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A Decision Theoretic Approach to Modeling Multiple Bounded Uncertainty Choice Data

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Abstract

The multiple bounded uncertainty choice (MBUC) value elicitation method allows respondents to indicate qualitative levels of uncertainty, as opposed to a simple yes or no, across a range of prices. We depart from previous analyses of MBUC data by arguing that the nature of the information contained in MBUC responses differs from that of alternative stated preference responses. Our framework assumes MBUC responses convey subjective probabilities. We examine the decision process of the researcher faced with estimating population parameters from MBUC sample responses. Using decision theory, we develop her optimal decision rule based on a specified loss function. Finally, we present an alternative estimation method based on the researcher's optimal decision rule and apply the proposed method to two MBUC studies. The resulting framework produces stable estimates and nests alternative methods of modeling MBUC responses.

Keywords: stated preference; willingness to pay; response uncertainty; decision theory

1. Introduction

In the process of applying stated-preference methods to measure consumer preferences, selecting, selecting a question format that meets the joint demands of the economic theory of choice and satisfies the cognitive limitations of respondents is certainly not an easy task. Many different choice formats have been developed and applied over the years: open-ended, payment card, multi-attribute discrete choice, dichotomous choice, double-bounded dichotomous choice, trichotomous choice, to name a few. There has been a progression in the development of new valuation questions away from the elicitation of censored responses towards interval and even non-locational responses such as "do nothing", "no vote", and "don't know". One terminal point in this progression parallels a recommendation Juster made 35 years ago in his analysis of durable good purchase intentions as a leading indicator [11]. He called for the use of questions that elicit odds information on how certain subjects are that they would purchase goods. In the context of non-market valuation a comparable format would elicit how certain respondents are that they would support the proposed change. This paper develops an estimator that is suited to this format. Using the basic tenets of decision theory, we develop a technique for inferring the population distribution of values for a good from responses that acknowledge the uncertainty of the stated choices. While our discussion emphasizes a question format that has been widely applied in the literature [24], the new method is generally applicable to a wide range of uncertainty formats. The estimator is illustrated with two applications. Each produces stable estimates and demonstrates the applicability of our method to policy-relevant issues.

Modeling the distribution of values across the population for formats involving choices that we can interpret as indicating a certain implicit value is fairly straightforward and involves applying the appropriate statistical technique, *e.g.* censored and/or truncated methods, etc. More complicated question formats impose higher cognitive costs on respondents and therefore confound the link between responses and values. Inclusion of the “no vote” or “do nothing” option forces the analyst to infer, by assumption, the intentions of respondents exercising this option. The inference could take the form of either “conservatively” recoding these responses as “no” responses or employing some other decision rule such as dropping these responses from the analysis of the population’s distribution of values. Question formats that elicit uncertainty responses require a similar decision process on the part of the analyst. The choice of decision rule has proved troublesome in the sense that different assumptions lead to different, and usually predictable, value estimates. Coding uncertain responses as “no” will obviously lead researchers to infer a lower distribution of values relative to coding the same uncertain responses as “yes” responses.

The analysis of stated choice data should consider both respondent motivation and the objectives of the analyst using these data.[2] Past research focuses largely on the first component. We address the imbalance by explicitly modeling the second. To analyze the implications for willingness-to-pay estimation, we propose a decision theoretic model of the research objectives. The research goals are defined in terms of characterizing the population distribution of values based on uncertainty responses. By specifying a behavioral model of respondent decision-making, we develop a loss function consistent with measuring the value distribution. Our

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[2]For ease of exposition, we consistently use feminine pronouns to refer to the analyst and masculine pronouns to refer to the respondent.

estimator is derived from this loss function, together with the constraints imposed by the available information.

Following a general discussion of respondent uncertainty in stated preference analyses, we introduce the elicitation method of interest in section 2. Section 3 examines arguments for the elicitation of probabilistic information from psychology and the literature on buying intentions. In section 4, we develop the decision theoretic model and the resulting estimator. Section 5 presents two applications of the technique using data on consumer preferences for a use-related resource activity, moose hunting in Maine, and a non-use amenity derived from the management of water releases from the Glen Canyon Dam. Section 6 outlines our conclusions and suggests next steps in this research.

2. Review of Prior Findings: Respondent uncertainty and the multiple bounded uncertainty choice format

There are several methods of eliciting uncertain responses. The first category of questions involves supplementing the "yes" and "no" response options in a dichotomous choice format with additional uncertain response options. For example, a qualitative uncertainty scale question can add a single uncertain response. In an application to noxious weeds control, Alberini and Champ [2] suggest classifying "not sure" respondents as "no" respondents based on similarities between the two classes of respondents.[3] Wang [23] provides an alternative interpretation of a "not sure" response. His random valuation model presumes that a respondent

[3]Carson et al. [6] found that many respondents who chose a "would-not-vote" option would have voted against the program if forced to make a decision. Based on this finding, they suggest recoding the "would-not-vote" responses as "no" responses. We argue that a response of "would-not-vote" differs from an uncertain response, the subject of our analysis.

chooses the "not sure" response option only when the offered bid amount lies close to the mean of his underlying value distribution. An extension to the basic logic by Ready et al. [17] uses a qualitative certainty scale question that allows the respondent to choose among six levels of response certainty for a single bid amount.

The second category of questions uses a quantitative uncertainty scale. Champ et al. [7] and Loomis and Ekstrand [14] follow a dichotomous choice question with an uncertainty question that asks respondents to indicate their levels of certainty on a 1-10 scale. Li and Mattsson [12] present a third method of identifying uncertain respondents by using a probabilistic assessment of respondent uncertainty.[4] Their follow-up certainty question asks the respondent to indicate, on a scale of 0 to 100%, how sure he is of his dichotomous choice response.

