information is available from another choice task, or if demographic characteristics provide information on the preferences of the individual, this information could be used to construct an informed prior. 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. More accurate information about the consumer should help us construct a more accurate measure of the task demands or complexity the consumer faces, but it may be that the benefit of such additional refinement is marginal.[7]

Note that for any given choice set C_n, entropy is constant across alternatives. Hence, it can be used to parametrize the scale of the error terms in model (7). In our empirical research, we assume that the scale factor for the r-th replication of the n-th respondent is given by

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[7]While we employ a simple prior in our empirical analysis, we have done some limited exploration of the implications of modifying this prior and re-estimating the models based on more informative priors (such as might be available from other studies or from iterative improvement within a study). Our limited experience indicates an insensitivity of our conclusions to more informative priors.

$$\mu_n^r(\tilde{H}_n^r|\theta) = \exp[\theta_1\tilde{H}_n^r + \theta_2(\tilde{H}_n^r)^2 + \theta_3\tilde{\psi}_n^r + \theta_4(\tilde{\psi}_n^r)^2] \qquad , \qquad (12)$$

which guarantees that the scale factor is always nonnegative. Other functional forms for the argument of

the exponentiation operator could be adopted that would permit testing hypotheses H1 and H2. However,

(12) has the appeal of simplicity, and so was adopted for our work.

4.0 CASE STUDIES

We have arranged our empirical work into two sections: first, we shall examine the evidence from

several SP choice studies indicating that accounting for choice complexity and cognitive burden impacts

inferences about taste parameters; next, we shall examine a case that contains both RP and SP data sources

and determine the extent to which differences in choice complexity impact the individual and pooled

estimates of these choice data.

4.1 Evidence of the Impact of Choice Complexity and Cumulative Cognitive Burden in SP Data

Table 1 presents a summary description of six SP choice studies in which we have individually or

jointly been involved in the past three years.[8] The first four studies involve choices that are more familiar

to environmental and resource economists: (1) campground site choice, (2) Caribou passive use

(Adamowicz et al. 1995), (3) moose hunting site selection (Adamowicz et al. 1996) and (4) mode choice at

a tourist recreation location. The remaining two studies, however, are quite different: (5) choice of frozen

concentrate orange juice and (6) provider selection for a certain consumer loan product. The latter were

included to enlarge the scope of applicability of our empirical findings.

To interpret the results to be presented later on, it is important that we understand how the SP

choice data were collected. These studies have a number of features in common:

1. The choice task was presented in the form of a paper and pencil exercise, with the choice alternatives

   presented as columns in a table, the first column of which named the attributes. The values of the

   attributes were provided in the cells of the table itself. The full task faced by a respondent had from 8

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[8]Where possible, we have included references about the studies. The remaining studies are of a proprietary nature,
and hence a number of details must remain undisclosed.

to 16 choice sets, depending upon the study; these were arrayed sequentially for the respondent, generally one to a page.

2. Within each study, all choice tasks had fixed choice set size.

3. A glossary of attributes and their levels, as well as instructions on how to perform the task (including a sample choice situation), preceded each choice task..

Essentially, the task display and choice collection format was the same in all the studies. Five of the studies were conducted in North America. In almost all studies respondents were either pre-recruited or recruited by random digit dial. With the exception of the moose hunting site selection (Study 3), respondents received a questionnaire in the mail; Study 3 brought respondents to a central facility.

The studies do differ, however, in a number of factors (again, see Table 1): each involves a different product or service, individual choice sets have 3 to 6 alternatives, product/service descriptions involve anywhere from 5 to 14 attributes, and respondents were exposed to 8 to 16 replications.

Table 1 makes it clear that the experimental designs underlying each study resulted in different entropy levels (calculated as per expression 10). Entropy, our proxy for choice complexity, can vary between 0 and the natural logarithm of the choice set size. An examination of Table 1 will show that the designs of five out of the six studies basically filled their entire theoretical entropy range. The exception to this was Study 6 (consumer loan provider), which had a truncated lower limit for the entropy range: the design's entropy levels ranged from 0.710 to 1.379, whereas the theoretical range is 0 to 1.386. For the moment, note that none of these experimental designs were originally drawn up with the intent of achieving any specific levels of entropy; instead, the design criterion was the achievement of orthogonality between attributes.

