Statistical Efficiency of Double-Bounded Dichotomous Choice Contingent Valuation

Michael Hanemann, John Loomis, and Barbara Kanninen

The statistical efficiency of conventional dichotomous choice contingent valuation surveys can be improved by asking each respondent a second dichotomous choice question which depends on the response to the first question—if the first response is "yes," the second bid is some amount greater than the first bid; while, if the first response is "no," the second bid is some amount smaller. This "double-bounded" approach is shown to be asymptotically more efficient than the conventional, "single-bounded" approach. Using data from a survey of Californians regarding their willingness to pay for wetlands in the San Joaquin Valley, we show that, in a finite sample, the gain in efficiency can be very substantial.

Key words: contingent valuation, wetlands, wildlife, willingness to pay.

The contingent valuation method (*CVM*) is one of the standard approaches for valuing nonmarketed resources, such as recreation, wildlife, and environmental quality. Initially, a bidding format was used to elicit willingness to pay (Randall, Ives, and Eastman). In some sense this traditional bidding method and the newer single-bound dichotomous choice questions represent bipolar ends of a continuum. At the bidding end, the respondent is asked a series of dichotomous choice questions until some point estimate of willingness to pay (*WTP*) is reached. At the other end, in the single-bound dichotomous choice *CVM*, pioneered by Bishop and Heberlein, only one dichotomous choice question is asked, and the dollar amount is treated as a threshold. If the good is valued more highly than the threshold dollar amount, the person answers "yes," otherwise "no." While this approach is easier on the respondent, it is statistically less efficient and requires a larger sample to attain a given level of precision.[1]

Our aim here is to show how the statistical efficiency of dichotomous choice *CVM* can be improved by asking the respondent to engage in two rounds of bidding: participants respond to a first dollar amount and then face a second question involving another dollar amount, higher or lower depending on the response to the first question. This "double-bounded" *CVM* approach was first proposed by Hanemann (1985) and Carson and first implemented by Carson, Hanemann, and Mitchell.[2] We describe the maximum likelihood (*ML*) estimation of this model, compare it with the *ML* estimation of the

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[1] This is noted, for example, by Cameron and by Mitchell and Carson.

[2] Carson, Hanemann, and Mitchell used iteratively re-weighted least squares rather than the *ML* estimation employed here. *ML* estimation was applied to double-bounded data by Carson and Mitchell. Cameron and James applied the double-bounded model to *CV* data obtained using a payment card; a similar model was estimated by Bergland and Kriesel.

conventional, single-bounded model, and derive the asymptotic gain in efficiency. This theoretical analysis is followed by a *CVM* survey of Californians regarding their *WTP* for protection of wetlands and wildlife habitat in the San Joaquin Valley. Both the single- and double-bounded models are fitted to this data. Computations of confidence intervals for a *WTP* measure permit a direct, empirical assessment of the gain in efficiency associated with the double-bounded model.

Theory

Single-Bounded Model

The conventional, single-bound *CVM* survey involves asking an individual if she would pay some given amount, B, to secure a given improvement in environmental quality. The probability of obtaining a "no" or a "yes" response can be represented, respectively, by

$$(1) \qquad \pi^n(B) = G(B;\theta),$$

$$(2) \qquad \pi^y(B) = 1 - G(B;\theta),$$

where $G(\bullet;\ \theta)$ is some statistical distribution function with parameter vector θ. As pointed out in Hanemann (1984), this statistical model can be interpreted as a utility-maximization response within a random utility context, where $G(\bullet;\ \theta)$ is the cumulative density function (cdf) of the individual's true maximum *WTP* because utility maximization implies

$$\Pr\{\text{No to } B\} \Leftrightarrow \Pr\{B > \text{maximum } WTP\},$$

$$\Pr\{\text{Yes to } B\} \Leftrightarrow \Pr\{B \leq \text{maximum } WTP\}.$$

In Bishop and Heberlein's pioneering study, $G(\bullet;\ \theta)$ is the log-logistic cdf:

