Willingness-to-Pay Estimates Using the Double-Bounded Dichotomous-Choice Contingent Valuation Format: A Test for Validity and Precision in a Bayesian Framework

Donald M. McLeod and Olvar Bergland

ABSTRACT. *The Double-Bounded Dichotomous-Choice (DB-DC) Contingent Valuation format is thought to yield more precise welfare estimates. Questions remain about its validity. The initial bid may represent information with which respondents update their willingness to pay. A Bayesian model of respondent decision making is estimated for two data sets. The results indicate updating or shifts in respondent willingness to pay between iterated valuations. Nonparametric testing of the welfare estimates reveals that the model incorporating updating yields different values from the standard model. The expected increases in the precision of the DB-DC welfare estimates are lost when updating occurs.* (JEL Q26)

I. INTRODUCTION

Eliciting satisfactory estimates of nonmarket values through contingent valuation (CV) methods remains a constant struggle to avoid bias and increase precision. A potential pitfall is giving respondents unintentional cues about the value of an environmental asset through arbitrary bids. This article provides new evidence of that unintentional influence when using the double-bounded dichotomous choice (DB-DC) format.

The DB-DC format poses a valuation question that leads to a follow-up question based on the response to the initial question. The central research question is to determine if the initial bid influences the response to the follow-up bid. If the respondent's distribution of willingness to pay (WTP) shifts (or is nonconstant) between the offered bids, then estimates of WTP using current DB-DC practices may be incorrectly modelled.

The objectives of this research are given as follows:

1. To develop a behavioral model for respondent decision-making under the DB-DC format;
2. To test if the initial bid level causes a shift in respondent WTP; and
3. To determine if the shift leads to changes in the precision of the estimated WTP, where objectives 2 and 3 are implemented using two data sets.

II. PREVIOUS RELEVANT RESEARCH

McFadden and Leonard (1993) and Hanemann et al. (1991) show that the size of the gains in parameter efficiency range from 100 to 400% when the response to the follow-up question is included. Hanemann et al. (1991) explicitly assume that respondents' successive valuations are independent. This implies that the individuals' distribution of WTP underlying their valuations does not change from the initial to the follow-up bid. This assumption is critical for an accurate interpretation of DB-DC estimates. McFadden and Leonard (1993) test for the consistency of

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The authors are, respectively, assistant professor, Department of Agricultural and Applied Economics, University of Wyoming, and senior scholar, Department of Economics and Social Sciences, Agricultural University of Norway. The authors gratefully acknowledge assistance from the Department of Agricultural and Resource Economics, Oregon State University, for supporting this research. Thanks to Kristin Magnussen and Alan Randall for sharing data sets. Special thanks also to David Ervin, Richard Adams, David Birkes, Jay Shogren, Dale Menkhaus, and Larry Van Tassel for helpful comments during the preparation of this manuscript. As always any errors in this manuscript are our sole responsibility.

preferences in the DB-DC format and conclude that some systematic bias is occurring.

Cameron and Quiggin (1994) hold that since the follow-up bid depends on the response to the initial bid, the two bid levels are dependent. This does not necessarily imply that the valuation response to the follow-up bid depends on the response to the initial bid. The analyst cannot necessarily predict whether the respondent will accept or reject the follow-up bid based on the response to the initial bid.

A case can be made for viewing the CV respondent as a Bayesian decision maker. Bayesian models have been constructed to estimate the impact that additional economic information has on the revision of prior beliefs.[1] Bayesian models have not been widely used in iterated CV formats.

Crocker and Shogren (1991) use a Bayesian format to indicate how an individual may formulate his preferences for a good with which he is unfamiliar. They indicate that under uncertainty incomplete preference learning may be optimal due to the investment involved in acquiring knowledge about the good. They also ask whether the individual is paying for an opportunity to consume the good rather than paying to actually consume it (buying a lottery ticket for the opportunity to purchase a loaf of bread rather than the bread itself).

Herriges and Shogren (1996) expand upon the Bayesian decision-making format and devise a test for the bias associated with anchoring on the initial bid in the DB-DC format. They indicate that the improvements that standard DB-DC formats offer may come at the cost of both the validity and precision of the WTP estimates.