4.1.1 Individual SP Case Analysis

Table 2 presents an overview of the estimation results for these six SP studies. We present the log likelihood values for both the (homoscedastic) MNL and the Heteroscedastic MNL models. The final column of the table presents the likelihood ratio statistic for the hypothesis that there is no effect of choice complexity or cumulative cognitive burden on respondents' choice behavior. This statistic jointly tests hypotheses H1 and H2, previously specified, by testing that the parameter vector $\theta = 0$ in the parametrized

scale function (12). In four of the six studies (namely, studies 1, 3, 4 and 5), the hypothesis that $\theta = 0$ cannot be rejected for $\alpha \leq 0.05$. In study 2, this hypothesis cannot be rejected for $\alpha \leq 0.16$. Only in study 6 is the hypothesis soundly rejected. (We shall subsequently discuss a possible explanation for this result in study 6.) The effect of entropy is strongest in study 1, which also happens to be the task with the greatest number of attributes (14) and the largest choice sets (6 alternatives). Thus, we find overall support for the notion that choice complexity and its cumulative effect impact the information that we receive from these SP choice tasks, conducted in the form we described above.

Let us now examine Table 2 for support for hypothesis H1 in the individual studies. To remind the reader, that hypothesis states that the variances (scales) of utilities should have a convex (concave) relationship with choice complexity. In terms of the parametrized scale function (12), under H1 we would expect parameter θ_1 to be positive and θ_2 negative. This occurs very clearly in two of the studies (1 and 4), for which the asymptotic t-statistics for these parameters are above 2.0 in absolute value. In the remaining studies the two parameters are not individually significantly different from zero. However, in most of the studies the two parameters nonetheless have the expected signs. Thus, we are led to conclude that in the studies examined there is some strong evidence that choice complexity impacts the inferences that can be drawn from respondents' choice behavior. (See also Section 4.1.2 below.)

Hypothesis H2 states that the cumulative cognitive burden imposed on the respondent will in general have a convex (concave) relationship with the variance (scale) of the utility functions. The reasoning behind this hypothesis is that respondents are assumed to go through a "learning-performance plateau-fatigue" sequence during the course of the task (see prior discussion in Section 2.1). The completion of the entire sequence will depend upon whether the task is long and complex enough, relative to some total effort level deemed acceptable by the respondent (perhaps akin to some "task effort" budget defined by him/her prior to undertaking the task). Under H2, and assuming that the sequence is completed, we expect that parameter θ_3 will be positive and θ_4 negative.

Table 2 shows that only studies 2 and 5 display statistically significant estimates for θ_3 and θ_4. In study 2 (Caribou passive use), we have the general concave form postulated in H2 between scale and cumulative effort. This is shown in Figure 3, where we plot estimated scale value versus cumulative

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entropy. We have assumed, for display purposes, that an individual either receives a sequence of eight less complex choice sets (each with entropy equal to 0.50) or eight more complex sets (entropy equal to 1.0). Note that in study 2 the maximal entropy is about 1.1. In either case, the estimated scale function peaks at a cumulative entropy of about one, which corresponds in the "easy" task to 2 choice sets and in the "hard" task to only one choice set. After that, the scale rapidly deteriorates towards zero (i.e. variance increases continuously).

A zero scale is a critical value because the corresponding choice behavior is essentially random, hence completely uninformative with respect to the tradeoffs. In Study 2 the task is unfamiliar to respondents (making tradeoffs between wilderness area sizes, forest industry employment, individual tax payments, etc). Respondents were asked to review a considerable amount of descriptive material before completing the task. The respondents appear to learn in the first few choice tasks as they engage in this unfamiliar activity. However, they appear to learn quickly and fatigue sets in after 3-4 choice sets. It may be that respondents learn to focus on key attributes to simplify the task and tire quickly once this heuristic is established. The "overhead" associated with the descriptive material may also contribute to their fatigue. As well, these choice sets included a *status quo* option. The cumulative cognitive burden may result in respondents choosing the *status quo* option as a means of dealing with the uncertainty, as in the experiments conducted by Tversky and Shafir (1992).