$$(3) \qquad G(B) = [1 + e^{a-b(\ln B)}]^{-1},$$

where $\theta \equiv (a, b)$. Another alternative is the logistic cdf:[3]

$$(4) \qquad G(B) = [1 + e^{a-b(B)}]^{-1}.$$

While other estimation techniques have equivalent asymptotic properties, it is convenient to focus on the *ML* estimator. Consider N participants in the single-bounded experiment, and let B_i^S be the bid offered to the ith participant. Then, the log-likelihood function for this set of responses is

$$(5) \qquad \ln L^S(\theta) = \sum_{i=1}^{N} \{d_i^y \ln \pi^y(B_i^S) + d_i^n \ln \pi^n(B_i^S)\}$$
$$= \sum_{i=1}^{n} \{d_i^y \ln [1 - G(B_i^S;\theta)] + d_i^n \ln G(B_i^S;\theta)\},$$

where d_i^y is 1 if the ith response is "yes" and 0 otherwise, while d_i^n is 1 if the ith response is "no" and 0 otherwise. The *ML* estimator, denoted $\hat{\theta}^S$, is the solution to the equation $\partial \ln L^S(\hat{\theta}^S)/\partial\theta = 0$. This estimator is consistent (though it may be biased in small samples) and asymptotically efficient.[4] Thus, the asymptotic variance-covariance matrix of $\hat{\theta}^S$ is given by the Cramer-Rao lower bound

$$(6) \qquad V^S(\hat{\theta}^S) = \left[-E\frac{\partial^2 \ln L^S(\hat{\theta}^S)}{\partial\theta\,\partial\theta'}\right]^{-1} \equiv I^S(\hat{\theta}^S)^{-1},$$

where $I^S(\hat{\theta}^S)$ is the information matrix.

Double-Bounded Model

Now consider an alternative format in which each participant is presented with two bids. The level of the second bid is contingent upon the response to the first bid. If the individual responds "yes" to the first bid, the second bid (to be denoted B_i^u) is some amount greater than the first bid ($B_i < B_i^u$); if the individual responds "no" to the first bid, the second bid (B_i^d) is some amount smaller than the first bid ($B_i^d < B_i$).[5]

Thus, there are four possible outcomes: (*a*) both answers are "yes"; (*b*) both answers are "no"; (*c*) a "yes" followed by a "no"; and (*d*) a "no" followed by a "yes." The likelihoods of

[3] Both distributions correspond to forms of the logit model. If the lognormal or normal cdf were used in place of (3) or (4), this would correspond to forms of the probit model. Other distribution functions could readily be employed, although logit and probit models are the most common to date.

[4] See Amemiya. For logit and probit models, McFadden and Haberman established the global concavity of the log-likelihood function in equation (5).

[5] This is easy to implement in a telephone or in-person interview; an example of how it might be implemented in a mail survey is given by Wegge, Hanemann, and Strand.

these outcomes are π^{yy}, π^{nn}, π^{yn}, and π^{ny}, respectively. Under the assumption of a utility-maximizing respondent, the formulas for these likelihoods are as follows. In the first case, we have $B_i^u > B_i$ and

$$(7)\quad \pi^{yy}(B_i, B_i^u) = \Pr\{B_i \le \max WTP \text{ and } B_i^u \le \max WTP\}$$
$$= \Pr\{B_i \le \max WTP | B_i^u \le \max WTP\} \Pr\{B_i^u \le \max WTP\}$$
$$= \Pr\{B_i^u \le \max WTP\} = 1 - G(B_i^u; \theta),$$

since, with $B_i^u > B_i$, $\Pr\{B_i \le \max WTP | B_i^u \le \max WTP\} \equiv 1$. Similarly, with $B_i^d < B_i$, $\Pr\{B_i^d \le \max WTP | B_i \le \max WTP\} \equiv 1$. Hence,

$$(8)\quad \pi^{nn}(B_i, B_i^d) = \Pr\{B_i > \max WTP \text{ and } B_i^d > \max WTP\} = G(B_i^d, \theta).$$

