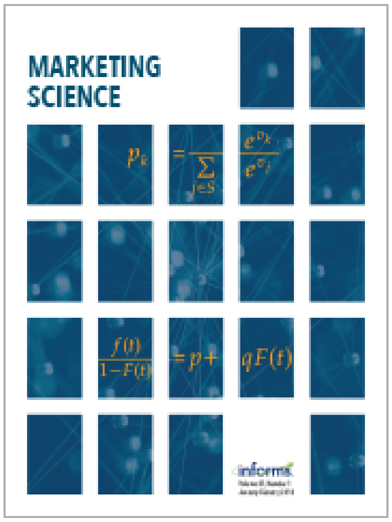

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Estimating Willingness to Pay with Exaggeration Bias-Corrected Contingent Valuation Method

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Estimates of the prices customers are willing to pay for new products or services using responses from survey questionnaires are notoriously biased on the high side. An approach to obtaining more realistic estimates is suggested here, called the exaggeration bias-corrected contingent valuation method (EBC-CVM). The method is an alternative to conventional contingent valuation methods (CVMs) that have been used in economics and, to a lesser extent, in marketing. Two experiments and one field study are presented to demonstrate the effectiveness of the method. In each case, the proposed method outperformed conventional CVMs in comparison with real choices or more realistic price estimates.

Key words: willingness to pay; contingent valuation method; exaggeration bias; new product pricing
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1. Introduction

The willingness to pay (WTP) for a good is defined as the maximum amount a customer is willing to pay for the good. Marketers often want to assess potential customers' WTP for a product, especially when developing a new product that has not yet been introduced in a market. The WTP for a market good can usually be estimated by analyzing market information such as the price and the customer's purchasing behavior. The WTP for a nonmarket good such as a new product cannot be estimated in the same manner because no transaction has been made and no information pertaining to the market is available to be observed. Hence, a different method is needed to estimate the WTP for a nonmarket good.

The contingent valuation method (CVM) has been extensively used by economists for estimating the value of nonmarket goods. See, for example, Cummings et al. (1986), Mitchell and Carson (1989), and Carson and Mitchell (1994).[1] The CVM has also been used as a pretest-market evaluation method in the marketing arena (Cameron and James 1987, Wertenbroch and Skiera 2002).

The CVM uses a sample survey asking respondents to value a nonmarket good of interest in a hypothetical situation where no actual transaction is required. It is widely known that a sample survey contains both sampling errors and nonsampling errors (Churchill and Iacobucci 2005). Unlike sampling errors, which affect the precision of estimates, nonsampling errors adversely affect the validity of inference. Consequently, a CVM relying on a sample survey without controlling for nonsampling errors would provide misleading inferences.

Because most nonsampling errors associated with the CVM are attributed to poorly designed survey instruments or vague, inconsistent, or misleading administration procedures, etc., they can be avoided through better design and administrative control of surveys. Numerous methods have been developed that enhance the credibility of surveys and make them more likely to produce reliable results. Many aspects of CVM surveys have been improved, including sampling design, instrument development, formulation of the various scenarios, questionnaire structure, etc. A good survey paper on this is Hanemann (1994).

However, there will always remain some nonsampling errors that cannot be removed by design or administrative control. For example, if the nonsampling errors are caused by respondents disguising the truth, they cannot be removed no matter how well the survey is developed and conducted. One of those kinds of nonsampling errors is the tendency to exaggerate, which is often commonly detected in surveys on valuation of new products. When asked about

[1] According to Carson and Mitchell (1994), until 1994 there had been about 1,600 CVM studies and papers from over 40 countries on many topics including transportation, sanitation, health, the arts, and education as well as the environment.