The final uncertainty question format, and the focus of our analysis, allows the respondent to indicate five qualitative levels of response certainty across a range of bid amounts [24]. In order to capture all relevant characteristics of the question, we refer to this format as the multiple bounded uncertainty choice (MBUC) format.[5] The MBUC format does not simply ask respondents whether or not they would pay the bids presented. Instead, it presents an identical set of bids to each respondent and asks him to indicate the likelihood that he would pay each bid

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[4]See Berrens et al. [3] for an application of a similar probabilistic approach.

[5]The MBUC format is found elsewhere in the literature under various names including the multiple bounded discrete choice format [24], the multiple bounded format with uncertain response options [1], and the multiple bounded format [5]. See Figure 1 for a sample question.

amount for the proposed improvement.[6] MBUC responses, therefore, do not translate directly into the statistical models traditionally used to model stated preference responses.

Analyses of MBUC responses require some assumption on the part of the analyst about how to interpret these responses within a choice context. The initial approach presented by Welsh and Poe [24] parallels the early treatment of the single uncertain response format and involves recoding the MBUC responses. Welsh and Poe offer three recodings based on different assumptions, which translate the MBUC responses into simple "Yes" and "No" responses. The first recoding, their "Definitely Yes Model", the most conservative of the three, recodes all "Definitely Yes" responses as "Yes" and all other responses as "No". The second recoding, the "Probably Yes Model" interprets "Definitely Yes" and "Probably Yes" responses as "Yes", all other responses as "No". The "Not Sure Model", the third recoding, adds an additional recoding of "Not Sure" responses to "Yes". Based on the various recoding assumptions, Welsh and Poe determine the bid levels at which respondents switch between recoded "Yes" and "No" responses. The switching intervals are the used to form the log likelihood contribution for each respondent.

Consider the sample response, taken from Welsh and Poe, given in Figure 1. The shaded responses indicate a sample response pattern. Table I presents the individual value inferences and log likelihood contributions for the sample respondent corresponding to the three Welsh-Poe recodings. V_i is the sample respondent's inferred willingness-to-pay, $F(\cdot)$ is the assumed

[6]As in Cameron et al. [5], we acknowledge but do not examine the potential incentive incompatibility of the MBUC format.

distribution function of population values, and θ is the vector of population parameters to be estimated.[7]

As expected, different recoding assumptions result in different WTP estimates. Welsh and Poe contrast the WTP estimates from three MBUC recodings to estimates obtained from dichotomous choice, payment card, and open ended question formats. The recoded responses provide slightly more information about the respondent's WTP than a dichotomous choice question since they provide both an upper and lower bound on WTP, rather than just one or the other. The recoding assumption, however, reduces the information potentially contained in the MBUC response to the equivalent of what would be derived from responses to a double-bounded dichotomous choice questions.[8] Moreover, they require the analyst to judge how "certain" are the inferred bounds derived from the uncertain responses provided during the survey.

To our knowledge, two other studies propose alternative methods of modeling MBUC data. Alberini et al. [1] provide two classes of models including adaptations of the random valuation model introduced by Wang [23] and random effects probit models. In their adapted random valuation models, Alberini et al. model the thresholds at which respondents switch

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[7]The individual log likelihood contribution is derived from a random utility specification. The analyst assumes that each respondent's value, known to the respondent but unknown to the analyst, is represented as follows: $V_i = x_i\theta + \varepsilon_i$. x_i is a vector of variables representing observable characteristics of the respondent and ε_i is an error component arising from factors not observed by the analyst. $F(\cdot)$ is the analyst-determined distribution function of ε_i. Note that this framework assumes no uncertainty on the part of each individual respondent.

[8]We use the "Definitely Yes Model" interpretation to illustrate. Based on the sample response, the "Definitely Yes Model" assigns probability one to the event $\{$respondent's true value lies in the interval $[\$10,\$20)\}$. This is identical to the value inference from a "Yes"/"No" response pair to a double-bounded question that sequentially offers bids \$10 and \$20. Similar logic applies to the "Probably Yes Model" and "Not Sure Model".

among the five MBUC responses options. One version of the model estimates the thresholds as constants whereas a second version assumes that the shift parameters depend on individual characteristics. Both random valuation models produce substantially greater WTP estimates relative to the other models examined by Alberini et al.

Recently, Cameron et al. [5] include the MBUC elicitation format as one of six hypothetical choice formats in a study with a broader set of objectives. The general goal of their analysis is to develop a comprehensive comparison of alternative question formats in estimating preference parameters in a model that uses a single preference specification to describe all formats. Their common preference model permits statistical tests of the equivalence of the preference parameters across different samples. To analyze the MBUC data, they consider an ordered logit, five-category generalization of a binary discrete choice model. Their MBUC results stand out relative to the other methods analyzed. They calculate the error dispersion of the MBUC data to be more than twice as large as the error variance for the dichotomous choice data. They also find significant differences in the preference parameter estimates between the two question formats.

Our analysis offers a potential explanation for the Cameron et al. findings on the MBUC format. The MBUC format elicits information about the respondent's subjective value distribution. The nature of this information differs from the information elicited by other stated-preference questions. As a result, the techniques traditionally used to obtain population parameters from stated-preference data must be altered in order to accommodate the specific nature of the MBUC-elicited information.