When a "yes" is followed by a "no," we have $B_i^u > B_i$ and

$$(9)\quad \pi^{yn}(B_i, B_i^u) = \Pr\{B_i \le \max WTP \le B_i^u\} = G(B_i^u; \theta) - G(B_i; \theta);$$

and when a "no" is followed by a "yes," we have $B_i^d < B_i$ and

$$(10)\quad \pi^{ny}(B_i, B_i^d) = \Pr\{B_i \ge \max WTP \ge B_i^d\} = G(B_i; \theta) - G(B_i^d; \theta).$$

In (9) and (10), the second bid allows the researcher to place both an upper and a lower bound on the respondent's unobserved true *WTP*, while in (7) and (8) the second bid sharpens the single bound—it raises the lower bound or lowers the upper bound.[6] Given a sample of *N* respondents, where B_i, B_i^u, and B_i^d are the bids used for the *i*th respondent, the log-likelihood function takes the form

$$(11)\quad \ln L^D(\theta) = \sum_{i=1}^{N} \{d_i^{yy} \ln \pi^{yy}(B_i, B_i^u) + d_i^{nn} \ln \pi^{nn}(B_i, B_i^d) + d_i^{yn} \ln \pi^{yn}(B_i, B_i^u) + d_i^{ny} \ln \pi^{ny}(B_i, B_i^d)\},$$

where d_i^{yy}, d_i^{nn}, d_i^{yn}, and d_i^{ny} are binary-valued indicator variables and the formulas for the corresponding response probabilities are given by (7)–(10). The *ML* estimator for the double-bounded model, $\hat{\theta}^D$, is the solution to the equation $\partial \ln L^D(\hat{\theta}^D)/\partial\theta = 0$. The asymptotic variance-covariance matrix for $\hat{\theta}^D$ is given by the analog of (6):

$$(12)\quad V^D(\hat{\theta}^D) = \left[-E\frac{\partial^2 \ln L^D(\hat{\theta}^D)}{\partial\theta\,\partial\theta'}\right]^{-1} \equiv I^D(\hat{\theta}^D)^{-1}.$$

The Estimators Compared

The efficiency of the single- and double-bounded *ML* estimators can be compared by examining their respective information matrices. Differentiating the log-likelihood functions and then taking expectations yields

$$I^S(\theta) = \sum_i I(B_i^S; \theta), \text{ and}$$
$$I^D(\theta) = \sum_i I(B_i, B_i^u, B_i^d; \theta),$$

where, for the *i*th observation,

$$(13)\quad I^S(B_i^S; \theta) = \frac{G_\theta(B_i^S; \theta)G_\theta(B_i^S; \theta)'}{G(B_i^S; \theta)\cdot[1 - G(B_i^S; \theta)]},$$

while

$$(14)\quad I^D(B_i, B_i^u, B_i^d; \theta) = \frac{G_\theta(B_i^u; \theta)G_\theta(B_i^u; \theta)'}{\pi^{yy}} + \frac{G_\theta(B_i^d; \theta)G_\theta(B_i^d; \theta)'}{\pi^{nn}} + \frac{QQ'}{\pi^{yn}} + \frac{RR'}{\pi^{ny}},$$

where π^{yy}, π^{nn}, π^{yn}, and π^{ny} are the probabilities on the right-hand side of (7)–(10) and the vectors Q and R are defined by $Q \equiv [G_\theta(B_i^u; \theta) - G_\theta(B_i; \theta)]$ and $R \equiv [G_\theta(B_i; \theta) - G_\theta(B_i^d; \theta)]$.

Our comparison of $\hat{\theta}^S$ and $\hat{\theta}^D$ will focus on three cases, corresponding to different ranges of bid values: in one case, the two estimators are equally efficient; in another, the double-bounded estimator is unambiguously more efficient; and,

[6] In the application to be reported below, double bounds were obtained for between a third and a half of the respondents, depending on the program being evaluated.

in the third case, the ranking of efficiencies is indeterminate.