future demand for a new product or service, respondents often exaggerate how much they would pay if it were available and thus present positive response bias (Klein and Sherman 1997). Exaggeration may also stem from new product enthusiasm, an attempt to influence the decision to market the product, a desire to please the interviewer, or the tendency in a survey for people to be less sensitive to total costs than they would be if they were making actual purchases. Whatever the reason, the exaggeration tendency is a commonly recognized problem in this type of survey. There are many experimental studies detecting the exaggeration tendency. For example, Cummings et al. (1995) showed the proportion of hypothetical yes responses (intention to purchase) exceeded that of real yes responses in a dichotomous choice contingent valuation (CV) context using three different consumer goods.[2] Johannesson et al. (1998) carried out similar experiments and got statistically significant results for the exaggeration tendency. Recently, Voelckner (2006) compared elicited WTPs across several methods[3] for measuring consumers' WTP and found substantial and significant differences between real and hypothetical WTP regardless of method. Therefore, using CVM without controlling for the tendency to exaggerate overestimates the customer's WTP and is called exaggeration bias in this paper.[4]

Existing approaches to correcting exaggeration bias can be divided into two groups. The first focuses on calibrating the responses. Blackburn et al. (1994), Champ et al. (1997), and Johannesson et al. (1999) among others have tried to calibrate the exaggerated responses into quasi-real ones based on self-assessed certainty, which is evaluated by respondents in a follow-up question. These researchers treated the so called "definitely yes" only as "real yes" while treating "just yes," "just no," and "definitely no" as "real no." However, there is little theory about how the hypothetical answers are sorted out into real "yes" and "no." It is difficult to believe that only those who say "definitely yes" in a hypothetical situation would answer "yes" in a real situation. Furthermore, it is doubtful that respondents assess the certainty of their answers truthfully in a follow-up question while answering the WTP question strategically. These approaches commonly depend on follow-up subjective assessments—the subjective certainty for the answers or subjective probability of commitment. The latter assessments would be as wrong as the WTP reports in a hypothetical survey because the assessments are asked in the same manner as the WTP question. The additional assessments can thus be another source of bias.

The second approach to reducing exaggeration bias is to transform the hypothetical WTP into the real WTP by assuming a functional relationship between them. Although the Box-Cox model (Box and Cox 1964) is a well-known example of this,[5] their transformation is at risk of misspecification. Horowitz (1996) presented a kernel-based nonparametric method for estimating the transformation function as an alternative to avoid misspecification. Klein and Sherman (1997) also proposed a procedure for estimating bias without making any parametric assumption about the transformation function. Instead, they assumed that there exist three different regimes for answering—underreporting, accurate reporting, and overreporting—and that a priori information is available about the threshold, called a "safety point," by which the regime changes. Although a feature of these approaches is that the possibility of underreporting is allowed as well as overreporting, we are skeptical about an underreporting regime where a respondent would understate his or her true WTP, even in a hypothetical survey.

An important development in modeling exaggeration bias was made by Hsiao and Sun (1998). They proposed a one-sided response bias model designed for the case where there is a positive probability of observing an exaggerated response. They assumed that an individual would make two independent preliminary WTPs before making a final choice, one based on the true preference and the other randomly drawn independent of the true preference. The individual then selects the larger WTP as the basis of the final choice. The probability of taking the seemingly desirable choice $P[I_i = 1]$ for the binary case is

$$P[I_i = 1] = p_i + q_i(1 - p_i), \tag{1}$$

where p_i is the probability of taking the desirable choice based on the true preference and q_i is the probability of taking it independent of the true preference.

This paper proposes and illustrates a new CVM to correct the exaggeration bias, which will be also interpreted as an application of the one-sided response model of Hsiao and Sun (1998). In §2, we propose an exaggeration bias-corrected CVM. In §3 we then show how well the model corrects the exaggeration bias by analyzing two existing experimental data sets. We also apply the model to analyze data from an actual CV survey in §4. Conclusions follow in §5.

[2] They used an electric juicemaker, a calculator, and a box of chocolates.

[3] These included the CVM, conjoint analysis, auction, and lotteries.

[4] The terminology of hypothetical bias is commonly used in environmental economics literature.

[5] A Box-Cox transformation is known up to a single real-valued parameter as $y_i^* = (y_i^\lambda - 1)/\lambda$, $\lambda \neq 0$, where y_i^* and y_i are true WTP and the biased WTP, respectively, and λ is a real-valued parameter.