In study 5 (frozen concentrate orange juice choice), we have statistically significant evidence that respondents remain in the "learning" phase of the sequence we mentioned above. Parameter θ_3 is statistically significant but negative in sign, while θ_4 is positive in sign, though marginally significant. Figure 3 shows the learning pattern quite clearly, indicating that scale increases with replication of the decisions. (The effect does not differ between the "easy" and "hard" choice set sequences.) A possible reason for this result is that respondents (the main shoppers in the households) found the choice sets somewhat unfamiliar at first, perhaps because orange juice choice may not be based on highly compensatory evaluations. This led to less consistency in behavior across individuals in the earlier choice sets to which they were exposed. However, as they progressed through the task, their preferences became clearer and led to more consistent behavior, reflected in higher scale (lower variance). This explanation is

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especially interesting when we consider that in this task respondents were exposed to 16 distinct choice sets, the highest among the studies presented here.

4.1.2 Cross-Product Class SP Case Analysis

Viewing the results presented thus far in Table 2, we were motivated to conduct an additional test. We posed ourselves the question: Could it be possible that the effect of choice task complexity is commensurable across these six SP choice studies? If such a condition were to hold, it would lend strong support to the generalizability of the study-by-study results discussed above.

Accordingly, we pooled the data for the six choice studies in such a fashion that taste parameters and cumulative cognitive burden parameters (i.e. the β vectors and the corresponding θ_3's and θ_4's) were maintained specific to each study. However, the impact of current choice task complexity was constrained to be equal across all six data sets. The resulting pooled model has 139 parameters and a log likelihood of -38,372.3; the corresponding individual studies have 146 parameters and a log likelihood of -38367.6. Hence, the hypothesis that the impact of choice task complexity is equal across the six studies can be tested with a chi-squared statistic of 9.4 with 7 degrees of freedom. The hypothesis cannot be rejected at the 95% confidence level.

To us, this is quite a surprising result. *A priori*, we would not have anticipated that the impact of task complexity on the scale of the underlying utility functions would generalize across six very different product classes. That they do may be the result of the degree of design and survey technique commonalities among them (see discussion above); however, another, non-exclusive explanation is that the entropy measure we proposed as an index of choice complexity adequately captures the impact of utility similarity between alternatives on the variance of tradeoffs implicit in choices across a relatively wide variety of product classes. As we shall subsequently note, this seeming generalizability encourages us to suggest certain uses of the choice complexity concept in the design of choice tasks.

Using the joint model, we are able to calculate that the optimal entropy is approximately 1.0, with a 95% confidence band of $\pm$0.2 entropy units, across the six studies (see Figure 4).[9] This means that the

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[9] The estimated variance was obtained by a Monte Carlo simulation.

choice scenarios with current entropies between about 0.8 and 1.2 yielded the highest scale (i.e. lowest variance) of the unobserved utility component. This in turn implies that scenarios in this range most contributed to the formation of the estimated taste parameters, and conversely, that scenarios with entropies well below 0.8 and well above 1.2 contributed more "confusion" to the estimation process than those within the confidence band.

It is interesting to compare this "optimal" band of [0.8,1.2] entropy to the design entropy values for each study (see Table 1). It will be noted that only study 6 (consumer loan product) has an entropy design range close to this "optimal" band. This may underlie the aforementioned result (see section 4.1.1) that only in study 6 was there no discernible effect of current entropy. The other five studies in Table 1 have scenarios with entropy values well outside this band, especially below the band. This may imply that the corresponding designs (geared at generating design matrices orthogonal in attributes) contain runs that are statistically uninformative with respect to tradeoff parameter inferences; that in fact, such scenarios increase rather than decrease variance, thus contributing to the "noise" instead of the taste parameter "signal" in the data.

4.2 Choice Complexity and the Combination of RP/SP Choice Data

The six SP case studies we examined in the previous section present quite clear evidence that choice complexity and cumulative cognitive burden can affect the quality of the information obtained from SP choice experiments. We now examine the impact of differential levels of complexity on the combination of multiple choice data sources, specifically, RP and SP data.

The data we utilize involve the selection of recreational hunting sites in Alberta, Canada. As described in greater detail in Adamowicz et al. (1996), RP choice data were collected from hunters in the form of "trip logs" that elicited information on all their hunting trips in the 1992 season. Thus, the RP choice data are actually frequencies of visitation to a number of different wildlife management units (WMU's). In addition, these hunters provided perceptions of quality attributes (moose populations, hunter congestion, hunter access, forestry activity). Other attributes (road quality and distance to site) were calculated by researchers.

