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ANALYZING DICHOTOMOUS CHOICE CONTINGENT VALUATION DATA WITH ZERO OBSERVATIONS: A MIXTURE MODEL*

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Modeling public behavior to the policy with the data from dichotomous choice contingent valuation (DCCV) surveys is often complicated by zero willingness to pay (WTP) responses in the sample. To deal with the zero responses to obtain appropriate welfare measure such as mean and median WTP, we consider a mixture model of WTP distributions to allow a point mass at zero. We also consider the conventional model and a spike model for comparison. Our application reported here portrays the usefulness of the mixture model to analyze DCCV data with zero observations.

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I. INTRODUCTION

The contingent valuation (CV) method is one of the most popular methods to assess the value of public goods.[1] It uses survey methods to elicit consumers' preferences by finding out how much consumers would be willing to pay for specified changes in the level of provision of a public good. This is a direct or non-market method, so that it essentially consists of formulating a contingent market in a questionnaire presented to the general or specific population.

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[1] For a complete review of the CV method see Mitchell and Carson (1989) and Bjornstad and Kahn (1996). For a critical view of the method see Hausmam (1993).

A stylized fact identified in previous CV studies is that the distribution of the willingness to pay (WTP) tends to be bimodal. Conventional models of WTP assume absolutely continuous distributions, therefore do not capture the bimodality. As a consequence, the estimation of the mean or median WTP is often unbelievably high and severely imprecise (e.g. An and Ayala, 1996).

In a market for private goods, those who decide to buy a certain good are by definition in-the-market. Those who choose not to buy the good have revealed that they are not willing to pay the going market price. Zero consumption of a good may occur because of corner solutions of the utility-maximizing problem (Yoo and Yang, 2000), but zero consumption may also arise when the good does not contribute at all to the individual's utility - a 'nongood' (Deaton and Muellbauser, 1980). In dichotomous choice (DC) CV studies, respondents are often assumed to be 'in-the-market' for a public good. Popular distributional assumptions such as the log-logistic, log-normal, or Weibull are examples of this, because they imply that all respondents have positive WTP. Zero WTP is seldom allowed in these kinds of studies. The mentioned distributions, along with other popular models using continuous distributions such as the logit and the probit model, provide examples of when zero WTP is excluded.

In order to deal with the problem and fully utilize the information in CV data, the analysis should consider the fact that some households would not be willing to pay for the conservation of some environmental goods. In this case, a more flexible specification of the WTP is required. One possibility is to use a mixture model, which incorporates the possibility that a respondent's WTP be actually zero. This situation can arise in the following scenario. It may well be the case that the proposed public good is so remote from the respondent's interest that he or she is completely indifferent to it (e.g., do not have a 'warm glow' from knowing that air quality will be improved). In this case, zero WTP represents honest responses.

Modeling zero WTP is a continuing effort in the CV literature (e.g. McFadden, 1994; Kriström, 1997; Kwak et al., 1997; Werner, 1999; Yoo et al., 2000, 2001a, 2001b). The purpose of this paper is, therefore, to use the mixture model when dealing with the DC-CV survey data with zero observations to obtain appropriate welfare measures such as the mean and median WTP. To this end, we specify the WTP distribution as a mixture of two distributions, one with a point mass at zero and the other with full support on the positive half of the real line. In addition, we concentrate on the statistical inferences of a mixture model using data from double bounded (DB) DC-CV surveys.

The remainder of the paper is organized as follows. Section II provides an explanation of zero response in CV. Section III presents the details on and discusses some issues related to the model we consider. The penultimate section explains data and estimation results. Some concluding remarks are made in the final section.

Ⅱ. ZERO RESPONSES IN CONTINGENT VALUATION

2.1 Dichotomous Choice Contingent Valuation

The elicitation of WTP is usually done in a DC format that has had great appeal since popularized by Hanemann (1984). Typically, a random sample of the population is asked a 'yes' or 'no' question if they are willing to contribute a specific amount towards the preservation of some environmental resource or the provision of public goods. Among its merits, apparent incentive compatibility and the elimination of protest bids rank high. Moreover, the blue ribbon CV panel of Arrow et al. (1993) strongly endorsed a DC question rather than open-ended question.[2] According to the blue ribbon panel, another advantage is that there is no strategic reason for the respondent to do other than answer truthfully, although a tendency to overestimate often appears even in connection with surveys concerning routine market goods.