2. The Model

In this section, we propose an exaggeration bias-corrected CVM, which we call EBC-CVM. In the traditional CVM, an individual is assumed to state his or her real WTP when being asked the WTP in a CV survey. In the EBC-CVM, an individual is assumed to compare the real WTP with an independent randomly drawn spurious WTP and then to take the larger one as his or her hypothetical WTP, which is presumed to be stated in a CV survey. In other words, an individual is assumed not to underreport his or her real WTP, but to correctly report or overreport it in a hypothetical situation. This should be intuitively acceptable because individuals are not likely to underreport their WTP intentionally in a hypothetical survey unless they want to hinder the producer from introducing the new product. Introduction of a new product means widening the choice set of products from which an individual can choose to purchase. An individual's utility cannot be decreased and may be increased as the choice set is widened. Note that the more products available to be purchased, the higher the level of satisfaction an individual may obtain. An individual would seem to have little incentive to underreport the real WTP, especially in a hypothetical survey situation where he or she has nothing to lose.

The answering mechanism of the EBC-CVM is modeled for individual i by

$$y_i^H = \max\{y_i^R, y_i^S\}, \quad y_i^S \sim G(y_i^S), \; i = 1, 2, \ldots, n, \tag{2}$$

where y_i^H is the hypothetical WTP, y_i^R is the real WTP, and y_i^S is the spurious WTP; and $G(y_i^S)$ is the cumulative distribution function of y_i^S.

A salient feature of the EBC-CVM is that the real WTP is only assumed to be related randomly with the hypothetical WTP. This is contrary to existing transformation approaches, where a functional relation between them is assumed. It would seem sensible to assume that the hypothetical WTP is determined randomly rather than systematically because it may depend on the mood, feelings, and context as well as personal psychological characteristics of the survey respondent.[6]

Noting that y_i^R is a random variable to a researcher even though it is not to the ith individual, the probability density of the hypothetical WTP is

$$h(y_i^H) = f(y_i^H)G(y_i^H) + F(y_i^H)g(y_i^H), \tag{3}$$

where h is the *pdf* of y_i^H; f and F are the *pdf* and *cdf* of y_i^R assumed by a researcher; and g and G are the *pdf* and *cdf* chosen for drawing y_i^S by an ith individual.

The *pdf* of y_i^H of Equation (3) can be used for the likelihood function of the open-ended CVM (often called the continuous CVM) in which the respondent is supposed to state his or her WTP directly (i.e., as opposed to responding yes or no to a researcher-provided value).

A more popular format of CVM is the closed-ended format (often called the referendum format). The closed-ended CVM is like a bidding game where the ith respondent is asked to make a referendum decision of taking or rejecting a bidding offer, for example, "Are you willing to pay \$$t_i$ for a nonmarket good?" Note that the bidding price is usually given differently to each respondent. In a closed-ended CV survey, an individual is assumed to answer yes if his or her hypothetical WTP exceeds the bidding price and no otherwise. The answering mechanism of the closed-ended EBC-CVM is

$$\begin{cases} I_i = 1 & \text{if } y_i^H \geq t_i, \\ I_i = 0 & \text{otherwise}, \end{cases} \qquad i = 1, 2, \ldots, n, \tag{4}$$

where indicators $I_i = 1$ and $I_i = 0$ denote yes and no, respectively, and t_i is the bidding price given differently to each individual. Then, the probability of $I_i = 1$ in EBC-CVM appears as in Equation (5)

$$\begin{aligned} P[I_i = 1] &= P[y_i^H \geq t_i] = P[\max\{y_i^R, y_i^S\} \geq t_i] \\ &= 1 - F(t_i)G(t_i) \\ &= (1 - F(t_i)) + F(t_i)(1 - G(t_i)). \end{aligned} \tag{5}$$

Note that the probability structure of the closed-ended EBC-CVM is the same as that of the one-sided response bias model because $(1 - F(t_i))$ is equivalent to p and $(1 - G(t_i))$ to q in Equation (1). The first term of $P[I_i = 1]$, $(1 - F(t_i))$, is the probability that an individual would answer yes in a real market where the true preference should be taken into consideration; the second term, $F(t_i)(1 - G(t_i))$ is the probability that he or she would answer yes in a survey but no in a real market. In this paper, we call the latter the exaggeration bias probability. The probability of answering yes is larger in EBC-CVM than in traditional CVM by the exaggeration bias probability. The traditional CVM should overestimate the WTP if individuals have a tendency to exaggerate their WTP in a survey.