First is the degenerate case where, for all i, $B_i = B_i^S$, $B_i^u = \infty$, and $B_i^d = 0$. In that case the double-bounded model collapses to the single-bounded model and one has $L^S(\theta) = L^D(\theta)$, $\hat{\theta}^S = \hat{\theta}^D$, and $V^S(\theta) = V^D(\theta)$.[7] Thus, if the second, follow-up, bid in a double-bounded experiment is made sufficiently large when the response to the first bid is a "yes," and sufficiently small when the response to the first bid is a "no," this ensures that it yields no additional information beyond that already contained in the response to the first bid. Hence, one can always mimic the outcome of a single-bounded experiment by choosing sufficiently extreme follow-up bids in a double-bounded experiment. As a corollary, this implies that, when the bids in single- and double-bounded experiments are optimally designed, the most efficient design for the double-bounded model will yield more efficient estimates of θ than the most efficient design for the single model.[8]

Second is the nondegenerate case where, for all i, $B_i = B_i^S$, $B_i < B_i^u < \infty$, and $0 < B_i^d < B_i$. That is, the bids from the single-bounded experiment are the same as the starting bids in a double-bounded experiment which then has nonextreme follow-up bids. In that case, subtraction of (13) from (14) and some manipulation yields the following formula for $\Delta_i \equiv I^D(B_i, B_i^u, B_i^d; \theta) - I^S(B_i^S; \theta)$:

$$\Delta_i = AA'/\gamma + WW'/\delta, \tag{15}$$

where $\gamma \equiv [1 - G(B_i^u; \theta)] \cdot [1 - G(B_i; \theta)] \cdot [G(B_i^u; \theta) - G(B_i; \theta)]$ and $\delta \equiv [G(B_i; \theta) - G(B_i^d; \theta)] \cdot G(B_i; \theta) \cdot G(B_i^d; \theta)$ are positive scalars, and A and W are vectors given by $A \equiv [G_\theta(B_i; \theta) \cdot (1 - G(B_i^u; \theta)) - G_\theta(B_i^u; \theta) \cdot (1 - G(B_i; \theta))]$ and $B \equiv [G_\theta(B_i^d; \theta) \cdot G(B_i; \theta) - G_\theta(B_i; \theta) \cdot G(B_i^d; \theta)]$. Because both AA' and WW' are positive semidefinite matrices, it follows that $I^D(\theta) \geq I^S(\theta)$ and $V^D(\theta) \leq V^S(\theta)$: $\hat{\theta}^D$ is asymptotically more efficient than $\hat{\theta}^S$.

Both of the preceding results rely on the assumption that the initial bid in the double-bounded experiment is the same as the bid in the single-bounded experiment. If this is not the case and $B_i \neq B_i^S$, then the difference Δ_i does not necessarily reduce to a positive semidefinite matrix and the relative efficiency of $\hat{\theta}^D$ versus $\hat{\theta}^S$ is unclear. It could happen, for example, that a single-bounded experiment with a nearly optimal design of bid B_i^S dominates a double-bounded experiment with a different, and poor, design of bid B_i.[9]

Application

The double-bounded approach was employed in a *CVM* study conducted for the Interagency San Joaquin Valley Drainage Program that focused on *WTP* for protecting wildlife and wetlands habitat in California's San Joaquin Valley (Jones and Stokes Associates). The survey involved a combination of mail and telephone media. Initial telephone calls were made to a random sample of households based on random digit dialing. The households were asked to participate in a survey and specify a time at which they could be called back in order to record their responses to the questionnaire. The questionnaire was mailed out and then the household was contacted at the appointed time, with additional phone calls made as needed.[10]

This format provides quality control with respect to the respondents' comprehension of the questionnaire and flexibility with regard to instrument design. Not every question in the script for the telephone interview needs to be included in the version of the questionnaire that is mailed out. This is a convenient way to handle complex branching. It also facilitates the implementation of the double-bounded *CV* model: The mail-out questionnaire contains only the first bid; while the second bid, which is contingent on the response to the first, is incorporated into the telephone script, as illustrated below.