These same hunters were also submitted to an SP task with sixteen replications, each involving choice between two generic WMU's (described using the same six attributes stated above) or not going moose hunting. The dependent discrete variable in this data source was the categorical choice indicator. These data have already been used as one of the six SP studies examined in Section 4.1 (i.e. study 3).

In-depth discussion of these data are given in Adamowicz et al. (1996), to which the reader is directed for further details. For the purposes of this exercise, we have utilized the entire RP sample available (representing a total of approximately 930 hunting trips), but have sampled from the full SP choice data available in such a way that both data sources have an equivalent number of trips represented. This obviates the need to specify a weighting scheme for the data sources when pooling them (see the discussion in Adamowicz et al. 1996), removing this as an issue in the combination process.

As we indicated previously in Table 1, the SP data (which involves trinomial choice sets) has an entropy range from 0.117 to 1.088, versus a theoretical maximum of 1.099 for trinomial sets. In comparison, the RP data has a much wider entropy range of 0.007 to 2.565. This difference is principally due to the fact that some hunters are aware of a large number of WMU's (a maximum RP choice set size of 13 different sites is observed in the data). The RP choice sets are based on the individual's awareness of sites and thus we would expect a correlation between individual's experience and their choice set size. The previously reported analysis of the Moose SP data (see Section 4.1) showed that choice complexity did not significantly affect the variance/scale of the estimated utilities. A point of great interest is whether the much wider entropy range in the RP data leads to a similar finding.

As described in note 1, there are often advantages associated with the joint estimation of SP and RP data. For the purposes of combining these two data sources, we shall utilize the following definition for the scale function of choice set n:

$$
\mu_n = \begin{cases} \exp[\alpha_1 \tilde{H}_n + \alpha_2 (\tilde{H}_n)^2] & \text{if n is an RP observation} \\ \exp[\theta_1 \tilde{H}_n^r + \theta_2 (\tilde{H}_n^r)^2 + \theta_3 \tilde{\psi}_n^r + \theta_4 (\tilde{\psi}_n^r)^2 + \theta_5] & \begin{array}{l} \text{if n is the r} - \text{th replication} \\ \text{of an SP observation} \end{array} \end{cases} \quad (13)
$$

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Note that in RP observations there is no effect of cumulative entropy since there are no replications.[10] We have also added a parameter θ_5) that captures average scale differences between RP and SP data sources, all other factors being equal. This scale function parameter has traditionally been the only one considered in combining RP and SP data sources (Adamowicz et al. 1994, Adamowicz et al. 1996, Ben-Akiva and Morikawa 1990, Ben-Akiva et al. 1994, Hensher 1994, Swait et al. 1994).

The usual approach to combining RP and SP data is to control for average scale differences between sources. In terms of scale function (13), only parameter θ_5 is allowed to vary. Table 3 shows the estimation results for this model in column (3). (Only parameters from scale function 13 are presented. All taste parameters are omitted for the sake of brevity and clarity.[11])The estimated value of θ_5 is significant at the 95% confidence level, and the traditional view of combining the two data sources would compare this model with the models in columns (1) and (2). The likelihood ratio statistic for the "traditional pooling" would then be 33.8 with 14 degrees of freedom. The corresponding chi-squared critical value at the 95% confidence level is 23.7, so the hypothesis of equal taste parameters across data sources is rejected, despite controlling for average scale factor differences between the data sets.

Table 3 also presents the estimation results for heteroscedastic MNL models of the Moose RP and SP data in columns (4) and (5). Comparing first the heteroscedastic MNL RP model of column (4) with its homoscedastic version in column (1), we note that the likelihood ratio statistic is 91.6 with 2 degrees of freedom. This shows the *very* strong effect that choice environment has on the RP choice data by itself. This stands in contrast to the SP data (columns 2 and 5 of Table 3), for which the equivalent statistic is 9.6 with 4 degrees of freedom. Thus, taken each by itself, the two data sources evince very different choice environment effects: very strong in the RP data, exhibiting a concave relationship between scale and complexity; and just significant at the 95% confidence level in the SP data, exhibiting the concave relationship postulated by hypothesis H1. We believe that one of the reasons the effect of choice complexity is so much stronger in the RP data than in the SP data is due to the former's much wider entropy range.