Analysis of MBUC responses requires linking the respondent's observed choices to his subjective value distribution. The recoding models of Welsh and Poe [24] provide three simple assumptions to accomplish this task. Juster [11] and Manski [15] raise similar issues related to the ability of intentions and probabilistic data to predict actual behavior. In the decades following the work of Juster and Manski, the literature on response uncertainty and on the ability of respondents to provide meaningful responses has dramatically expanded. We use this new research to supplement the messages of Juster and Manski.

3. Lessons from psychology and economic analyses of intentions data

Research in psychology on using qualitative or quantitative probability scales in relation to subjective probabilities provides three insights relevant to our framework. First, people's verbal probability statements do convey subjective probabilities. Psychologists refer to statements such as "likely" and "probably" as verbal probabilities since subjects associate these words with numeric subjective probabilities. Thus, MBUC respondents who interpret "Definitely Yes", "Probably Yes", etc. in a similar fashion provide information about their subjective choice probabilities. Of course, the interpretation of verbal probabilities does vary across subjects [4, 13, 21]. Because of this variation, some authors have rejected the use of verbal probability statements in favor of numerical likelihood scales or probabilities.

Second, respondents have the cognitive ability to understand the task they face in answering a MBUC question. The psychology literature suggests that subjects are comfortable conveying and receiving probabilistic information [8, 21, 22]. Wallsten et al. [22] found that subjects conveying probabilistic information preferred using verbal statements of probability to numerical expressions. When asked why, subjects noted that doing so was easier and more natural.

Third, probabilistic questions may decrease non-response rates. Flannelly et al. [9] ran three experiments in which respondents were simultaneously asked a 0-10 probability scale question and a dichotomous choice question. They found that, regardless of the question order, the percentage of failures to answer was twice as high for the dichotomous choice questions than for the probability questions. Extending their earlier work, Flannelly et al. [10] observed a similar outcome.[9]

We can gain further insight into the potential interpretation of MBUC questions for the estimation of preferences by considering economic analyses of intentions data. We refer to an intentions question as one which elicits a non-probabilistic (yes or no) response based on the likelihood of a specified event. We borrow the following example of a voting intentions question from Manski [15] :

"For whom do you expect to vote in the coming election, candidate 0 or candidate 1?"

Survey research contains many such examples, from fertility surveys to surveys of durable good purchases and income expectations. In contrast to an intentions question, we refer to a probabilistic question as one which elicits a probabilistic response, either verbal or numeric, based on the respondent's subjective probability of an event.

Juster [11] examines the ability of intentions and probabilistic responses to predict actual purchases of durable goods. In his analysis of automobile purchases, he finds that with the

[9]See Ready et al. [17] and Whitehead et al. [25] for a discussion of non-response rates in stated preference analyses with uncertain response options.

inclusion of purchase probabilities, intentions exhibit no net association with actual purchases. Purchase probabilities, however, continue to be significantly related to purchases before and after the inclusion of intentions. In addition, Juster reports a stronger relationship between covariates and purchase probabilities versus intentions. Juster's observations suggest that probabilistic information may help to explain some of the unobserved heterogeneity across respondents. Based on his results, Juster concludes that a survey of explicit probabilities provides a more efficient method of estimating purchase probabilities than a survey of buying intentions. The MBUC format provides an opportunity to examine the use of probabilistic responses in stated preference analyses.

4. A loss function approach

We now address the task of modeling MBUC responses. The uncertainty involved in the analysis of MBUC responses must be recognized as a combination of uncertainty on the part of the respondent and uncertainty on the part of the researcher. As a result, it makes sense to consider both the relationship of stated preference questions and the goal(s) of the research, and the respondent interpretation of the MBUC responses in designing an estimation strategy for using these data to recover preference information.

We assume the research goal is to estimate the mean of the underlying population distribution of economic values. We partition the analysis of MBUC data into two stages.[10] First, the researcher must determine how to use individual-level data, the individual's MBUC responses, to draw inferences regarding the individual's value. Second, she must use these inferences to characterize the population distribution of values.

[10] This intuition applies more generally to other stated-preference elicitation methods.

The first stage requires a behavioral model linking the respondent's preferences to his MBUC responses. Uncertainty on the part of the respondent is addressed in the first stage. We assume that each individual's valuation of the good may be described as a random variable with distribution function, $G_i(\bullet)$, known only to respondent *i*. Given this representation, individual *i*'s subjective probability that his true value for the good lies above some value *b* is given by $P_i(V_i > b) = 1 - G_i(b)$ where V_i represents *i*'s random value.

We define a mapping between the categorical MBUC responses and individual subjective survival probabilities. As a basis for our benchmark mapping, we examine three psychology studies that provide point estimates of the subjective probabilities associated with various verbal probability terms [16, 18, 19]. While none provides exact matches for the verbal probabilities found in the MBUC format (Probably Yes and No, Definitely Yes and No), all provide subjective probability estimates associated with similar terms "probable" and "improbable". The mean probability estimate across the three studies is 0.75 for the term "probable" and 0.15 for the term "improbable" interpreted as $Pr(event\ occurs) = 0.75$ and $Pr(event\ occurs) = 0.15$, respectively. Since we use the MBUC responses to describe the respondent's uncertain value, the event of interest is {respondent *i*'s value lies above *b*, $V_i > b\}$. Based on this assessment, our benchmark model assumes that, for a respondent choosing the "Probably Yes" ("Probably No", respectively) response when presented with bid *b*, $P_i(V_i > b) = 1 - G_i(b) = 0.75$ (0.15, respectively). Keeping with the existing stated preference literature, we assume that a "Definitely Yes" response implies a survival probability of one. Similarly, a "Definitely No" response corresponds to a survival probability of zero. We assign probability of 0.5 to "Not

Sure" responses. In the discussion of our empirical results, we investigate the sensitivity of our estimates to changes in the subjective probability assignment.