In particular, the double bounded DC (DBDC) question, which was proposed by Hanemann (1985), is the frequently used elicitation method in CV studies, since it has been shown to substantially increase efficiency associated with the DC model (Hanemann et al., 1991). A DBDC question presents each respondent a sequence of two bids and asks for a 'yes' or 'no' vote on whether the respondent's WTP equals or exceeds each bid. The second bid is conditioned on the respondent's response to the first bid; lower if the first response is 'no' and higher if it is 'yes'. The gain in statistical efficiency arises from the series of WTP questions that allows the researcher to bracket many of the respondent's WTP amounts between two of the monetary bid amounts.

2.2 A model of WTP

An individual's optimal WTP can be derived within the constrained utility maximization framework. That is, the individual maximizes utility subject to a budget constraint:

$$\max_{y,Z}\,[\,U(y,\ Z;\ h)|y+Z\leq m],$$

where $U(\cdot)$ is the utility function, y is WTP, Z is all other expenditures, h is a vector of personal characteristics, and m is income. Assuming the utility function $U(\cdot)$ is continuous and quasi-concave, then the optimal WTP can be expressed as a function of the respondent's tastes or personal characteristics, as well as variables representing both their educational and economic situations.

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[2] The most common criticism of the open-ended format is that it puts pressure on respondents to determine a value, thus tending to produce an unacceptably large number of non-responses or protest zero responses to the WTP questions (Mitchell and Carson, 1989).

In reality, an individual's choice is also subject to non-negativity constraints, and, therefore, a corner solution could result. There are another reasons for corner solution in consumption, because corner solutions arise in the theory of demand for private goods in a variety of circumstances. First, goods may be mutually exclusive for logical or institutional reasons, they may be perfect substitute, or the indifference curves may interest the axis in some dimension, etc. (Cummings et al., 1994). Second, when the theory is extended to include public goods, the same kind of corner solutions can arise.

In practice, zero values, which are from corner solution are, often found in CV studies using open-ended valuation questions (Mitchell and Carson, 1989). The zero responses in the sample often complicate modeling household behavior and examining the process generating a household's WTP (Donaldson et al., 1998; Yoo and Yang, 2000). Zero consumption of a good can be viewed in terms of whether the person is in-the-market or not. A person enters a market if he or she finds the price lower than his or her WTP. One often distinguishes between the intensive and extensive margin of choice. The latter refers to a discrete switch induced by a price change (e.g., from zero to some positive level), while the former refers to a marginal change of consumption, given that the consumer is already in-the-market. For certain goods, the individual may find that the good does not contribute positively to utility and would not buy it, even at a zero price. Finally, there may be goods over which the consumer has no preferences; they do not belong to the consumer's utility function.

Mitchell and Carson (1989) note that the scenario must be so designed that respondents who are not willing to pay anything for the amenity feel comfortable in giving such response. Such responses are not uncommon when an open-ended valuation question is used, and they present no further problems when calculating descriptive statistics such as the mean or the median. When using the DC question format, the handling of zero responses is somewhat more involved.

2.3 Literature Review on Dealing with Zero Responses

Three ways to deal with zero WTP responses from DBDC-CV surveys have been proposed. First, Hanemann and Kanninen (1999) suggested a censored Box-Cox model, which is similar to the Tobit model (Tobin, 1958). Second, An and Ayala (1996) and Werner (1999) used mixture models of WTP distributions to allow a point mass at zero, and Kriström (1997) suggested spike models to take into account a spike at zero which is the truncation at zero of the negative part of the WTP distribution. Finally, Yoo et al. (2001a) proposed a two-equation model, which incorporates a two-level decision structure, a decision on whether to participate in having WTP and a decision on the WTP amount conditional on deciding to participate.

The mixture models may allow for different parameters and different covariates in the non-stochastic component, depending on whether the individual likes or dislikes the proposed policy, and provide more flexibility than the censored Box-Cox model. Furthermore, the conventional model and the spike model can be interpreted as special case of the mixture model, which will be explained in section IV. Thus we suggest the mixture model as a way to accommodate corner solutions and apply the model to data on air quality valuation as an illustrating example.