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[10] If time series data were available we could model cumulative entropy in an RP setting, where it may be interpreted as a proxy for experience.
[11] Full modeling results will be made available upon request.

Now let us consider pooling the two data sets, considering the impact of choice complexity on both RP and SP sources. Column (6) presents this combined model. It is immediately apparent that θ_1 and θ_2, marginally significant in the SP entropy model in column (5), become well-defined and statistically significant in the joint model of column (6). This may be due to the extended entropy range of the RP data. In this combined model, the effect of cumulative cognitive burden on scale basically disappears, as evidenced by the low t-ratios of θ_3 and θ_4. Interestingly, parameter θ_5, which *ceteris paribus* measures the average scale difference between the two data sources, is not significantly different from zero in column (6), whereas it was significantly different from zero in the "traditional pooling" model of column (3). As for the parameters defining the impact of choice complexity on the RP data (α_1 and α_2), these continue to have a strong effect on the scale factor (though the quadratic effect is only significant at the 90% confidence level), as in column (4).

We are interested in two questions involving the full model in column (6). First, does the pooling of RP and SP data sources benefit from the consideration of choice complexity in both data sources vis-à-vis the traditional method? To answer this question, we calculate the likelihood ratio statistic between models (6) and (3) to be 78.4 with 6 degrees of freedom, which compared to the critical value of 12.6 (at the 95% confidence level) leads us to conclude that the answer is a categorical "yes"! The second question is motivated by the observation made above that the RP and SP data cannot be pooled by the "traditional" method: does consideration of choice complexity in the pooling process enable one to pool these two data sources? While one would also have liked the answer to this question to be "yes", we must unfortunately report that the answer is "no". This is due to the large likelihood ratio statistic of 56.6 with 14 degrees of freedom, based on the comparison of model (6) against models (4) and (5). Note that this hypothesis has an even larger statistic than was the case in the "traditional" pooling process (models 1, 2 and 3), for which the value was 33.8 with 14 degrees of freedom. However, this likelihood ratio test is very rigorous and seems to overstate the differences between the parameter vectors. The linear relationship between the two vectors, which indicates that they are equal up to a positive scale, is clearly displayed in Figure 5.

Taken together, the results in this section indicate two things to us. First, consideration of the impact of choice complexity in pooling of multiple choice data sources is strongly supported by the

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example. We surmise this result is generalizable. Second, pooling of multiple data sources is a recognizably complicated affair, based on a myriad of assumptions. Examination of the parameters on entropy in Table 3 for RP and SP choices reveals that the impact of entropy on these data types is quite different. This is illustrated in Figure 6 where the scale function parameters from model (6) are used to construct scale factor estimates by data source. Note that the RP scale rises with entropy while the SP scale peaks at about 0.7. Higher entropy in the RP context may indicate individuals with more experience (and thus larger choice set sizes). The design used in the SP task contains few complicated choices and thus only parallels the RP context for low entropy choices (or inexperienced recreationists). This may be a substantial component in explaining the rejection of the hypothesis of pooling. This raises the issue of designing SP tasks to replicate environments of the application of interest. We return to this issue below.

5. DISCUSSION

Our study of six SP choice experiments has lent strong support to the idea that the decision environment and choice task characteristics can influence the quality of the statistical information obtained from the data. In the cases in which the effect of choice complexity was less important, it may well be due to limitations in the experimental design (specifically, a limited entropy range) rather than an absence of impact.

In our opinion, one of the results of great import for future work was our inability to reject the hypothesis that the impact of choice complexity on latent utility scale was the same across the six SP studies examined. This points to a possible generalizable use of the entropy measure to characterize choice task difficulty across a range of product classes. This would permit use of the complexity concept to formulate general SP choice task design principles (more about this in the following section). The emergence of this somewhat general result across a variety of product types may be considered as evidence for the notion that individuals do process alternatives on the basis of their attribute components, along the lines of Lancasterian demand theory.