In the second stage, the researcher chooses the appropriate estimation method. Most analyses of stated preference data employ maximum likelihood estimation because of its convenient link to random utility models. Our assumption of maximum likelihood estimation suggests an explicit goal for the first stage of analysis. Specifically, the researcher's first-stage goal is to arrive at some form of censored, or ideally exact, log likelihood contribution for each individual that will be used in the second stage to estimate distributional parameters for the population values.

In more general terms, the researcher uses the first stage to extract the maximum amount of information about the *individual*'s value from his response to the chosen stated preference question. Relative to alternative question formats such as dichotomous choice and open-ended, the MBUC format has the potential for increasing the amount of first stage information available to the researcher. Below, we present an analysis of the first-stage decision process of an analyst faced with the task of obtaining parameter estimates from responses to an MBUC question. We employ decision theory to examine the analyst's decision and derive an expression for her optimal first-stage decision rule, the form of the log likelihood contribution for each respondent.

4.1 An optimal decision rule for continuous uncertainty responses

Two steps are required to analyze the MBUC responses. First, we develop a continuous version of response uncertainty in order to derive the decision rule. Second, we adapt the optimal decision rule for the continuous case in order to analyze discrete MBUC verbal probability responses. To conceptualize this process, suppose that instead of providing likelihood responses for a fixed number of bids, respondents report uncertainty responses for the entire real line. In this case, instead of assuming choices are reported from the qualitative categories ("Definitely Yes", "Probably Yes", . . .), we assume responses fall within the unit interval [0,1]. The reported uncertainty responses along the continuum trace out a respondent's subjective hazard function for his random value. Assuming our project is considered a good by the individual, the chance of supporting the project at a price of zero is assumed to be one. As we move to higher amounts in the bid space, the chances of support decline and eventually reach zero.

Letting $R_i(b)$ denote the uncertain response provided by respondent *i* for supporting the project at a cost of *b*, we specify the following relationship between his response and his subjective probability distribution:

$$R_i(b) = P_i(V_i > b) = 1 - P_i(V_i < b) = 1 - G_i(b) \qquad \textbf{(1)}$$

Respondents simply report the probability of supporting the project at a cost of *b*, which is equivalent to the survival function of the random value V_i evaluated at *b*.

Based on the assumed relationship between the respondent's value distribution and his responses, the researcher's explicit objective is to form a log likelihood contribution for each respondent *i* consistent with the continuum of uncertainty responses provided by respondent *i*. A decision rule is merely an exact expression for the log likelihood contribution of respondent *i*. Let δ represent a decision rule for the researcher. Using decision theory, we specify a loss function for deviations from the log likelihood contribution evaluated at a realization of the random value V_i. We denote the loss function as $l(L(\theta;\ v_i),\ \delta)$ where v_i represents a realization of V_i, θ is a vector of parameters that describe the distribution of the population values, and $L(\theta;\ v_i)$ denotes the value of the log likelihood contribution for respondent *i* with value realization v_i. With a specific loss function in mind, we can evaluate the performance of any decision rule δ based on the average loss associated with that decision rule given by:

(2) $$\textit{Average loss of } \delta = E_i[l(L(\theta;\ v_i),\ \delta)]$$

We use the expression $E_i(\ )$ to denote the expectation based on the respondent's subjective distribution of V_i, the source of uncertain information. Assuming quadratic loss,[11]

(3) $$l(L(\theta;\ v_i);\ \delta) = (L(\theta;\ v_i) - \delta)^2,$$

the decision problem reduces to:

(4) $$\min_{\delta} = E_i[\ \left(L(\theta;\ V_i) - \delta \right)^2\ ].$$

The optimal decision rule under quadratic loss is the expected log likelihood contribution based on the respondent's subjective probability distribution:

(5) $$\delta^* = E_i[\ L(\theta;\ v_i)\ ]$$

[11]The absolute deviation loss function is a logical alternative which implies an optimal decision rule equal to the median, instead of mean, log likelihood contribution. For simplicity, we focus on the quadratic loss function throughout our analysis.

Recall that in the case of continuous uncertain responses, the responses trace out the respondent's subjective probability function. We use this information to calculate the expectation, which is given by:

$$\delta^{*} = E_i[\ L(\theta;\ V_i)\ ] = \int_{-\infty}^{\infty} L(\theta;\ v)\ dP_i(v) \tag{6}$$

Note that the expectation in **(6)** takes the form of weighting the value of the log likelihood contribution against the marginal probabilities, $dP_i(v)$ (*i.e.* the change in the distribution function). We now adapt the optimal decision rule developed with continuous uncertainty responses in order to obtain an expression compatible with a discrete number of uncertain responses.

4.2 An optimal decision rule for discrete uncertainty responses

The technique proposed in the previous section applies, with some modifications, to the analysis of MBUC responses. Consider discrete uncertainty responses where, as with the continuous model, respondents answer in terms of their subjective survival probability; individual *i*'s response to bid *k*, $R_i(b_k)$, lies in the unit interval. In the discrete case, however, respondents report subjective probabilities for a discrete number of bid amounts, *K*.

$$R_i(b_k) = P_i(V_i > b_k) = 1 - P_i(V_i < b_k) \tag{7}$$

The *K* bids partition the real line, the possible range of bid values, into *K+1* intervals given by

(8) $$\mathrm{K} = \{(-\infty,\ b_1],\ (b_1,\ b_2],\ \ldots,\ (b_{K-1},\ b_K],\ (b_K,\ \infty)\}$$

A realization of respondent *i*'s random value, which again we denote as v_i, would fall into one of the intervals formed by the bid partition. In the discrete case, the uncertain responses do not reveal the respondent's entire value distribution. The researcher is therefore unable to calculate the exact log likelihood contribution for each respondent. The *K* responses do, however, permit formation of an interval censored log likelihood contribution for each respondent.