Ⅲ. THE MODEL

3.1 Basic WTP Model

The utility difference model used by Hanemann (1984, 1989) provides one method for developing Hicksian compensated measures from DC-CV data.[3] The observed discrete choice response of each individual is assumed to reflect a utility maximization process. We recognize WTP (hereafter denoted as C) is a random variable with a cumulative distribution function (cdf) defined here as $G_C(\,\cdot\,;\theta)$, where θ is a vector of parameters. The probability that each respondent maximizes utility by answering 'yes' and agrees to pay the bid amount, A, can be expressed as:

$$\Pr\{\text{response is 'yes'}\}=\Pr\{C\geq A\}\equiv 1-G_C(A;\theta) \quad (1)$$

This result indicates that the fitting of the binary response model (1) can be interpreted as estimating θ. When C can be positive or negative the mean (hereafter denoted as C^+) is calculated as:

$$C^+=E(C)=\int_0^\infty [1-G_C(A;\theta)dA]-\int_{-\infty}^0 G_C(A;\theta)dA. \quad (2)$$

In addition, the median WTP (hereafter denoted as C^*) is obtained by solving for C^* in the following equation:

$$G_C(C^*;\theta)=0.5 \quad (3)$$

3.2 Conventional DBDC Model

This section focuses on the theoretical aspects of DBDC-CV surveys based on Hanemann et al. (1991). Let be the index for each respondent in the sample. When each respondent is presented with two bids, there are four possible

[3] Alternatively, the WTP-function approach to DC-CV models was discussed by Cameron and James (1987).

outcomes: (a) both answers are 'yes' (yes-yes); (b) both answers are 'no' (no-no); (c) a 'yes' followed by a 'no' (yes-no); and (d) a 'no' followed by a 'yes' (no-yes) whose binary-valued indicator variables are I_i^{YY}, I_i^{YN}, I_i^{NY}, and I_i^{NN}, respectively, such that:

$$\begin{aligned} I_i^{YY} &= 1(\,i\text{th respondent's response is 'yes-yes'}) \\ I_i^{YN} &= 1(\,i\text{th respondent's response is 'yes-no'}), \\ I_i^{NY} &= 1(\,i\text{th respondent's response is 'no-yes'}) \\ I_i^{NN} &= 1(\,i\text{th respondent's response is 'no-no'}) \end{aligned} \tag{4}$$

where $1(\cdot)$ is an indicator function, whose value is one if the argument is true and zero otherwise.

Given the assumption of a utility-maximizing respondent where A_i is the first bid, $A_i^u(A_i < A_i^u)$ is the higher second bid when the individual responds 'yes' to the first bid, and $A_i^d(A_i > A_i^d)$ is the lower second bid when the individual responds 'no' to the first bid, the log-likelihood function takes the form:

$$\begin{aligned} \ln L = \sum_{i=1}^{N} \{ & I_i^{YY} \ln[1 - G_C(A_i^u;\theta)] \\ & + I_i^{YN} \ln[G_C(A_i^u;\theta) - G_C(A_i;\theta)]. \\ & + I_i^{NY} \ln[G_C(A_i;\theta) - G_C(A_i^d;\theta)] \\ & + I_i^{NN} \ln G_C(A_i^d;\theta)\} \end{aligned} \tag{5}$$

We assume that the WTP follows a Weibull distribution in conventional model to compare the result:

$$G_C(A;\gamma,\alpha) = 1 - \exp(-\gamma A^{\alpha}). \tag{6}$$

Using equations (2), (3) and (6), we can measure the mean and median WTP based on a Weibull distribution as follows:

$$C^{+} = (1/\gamma)^{1/\alpha}\Gamma(1 + 1/\alpha), \tag{7}$$

and

$$C^{*} = [-(1/\gamma)\ln 0.5]^{1/\alpha}, \tag{8}$$

respectively.

3.3 A Mixture Model with Weibull Distribution

The conventional model doesn't incorporate the possibility of zero WTP because the cdf of WTP is usually assumed to be absolutely continuous. The mixture model proposed here can be interpreted as the mixture of two distributions, which not only incorporates zero WTP, but also nests conventional model (5) as a special case. The model and a more formal presentation of the theoretical underpinnings of the situation are described below. We note that the 'no-no' respondents are composed of two groups: those who really have a zero WTP, and those who have a positive WTP that is less than A_i^d. For people who gave a 'no-no' response, a third follow-up question was asked: "Are you willing to pay anything at all?" Those providing a 'no' answer to this question represent a valid representation of their zero WTP. Thus, the answer to the question allows us to estimate the spike model. That is, 'no-no-no' answers are taken as zero responses.