The *CV* study focused on five environmental programs.[11] The first two related to wetlands habitat in the San Joaquin Valley. One program would maintain wetlands habitat at current con-

[7] This follows since $\lim_{B\to\infty} G(B; \theta) = 1$, $\lim_{B\to 0} G(B; \theta) = 0$, and $\lim_{B\to\infty} G_\theta(B; \theta) = \lim_{B\to 0} G_\theta(B; \theta) = 0$. Substituting these into (5), (11), (13), and (14) yields the result. Note the assumption here that the lower end of the support of $G(B; \theta)$ is zero—i.e., *WTP* is nonnegative. If a negative *WTP* is possible, then the degenerate case involves setting $B_i^d = -\infty$ rather than $B_i^d = 0$.

[8] This is because the most efficient design for the single-bounded experiment can always be mimicked, and then improved upon, with an appropriate choice of bids in a double-bounded experiment. For an analysis of optimal bid design in single-bounded models, see Minkin, Chaloner and Larntz, and Alberini and Carson; for optimal bid design in double-bounded models, see Kanninen.

[9] Our earlier result establishes that this cannot happen when both bids are optimally designed.

[10] A more detailed description of the survey is provided in Jones and Stokes Associates, together with a copy of the questionnaire and the scripts for the telephone interviews.

[11] As explained in the introduction to the mail-out questionnaire, the context for these programs is the long-term decline in the San Joaquin Valley's wetlands because of farmland conversion and water resources development since the 1850s.

ditions; without this action, wetlands acreages in the Valley will decrease. The other program would go beyond maintenance to improve wetland habitat above current levels. There was a similar pair of programs relating to the exposure of wildlife to contaminated agricultural drainage water stored in evaporation ponds at various locations in the valley: One program would prevent any increase in exposure of wildlife to contamination, thereby maintaining current conditions, and the other program would improve conditions by reducing wildlife exposure to contaminated waters. The last program dealt with restoring flows in the upper San Joaquin River, below Friant Dam, which affect salmon and other fish in the river and wildlife and vegetation along the river banks. This program would increase flows and fish populations along the stretch of the river.

The mail-out questionnaire informed subjects that they would be asked to consider these five programs, then described each in some detail and asked the discrete choice *WTP* question. This question was intended to reflect the household's total annual *WTP* for the program, including recreation use, option, and existence values (Randall and Stoll; Loomis, Peterson, and Sorg). The format was a voter referendum, and the payment vehicle was additional taxes. In the case of wetland maintenance, for example, the text in the mail-out questionnaire read: "If the wetlands habitat and wildlife *maintenance* program were the only program you had an opportunity to vote on, and this maintenance program cost every household in California $___ each year in additional taxes, would you vote for it?" In the telephone interview, the interviewer then followed up with: "What if the cost were $___?" The same wording sequence was used with the other programs.

The bids used for the wetlands maintenance program are displayed in table 1. The first column shows the initial bid (B) that was printed in the mail-out questionnaire, B^d is the second bid used by the telephone interviewer if the response to the first bid was "no"; B^u is the second bid if the response was "yes." There were five separate sets of bids, distributed randomly across the participants in the survey.[12] These bids were selected on the basis of results obtained in a very small pretest, from which an informal estimate of the *WTP* distribution, $G(B;\ \theta)$, was derived. The bids correspond to upper and lower quantiles of this distribution, arrayed around the median.