The parallel decision theory problem is to minimize the average loss, where the event space for our log likelihood function, , is given by:

(9) $$= \left\{\ \log[F(b_1,\ \theta)],\ \log[F(b_2,\ \theta)\ -\ F(b_1,\ \theta)],\ \ldots,\ \log[1-F(b_k\ ,\theta)]\ \right\}$$

Here *F* represents the assumed distribution function for the population values. Note that the interval-nature of the event space arises from uncertainty on the part of the analyst over the location of the population mean value. Under quadratic loss, the implied decision rule is still to use the expected log likelihood contribution. The expectation takes on a different form in the discrete case due to change in event space determined by the *K* bids. The probability weights are given by changes in the subjective probabilities determined by the uncertainty responses provided by the respondent, which arise from respondent uncertainty over his true value. The optimal decision rule for the discrete case combines both sources of uncertainty, through P_i and *F*, and is given by:

$$\delta^* = E_i[\ L(\theta;\ V_i)\ ] = P_i(V_i < b_1) \cdot \log[F(b_1,\ \theta)]$$

(10)
$$+ \sum_{j=2}^{K} \left[P_i(V_i < b_j) - P_i(V_i < b_{j-1}\right] \cdot \log[F(b_j,\ \theta) - F(b_{j-1},\ \theta)]$$

$$+ \left[P_i(V_i > b_K\right] \cdot \log[1 - F(b_K,\ \theta)]$$

MBUC responses indicate response uncertainty on a qualitative scale. Therefore, the final step in applying the framework to MBUC data is to compute the P_i's associated with each respondent's pattern of MBUC responses using the assumed mapping from MBUC responses to subjective probabilities. Based on a specific parameterization of willingness-to-pay, we apply maximum likelihood estimation to obtain parameter estimates.

5. Implementation of the decision theoretic model

To illustrate the method, we examine two studies relying on the MBUC format that have also attracted attention in the literature. The studies differ along several dimensions including payment vehicle and sampling frame. The most notable difference between the two studies is in the nature of the goods analyzed. As a result, the two studies measure different types of values. The first application involves use values while the second measures non-use values. The MBUC data used in the first application come from a survey of moose hunters conducted in Maine in 1997. The study examines hunters's values for access to the resource. Since access to the hunt has private good characteristics, the study measures use values. For the second application, we examine the preservation of Colorado River-related resources located partially within Grand Canyon National Park. Fluctuations of water flowing from the Glen Canyon Dam (GCD) caused a decrease in the number and size of beaches along the Colorado River, changes in the habitats of terrestrial and aquatic animals, and a decrease in the quality of river-related recreational activities. Because of the national prominence of the Grand Canyon and the unavailability of close substitutes, people are likely to have non-use values the resources measured in this study.

For each set of MBUC responses, we initially present parameter estimates from four models: the benchmark decision theory model and the three Welsh-Poe [24] recoding models, the "Definitely Yes Model", "Probably Yes Model", and "Not Sure Model." We subsequently reestimate the decision theory model with alternative probabilities to test the sensitivity of our estimates to changes in assignment of probabilities. In order to emphasize the estimation methods, we assume the following simple parameterization of WTP:

$$WTP_i = \beta + \upsilon_i \tag{11}$$

where υ_i is distributed normally with zero mean and standard deviation σ. Given our assumptions, WTP_i is distributed normally with mean β and standard deviation σ. For each probit model, we provide estimates of β and σ. All models are estimated with the MAXLIK application in GAUSS.

5.1 Maine moose hunting

Four versions of the survey were developed and distributed among 1500 hunters several days after the completion of the six day moose hunting season.[12] The survey asked respondents to list their moose hunting expenditures for the season. Total hunting expenditures were subsequently used as the payment vehicle for the MBUC question. Respondents were asked if

[12] A more detailed explanation and an empirical analysis of the data are found in Roach, Boyle, and Welsh [20].

they would have gone hunting if their hunting expenditures had increased by the various bid amounts. We focus on the version of the survey in which respondents faced an MBUC question with the following 10 bids: \$1, \$200, \$500, \$800, \$1100, \$1400, \$1700, \$2000, \$2400, \$3000. The 10 bids were chosen based on a previous survey of moose hunters. 221 of the 300 surveys distributed were used in the analysis.

Table III presents estimation results for the three recoding models and the benchmark decision theory model. Parameter estimates in each of the four models are significant at the 1% level. As expected, the "Definitely Yes Model" produces the smallest parameter estimates. Moving from the "Definitely Yes Model" to the "Not Sure Model", the number of "Yes" responses increases, resulting in larger mean WTP estimates. The benchmark decision theory model assumes $P_i(V_i > b) = 1,\ 0.75,\ 0.5\ ,0.15,\ 1$ for "Definitely Yes" through "Definitely No" responses, respectively. The benchmark probability assignment is based on the estimates from the psychology literature discussed in section 4. The mean estimate from the benchmark decision theory model, \$940.38, lies in between the mean estimates from the "Probably Yes Model" and the "Not Sure Model". We do not, however, view this as an endorsement of either recoding models since the recoding models mask valuable information provided by the MBUC responses.