For each respondent i, I_i^{NN} in equation (4) is classified into I_i^{NNY} and I_i^{NNN} such that:

$$I_i^{NNY} = 1(\, i\text{th respondent's response is 'no-no-yes'}). \tag{9}$$
$$I_i^{NNN} = 1(\, i\text{th respondent's response is 'no-no-no'})$$

Let us assume the cdf of the true WTP to have the following form:

$$G_C(A; \rho, \theta) = \begin{cases} 0, & \text{if } A < 0 \\ \rho, & \text{if } A = 0, \\ \rho + (1-\rho)F(A;\theta), & \text{if } A > 0 \end{cases} \tag{10}$$

where $F(A;\theta)$ is an absolutely continuous cdf such that $F(0;\theta) = 0$. As we can see form expression (10), $G_C(A;\rho,\theta)$ is not absolutely continuous. It has a point mass at zero, represented by the parameter ρ. With probability ρ, the WTP is drawn from the first distribution that has a unit mass of $A = 0$. With probability $1-\rho$, the WTP is drawn from the second distribution $F(A;\theta)$. It is obvious that if $\rho = 0$, the mixture model specializes to the conventional model.

For mixture model, in order to restrict ρ to lie between zero and one we can fit it as a logistic distribution:

$$\rho = \frac{e^{\sigma}}{1+e^{\sigma}}, \qquad 0 < \rho < 1. \tag{11}$$

The positive values of WTP can be assumed to follow one of Weibull, Gamma, log-normal, and Beta distributions, and they restrict WTP to be nonnegative (Habb and McConnell, 1998). According to former studies (An and Ayala, 1996; Werner, 1999), we will assume that positive part of WTP is Weibull random variable, that is:

$$F(A;\gamma,\alpha)=1-\exp(-\gamma A^{\alpha}). \tag{12}$$

The log-likelihood function for the mixture model with no covariate is given by:

$$\begin{aligned}\ln L = \sum_{i=1}^{N} \ln\{ & I_i^{YY}[(1-\rho)(1-F(A_i^H;\gamma,\alpha))] \\ & + I_i^{YN}[(1-\rho)(F(A_i^H;\gamma,\alpha)-F(A_i;\gamma,\alpha))]. \\ & + I_i^{NY}[(1-\rho)(F(A_i;\gamma,\alpha)-F(A_i^L;\gamma,\alpha))] \\ & + I_i^{NNY}[(1-\rho)(1-F(A_i^L;\gamma,\alpha))]+I_i^{NNN}\cdot\rho\}\end{aligned} \tag{13}$$

The formulas of the mean and the median WTP are given by:

$$C^{+}=[1-\rho](1/\gamma)^{1/\alpha}\Gamma(1+1/\alpha) \tag{14}$$

and

$$C^{*}=\begin{cases}[-(1/\gamma)\ln(1/2(1-\rho))]^{1/\alpha}, & \text{if } \rho\le 0.5 \\ 0, & \text{if } \rho>0.5\end{cases}. \tag{15}$$

Let the probability of individual i having zero WTP be given by $\rho(z_i'\beta)$, and the distribution of positive WTP values given by $F(A|w_i';\theta)$, that is, they depend on covariates z_i and w_i, respectively, that vary across individuals:

$$\rho_i=\frac{e\times\rho(z_i'\beta)}{1+e\times\rho(z_i'\beta)} \tag{16}$$

Similarly, WTP can be fitted using Weibull distribution:

$$F(A|w_i'\delta,\alpha)=1-\exp(-w_i'\delta\cdot A^{\alpha}). \tag{17}$$

3.4 A Spike Model

Another possibility is to use spike models suggested by Kriström (1997) when dealing with the DBDC-CV survey data with zero observations. A spike models take into account a spike at zero which is the truncation at zero of the negative part of the WTP distribution. The model assume that WTP is distributed as a logistic on the positive axis. The log-likelihood function for the spike model with no covariate is given by:

$$\ln L = \sum_{i=1}^{N}\{I_i^{YY}\ln[1-G_C(A_i^H)]$$

$$+I_i^{YN}\ln[G_C(A_i^H)-G_C(A_i)], \quad (18)$$
$$+I_i^{NY}\ln[G_C(A_i)-G_C(A_i^L)]$$
$$+I_i^{NNY}\ln[G_C(A_i^L)-G_C(0)+I_i^{NNN}\ln[G_C(0)]]$$

where:

$$G_C(A)=\begin{cases}[1+\exp(a-bA)]^{-1} & \text{if } A>0\\ [1+\exp(a)]^{-1} & \text{if } A=0.\\ 0 & \text{if } A<0\end{cases} \quad (19)$$

Thus, the spike is defined by $\ln[1+\exp(a)]^{-1}$. Using equations (2), (3) and (19), the mean and median WTP in spike model can be calculated as:

$$C^{+}=(1/b)\ln[1+\exp(a)], \quad (20)$$

and

$$C^{*}=\begin{cases}a/b, & \text{if } [1+\exp(a)]^{-1}<0.5\\ 0 & \text{otherwise}\end{cases}, \quad (21)$$

respectively.