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As hypothesized by us (and supported by literature in the human decision making area) the relationship between the variance of latent utilities and choice complexity has been found to be convex in the cases examined. Thus, increasing complexity improves (i.e. decreases variance) choice modeling estimation results to a point, but thereafter additional complexity increases "noise" levels in the data. This corresponds to the Bettman et al. (1993) results on choice in situations with negatively correlated attributes, which suggest that consumers "take on" SP choice tasks with more interest and commitment than in other decision situations. At some point, however, increasing complexity leads to idiosyncratic behavior, which increases variance (in analogy to Keller and Staelin's 1987 decision-effectiveness hypothesis).

We have also found that cumulative effort (or cumulative cognitive burden) in an SP task can have an effect on the quality of the information derived from the choice experiment. We have postulated that consumers undergo a "learning-performance plateau-fatigue" sequence during the course of the choice task, for which there is some support among the six data sets we examined. Figure 3 illustrates that the entire sequence may or may not be played out in any particular study, but we certainly believe that cumulative cognitive burden should be a factor in designing any SP choice task.

Though we developed our conceptual framework and approach based on our interest in choice experiments and the application of SP models to real markets, we have also seen in Section 4.2 that the analysis of RP choice data can benefit from modeling the impact of choice environment. In the single example presented in Section 4.2, the effect of complexity on the RP model way significant. In the case of RP data, making the scale factor for each individual respondent a function of entropy (or some other measure of choice set complexity) is a way to rank choice sets in terms of their contribution to establishing taste parameters estimates. We believe the application of our concepts to RP data deserves future research.

As we stated in closing Section 4.2, it would seem that modeling the effect of choice complexity on the variance of utilities is helpful when pooling RP and SP data sources. However, our results with this one application indicate that we may currently be taking too simplistic an approach to combining multiple data sources. We are moving beyond modeling the average variance differences between data types and are beginning to model the components of variance within and between data series. Including choice

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complexity in the combined scale function improves joint model fit by a large amount, but it may also serve to differentiate RP and SP tasks more sharply. This should not discourage us, of course, but instead lead us to seek further factors to consider that will eventually enable pooling of the data sources.

One such factor is the replication of application context entropy levels in the SP task. In our RP/SP case study, for example, the SP entropy levels are noticeably lower than the RP context (see Figure 6). This may be a significant contributor to the rejection of the hypothesis of equal taste parameters. An important question in designing SP tasks should be the degree to which its choice context matches the application's complexity level.

6. CONCLUSION AND EXTENSIONS

Some economists (e.g. Heiner 1983, de Palma et al. 1994), but generally psychologists and consumer behavior researchers (e.g. Bettman et al. 1993, Keller and Staelin 1987, Tversky and Shafir 1992), have put forth the idea that consumer choice behavior can be affected by context and decision environment complexity. We have developed a specific model form that enables us to test this idea empirically. Our examination of several SP choice experiments and one RP data set lends strong support that what we term "choice complexity" is an important factor to consider when modeling choice behavior, both at the task design stage and during econometric model estimation. Complexity can also impact the pooling of multiple choice data sources.

Individuals display a wide distribution of information processing capability. For example, level of expertise should lead to different signal to noise ratios between individual respondents. Certain socio-demographics may be correlated with respondents' ability to process information. Thus, an interesting avenue for research would be testing for the effect of different indicators of processing capabilities when collecting and modeling SP choice data.

The results presented in this paper are very strongly dependent upon the operationalization of choice complexity through the entropy measure. We have defined an approximate entropy index assuming equal weights for all attributes. Future research should more closely examine the impact of this assumption.

Limited testing on our part indicates, however, that sensitivity of the results to refinements of the prior weights may be quite low.

An important *caveat* applies to our work, as well as that of almost all empirical choice modeling work in the literature: we continue to assume that individuals behave in a compensatory fashion. Research in psychology and consumer behavior has long suggested that individuals may adopt a number of different decision strategies as a function of choice complexity. In fact, we have argued that one of the possible reasons for the convexity of the relationship between variance and complexity is that at high complexity levels choice behavior across a group of individuals becomes less consistent (i.e. variance increases). This upturn in variance may be due to the employment of different strategies by different individuals in the sample. Thus, a necessary avenue for future research is to investigate choice models that recognize this heterogeneity in decision strategies as a means to utilize alternative model forms as a function of the choice context.