This study offers empirical evidence in the distortion of the WTP estimates incurred by the initial bid in the DB-DC format. Shifts can be detected in the respondent WTP by incorporating a Bayesian model of decision making into the DB-DC estimation. Two data sets are estimated using the standard DB-DC format modified to reveal the presence of Bayesian updating. The estimates are compared with a single valuation question (the dichotomous choice [DC-CV])[2] and a standard DB-DC format. The former is a single-bounded analysis from a double-bounded data set ignoring the second valuation elicitation. The three WTP estimates are examined for differences in size and precision.

III. THEORY AND METHODS

One way to view the valuation exercise for the respondent is as decision making under uncertainty. The respondent may have imperfect prior information about the nonmarket good to be valued. Individuals could be viewed as Bayesian decision-makers with weak or malleable priors. Suppose that a respondent's reported WTP, Y, is a function of the offered initial bid, τ, and the initial WTP, Y_o known only to the respondent, are related as follows:

$$Y = f(\tau, Y_o).$$

The expected value (EV) of Y for the given value Y_o is as follows:

$$EV(Y) = \int \tau f(\tau, Y_o)d\tau. \quad [1]$$

The expected value of the CV good to the respondent covers a distribution of initial WTP's as follows:

$$EV(good) = \int EV(Y)g(Y)dY. \quad [2]$$

The probability distribution function (pdf) given as $g(\cdot)$ would evidence Bayesian updating if present. When τ is related to the estimated WTP, the updating pdf incorporating the new information is as follows:

$$g(Y_o|\tau) = \frac{f(\tau|Y_o)g(Y_o)}{\int f(\tau|Y)g(Y)dY}. \quad [3]$$

Note how this simplifies. τ is known for each respondent. Y_o is unknown but operationalized by the appropriate sociodemographic variables and associated coefficients which themselves are known or estimated. The purpose of the analysis that follows from the above is to verify that $g(\cdot)$ exists, rather than to specify its precise statistical form.

Viscusi (1989) changes the way that probabilities enter a expected utility model by including parameters that reflect a level of precision in the probabilities. Information is viewed as imperfect and is reformulated in a Bayesian manner.[3] Horowitz (1993) uses a similar Bayesian construction of updating to model how respondents update their prior values for environmental amenities. Suppose that initial bid offered, τ_i, is perceived by the respondent as additional information. The reported WTP can be constructed from the initial WTP[4] and the initial bid. The potential for respondent updating can be modelled utilizing a Bayesian adaptive response approach. This process is best shown for the DB-DC format as follows:

$$Y = (\theta Y_0 + \xi\tau)/(\theta + \xi). \quad [4]$$

The above can be re-written, setting $\xi = 1$ since τ is known precisely, as

$$Y = (\theta/(1 + \theta))Y_o + (1/(1 + \theta))\tau \quad [5]^5$$

where

Y = the updated WTP,
θ = the precision of the initial WTP,
Y_o = the initial WTP, and equal to a combination of explanatory variables and a random error factor,
ξ = the precision of the new information (initial bid), and
τ = the initial bid.

This procedure holds implications for the four DB-DC bid groups formed by the responses to the initial and second bids.

$$y_i = \begin{cases} 1 \text{ if } & (Y_o < \tau_i) \text{ and } (Y < L2) \quad \text{(NO,NO);} \\ 2 \text{ if } & (Y_o < \tau_i) \text{ and } (Y > L2) \quad \text{(NO,YES);} \\ 3 \text{ if } & (Y_o > \tau_i) \text{ and } (Y < H2) \quad \text{(YES,NO);} \\ 4 \text{ if } & (Y_o > \tau_i) \text{ and } (Y > H2) \quad \text{(YES,YES);} \end{cases}$$

where y_i is the observed response, $L2$ is the low second bid (first response is "no") and $H2$ is the high second bid (first response is "yes"). The above four expressions are all conditional probability statements. Please see the appendix for the structure of the DB-DC format.