3.5 Mixture model with truncated logistic distribution at zero

For comparison to the spike model, we will assume that WTP is distributed as a truncated logistic distribution at zero. Let us assume the cdf of the true WTP to have the following form:

$$G_c(A;\rho,\theta)=\begin{cases}0, & \text{if } A<0\\ \rho, & \text{if } A=0\\ \rho+(1-\rho)\times & \\ [\{1+\exp(-a)\}F(A;\theta)-\exp(-a)], & \text{if } A>0\end{cases}, \quad (22)$$

where

$$F(A;a,b)=[1+\exp(a-bA)]^{-1}. \quad (23)$$

The log-likelihood function for the mixture model with equation (22) is given by:

$$\ln L=\sum_{i=1}^{N}\ln\{I_i^{YY}[(1-\rho)(1-F(A_i^H;a,b))]$$
$$+I_i^{YN}[(1-\rho)(F(A_i^H;a,b)-F(A_i;a,b))]. \quad (24)$$

$$+I_i^{NY}[(1-\rho)(F(A_i^H;a,b)-F(A_i^L;a,b))]$$
$$+I_i^{YYY}[(1-\rho)(F(A_i^L;a,b))]+I_i^{NNN}\cdot\rho\}$$

The formulas of the mean and the median WTP are given by:

$$C^+=(1/b)(1-\rho)\{1+\exp(-a)\}\ln\{1+\exp(a)\}, \tag{25}$$

and

$$C^*=\begin{cases}(1/b)\{a+\ln[1-2\rho+2(1-\rho)\exp(-a)]\}, & \text{if } \rho\le 0.5\\ 0, & \text{if } \rho>0.5\end{cases}, \tag{26}$$

respectively.

IV. RESULTS

4.1 WTP Responses

To examine the usefulness of the mixture model described above, as an illustrating example, we use the data from the survey conducted in Yoo and Chae (2001). The findings from the survey are based on the analysis of 400 interviews. Table 1 presents the distribution of responses to the valuation question, indicating the total number and percentage of respondents who stated that they would be willing to pay for the policy at each bid level, ranging from 10,000 to 40,000 won per year. Note that the percentage of 'yes' responses to the first bid amount falls, roughly, as the bid increases. For example, 72% favored the policy at an annual cost of 10,000 won, whereas only 14% approved of it at the 40,000 won level.

It was a surprising result to us that 22.8% declined to pay anything toward air pollution problem. It appears that our current economic crisis and taxation policies of the government made many respondents reject the notion of paying

[Table 1] Distribution of responses by bid amount

		Number of responses (%)				
First bid (won)	Sample size	"Yes-Yes" Votes	"Yes-No" Votes	"No-Yes" Votes	"No-No-Yes" Votes	"No-No-No" Votes
10,000	100	31	41	14	3	11
20,000	100	4	36	34	6	20
30,000	100	3	18	37	16	26
40,000	100	2	12	38	14	34

Note: The second bid is double the first bid if the respondent's response to the first bid is yes and half the first bid if it is no.

additional taxes even though they perceived the importance of air pollution problem to improve. As discussed above, a zero response could be consistent with economic behavior, indicating that the individual derived no benefits from the good or faced income constraints. The mixture model, therefore, appears to be ideally suited for estimating WTP in our sample, since a sizable fraction of the population has a zero WTP.