Our results point to an exciting line of research in the design of SP choice tasks. Today, the individual choice sets that an individual respondent will encounter are generally selected so as to meet certain *desirable statistical properties* (e.g. attribute orthogonality) that will be especially useful during the model estimation stage. This results in some number of choice sets that must be shown to respondents. Then, generally on the basis of experience (or at most, on the basis of some pre-testing), some number of replications per respondent is decided upon. Clearly, the experimental designs are defined completely independently of respondents' cognitive abilities and their willingness to expend some "cognitive budget" during the task. This paper has shown that it is possible to account *a posteriori* for the effect of task complexity and cumulative respondent effort. However, using the concepts developed in this paper, would it not seem eminently possible to develop a SP choice *task* design principle that sought to maximize the signal-to-noise ratio (i.e. information content) of the data to be collected, subject to constraints related to respondents' cognitive abilities and "cognitive budgets"? This new design principle would not simply be applied to design the choice sets, such as current technologies do, but also to determine choice set sequencing and task length for different types of respondents.

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Table 1 - SP Study Descriptions

Study	# Resp.	Task Characteristics			Design Entropy Characteristics		
		Choice Set Size	# Attributes	# Repl.	Design Minimum	Design Maximum	Theoretical Maximum
1. Campground Choice	1,786	6	14	8	0.050	1.568	1.792
2. Caribou Passive Use	364	3	5	8	0.000	1.099	1.099
3. Moose Hunting Site Selection	104	3	6	16	0.117	1.088	1.099
4. Tourism Site Mode Choice	425	3	5	10	0.040	1.099	1.099
5. Frozen Concentrate Orange Juice	280	4	5	16	0.107	1.229	1.386
6. Consumer Loan Product	862	4	12	12	0.710	1.379	1.386

Table 2 - Impact of Choice Complexity and Cumulative Cognitive Burden in Six SP Choice Studies

Study	Homoscedastic MNL Model		Heteroscedastic MNL Model						Likelihood Ratio Statistic Calc. (df)
	# Param	Log Lik	# Params	Log Lik	$\hat{\theta}_1$ (t-stat)	$\hat{\theta}_2$ (t-stat)	$\hat{\theta}_3$ (t-stat)	$\hat{\theta}_4$ (t-stat)	
1. Campground Choice	s19	-15590.9	23	-15583.5	0.295 (2.6)	-0.156 (-2.3)	-0.023 (-1.4)	0.002 (0.7)	14.8 (4)
2. Caribou Passive Use	12	-2658.2	16	-2654.9	-0.159 (-0.7)	0.353 (1.7)	0.580 (3.2)	-0.285 (-2.9)	6.6 (4)
3. Moose Hunting Site Selection	28	-692.9	32	-688.1	2.042 (1.6)	-1.735 (-1.7)	-0.085 (-1.0)	0.011 (1.2)	9.6 (4)
4. Tourism Site Mode Choice	21	-2960.8	23	-2957.9	1.957 (2.4)	-0-	0.161 (1.5)	-0-	5.8 (2)
5. Frozen Concentrate Orange Juice	13	-3783.2	17	-3778.5	0.868 (1.3)	-0.476 (-1.1)	-0.065 (-2.3)	0.004 (1.7)	9.4 (4)
6. Consumer Loan Product	33	-12705.4	35	-12704.7	0.108 (0.6)	-0-	-0.005 (-1.1)	-0-	1.4 (2)
7. Six Pooled Products	—	—	139	-38372.3	0.296 (2.9)	-0.152 (-2.4)	—	—	9.4 (7)

Cumulative Entropy:			$\hat{\theta}_3$	$\hat{\theta}_4$
		Campground Choice	-0.025 (-1.5)	0.002 (0.7)
		Caribou Passive Use	0.500 (2.0)	-0.255 (-1.9)
		Moose Hunting Site Selection	-0.148 (-1.8)	0.018 (2.2)
		Tourism Site Mode Choice	0.071 (0.3)	-0.018 (-0.4)
		Frozen Concentrate Orange Juice	-0.062 (-2.3)	0.004 (1.7)
		Consumer Loan Product	-0.028 (-1.7)	0.002 (1.5)

Table 3 - Estimation Results, Combination of Moose Hunting Site Selection RP and SP Data