Table III examines the sensitivity of the parameter estimates to changes in the assignment of subjective probabilities. Estimates from the benchmark model are presented in the final column of Table III. For comparison to the benchmark model, we present parameter estimates from two symmetric probability assignments in columns one and two.[13] The first symmetric model places more weight on the “definite” responses while the second symmetric model places more weight on the “probably” responses. The results suggest that, within the class of symmetric (and approximately symmetric) assignments, the parameter estimates from the decision theory model are relatively insensitive to the subjective probability assignment. The estimated mean WTP values based on these assignments range from $940.38 to $961.49. In contrast, the estimated mean WTP values from the three recoding models span a much larger range, from $586.99 to $1089.77. In the final column of Table III, we present estimation results from an asymmetric probability assignment that places more weight on the “no” responses. As expected, this asymmetric assignment produces a smaller estimate of mean WTP than the other assignments. The asymmetric assignment, however, hints at the ability of the decision theory model to nest the various recoding models. For example, the decision theory model with probability assignment 0, 1, 1, 1, and 1 is identical to the Welsh-Poe “Definitely Yes Model”. Therefore, the decision theory model provides a useful framework and accommodates alternative assumptions about respondent interpretation of verbal probability statements.

5.2 Regulating flow fluctuations of Glen Canyon Dam

Releases from the Glen Canyon Dam (GCD) were selected to meet peak electricity demand. This pattern resulted in substantial daily fluctuations in river flows below the dam. Flow fluctuations damaged Colorado river-related resources such as sand bars, animal habitats,

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[13]While the symmetric models have intuitive appeal, the psychology studies we reviewed suggest that subject interpretation of verbal probability statements similar to those found in the MBUC format is only approximately symmetric. An endorsement of any particular assignment requires an investigation of respondent interpretation of the exact probabilistic words used in the MBUC format.

and recreational activities. The Glen Canyon Non-Use Value Study, conducted between 1990 and 1995, was designed to value three proposals to reduce daily fluctuations in river flows below the Glen Canyon Dam.[14] Reductions in flow fluctuations would decrease impacts to downstream resources at a cost of increased electricity prices for those areas receiving power from the GCD electric facility.

We use MBUC responses from three of the nine GCD pilot study versions. Respondents for pilot versions 1-3 were drawn from a national sample based on residential telephone directory listings. The payment vehicle, increased taxes, and 13 bid amounts ($0.10, $0.50, $1, $5, $10, $20, $30, $40, $50, $75, $100, $150, $200) were constant across the three survey versions. The three versions differed in the flow alternative, and therefore the expected environmental benefits. Versions 1-3 offered a moderate fluctuating flow alternative, low fluctuating flow alternative, and seasonally adjusted steady flow alternative respectively. Since expected environmental benefits increase with lower flow fluctuations and flow fluctuations decreased from version 1 to version 3, a comparison of mean WTP estimates permits an investigation of scope sensitivity. We expect version 3 to yield the largest mean WTP estimates. MBUC responses are available only for those respondents who said they would support the proposed alternative at zero cost.[15] This format is not an issue for the current example but would raise general questions if adopted in a full scale study.

[14]On October 9, 1996, Secretary of the Interior Bruce Babbitt signed a measure to implement a modified version of one of the low fluctuating flow alternative highlighting the potential importance of valuation in influencing policy.

[15]Sample sizes for the three versions are 91, 92, and 82 respectively.

Table IV presents estimation results for each version of the three recoding models and the benchmark decision theory model. As in the first application, the mean WTP estimates from each of the three decision theory models fall between the respective estimates from the "Probably Yes Model" and the "Not Sure Model". The final column of table IV suggests that the decision theory estimates are sensitive to changes in the scope of the good under analysis.[16] Our expectation that estimated mean WTP from version 3 should exceed estimates from versions 1 and 2 is also confirmed. Table V presents parameter estimates from the alternative symmetric and asymmetric probability assignments. As with the first example, estimated mean WTP is much less sensitive to changes in the assumptions of the decision theory models than those of the recoding models.

Can we identify a factor that contributes to the stability of the mean WTP estimates from the decision theory model? At first glance, it appears that a higher level of respondent certainty, measured by the percentage of respondents who choose only "definite" responses, decreases the variability of the resulting mean WTP estimates.

To further examine the potential information gains to respondent certainty, we construct a measure of the relative range of the mean WTP estimates. The log ratio of the range of mean WTP estimates to the mean WTP estimate from the benchmark decision theory model measures the relative range of mean estimates for each study.[17] Figure 2 shows the relationship between

[16]Note that contrary to our expectations, estimated mean WTP from version 1 exceeds estimated mean WTP from version 2 but the values are statistically indistinguishable.

[17]We include the two symmetric assignments and the benchmark assignments in our calculation of the range of mean WTP estimates.

the percent of respondents who chose only "definite" responses and the relative range of estimates for the three versions of the GCD study.

As expected, the stability of estimated mean WTP increases with the level of respondent certainty. The observed negative relationship between respondent certainty and the range of estimates is, however, a result of the construction of our framework (*i.e.* the assumed relationship between qualitative responses and probabilities). A formal test of this relationship requires conducting a survey that explicitly elicits subjective probabilities, thus eliminating the need for the researcher-determined probability assignment. The figure also suggests that additional information gains are possible with further increases in respondent certainty.