Assuming that the real WTP is linearly decomposed into a nonstochastic component and a stochastic normal error term such as

$$y_i^R = x_i'\beta_0 + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2), \tag{6}$$

where x_i is a vector of covariates, β is a vector of parameters, and ε_i is an error term. We also assume

[6] It may be true that each responding person has a built-in tendency to exaggerate (or not) that may be captured by an unknown transformation of their reported WTP, as in the approaches of Horowitz (1996) and Klein and Sherman (1997). In the absence of knowing the appropriate transformation for each respondent, it is plausible to treat it as random from the viewpoint of the researcher.

that y_i^S follows the same *cdf* as y_i^R. This assumption is not only for convenience but also has a rationale. It is not unreasonable to assume that individuals draw the spurious WTP from the same distribution that the researcher assumes for the real WTP. Then, the log likelihood functions of EBC-CVM turn out to be as Equation (7)

open-ended CVM:

$$\ln L(\beta, \sigma \mid x, y) = \sum_{i=1}^{n} \ln 2\phi\left(\frac{y_i^H - x_i'\beta}{\sigma}\right)\Phi\left(\frac{y_i^H - x_i'\beta}{\sigma}\right)$$

closed-ended CVM:

$$\ln L(\beta, \sigma \mid x, y, t) = \sum_{i=1}^{n}\left[I_i \ln\left\{1 - \Phi\left(\frac{t_i - x_i'\beta}{\sigma}\right)^2\right\} + (1 - I_i)\ln \Phi\left(\frac{t_i - x_i'\beta}{\sigma}\right)^2\right], \tag{7}$$

where ϕ and $\Phi(.)$ denote, respectively, the *pdf* and *cdf* of the standard normal distribution.

3. How Well Does the EBC-CVM Work?

We applied the EBC-CVM to experimental data collected by Johannesson et al. (1998), which will be called "JLJ" after the last names of the authors. They carried out an experiment to see how different hypothetical decisions in a survey are from real decisions for a customer good. They randomly divided undergraduate students of Luud University in Sweden into two groups. The first was asked two hypothetical and two real questions, while the second group was asked only a real question. The hypothetical question asked whether they would pay a certain price for a box of Belgian chocolates if it were available, while the real question asked them to actually buy it or not at the same price. The hypothetical question was followed by a follow-up question in which the subjects who answered yes to the hypothetical question were asked if they were fairly sure or absolutely sure about their yes answer.

Johannesson et al. (1998) summarized the experiment results by presenting the following claims:

(1) The standard hypothetical dichotomous (referendum) CV responses overestimate the WTP.

(2) A conservative interpretation of the hypothetical responses in which only answers of absolutely sure yes are treated as real yes underestimates the WTP.

(3) The exaggeration bias is rarely observed around low bids while it is often observed around high bids.[7]

[7] Johannesson et al. (1998) observed that the difference between hypothetical and real yes responses was not distinct at the two low bid amounts, SEK 20 and SEK 30, but relatively distinct at the highest bid amount, SEK 50. (SEK denotes Swedish Krona, the Swedish monetary unit.)

The EBC-CVM can be used as an alternative approach to dealing with the first two claims and to explaining theoretically the last.

Assuming the probit model for dichotomous responses, we estimated the EBC-CVM only for the standard CV data while estimating the conventional CVM for four kinds of data for comparison. The mean WTP is estimated by $1/n\sum_{i=1}^{n} x_i'\hat{\beta}$, where $\hat{\beta}$ is the vector of the coefficient estimates of the WTP function.