The standard assumption for the DB-DC format is that the respondent's true valuation is not altered by the size of the bids presented to him. It follows that if the probability of a given response to the initial bid is independent of the response to the second bid, then the WTP of the respondent has not been influenced by the initial bid. Written as probability statements one would have for responses in category $y_i = 1$ (NO/NO):

$$\Pr\{(Y_o < \tau_i) \text{ and } (Y < L2)\}. \quad [6]$$

Substituting the right hand side of equation [5] for Y (an unknown) the following is obtained:

$$\Pr\{(Y_o < \tau_i) \text{ and } [(\theta/(1 + \theta))Y_o + (1/(1 + \theta))\tau_i] < L2\}. \quad [7]$$

By manipulating the second half of the probability statement, the following is obtained

[1] For example the effects of product risk information on consumer purchases (Viscusi 1985); of workers' assessment of occupational risk (Viscusi and O'Connor 1984); of extension information on livestock management (Knight, Johnson, and Finley 1987); of the sequential adoption of agricultural innovation by farm operators (Leathers and Smale 1991); of pesticide information on crop management (Pingali and Carlson 1985); and of changes in producer behavior on the design of policy mechanisms regulating nonpoint source pollution (Cabe and Herriges 1992).

[2] The possibility of updating in the single valuation context is explored in the analysis of yea-saying. See Kanninen 1993, for example.

[3] Viscusi shows the Bayesian structure for updating by parameterizing a bivariate model which follows from a Bernoulli distribution.

[4] The initial WTP given follows Cameron (1988) as the function of sociodemographic variables and the associated coefficients. These arguments serve as indicators from which prior expectations originate. An error term is included to indicate that the initial WTP is known only to the respondent. For further discussion see McConnell (1990).

[5] The precision of both the prior and the updating information are important as each can be viewed as providing incomplete information. For further discussion see Viscusi (1989).

$$\Pr\{(Y_o < \tau_i) \text{ and } (Y_o < L2 - 1/\theta(\tau_i - L2))\}$$
$$= \Pr\{(Y_o < \tau_i) \text{ and } (Y_o + 1/\theta(\tau_i - L2) < L2)\}. \quad [8]$$

The above is a formulation of the problem of bias detection that has as unknowns estimable parameters. Y_o is estimated by a vector of sociodemographic information $\beta'\chi$, with a random error term.

The probability statement [8] arises from the assumed Bayesian structure of the adaptive response procedure. No updating of the WTP occurs when θ is very large, which implies that $1/\theta$ is approximately equal to 0. Let δ, the updating parameter, be equal to $1/\theta$. The resulting hypothesis is:

H_o: The initial bid does not change the initial distribution of WTP and hence δ equals 0.

This implies the alternative hypothesis:

H_A: The initial bid changes the initial distribution of WTP and hence δ does not equal 0.

The rejection of H_o would mean that respondents are updating their initial distribution of WTP with the initial bid. They are then interpreting the initial bid as some benchmark in a way that was not intended in the design of the CV survey. Such updating would lead to invalid measures of welfare benefits (WTP) in DB-DC estimation where the updating is not accounted for in the model. This hypothesis test is constructed to detect updating assuming a Bayesian decision making framework.[6] The reader must be reminded that this test is not intended to verify whether respondents are Bayesian decision makers or not.

The probability expression given above as [8] for the response category $y_i = 1$ can be rewritten in terms of a normal cumulative distribution function, Φ, substituting $\beta'\chi$ for Y_o as

$$\Phi[(L2 - \delta(\tau - L2) - \beta'\chi)/\sigma] \quad [9]$$

$\beta'\chi$ would approximate the systematic component of Y_o. σ denotes the square root of the variance. $\tau - L2$ would take the form of an explanatory variable χ_o since both of the bids are known to the researcher. The standard DB-DC format restricts δ to zero, does not allow for updating and is titled the "restricted model." Where δ is nonzero and the possibility of updating exists, an "unrestricted model" is evoked.

IV. DATA AND ESTIMATION RESULTS

Two data sets are employed in the testing procedure. One is a Norwegian pollution policy for the North Sea used by Magnussen (1992b). Magnussen (1992b) reports estimates of data from a survey of Norwegians concerning the North Sea Plan (NSP), a multi-national policy designed to reduce eutrophication in the North Sea. Methodological details and study results are reported in Magnussen (1992a). A second is a U.S. national policy evaluation referendum survey (NPER) administered by Randall et al. (1985). Results of the latter survey are published in Randall and Kriesel (1990) and Mitchell and Carson (1989). Individuals were asked their WTP for a 25% reduction in U.S. national air and water pollution. The contingent scenario is portrayed as a collective good which is to be implemented through a standardized national policy over the course of five years.