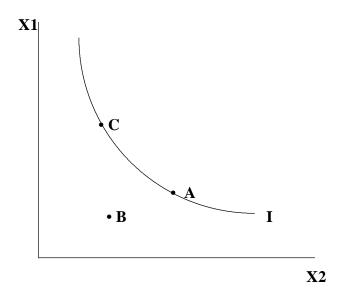| Scale Function Parameters	(1) RP (t-stats)	(2) SP (t-stats)	(3) RP+SP (t-stats)	(4) RP (Entropy) (t-stats)	(5) SP (Entropy) (t-stats)	(6) RP+SP (Entropy) (t-stats)
$\hat{\theta}_1$	—	—	—	—	2.042 (1.6)	3.974 (3.2)
$\hat{\theta}_2$	—	—	—	—	-1.736 (-1.7)	-2.954 (-3.0)
$\hat{\theta}_3$	—	—	—	—	-0.085 (-1.0)	-0.049 (-0.6)
$\hat{\theta}_4$	—	—	—	—	0.011 (1.2)	0.005 (0.6)
$\hat{\theta}_5$	—	—	-0.280 (-2.4)	—	—	0.507 (0.8)
$\hat{\alpha}_1$	—	—	—	2.784 (3.7)	—	1.849 (3.0)
$\hat{\alpha}_2$	—	—	—	-0.562 (-2.6)	—	-0.313 (-1.7)
Total # Parameters	21	28	35	23	32	41
Log Likelihood @ Conv.	-1378.8	-692.9	-2088.6	-1333.0	-688.1	-2049.4

Figure 1 - Preferences and Alternatives

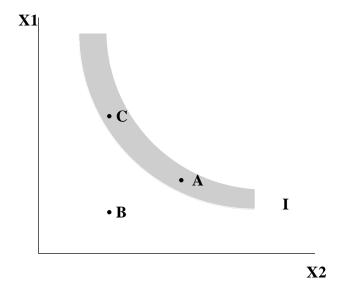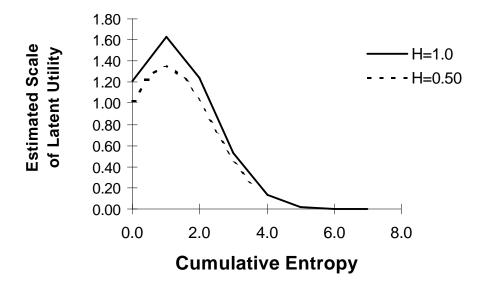**Figure 2 - Uncertain Preferences and Alternatives**

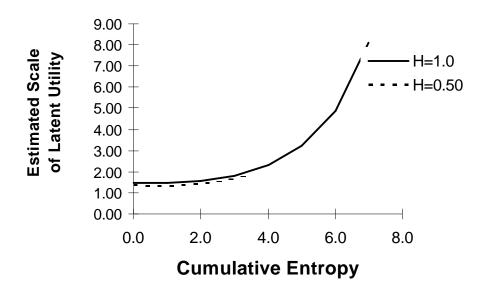**Figure 3 - Estimated Relationship Between Utility Scale and Cumulative Cognitive Burden**

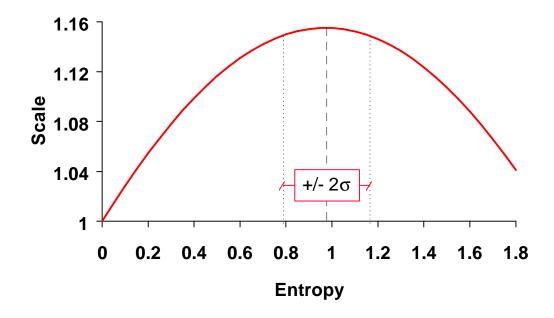**Figure 4 - Estimated Relationship Between Utility Scale and Choice Complexity (Joint Model)**

Figure 5 - Proportionality of Pooled Coefficients with and without Entropy
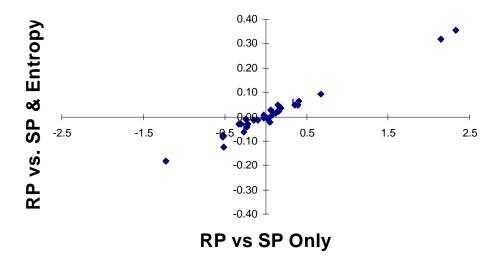
Figure 6 - Comparison of Moose Hunting Site Selection Estimated RP and SP Scale Factors as a Function of Complexity