Table 1 shows the estimation results of the WTP. The conventional probit CVM, in which the hypothetical yes answers are treated as the real yes responses, estimates the mean WTP by SEK 36.12, which is much higher than SEK 29.59, the real mean WTP estimated by using the responses collected in the real situation. If the absolutely sure yes is only treated as the real yes, as suggested by Johannesson et al. (1999) and Champ et al. (1997) among others, the probit CVM would estimate the WTP much lower than the real one as shown in Table 1. The mean WTP was estimated by SEK 24.80 for the case of absolutely sure yes. So the method overcorrected the exaggeration bias.

Strikingly, using the hypothetical responses, the EBC-CVM gives a very similar mean estimate of WTP, SEK 28.51, to the mean estimate obtained by the CVM with the real responses. This shows that the EBC-CVM can be a solution for the first two claims raised by Johannesson et al. (1998) because it can successfully correct the exaggeration bias.

Sometimes we are also interested in prediction accuracy. To compare the models in terms of the prediction accuracy, we predict the binary answers of yes or no by comparing the bidding price with the estimated WTP for the experimental sample collected from the real trading situation, and then compare them with the actual observed answers.

Table 2 shows all combinations of predicted and actual binary answers. The overall accuracy measures, defined as the ratio of the sum of diagonal entries over the total number, are reported at the right bottom corner of the tables. While both the CVM and EBC-CVM using the conventional CV data predict more accurately than the CVM using the calibrated CV data in which only absolute yes answers are treated as real yes, the CVM performs as well as the EBC-CVM in terms of overall accuracy. However, it is an overall measure, not distinguishing its accuracy in predicting yes from that in predicting no. The prediction precision measures how many individuals who are predicted to say yes (no) actually say yes (no), while the recall precision measures how many individuals who actually say yes (no) would be predicted to say yes (no).

Examining the prediction precision measures, we see that the CVM predicts the yes answer poorly while predicting the no answer very precisely. This

Table 1 Comparison Between CVM and EBC-CVM With JLJ Data

Model	CVM/PROBIT				EBC-CVM
Group	Between	Within			Within
Yes in use**	Real yes	Standard yes	Absolutely sure yes	Real yes	Standard yes
CONSTANT	2.9051 (9.6365)**	3.4566 (9.2340)	3.4391 (9.3503)	3.4583 (11.3405)	3.1864 (8.7342)
SEX***	−0.0002 (−0.0618)	0.0323 (0.2769)	0.0720 (0.5650)	0.1647 (1.5777)	0.0338 (0.2921)
AGE	0.0002 (0.0225)	−0.0015 (−0.7567)	−0.0011 (−0.6119)	−0.0010 (−0.8902)	−0.0015 (−0.7379)
LOAN	0.1878 (1.7314)	−0.0270 (−0.2019)	0.0922 (0.6280)	−0.0853 (−0.7308)	−0.0359 (−0.2685)
INCOME	−0.0298 (−0.2883)	−0.0545 (−0.4587)	−0.1598 (−1.2627)	−0.1723 (−1.6396)	−0.0603 (−0.5054)
CHOC	0.0131 (0.5815)	−0.0175 (−0.4809)	−0.0562 (−1.4449)	−0.0350 (−1.1383)	−0.0165 (−0.4621)
OFTEN	0.0013 (1.9961)	0.0008 (1.3686)	−0.0003 (−0.3735)	0.0006 (1.1237)	0.0008 (1.3734)
ESTPRICE	0.0016 (1.3849)	0.0021 (1.1825)	0.0020 (1.2454)	0.0018 (1.2763)	0.0020 (1.1745)
SIGMA	0.3000 (6.4046)	0.4026 (6.2999)	0.3916 (5.0005)	0.3133 (5.9517)	0.4882 (6.2405)
Log likelihood	−0.3465	−0.4744	−0.4221	−0.3985	−0.4742
Mean WTP	29.59	36.12	24.80	28.27	28.51

*t-values are in parentheses.

**Standard yes means yes answers to the standard CV question; absolutely sure yes means absolutely sure yes answers to the follow-up question in the hypothetical CV survey, real yes within groups means yes answers to the real question within the hypothetical CV survey; and real yes between groups means yes answers to the real question in a real marketlike situation.