6. Conclusions

Probabilistic words convey subjective probabilities. Multiple bounded uncertainty choice (MBUC) responses provide a basis for quantifying respondent uncertainty. We use this insight as a basis for a new method to evaluate respondents's economic valuations of policies based on MBUC responses. Our approach links qualitative uncertainty responses to subjective probabilities and recognizes two distinct sources of uncertainty, one on the part of the respondent and the other on the part of the researcher. Our method requires the analyst to specify an explicit research goal. For the method developed here, the goal is taken to be the estimation of parameters that describe the population distribution of economic values from MBUC data. Using decision theory, we derive an expression for the researcher's optimal choice of log likelihood contribution for each respondent based on a loss function consistent with the research goal. We illustrate how the resulting framework can be used to incorporate probabilistic information from MBUC responses into the estimation of population values. Analyses of two MBUC studies find that, compared to mean WTP estimates obtained using recoding methods, estimates resulting from our decision theory-based framework are relatively insensitive to changes in the researcher-imposed information.

To recognize the joint problems posed by the economic modeling of choice as well as the cognitive constraints in explaining hypothetical programs and eliciting corresponding choices, stated preference methods have moved away from the elicitation of censored or interval responses towards probabilistic responses. Our method uses probabilistic, stated-preference responses to estimate population parameters. The application of our technique to MBUC responses should be viewed as part of a more general framework for analyzing probabilistic responses.

References

1. A. Alberini, K. J. Boyle and M. P. Welsh, Analysis of Contingent Valuation Data with Multiple Bids and Response Options Allowing Respondents to Express Uncertainty, *J. Environ. Econom. Management*, forthcoming.

2. A. Alberini and P. A. Champ, "An Approach for Dealing with Uncertain Responses to a Contingent Valuation Question," presented at W-133 meetings in Colorado Springs, Colorado, (1998).

3. R. P. Berrens, H. Jenkins-Smith, A.K. Bohara, and C.L. Silva, "Further Investigation of Voluntary Contribution Contingent Valuation: Fair Share, Time of Contribution, and Respondent Uncertainty," *J. Environ. Econom. Management*, forthcoming (2001).

4. R. Beyth-Marom, How Probable is Probable? A Numerical Translation of Verbal Probability Expressions, *Journal of Forecasting* **1**, 257-269 (1982).

5. T. A. Cameron, G. L. Poe, R. G. Ethier, and W. D. Schulze, Alternative Nonmarket Value-elicitation Methods: Are the Underlying Preferences the Same?, *J. Environ. Econom. Management*, forthcoming.

6. R. T. Carson, W. M. Hanemann, R. J. Kopp, J. A. Krosnick, R. C. Mitchell, S. Presser, P. A. Rudd, and V. K. Smith, Referendum Design and Contingent Valuation: The NOAA Panel's No-Vote Recommendation, *Rev. Econ. and Statist.*, **80**, 484-487 (1998).

7. P. A. Champ, R. C. Bishop, T. C. Brown, and D. W. McCollum, Using Donation Mechanisms to Value Nonuse Benefits of Public Goods, *J. Environ. Econom. Management*, **33**, 151-162 (1997).

8. I. Erev and B.L. Cohen, Verbal Versus Numerical Probabilities: Efficiency, Biases, and the Preference Paradox, *Organizational Behavior and Human Decision Processes* **45**, 1-18 (1990).

9. K. J. Flannelly, L. T. Flannelly, and M. S. McLeod, Jr., Comparison of Election Predictions, Voter Certainty and Candidate Choice on Political Polls, *Journal of the Market Research Society* **40(4)**, 337-346 (1998).

10. K. J. Flannelly, L. T. Flannelly, and M. S. McLeod, Jr., Comparison of Forced-Choice and Subjective Probability Scales Measuring Behavioral Intentions, *Psychological Reports* **86**, 321-332 (2000).

11. F. T. Juster, Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design, *J. Amer. Statist. Assoc.* **61**, 658-696 (1966).

12. C. Li and L. Mattsson, Discrete Choice under Preference Uncertainty: An Improved Structural Model for Contingent Valuation, *J. Environ. Econom. Management* **28**, 256-269 (1995).

13. S. Lichtenstein, and J.R. Newman, Empirical Scaling of Common Verbal Phrases Associated with Numerical Probabilities, *Psychonomic Science* **9**, 563-564 (1967).

14. J. Loomis and E. Ekstrand, Alternative Approaches for Incorporating Respondent Uncertainty When Estimating Willingness to Pay: The Case of the Mexican Spotted Owl, *Ecol. Econ.* **27**, 29-41 (1998).

15. C. F. Manski, The Use of Intentions Data to Predict Behavior: A Best-Case Analysis, *J. Am. Statist. Assoc.* **85**, 934-940 (1990).

16. F. Mosteller and C. Youtz, Quantifying Probabilistic Expressions, *Statist. Sci.* **5**, 2-34 (1990).

17. R. C. Ready, J. C. Whitehead, and G. C. Blomquist, Contingent Valuation When Respondents Are Ambivalent, *J. Environ. Econom. Management* **29**, 181-196 (1995).

18. R. Reagan, F. Mosteller, and C. Youtz, Quantitative Meanings of Verbal Probability Expressions, *J. Appl. Psychology* **74**, 433-442 (1989).

19. S. Renooij and C. Witteman, Talking Probabilities: Communicating Probabilistic Information with Words and Numbers, *International Journal of Approximate Reasoning* **22**, 169-194 (1999).

20. B. Roach, K. J. Boyle, and M. P. Welsh, "Testing Bid Design Effects in Multiple-Bounded Contingent Valuation Questions", draft manuscript, University of Maine (2000).

21. T. S. Wallsten, D.V. Budescu, A. Rapoport, R. Zwick, and B. Forsyth, Measuring the Vagueness to Probability Terms, *J. Experiment. Psychol.*, **115(4)**, 348-365 (1986).

22. T. S. Wallsten, D.V. Budescu, R. Zwick, and S.M. Kemp, Preferences and Reasons for Communicating Probabilistic Information in Verbal or Numerical Terms, *Bulletin of the Psychonomic Society* **31(2)**, 135-138 (1993).