A normal error distribution is used in the maximum likelihood estimation in order to be consistent with the estimation conducted by Bergland and Kriesel (1991) for the NPER data and that performed by Magnussen (1992b) on the NSP data. The distribution was presumably chosen for the ease of analysis. It also does not place as much emphasis on observations found out on the tail of the distribution as the logistic distribution. There is some evidence that dichotomous choice estimates of WTP can be driven by extreme values (Alberini 1995).

The NPER model has two co-variates unrelated to the bias test. The co-variates and parameters are as follows:

[6] Not rejecting H_o could still allow for a behavioral model wherein CV respondents could still be viewed as Bayesians. This outcome would mean that the bids offered at random to the survey sample matched the respondent's prior with a high degree of precision. Thus updating would not occur.

$$\beta'\chi = \alpha + \text{BATT}*ATT + \text{BINC}*INC. \quad [10]$$

where *ATT* is the attitude co-variate and *INC* is the annual household income argument. BATT and BINC are the coefficients to be estimated and α is the intercept term to be estimated. The attitude (*ATT*) variable indicates a greater degree of pro-environment sentiment, the larger the argument value. In the case of both of these arguments, it is hypothesized that both would be significant and have a positive sign.

The NPER model nontest arguments, *ATT* and *INC*, have significant estimated coefficients with the hypothesized signs (see Table 1). The likelihood ratio results for the test of the hypothesis, LR-DB-DC, indicates a significant difference between the restricted and unrestricted models. The hypothesis, that δ is equal to zero and that no Bayesian updating occurs, is not supported by the test results. This outcome is substantiated by the statistical significance of δ. The appendix provides the bid structures and responses.

The NSP model has seven co-variates. The model is given below:

$$\beta'\chi = \alpha + \text{BA1}*A1 + \text{BA2}*A2 + \text{BHED}*HED + \text{BSPH}*SPH + \text{BNSP}*NSP + \text{BAGE}*AGE + \text{BINC}*INC. \quad [11]$$

The *A* variables are dummies indicating levels of concern about environmental protection with *A1* as the most concerned. *HED* indicates that the respondent had received post secondary education. *SPH* indicates that the individual constituted a single person household. *NSP* indicates that the respondent lives in the region where the policy was implemented. The NSP bid structures and responses are given in the appendix.

The nontest parameter estimates all have the hypothesized signs in the NSP models. The attitude parameters yield results consistent with their expected signs (see Table 2). The test of the hypothesis statistic, LR-DB-DC, indicates a significant difference between the unrestricted and restricted models. The result shows that the alternative hypothesis, that is, shifts occur in the respondents' distribution of WTP, cannot be rejected. The statistical significance of δ verifies the above outcome. Tests for both data sets indicate that the respondents' WTP shift after the initial bid is revealed.

Welfare Estimates

The conditional WTP calculation is based on the assumption that the nonmarket goods considered in the CV are valuable, *ex ante*, to the surveyed individuals. Hence the calculation for WTP is restricted to be nonnegative. This approach utilizes the parameter estimates from the nonlinear maximum like-

TABLE 1
COMPARISON OF ESTIMATES WITH THE NPER DATA

Parameter	DC-CV Estimate	DB-DC$_R$ Estimate	DB-DC$_U$ Estimate
α	−698.99*	−291.03**	−576.43**
BATT	46.98***	33.38***	46.93***
BINC	13.70***	7.82***	11.11***
δ	—	—	0.41+
σ	743.70	499.54	697.74
LR-Slope	—	103.24***	110.78***
LR-DB-DC	—	—	7.54**

Note: $N = 623$.
+ indicates that the value is significant at the 0.10 level.
* indicates that the value is significant at the 0.05 level.
** indicates that the value is significant at the 0.01 level.
*** indicates that the value is significant at the 0.001 level.

TABLE 2
COMPARISON OF ESTIMATES WITH THE NSP DATA

Parameter	DC-CV Estimate	$DB\text{-}DC_R$ Estimate	$DB\text{-}DC_U$ Estimate
α	413.70	965.47	−212.86
BA1	6,803.49***	5,443.85***	7,260.81***
BA2	3,215.70**	2,679.59***	3,383.45**
BHED	1,785.22*	1,511.69*	1,807.90*
BSPH	−1,704.99+	−1,283.97*	−1,397.81
BNSP	2,659.55***	2,338.15**	3,267.07***
BAGE	−25.06	−42.74**	−62.24**
BINC	1.93	3.87*	6.25*
δ	—	—	0.89***
σ	5,892.58	4,827.55	7,022.99
LR-Slope	—	133.9***	186.7***
LR-DB-DC	—	—	52.8***