4.2 Estimation Results

We first estimated the conventional model (equation (5)) and the mixture model (equation (13)) without covariates by the maximum likelihood (ML) estimation method. The conventional model assumes that the third follow-up question has not been used. Table 2 describes estimation results from the DBDC data models. All the estimated parameters in both models are statistically significant. We can see a direct comparison of the result obtained from the conventional model with the mixture model. To test the validity of the conventional model, we need to test $H_0 : \rho = 0$ in the mixture model. The only complication is that under the null hypothesis, the true parameter ρ is on the

[Table 2] Estimation results for the conventional model using Weibull and mixture model

Variables	Conventional model	Mixture model
α	1.407 (19.106)**	1.818 (19.224)**
γ	0.325 (10.842)**	0.162 (8.015)**
ρ		0.228 (10.854)**
N	400	400
Log-likelihood	-480.699	-586.860
Mean WTP	20,232	18,689
t-value[a]	(25.311)**	(22.126)**
95% CI[b]	[18,828-21,996]	[17,120-20,534]
Median WTP	17,121	17,221
t-value[a]	(21.603)**	(17.204)**
95% CI[b]	[15,685-18,850]	[15,225-19,362]

Notes: The numbers in parentheses below the coefficient estimates are t-statistics, computed from the analytic second derivatives of the log-likelihood. ** indicates significance at the 1% level. Mean and median are calculated by the use of Delta method. [a] t-values are calculated by the use of Delta method. [b] CI denotes the confidence interval, computed by the use of the Monte Carlo simulation technique suggested by Krinsky and Robb (1986) with 5,000 replications.

boundary of the parameter space [0.1] , and therefore, a one-sided t-test would be required.

The estimator for ρ of the mixture model is statistically significant at the 1% level. This rejects the null hypothesis that ρ is equal to zero. The result implies that the mixture model outperforms the conventional model. In fact, the estimated ρ is 22.8%. This indicates that a substantial proportion of the population is indifferent to the argued environmental damage (22.8%). This feature of the data is better captured by the mixture model than by the conventional one.

We compare welfare measures from mixture model with those from conventional model. Since the mixture model is a correct specification from the validity test result, differences between welfare measures from the mixture model and those from the conventional model may be viewed as indicating the usefulness of the mixture model. Welfare measures of the mean and median WTPs and their 95% confidence intervals are provided in Table 2.[4] The

[Table 3] Estimation results for mixture model and spike model using a logistic distribution.

	Mixture Model	Spike Model
a	2.435 (9.086)**	1.405 (11.899)**
b	1.171 (12.272)**	0.868 (18.416)**
$\rho(spike)^a$	0.228 (10.854)**	0.197 (10.550)**
N	400	400
Log-likelihood	-587.197	-595.071
Mean WTP	18,078	18,716
t-value[b]	(22.675)**	(21.314)**
95% CI[c]	[16,543-19,731]	[17,104-20,568]
Median WTP	17,507	16,187
t-value[b]	(17.592)**	(15.752)**
95% CI[c]	[15,481-19,392]	[14,195-18,263]

Notes: The numbers in parentheses below the coefficient estimates are t-statistics, computed from the analytic second derivatives of the log-likelihood. ** indicates significance at the 1% level. Mean and median are calculated by the use of Delta method. [a] spike belongs to the spike model while ρ belongs to the mixture model. [b] t-values are calculated by the use of Delta method. [c] CI denotes the confidence interval, computed by the use of the Monte Carlo simulation technique suggested by Krinsky and Robb (1986) with 5,000 replications.

[4] We used the Monte Carlo simulation technique of Krinsky and Robb (1986) to get the 95% confidence intervals by employing 5,000 replications and omitting 2.5% of the observations from the both tails.

improvement in terms of welfare measures is significant. The conventional model gives an estimated mean of 20,232 won. However, the mean in the mixture model, computed as 18,689 won, is lower than the mean in the conventional model. The values for the mean WTP obtained from the conventional model are not reliable as point estimators of WTP. This is a consequence of fitting a bimodal distribution with a uni-modal Weibull. The mean values from the mixture model, on the other hand, are reasonable. This indicates that for the specific data, we can see the overestimation of the conventional model.

We estimated the mixture model with the spike model (equation (18)) and a truncated logistic distribution at zero (equation (24)) by the ML estimation method using logistic distribution. Table 3 compares the estimation results from mixture model and the spike model. All the parameters in two models are statistically significant at the 1% level. The spike 19.7% and the ρ is calculated as 22.8%. These are close to the observed fraction of people declining to pay (22.8%).