23. H. Wang, Treatment of 'Don't Know' Responses in Contingent Valuation Surveys: A Random Valuation Model, *J. Environ. Econom. Management* **32**, 219-232 (1997).

24. M. P. Welsh and G. L. Poe, Elicitation Effects in Contingent Valuation: Comparisons to a Multiple Bounded Discrete Choice Approach, *J. Environ. Econom. Management* **36**, 170-185 (1998).

25. J. C. Whitehead, G.C. Blomquist, R.C. Ready, and J.Huang, Construct Validity of Dichotomous and Polychotomous Choice Continent Valuation Questions, *Environmental and Resource Economics* **11**, 107-116 (1998).

Figure 1: Multiple Bounded Uncertainty Choice Sample Response

Would you vote for the proposal if passage of the proposal would cost you these amounts for every year for the foreseeable future? (CIRCLE ONE LETTER FOR EACH DOLLAR AMOUNT TO SHOW HOW YOU WOULD VOTE)

Cost to you per year?	Definitely No	Probably No	Not Sure	Probably Yes	Definitely Yes
10¢	A	B	C	D	E
50¢	A	B	C	D	E
$1	A	B	C	D	E
$5	A	B	C	D	E
$10	A	B	C	D	E
$20	A	B	C	D	E
$30	A	B	C	D	E
$40	A	B	C	D	E
$50	A	B	C	D	E
$75	A	B	C	D	E
$100	A	B	C	D	E
$150	A	B	C	D	E
$200	A	B	C	D	E

Table I: Individual Value Inference and Log likelihood Contributions for Welsh and Poe Sample Respondent in Figure 1

Welsh-Poe Recoding Model	Individual Value Inference	Log Likelihood Contribution
Definitely Yes	$V_i \in [\$10,\ \$20)$	$\log[F(20;\ \theta) - F(10;\ \theta)]$
Probably Yes	$V_i \in [\$30,\ \$40)$	$\log[F(40;\ \theta) - F(30;\ \theta)]$
Not Sure	$V_i \in [\$40,\ \$50)$	$\log[F(50;\ \theta) - F(40;\ \theta)]$

Table II: Estimation Results for Maine Moose Hunting Study[1]

	Definitely Yes Model	Probably Yes Model	Not Sure Model	Benchmark Decision Theory Model
Beta	586.99 (44.59)	815.37 (48.77)	1089.77 (56.06)	940.38 (57.34)
Sigma	671.58 (33.12)	735.66 (36.41)	845.39 (42.48)	852.82 (43.40)

[1] Standard errors in parentheses.

Table III: Estimation Results for Maine Moose Hunting Study–Sensitivity of decision theory estimates to assignment of probabilities[1]

	Symmetric Assignments		Asymmetric Assignments	
Probability Assignment	**1, 0.99, 0.5, 0.01, 0**	**1, 0.6, 0.5, 0.4, 0**	**Benchmark[2]: 1, 0.75, 0.5, 0.15, 0**	**1, 0.99, 0.98, 0.5, 0**
Beta	952.30 (53.37)	961.49 (60.67)	940.38 (57.34)	715.84 (47.79)
Sigma	806.39 (40.24)	912.77 (46.49)	852.82 (43.40)	734.09 (36.43)

[1] Standard errors in parentheses.
[2] Probability assignment based on psychology estimates.

Table IV: Estimation Results for Glen Canyon Pilot Study[1]

	Definitely Yes Model	Probably Yes Model	Not Sure Model	Benchmark Decision Theory Model
Version 1				
Beta	39.39 (6.11)	66.77 (6.68)	116.57 (11.28)	90.29 (10.20)
Sigma	57.36 (4.80)	62.86 (5.62)	101.51 (10.28)	93.39 (8.61)
Version 2				
Beta	38.63 (7.40)	68.61 (8.36)	112.44 (10.80)	88.43 (10.62)
Sigma	68.91 (6.21)	78.07 (6.99)	98.67 (9.88)	98.05 (9.39)
Version 3				
Beta	57.57 (8.22)	88.70 (9.82)	120.29 (12.45)	102.06 (11.50)
Sigma	72.21 (6.50)	87.04 (8.38)	106.30 (11.26)	98.61 (9.84)

[1] Standard errors in parentheses.

Table V: Estimation Results for Glen Canyon Pilot Study–Sensitivity of decision theory estimates to assignment of probabilities[1]

	Symmetric Assignments		Asymmetric Assignments	
Probability Assignment	**1, 0.99, 0.5, 0.01, 0**	**1, 0.6, 0.5, 0.4, 0**	**Benchmark[2]: 1, 0.75, 0.5, 0.15, 0**	**1, 0.99, 0.98, 0.5, 0**
Version 1				
Beta	92.22 (9.42)	100.46 (11.95)	90.29 (10.20)	53.61 (6.80)
Sigma	85.18 (7.76)	107.20 (10.46)	93.39 (8.61)	64.08 (5.23)
Version 2				
Beta	89.87 (9.91)	95.19 (12.10)	88.43 (10.62)	54.50 (8.19)
Sigma	91.16 (8.87)	109.47 (10.95)	98.05 (9.39)	76.59 (6.74)
Version 3				
Beta	105.28 (11.08)	106.12 (12.10)	102.06 (11.50)	74.31 (9.22)
Sigma	96.18 (9.53)	104.35 (10.69)	98.61 (9.84)	81.47 (7.57)

[1] Standard errors in parentheses.
[2] Probability assignment based on psychology estimates.

Figure 2: Information Gains from Respondent Certainty