***SEX is 0 for female and 1 for male; AGE is in years; LOAN is 1 if the subject has a study loan and 0 otherwise; INCOME is 1 if the subject has no additional income apart from a possible study loan and 0 otherwise; CHOC indicates how much the subject likes the taste of chocolate on a scale between not tasty at all (0) and very tasty (10); OFTEN indicates how many times per year the subject buys chocolate; ESTPRICE is the estimated price by the subject; and SIGMA is the standard deviation of the error terms of the WTP equation.

prediction result reflects the so-called hypothetical bias, which means some respondents would say no in a real transaction even though they say yes in a CV survey. Small wonder that the CVM, without taking any special consideration of the exaggeration bias, brings about such off-balanced prediction errors. By contrast, the EBC-CVM is well-balanced in predicting both yes and no as shown in the relatively similar prediction precisions of both yes and no answers. This is also a natural result because the EBC-CVM assumes a different answering mechanism reflecting the exaggeration tendency. We can also make similar arguments in terms of the recall precision.

Table 2 Precision of Real Answer Prediction

	Actual response			
	Yes	No	Sum	Prediction precision
(A) Traditional CVM with conventional CV data				
Predicted response				
Yes	49	18	67	0.73
No	3	49	52	0.94
Sum	52	67	119	
Recall precision	0.94	0.73		0.82
(B) Traditional CVM with calibrated CV data*				
Predicted response				
Yes	36	10	46	0.78
No	16	57	73	0.78
Sum	52	67	119	
Recall precision	0.69	0.85		0.78
(C) EBC-CVM with conventional CV data				
Predicted response				
Yes	42	12	54	0.78
No	10	55	65	0.85
Sum	52	67	119	
Recall precision	0.81	0.82		0.82

*Only absolutely yes is treated as yes.

The third claim raised in JLJ can also be explained simply by the EBC-CVM. There is not much difference between hypothetical and real yes responses at low or high bid amounts in the EBC-CVM because the exaggeration bias probability $F(t_i)(1-G(t_i))$ should be small for very low or very high bids. The exaggeration bias would virtually disappear for extremely low or high bids. For example, if being asked a WTP of $100 for a Swiss chocolate bar, all of the respondents may answer definitely no even in a hypothetical situation. If a $1 price were given, they would probably answer yes in both hypothetical and real situations. Thus, half of the third claim is demonstrated by the EBC-CVM, but the remaining half is not. The fact that the exaggeration bias is often observed around very high bids is doubtful. Perhaps the bids JLJ regarded as high were only fairly high. The exaggeration bias should disappear around extremely high bids.

Another application is made to see whether the EBC-CVM worked well for the JLJ experimental data only by chance. Blumenschein et al. (2001) used experimental data for a cross-check. We will call their data "BJYF" after the authors' last names in their paper. The BJYF data are designed differently from the JLJ data. While the JLJ data were collected from a laboratory experiment, the BJYF data were collected

Table 3 Comparison Between CVM and EBC-CVM With BJYF Data

Model	CVM/probit			EBC-CVM/probit
Yes in use	Real yes	Standard yes	Definitely sure yes	Standard yes
CONSTANT	1.1064 (0.4594)	2.8745 (3.4211)	2.2602 (2.6775)	2.0012 (2.2284)
EDU**	0.0068 (0.0414)	−0.0462 (−0.7573)	−0.0848 (−1.3990)	−0.0468 (−0.7714)
INCOME	−0.0085 (−0.3423)	0.0102 (1.0687)	0.0124 (1.5080)	0.0100 (1.0715)
SEVD1	−0.1259 (−0.1210)	0.5131 (0.8913)	0.7803 (1.2280)	0.5267 (0.9052)
SEVD2	−0.8987 (−0.7117)	0.6754 (1.0260)	0.6556 (0.9301)	0.6797 (1.0253)
SIGMA	2.2503 (1.4329)	1.3264 (3.1764)	0.9506 (2.7342)	1.5923 (3.1676)
Log likelihood	−0.3777	−0.5831	−0.3226	−0.5832
Mean WTP	26.1877	51.0676	14.5091	31.4118

*t-values are in parentheses.