The validity of the spike model can be easily verified by testing the simple nonlinear restriction given by $\rho=\{1+\exp(a)\}^{-1}$. Given that $\chi^2_{0.01}(1)=6.63$, we can reject the hypothesis, because the chi-square statistic is calculated as 5.75. Because the mixture model is non-restricted model while the spike model is

[Table 4] Definition and sample statistics of variables

Variable	Definition	Mean	Standard deviation
INTEREST	Dummy for having an interest in air pollution problem (0 = No; 1 = Yes)	0.275	0.447
BELIEF	Degree of belief in the proposed ozone pollution control policy (1 = Very little; 2 = Little; 3 = Average; 4 = Much; 5 = Very much)	2.580	0.846
EDUCATION	Dummy for education level of high school graduate (0 = No; 1 = Yes)	0.868	0.339
INCOME	Monthly household total income after tax deduction (Unit: 10,000 won)	244.294	96.436

[Table 5] Estimation results of mixture model with covariates

	Variables	Coefficients
α		2.504 (18.118)**
γ	Intercept	-0.240 (-0.552)
	INTEREST	-0.559 (-3.365)**
	BELIEF	0.093 (0.923)
	EDUCATION	-1.554 (-5.487)**
	INCOME	-0.004 (-4.644)**
ρ	Intercept	1.535 (2.576)*
	INTEREST	-1.413 (-3.573)**
	BELIEF	-0.5887 (-3.941)**
	EDUCATION	-0.627 (-1.952)**
	INCOME	-0.003 (-1.967)*
Mean WTP		20,498 (25.541)**
Median WTP		21,128 (24.969)**
Log-likelihood		-481.4310

Notes: t-statistics, computed from the second analytic derivative of the log-likelihood function, are reported in parentheses below the coefficients. ** and * indicate the significance at the 1% and 5% levels, respectively.

restricted, mixture model includes the spike model as a special case. Therefore, for this particular case, it is more suitable to use the mixture model with a truncated logistic than the spike model with a logistic distribution. To estimate the mean WTP, we used equation (20) in spike model and equation (25) in the mixture model.

It is common to test for internal consistency (theoretical validity) in CV studies by estimating the models with covariates. Definitions and sample statistics of variables used in estimating the mixture model with covariates are shown in Table 4. Table 5 reports the estimation results. With the exception of some variables such as BELIEF, coefficients of most variables in Table 4 are significant at the 5% level and all estimated relationships are consistent with our expectation.

V. CONCLUSIONS

The DBDC model has proved a very attractive mechanism for eliciting preferences in the CV method. However, modeling household behavior with the data from DBDC-CV survey is often complicated by zero responses in the sample. The theoretical and empirical literature on dealing with such data has continued to grow. We proposed and applied a mixture model that generalized the conventional way to model WTP responses, by allowing the distribution to have a possible point mass at zero. The mixture model is better than the conventional model in capturing the common bimodality feature of the WTP distribution. The mixture model nests both the conventional model and the spike model as special case. Statistical tests of such restrictions can be easily done. In this specific application reported here, validity tests of the mixture model over conventional and spike models show that the mixture model performs very well. Because the mixture model is not computationally difficult to estimate, it offers a practical as well as a theoretically promising way of dealing with DBDC-CV data with zero observations.

We also discussed the estimation of the mixture model, when data on 'no-no-no' responses are available. One of the main advantages of the mixture model is that it is the consistent estimator while the conventional model is inconsistent. The probability of zero WTP, represented by parameter ρ, is separately identified and can be consistently estimated. Although this is a natural consequence of having more data, it shows a potential trade-off that CV practitioners face. Given a base of DBDC-CV surveys, two ways of improving the efficiency of the estimations are either to increase the sample size, or to ask an additional question only to the 'no-no' respondents. Due to the usually high costs of increasing the sample size, asking a follow-up question seems to be an inexpensive way of achieving this objective.

Even though this paper refers to an application of the mixture model to a DBDC setting, the model is flexible enough to be applied to any of the elicitation methods used in CV studies. For example if the single-bounded DC questions are used, with or without the follow-up question asking whether the respondent is willing to pay anything, the estimation and testing procedure will be similar.

REFERENCES

An, Y. and R. Ayala (1995), "A Mixture Model of Willingness to Pay Distributions," *Department of Economics Working Paper*, Duke University, No. 95-21.

Arrow, K., R. Solow, E. Leamer, P. Portney, R. Randner and H. Schuman (1993), *Report of the NOAA Panel on Contingent Valuation*, National Oceanic and Atmospheric Administration, U.S. Department of Commerce, Washington, DC.

Bjornstad, D. and J. R. Kahn (1996), *The Contingent Valuation of Environmental Resources*, Edward Elgar.