Note: $N = 625$.
+ indicates that the value is significant at the 0.10 level.
* indicates that the value is significant at the 0.05 level.
** indicates that the value is significant at the 0.01 level.
*** indicates that the value is significant at the 0.001 level.

lihood estimation (MLE) and incorporates them into the equation for the mean of a censored normal variable. The censored normal variable is the conditional WTP given that its values are restricted to being nonnegative. The equation for the mean of the conditional value of WTP is found in Maddala (1983, 161) and is given as:

$$E(Y{:}\ Y \geq 0) = \beta'\chi + \sigma[\phi(\alpha)/(1 - \Phi(\alpha))]. \quad [12]$$

Equation [12] is used to calculate the WTP for the restricted and unrestricted DB-DC models as well as the DC-CV models for the two data sets. The expression arises from the following relation for any respondent as:

$$Y = \beta'\chi + \upsilon \quad [13]$$

where

$$Y = \text{WTP},$$

$\beta'\chi$ = the systematic component of Y with a vector of respondent characteristics, χ, with parameters β and υ = the nonsystematic component of Y, an error term. The cumulative distribution function (*cdf*) and the probability distribution function (*pdf*) follow from the normality of the error distribution. Using the moments of a censored normal the *pdf* of the normalized parameters is given as:

$$f(x) = \begin{cases} \phi(\alpha) & \text{if } Y \geq 0 \\ 0 & \text{if } Y < 0, \end{cases} \quad [14]$$

where

$$\alpha = (0 - \beta'\chi)/\sigma.$$

The *cdf* is given as:

$$F(x) = \begin{cases} \Phi(\alpha) & \text{if } Y \geq 0 \\ 0 & \text{if } Y < 0. \end{cases} \quad [15]$$

The β and σ are parameter estimates obtained from the MLE of the valuation format.[7]

The WTP estimates are themselves based on estimates from the MLE. The estimation of the β and σ parameters involve nonlinear procedures using multiple random (explanatory) variables with unknown distributions. The WTP estimates, then, are random variables with unknown distributions. To obtain the standard errors for the WTP estimates, a bootstrapping technique is employed.

Bootstrapping is a simulation technique based on parametric estimates of the underlying distribution of WTP using an iterative resampling algorithm. The bootstrapping technique has been developed by Efron (1979) and Efron and Tibshirani (1986). It has been adapted for use in CV analysis by Bergland et al. (1990) and Duffield and Patterson (1991). Details of the bootstrapping procedure used in this paper are provided in the appendix.

The results of the WTP calculations for the two data sets are given in Table 3. For notational purposes define the following: $DB\text{-}DC_R$ stands for the restricted DB-DC model (assuming no updating) and $DB\text{-}DC_U$ denotes the unrestricted DB-DC model (providing for possible updating). Judging from Table 3, the use of the $DB\text{-}DC_R$ leads to a reduction in WTP when compared to the DC-CV WTP for the two data sets. The unrestricted model yields WTP estimates somewhat comparable to the DC-CV WTP. The revision of WTP by the respondent raises the estimated WTP. The DB-DC WTP estimate is not as conservative a welfare measure if Bayesian updating is incorporated into the model.

The standard errors indicate the precision of the different WTP estimates. The $DB\text{-}DC_R$ model provides the smallest standard errors obtained from the bootstrap samples for both data sets. The precision of the $DB\text{-}DC_U$ WTP exceeds that of the DC-CV WTP estimate in the NPER model and is about the same in the NSP model. Where Bayesian updating is occurring, the DB-DC estimates tend to show less efficiency gains than the standard DB-DC models.

The $DB\text{-}DC_R$ model provided more precise welfare estimates when compared to the single question approach in previous work. The assumption of a constant WTP underlying the restricted model has been rejected. Given the MLE and associated test of hypothesis results, it is necessary to determine whether the WTP of the unrestricted model is statistically different from the WTP of the restricted model.

When the underlying distribution of some data is not easily specified, nonparametric tests provide a means of analyzing the data. The WTP estimates given in Table 3 come from unknown distributions. Wilcoxon's signed rank test is conducted to ascertain whether the WTP estimates from the DC-CV and the $DB\text{-}DC_R$ MLE differ statistically from the $DB\text{-}DC_U$ WTP estimates.