The survey was conducted in May 1989, by a professional survey organization. Three geographical areas were targeted: the San Joaquin Valley; the rest of California; and Oregon, Washington, and Nevada, which are neighboring states along the Pacific Flyway. The survey organization established contact with 1,960 households containing an eligible respondent. Of these, 1,239 agreed to participate (63.1%).[13] After the questionnaire had been mailed, the survey company was able to contact 1,058 of these households within the time available; of these, 1,004 completed interviews (94.9%), while 54 refused to participate. The distribution of the completed interviews, by area, was San Joaquin Valley, 227; rest of California, 576; and out-of-state, 201.

Table 1. Alternative Bids for the Wetlands Maintenance Program

B	B^d	B^u
40	25	80
50	25	110
65	30	125
80	40	125
110	55	170

Note: B is initial bid (annual increment in household taxes, in dollars); B^d is second bid if response to first bid was "no." B^u is second bid if response to first bid was "yes."

Results

For the purpose of examining the statistical efficiency of double- versus single-bounded dichotomous choice *CV* questions, the data collected in the survey were used to estimate two models. A conventional, single-bounded model was estimated from the responses to the first bid; then, a double-bounded model was estimated from the responses to both the first and second bids. Both models were estimated by maximum

[12] For wetlands improvement there were 18 sets of bids, each higher to some degree than the corresponding wetlands maintenance bids, with a maximum B^u of $375. There were similar acts of bids for the two wildlife contamination programs (the highest bid was $500) and the salmon improvement program (the highest bid was $225). These bids are exhibited in Jones and Stokes Associates.

[13] Of the 721 refusals, 202 hung up immediately after the interviewer started the introduction without further interaction, 90 said they were too busy to talk now, 51 were unwilling to give out their address, and 28 said that they do not participate in surveys. Of the rest, 154 were not probed for their reason, 146 said that they were not interested, 14 expressed negative views about the environment or the government's management of natural resources, and 36 gave various miscellaneous reasons other than those listed above.

likelihood, using the likelihood function in (5) for the single-bounded model and that in (11) for the double-bounded model.[14]

In both cases, a variety of models were estimated, using the logistic cdf, (4), as well as the log-logistic cdf, (3), both with and without attitudinal and sociodemographic variables added to the intercept term in the exponents of (3) and (4). These models were estimated separately for each subsample. The full set of results is reported in Jones and Stokes Associates. To save space, we report here the results for the sample of households from the rest of California, using the logistic model without covariates; the other results are very similar and lead to the same conclusions.[15] The estimates of the intercept and the slope coefficient in (4) are presented in table 2 for both the single- and double-bounded models.

In the notation employed above, this application constitutes a case where $B_i = B_i^S$; hence, the coefficient estimates from the double-bounded model are asymptotically more efficient than those from the single-bounded model. What do our empirical results show about the relative efficiencies in a finite sample? This will be considered here from three perspectives: The precision of the estimates of the coefficients a and b; the goodness of fit of the estimated *WTP* model; and the precision of the estimates of welfare measures derived from the underlying coefficient estimates.

Table 3 presents the estimated variance-covariance matrices for the single- and double-bounded *ML* estimates of a and b corresponding to the wetland maintenance program; the results for all the other programs are very similar. The estimated variance of b is smaller by a factor of about 10 in the double-bounded model compared to the single-bounded model, the variance of a is smaller by a factor of 3, and the covariance term is smaller by a factor of 6. This translates into much higher t-statistics for the double-bounded model, as table 2 shows. Also, both measures of goodness of fit—the chi-squared statistic and McFadden's pseudo R^2—are substantially higher for the double-bounded model. For example, for the contamination maintenance program the pseudo-R^2 statistic is 0.12 for the double-bounded model versus 0.03 for the single-bounded model.

The ultimate aim in fitting a statistical model

[14] The program GQOPT was used to maximize the likelihood function for the double-bounded model; both GQOPT and the logit module of SHAZAM were used for the single-bound model, and they gave identical results. In addition to GQOPT, packages such as GAUSS, LIMDEP, SAS, and SYSTAT provide maximization routines. A special subroutine called SURVIVAL is available for SYSTAT users to estimate the double-bounded model based on the lognormal, log-logistic and Weibull distributions.