Cameron, T. A. and D. James (1987), "Efficient Estimation Methods for 'Closed-Ended' Contingent Valuation Surveys," *Review of Economics and Statistics*, vol. 69, 269-276.

Cummings, R. G., P. T. Ganderton, and T. McGuckin (1994), "Substitution Effects in CVM Values," *American Journal of Agricultural Economics,* vol. 76, 205-214.

Deaton, A. and J. Muellbauer (1980), *Economics and Consumer Behavior*, Cambridge: Cambridge University Press.

Donaldson C., A. M. Jones, T. J. Mapp and J. A. Olson (1998), "Limited Dependent Variables in Willingness to Pay Studies: Applications in Health Care," *Applied Economics*, vol. 30, 667-677.

Haab, T. C. and K. E. McConnell (1998), "Referendum Models and Economic Values: Theoretical, Intuitive, and Practical Bounds on Willingness to Pay," *Land Economics*, vol. 74, 216-229.

Hanemann, W. M. (1984), "Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses," *American Journal of Agricultural Economics*, vol. 66, 332-341.

Hanemann, W. M. (1985), "Some Issue in Continuous- and Discrete- Response Contingent Valuation studies," *Northeastern Journal of Agricultural Economics and Resource Economics*, vol. 14, 5-13.

Hanemann, W. M. (1989), "Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses: reply," *American Journal of Agricultural Economics*, vol. 71, 1057-1061.

Hanemann, W. M. and B. Kanninen (1999), "Statistical Considerations in CVM, in I. J. Bateman and K. G. Willis, eds.," *Valuing Environmental Preferences: Theory and Practice of the Contingent Valuation Method in the US, EU and Developing Countries*, Oxford: Oxford University Press.

Hanemann, W. M., J. Loomis and B. Kanninen (1991), "Statistical Efficiency of Double-Bounded Dichotomous Choice Contingent Valuation," *American Journal of Agricultural Economics*, vol. 73, 1255-1263.

Hausman, J. (1993), *Contingent Valuation: A Critical Assessment*, Amsterdam: North-Holland.

Kriström, B. (1997), "Spike Models in Contingent Valuation," *American Journal of Agricultural Economics*, vol. 79, 1013-1023.

Krinsky, I. and A. L. Robb (1986), "On Approximating the Statistical Properties of Elasticities," *Review of Economics and Statistics*, vol. 68, 715-719.

Kwak, S. -J., J. Lee and C. S. Russell (1997), "Dealing with Censored Data from Contingent Valuation Surveys: Symmetrically-trimmed Least Squares Estimation," *Southern Economic Journal*, vol. 63, 743-750.

McFadden, D. (1994), "Contingent Valuation and Social Choice," *American Journal of Agricultural Economics*, vol. 63, 689-708.

Mitchell, R. C. and R. T. Carson (1989), *Using Surveys to Value Public Goods: The Contingent Valuation Method*, Washington D.C.: Resources for the Future.

Tobin, J (1958). "Estimation of Relationships for Limited Dependent Variables," *Econometrica*, vol. 26, 24-36.

Werner, M. (1999), "Allowing for Zero in Dichotomous Choice Contingent Valuation Models," *Journal of Business and Economic Statistics*, vol. 17, no. 4, 479-486.

Yoo, S. -H., S. -J. Kwak and T. -Y. Kim (2001a), "Modeling Willingness to Pay Responses from Dichotomous Choice Contingent Valuation Surveys with Zero Observations," *Applied Economics*, vol. 33, no. 4, 523-529.

Yoo, S. -H, S. -J. Kwak and T. -Y. Kim (2000), "Dealing with Zero Response Data from Contingent Valuation Surveys: Application of Least Absolute Deviations Estimator," *Applied Economics Letters*, vol. 7, no. 3, 181-184.

Yoo, S. -H., T. -Y. Kim and J. -K. Lee (2001b), "Modeling Zero Response Data from Willingness to Pay Surveys: A Semi-parametric Estimation," *Economics Letters*, vol. 71, no. 2, 191-196.

Yoo, S. -H. and K. -S. Chae (2001), "Measuring the Economic Benefits of the Ozone Pollution Control Policy in Seoul: Results of a Contingent Valuation Survey," *Urban Studies*, vol. 38, no. 1, 49-60.

Yoo, S. -H. and C. -Y. Yang (2000), "Dealing with Bottled Water Expenditures Data with Zero Observations: A Semiparametric Specification," *Economics Letters*, vol. 66, no. 2, 151-157.