**EDU is years in school; INCOME is personal annual income in thousands; SEVD1 is 1 if the subject self-perceives his or her asthma as moderate and 0 otherwise; SEVD2 is 1 if the subject self-perceives his or her asthma as severe and 0 otherwise; SIGMA is the standard deviation of the error terms of the WTP equation.

from a field experiment. The weakness of the laboratory experiment is that it was carried out under rather artificial conditions, using mainly college students as subjects. The field experiment was conducted with purchasers in a real market situation. In this sense, the field experiment was more marketlike than the laboratory experiment.

The BJYF experiment examined people's valuation of a pharmacist-provided asthma management program. Subjects were divided into a hypothetical group and a real group. The subjects in the hypothetical group were asked both a referendum format CV question and a follow-up question to check the respondents' certainty about their answer. The subjects in the real group, who were allowed to actually purchase the program, were asked only whether they would purchase or not.

We estimated the mean WTP in each experimental group by the conventional probit CVM. The results are shown in Table 3. In the hypothetical group, the mean WTP was estimated to be $51.07 when using the referendum CV answers directly, and $14.51 when treating the definitely yes as the real yes, which should be compared with the estimated mean WTP in the real group, $26.19. It was found that the conventional CVM overestimated the WTP with the uncalibrated data and underestimated the WTP with the calibrated data. We suspect that calibrating the data would not be enough to reduce the exaggeration bias with the conventional CVM.

We also estimated the mean WTP in the hypothetical group using the EBC-CVM. The estimated mean WTP with the EBC-CVM was $31.41, which was much closer to the real mean WTP than the estimates by the conventional CVM.

4. An Empirical Application

To illustrate how differently both models would estimate the WTP even with the same data, in this section, we will apply both the EBC-CVM and CVM to data from an actual CV study.

The CV survey data available to us was from a study of programs to conserve old-growth forest for an endangered species habitat in the United States. The CV survey was conducted in a double-bounded referendum format by the Northwest Research Group. Each respondent was asked two referendum questions sequentially. First, they were asked whether they were willing to pay a predetermined starting bid price, and then asked the same question with an adjusted bid price. If the first question was answered affirmatively (negatively), the follow-up bid price was doubled (halved). In this way, two sequential referendum data points can be obtained from each respondent. However, only the first referendum response data are used for the empirical comparison of the WTP estimates in this section. We focus on the difference in WTP estimates obtained from two competing CVMs in a simple referendum survey in which each respondent is asked a single referendum format CV question.

The sample consists of 200 responses to a telephone survey in which the respondents were asked their willingness to pay a one-time bid price for a donation to a reputable nonprofit conservation organization to acquire some old-growth forest. There are three different bid prices $5, $10, and $50. Table 4 shows the number and percentage of yes responses for each bid price. The percentage of yes responses decreases at

Table 4 Percentage of Yes Answers

Bidding price	No. of yes/no. of samples	Percentage of yes (%)
$5	45/48	93.75
$10	39/46	84.78
$50	22/35	62.86
Total	106/129	82.17

Table 5 Descriptive Statistics of Variables in the WTP Model

Variable name	Description	Mean (proportion)	Standard deviation
t_i	Bidding prices given to each respondent	18.99	19.11
AGE	Age	47.36	14.16
EDU	Years of schooling	14.97	2.82
INC	Income ($1,000)	63.00	45.24
N18	Number of family members above age 18	0.69	1.04
IMP	Importance of protecting habitat for threatened or endangered species as a national goal (1: extremely important, 2: very important, 3: not very important, 4: not important at all)	3.04	0.81
NPO	= 1 if prefer the nonprofit conservation organization most to have made the purchase and managed the property; = 0 otherwise	0.52	0.50
EFFNPO	10-point scale measure for subjective evaluation of efficiency of nonprofit conservation organization purchasing property ("0" means "very ineffective"; "10" means "very effective").	6.58	2.99
ENV	= 1 if feel too much; = 2 if feel about right; = 3 if feel too little about the money that we spend, as a nation, on protecting the environment.	2.50	0.68

the higher bid prices, consistent with a downward-sloping demand curve.