[15] Indeed, a likelihood ratio test showed that the data from households in the rest of California could be pooled with the data from households in the San Joaquin Valley.

Table 2. Coefficient Estimates for Single- and Double-Bounded Models

	Single-Bounded Model		Double-Bounded Model	
	Intercept ($\hat{a}$)	Slope ($-\hat{b}$)	Intercept ($\hat{a}$)	Slope ($-\hat{b}$)
Wetland maintenance				
Coefficient estimate	2.68	−0.0107	3.77	−0.0249
t-statistic	(6.51)	(−1.91)	(16.74)	(−13.94)
χ^2/pseudo R^2	3.56	0.01	161.48	0.16
Wetland improvement				
Coefficient estimate	1.94	−0.0077	3.042	−0.0123
t-statistic	(6.76)	(−3.97)	(17.73)	(−14.75)
χ^2/pseudo R^2	16.10	0.03	281.18	0.23
Contamination maintenance				
Coefficient estimate	3.35	−0.0158	3.61	−0.0194
t-statistic	(7.62)	(−3.35)	(17.49)	(−14.57)
χ^2/pseudo R^2	11.14	0.03	115.48	0.12
Contamination improvement				
Coefficient estimate	1.74	−0.00634	2.87	−0.0095
t-statistic	(6.40)	(−3.96)	(17.74)	(−14.86)
χ^2/pseudo R^2	16.07	0.03	347.74	0.28
Salmon improvement				
Coefficient estimate	2.18	−0.0068	3.45	−0.0192
t-statistic	(6.10)	(−1.68)	(16.85)	(−14.04)
χ^2/pseudo R^2	2.77	0.01	289.78	0.25

Table 3. Estimated Variance-Covariance Matrix, Wetland Maintenance Program

$$\begin{bmatrix} 1.69 \times 10^{-1} & -2.16 \times 10^{-3} \\ -2.16 \times 10^{-3} & 3.10 \times 10^{-5} \end{bmatrix} \begin{bmatrix} 0.51 \times 10^{-1} & -3.61 \times 10^{-4} \\ -3.61 \times 10^{-4} & 3.19 \times 10^{-6} \end{bmatrix}$$

(*a*) Single-bounded model (*b*) Double-bounded model

to the *CV* responses is to derive a summary measure of the *WTP* distribution $G(B; \theta)$. The summary statistic is a function of the parameters in θ. For the logistic model (4), for example, the mean and median *WTP* are given by $WTP^* = a/b$, while the truncated mean is given by Hanemann (1989) as $WTP^+ = \ln(1 + e^a)/b$. For the coefficient values in table 2, there is virtually no difference between these two alternative welfare measures across all programs. For the wetland maintenance program, for example, the single-bounded coefficients yield estimates of $WTP^* = \$250$ and $WTP^+ = \$257$; the double-bounded coefficients yield lower, but equally close, values of $WTP^* = \$151$ and $WTP^+ = \$152$. For simplicity, we focus here on the estimates of WTP^+, which are reported for both models in table 4.[16]

Since these are derived from the *ML* estimates of a and b, they are random variables; their distribution depends on that of the *ML* estimators, which are asymptotically normal with variance-covariance matrices such as those shown in table 3. In order to obtain confidence intervals for the point estimates of WTP^+, we used Krinsky and Robb's Monte Carlo simulation technique as adapted by Park, Loomis, and Creel. This involved simulating the bivariate normal distribution of a and b, using the *ML* estimates of the coefficients and the variance-covariance matrix, and calculating WTP^+ for each replicate of a and b, thereby generating an empirical distribution function for WTP^+.[17] The 90% confidence interval was obtained by omitting 5% of the observations from both tails. These confidence intervals are shown in table 4. The difference between the single- and double-bounded models is striking. For the wetland improvement program, for example, the confidence interval for WTP^+ is \$231–\$360 for the single-bounded model versus \$235–\$268 for the double-bounded model, approximately a fourfold difference. There is a similar or larger gain in precision for the other programs.