The Wilcoxon test is used to detect differences in paired data. In the case of the WTP estimates, they are tested pairwise with the WTP from the unrestricted model. The test can be used to compare estimates from the same sample with some chosen or preferred value. The Wilcoxon test assumes a symmetric distribution for each difference but not that each difference is from the same distribution. See Lehman (1974) for further discussion. The hypotheses concerning the WTP estimates can be defined by four statements.

A. For the NPER bootstrap sample:

$\mathbf{H_{01}}$: The DC-CV WTP is equal to the $DB\text{-}DC_U$ WTP; and

$\mathbf{H_{02}}$: The $DB\text{-}DC_R$ WTP is equal to the $DB\text{-}DC_U$ WTP.

B. For the NSP bootstrap sample:

$\mathbf{H_{03}}$: The DC-CV WTP is equal to the $DB\text{-}DC_U$ WTP; and

$\mathbf{H_{04}}$: The $DB\text{-}DC_R$ WTP is equal to the $DB\text{-}DC_U$ WTP.

The tests are conducted pairwise on the bootstrap estimates for the WTP from the three models. Each calculated statistic has degrees of freedom equal to the bootstrap

TABLE 3
ESTIMATES OF WTP AND THE STANDARD ERRORS

Model	Conditional WTP	Standard Errors
NPER Data Set (Dollars) T = 124 Bootstrap Draws		
DC-CV	1,026.18	166.69
$DB\text{-}DC_R$	807.68	23.03
$DB\text{-}DC_U$	921.43	82.94
NSP Data Set (NOK) T = 125 Bootstrap Draws		
DC-CV	7,600.33	486.76
$DB\text{-}DC_R$	6,475.37	289.31
$DB\text{-}DC_U$	7,690.11	495.52

[7] The use of MLE techniques to calculate WTP directly has been exploited previously by Cameron and James (1987a, 1987b).

TABLE 4
WILCOXON SIGN RANK TEST FOR THE BOOTSTRAP ESTIMATES OF WTP

	DC-CV with DB-DC$_U$	DB-DC$_R$ with DB-DC$_U$
NPER	5.63**	8.61**
NSP	1.63*	9.46**

* indicates that the p-value < 0.105.
** indicates that the p-value < 0.001.

sample size and is distributed as a standard normal. The calculated values for the NPER and NSP models are provided in Table 4.

The nonparametric test reveals that there is a significant difference between the DB-DC$_U$ and the other models of CV welfare estimation, with one exception. $\mathbf{H}_{o1}$, $\mathbf{H}_{o2}$ and $\mathbf{H}_{o4}$ can all be rejected, but $\mathbf{H}_{o3}$ can not be safely rejected on the basis of the test. Recall from Table 3, that the estimated WTP and the size of the standard errors are approximately equal for the DB-DC$_U$ and the DC-CV models. The important tests of hypothesis concern the rejection of $\mathbf{H}_{o2}$ and $\mathbf{H}_{o4}$.

The inclusion of a parameter (δ) that can indicate shifts in respondent WTP has several effects. The WTP estimates for the two DB-DC models are significantly different. The structure of the DB-DC$_U$ yields an increase in the WTP estimates in both data sets. Updating has increased the WTP estimates while decreasing the precision of the estimates.

The bias detected may work in either direction. It seems intuitive that the greater the impact on WTP estimates due to updating, the less precise the estimate. Herriges and Shogren (1996) indicate that the level of anchoring (here updating) and supposed precision gains of the welfare estimate are correlated.

V. CONCLUSIONS

The DB-DC$_U$ model, by statistically accounting for respondent updating, requires CV researchers to reassess the effect of the initial bid in the DB-DC format. The size of the difference between the two bids may represent a change in the relative price ratio of the nonmarket good to all other goods for the respondents. An individual's distribution of WTP shifts in response to perceived shifts in the "price" of the nonmarket good. This updating by the respondent should be incorporated into the CV modelling when the DB-DC format is used. The increased precision in the estimated WTP by asking a follow-up question is not as large, or even nonexistent, when Bayesian updating is accounted for in the estimation.