As explanatory variables in this illustration, we used a limited set of the available variables, which are described in Table 5. This minimalist modeling effort stems from the fact that we are not pretending that this paper has anything conclusive to say about the actual value of the old-growth forest. We are merely demonstrating a comparison between the conventional CVM and EBC-CVM.

Assuming a linear WTP function with normally distributed error terms, Table 6 gives the maximum likelihood estimates of the coefficients from the CVM and EBC-CVM. Also shown, for comparison, are the averages of fitted WTPs computed by using the estimated coefficients of the WTP function. As expected, the WTP is estimated much higher by the traditional CVM than by the EBC-CVM. The average across our sample of the fitted WTP is $112.77 for the traditional CVM, which is about three times higher than $38.51 for the EBC-CVM. Note that the WTP estimated by traditional CVM lies above the range of the bid prices given to the respondents, while the WTP estimated by EBC-CVM, lies within the range. In this sense, we would say the EBC-CVM gives a more reasonable estimate of WTP than the traditional CVM.

Table 6 Estimation Results of Forest Land Valuation

	Traditional CVM/probit	EBC-CVM/probit
CONSTANT	3.2698 (1.6935)	2.1972 (1.1596)
AGE	−0.0042 (−0.2541)	−0.0046 (−0.2808)
EDU	−0.0773 (−0.8072)	−0.0768 (−0.8038)
INC	−0.0027 (−0.4440)	−0.0025 (−0.4157)
N18	0.1322 (0.4773)	0.1249 (0.4595)
IMP	−0.4620 (−1.2450)	−0.4635 (−1.2497)
NPO	1.1706 (2.2311)	1.1810 (2.2759)
EFFNPO	0.0547 (0.5851)	0.0553 (0.5923)
ENV	1.1330 (2.5906)	1.1323 (2.5797)
SIGMA	1.5646 (4.0631)	1.9477 (4.2085)
Log likelihood	−0.2810	−0.2808
Mean WTP	112.77	38.51

5. Conclusion

It is well known that respondents in a CVS exaggerate their WTP and tend to give yes answers to the question about their willingness to pay a bid price. Therefore, the conventional CVM tends to have an exaggeration bias in estimating WTP. Although many efforts have been made to reduce this bias, only a few approaches have succeeded.

In this paper, we propose an alternative model, called exaggeration bias-corrected CVM (EBC-CVM), to reduce the exaggeration bias. The EBC-CVM can be interpreted as a new application of the one-sided response bias model proposed by Hsiao and Sun (1998).

We demonstrated how well the EBC-CVM would estimate the WTP by applying the model to both laboratory and field experimental CV data. From the EBC-CVM, we obtained an estimated mean WTP that was quite close to the estimated real mean WTP obtained from the real transaction data. In contrast, the CVM provided an estimated mean WTP that was far above the estimated real mean WTP. Last, we applied the EBC-CVM to CV data from a real study to demonstrate the applicability of the model in a real world context. As expected, we obtained considerably lower WTP estimates from the EBC-CVM than from conventional CVM.

These results could depend on our distributional assumption, i.e., normality. If we were to replace the normal distribution with another distribution, we could end up with somewhat different numerical estimates for WTP. How sensitive the results are to the distributional assumption is left for future research.

Of greater potential concern about the EBC-CVM is how it can be validated. The EBC-CVM will reduce the exaggeration bias of the CVM because it will clearly estimate the WTP lower than the conventional CVM by the model structure. Still, we cannot exclude the possibility that the EBC-CVM may underestimate the WTP. If respondents correctly report or underreport their WTP, then the EBC-CVM will necessarily produce estimates that are biased on the low side. However, we believe this is very unlikely in a real world situation because respondents have little incentive to do so. Rather, we are concerned about the possibility of overcorrection. To address this concern, many more experiments need to be performed. However, we contend that in most cases managers would prefer conservative WTP estimates, rather higher estimates, which could result in unexpectedly low demand for new products.

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