In addition to the tighter confidence interval, the double-bounded model tends to yield a lower point estimate for WTP^+. These two phenomena are related. Observe that the bids in table 1 are low relative to the estimates of WTP^+ in table 4. The initial bids, B, for wetland maintenance were arrayed around \$65, which was our guess at the median *WTP* based on very limited pretest results, while the final estimates of WTP^* and WTP^+ were closer to \$150. This phenomenon

[16] These should not necessarily be regarded as our final assessment of California households' willingness to pay to protect wildlife and wetlands habitat in the San Joaquin Valley because we are conducting additional research with the double-bounded data aimed at exploring other probability distributions for $G(B; \theta)$ and alternative, nonparametric estimators of WTP^+ and WTP^*. The results of that research will be reported separately.

[17] In each simulation, 4,000 replications were employed.

Table 4. Estimates of WTP^+ (\$/yr) for California Households

	Single-Bounded Model		Double-Bounded Model	
Program	Point Estimate	90% Confidence Internal	Point Estimate	90% Confidence Interval
Wetland maintenance	257	167–983	152	123–188
Wetland improvement	269	231–360	251	235–268
Contamination maintenance	214	171–345	187	177–199
Contamination improvement	300	248–431	308	289–331
Salmon improvement	336	206–1,681	181	171–193

occurred with all the programs. An optimal design would have put B closer to WTP^*. Because of this, the great majority of subjects responded "yes" to the initial bids. Given this preponderance of "yes" responses, we could readily infer that WTP^* and WTP^+ were some amount larger than B, but we were hard pressed to determine how much larger.[18] It was only when subjects responded "no" to some of the follow-up bids B^u that we were able to pin down the value of WTP^* or WTP^+. This explains why our single-bounded estimates, which rely only on the response to B, not only had a larger confidence interval but also generated a higher point estimate for WTP^* and WTP^+.[19] It illustrates an advantage of the double-bounded approach, that it can provide an insurance policy against a poor choice of initial bid: B^u recoups against too low a choice of B, and B^d against too high a choice.

One reason why CV researchers moved away from the iterative bidding format was concern over starting point bias (Boyle, Bishop, and Welsh). Could the same problem arise with double-bounded CV models? To the extent that respondents' weariness with multiple bid iterations is a cause of the starting point bias, this is unlikely to be a factor in double-bounded models with a single follow-up bid. Other possible causes are anchoring and yea-saying. Because the second bid in the double-bounded model is, by design, very different from the first bid, anchoring is unlikely to be a factor here. Yea-saying cannot be ruled out a priori. One test is to examine the proportion of "yes" responses to B^u. In doing this, it must be remembered that the respondents offered B^u are not a random sample of the population: they are the censored sample for whom $WTP \geq B$. Once this is taken into account, it turns out with our data that respondents are significantly less likely to say "yes" to B^u than would be expected on the basis of their responses to the initial bid B, which controverts the hypothesis of yea-saying in the responses to the second bid.

Conclusions

In the first part of this paper we established that the double-bounded dichotomous choice CV model is asymptotically more efficient than the single-bounded model. In the second part we found that, for our data set, this result certainly carries over to finite samples: the confidence intervals for summary measures such as WTP^+ were greatly reduced by using the double-bounded model. In this case, adding a follow-up bid to a conventional, dichotomous choice CV survey substantially improved the statistical information provided by the data.

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[18] Technically, the function $1 - G(B; \hat{\theta}^S)$ was relatively flat in the vicinity of the B_i's.

[19] The one case where the single-bounded model did not generate a larger point estimate of WTP^+ (the contamination improvement program) involved the highest initial bids of all programs, some of which were much larger than the final estimate of WTP^+. This case received the smallest fraction of "yes" responses to the initial bids.

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[Footnotes]

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