APPENDIX

BID LEVELS FOR THE NPER STUDY

Initial Bids		Follow-up Bids
Range:	\$75 to 750	\$50 or \$1000
Number:	10	The above 2 bids

BID LEVELS FOR THE NSP STUDY

Initial Bids	Follow-up Bids
Range: 100 NOK – 10,000	±50% of the initial bid
Number: 6	1 high, 1 low based on the initial bid

THE PERCENTAGE OF THE TOTAL SAMPLE IN EACH RESPONSE CATEGORY FOR THE DB-DC FORMAT

DB-DC Response Categories for the NPER Data Set

Responses	Fraction of Sample
NO, NO	0.09
NO, YES	0.23
YES, NO	0.37
YES, YES	0.31

Sample size = 623

DB-DC Response Categories for the NSP Data Set

Responses	Fraction of Sample
NO, NO	0.23
NO, YES	0.17
YES, NO	0.19
YES, YES	0.41

Sample size = 625

THE FORM OF THE DB-DC MODEL

Following Hanemann et al. (1991) a two-part likelihood function which, when a follow-up bid is offered, can be expanded into a four-part likelihood function. The respondent answers two questions for the DB-DC with the final reply falling within one of four bid categories:

$$y_i = \begin{cases} 1 \text{ if } & Y < L2; \\ 2 \text{ if } & L2 < Y < \tau_i; \\ 3 \text{ if } & \tau_i < Y < H2; \\ 4 \text{ if } & H2 < Y; \end{cases}$$

where y_i is the observed response, τ_i is the initial bid,

Y is the respondents' true WTP,
$L2$ is the low second bid (first response is "no"), and
$H2$ is the high second bid (first response is "yes").
The log of the likelihood of the DB-DC model is as follows:

$$\begin{aligned} £ = \mathrm{Ln}\{ & (I_i^a)(I_i^b)\Sigma\Phi(W2_i) \\ & + (1 - I_i^a)(I_i^b)\Sigma[\Phi(W1_i) - \Phi(W2_i)] \\ & + (I_i^a)(1 - I_i^b)\Sigma[\Phi(W2_i) - \Phi(W1_i)] \\ & + (1 - I_i^a)(1 - I_i^b)\Sigma[1 - \Phi(W2_i)]\}. \end{aligned}$$

Where

I_i^a = 1 if $Y_i > \tau_i$, = 0 otherwise;
I_i^b = 1 if $Y_i >$ Bid2, (Bid2 being either $L2$ or $H2$) = 0 otherwise;

where

$W1_i = (\tau_i - \beta'\chi_i)/\sigma$;
$W2_i = (\text{Bid2} - \beta'\chi_i)/\sigma$ in the restricted model (independent valuation assumption);
$W2_i = (\text{Bid2} + \delta^*\chi_{oi} - \beta'\chi_i)/\sigma$ in the unrestricted model (assuming Bayesian updating);
Φ = normal cumulative distribution function (assuming a normally distributed error); and
χ_{oi} = Bid2 $- \tau_i$ in the unrestricted model.

THE BOOTSTRAPPING PROCEDURE

For the NSP and NPER data sets, the following bootstrap procedure was utilized:

1. 120 bootstrap samples were taken for each data set;
2. each bootstrap sample consists of 620-odd bootstrap draws;
3. each bootstrap draw is taken from the original data sets with replacement at random;
4. the DC-CV, DB-DC$_R$, and DB-DC$_U$ maximum likelihood estimation are performed on each bootstrap sample;
5. The results of the MLEs and average values for the covariates in each data set are used to estimate a bootstrap WTP estimate;

There are a variety of ways to bootstrap standard errors. The approach used here will sample directly from the observed data. The standard errors are numerically evaluated by the use of an algorithm. Following Bergland et al. (1990), the algorithm has three basic steps:

1. T independent (bootstrap) draws are taken from the original data via a random number generator;
2. for each draw ($i = 1, \ldots, T$; each i equal in quantity to the original sample size) the MLE is performed and the WTP is evaluated for each valuation format; and
3. the bootstrap WTP standard errors are calculated as

$$\sigma_{WTP} = \left\{ \sum_i^T (\text{WTP}_i^* - \text{MWTP})^2/(T - 1) \right\}^{1/2},$$

where

$$\text{MWTP} = (1/T)\sum_i^T \text{WTP}_i^* \text{ and}$$

WTP_i^* = WTP evaluated at each sample i.

For standard error bootstrapping T should equal at least 100 iterations. The size of the data sets used here ($N > 600$) should lead to precise bootstrap standard errors.

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