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A Decision Theoretic Approach to Modeling Multiple Bounded Uncertainty Choice Data[1]

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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 a6bpunm0v

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

[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.

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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.

[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: $V_i = x_i! + "_i$. x_i is a vector of variables representing observable characteristics of the respondent and $"_i$ is an error component arising from factors not observed by the analyst. $F(\cdot)$ is the analyst-determined distribution function of $"_i$. Note that this

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 sig(c)4.7(e)4.7(mode)4.7(l pe)4.7(r)iw[(characte1.3(t]TJe)4.7(4.7(n)0.9(c)4.7(e)4.7(mo th

[9]See Ready et al. [17] and Whitehead et al. [25] for a discussion of non-response rates in

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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”, “Probab.8(e)4.8(s)0.2(.e>ita)4.8(tive)]P we a c

(1) $$R_i(b) = P_i(V_i > b) = 1 - P_i(V_i < b) = 1 - G_i(b)$$

of V_i, $!$ is a vector of parameters that describe the distribution of the population values, and $L(!;\ v_i)$ denotes the value of the log likelihood contribution for respondent *i* with value

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

(3) $$l(L(!;\ v_i);\ \#) = (L(!;\ v_i) - \#)^2,$$

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

(5) $$\#^* = E_i[\ L(!;\ v_i)\ ]$$

[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.

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

$$R_i(b_k) = P_i(V_i > b_k) = 1 - P_i(V_i < b$$

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

$= \{$

$$\#^{*} = E_i[\ L(!;\ V_i)\ ] = P_i(V_i < b_{i1}) \cdot \log[FV]$$

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:

(11) $$WTP_i = \% + \&_i$$

where $\&_i$ is distributed normally with zero mean and standard deviation $'$. Given our assumptions, WTP_i is distributed normally with mean $\%$ and standard deviation $'$. For each

[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

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[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.

Table IV presents estimation results for each version of the three recoding models and the

[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

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

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.