Estimation of Average Willingness to Pay from Double Bounded Dichotomous Choice Data: Does the “Follow Up” matter?†

Abstract

In Double Bounded Dichotomous Choice (DBDC) Contingent Valuation (CV) studies estimated parameters of the first response equations are used to obtain Mean WTP because of the anchoring bias inherent in follow up responses. In this paper we show that through an efficient scheme of bid design and using a recursive probit model one can arrive at estimates of mean WTP using the follow up responses that are both efficient and robust compared to the standard Interval Data Model and Bivariate Probit Model.

JEL Classifications: C 35, Q 51, Q 53.
Keywords: Contingent Valuation; Kernel Density; Krinsky Robb; Recursive Probit.

† The Contingent Valuation Study reported in this paper was funded by UGC. The cordial help of Bally Municipality officials during field visits is gratefully acknowledged. For comments on an earlier version of this paper we are grateful to Dipankar Coondo, Economic Research Unit, Indian Statistical Institute, Kolkata and the participants of the 44th Annual Conference of Indian Econometric Society held in Hyderabad.
I. Introduction

For the last few decades Contingent Valuation Method has become a quintessential tool for estimating the notional demand curve of non-marketed goods. The CVM attempts to generate points of the Total Value Curve (TVC) by inferring stakeholders willingness to pay (WTP) for a hypothetical commodity\(^1\). Naturally, self reported monetary values require appropriate filtering, as WTP is likely to vary with individual characteristics. Empirical tractability, thus, warrants imposition of parametric restrictions on the distribution of WTP. This can either follow from the choice theoretic specifications of stochastic utility models (Hanemann, 1984) or directly assuming a probability distribution function of WTP (Cameron, 1988)\(^2\).

The initial application of CV by Davis (1963) made use of the so called “bidding game” to estimate individuals WTP\(^3\). Here the respondents are offered a series of bids and a ‘no’ response is taken as indicating that for the offered bid the household is above his TVC while he would answer ‘yes’ if for the posted bid he lies on or below his TVC (See Figure 1). The game stops when the respondent refuses to pay a particular bid and that is considered his final WTP. However, the possibility that starting bid in the bidding game could influence the final WTP estimate lead to the “open ended question format (OE)” where the respondents are directly asked the amount they are willing to pay for the offered non market good. In recognition of the strategic bias\(^4\) inherent in OE formats Mitchell and Carson (1981) introduced what is called the payment card approach. In this approach respondents are shown a series of values and asked to choose the one that best matches their preference.

---

\(^1\) Assuming that the individuals utility is defined over a non-market good \((Q_0)\) and Hicksian composite \((Y)\), the TVC is the locus of all points for which \(U(Q_0, Y) = U(Q_1, Y - WTP)\) where \(Q_1\) denotes a change in the level of non-market good and \(WTP\) is the individual WTP for availing the proposed change (Brookshire et. al., 1980).

\(^2\) Hanemann and Kannien (1999) notes that with appropriate choice of distributions both the approaches yield identical expressions for WTP.

\(^3\) For a historical account of Contingent Valuation studies see Carson and Hanneman (2005)

\(^4\) Strategic Bias arises from the possibility that the respondent may actually understate his true WTP. However, the empirical evidence of the bias paints exactly opposite picture. Explaining the overstating of WTP, Carson and Grove (2007) argue that this tendency arises from free riding motives of the individuals where they think that their consent would only encourage the provision of the good while they can adjust their purchase decisions later. If the quantity of the good is increasing in the money raised there is always an incentive to yeasaying irrespective of the difference between his latent WTP and the posted price.
One important feature of these early attempts was to generate the point estimate of WTP using continuous response CV questions that was later extended by Bishop and Herberlein (1979, 1980) into closed ended referendum type of questions. In this format respondents are allotted a single bid and enquired whether for the proposed programme she is willing to pay the amount. Clearly, this involved putting bound on WTP (P_N and P_Y in Figure 1) and subsequently came to be known as Single Bounded Dichotomous Choice (SBDC).

Judging the relative efficiency of the elicitation formats the NOAA panel\(^5\) made a strong case against Open Ended (OE) questions and recommended that the “take it or leave it” type of questioning format of the SBDC closely mimics the price mechanism and should be the standard practice in CV surveys. The DC question format treated WTP amounts as latent variables but used binary responses to gauge the distance of the offered bid from the boundary of his preference set i.e. the TVC. In spite of its ability to filter away free riding motives the initial version of DC questions was found to provide limited information about the WTP distribution\(^6\). To arrive at WTP estimates that are more cogent the recent favourite in CVM studies is the Double Bounded Dichotomous Choice (DBDC) approach. Here, respondents are presented with a “follow up” question in addition to the “yes-no” options of the SBDC. The follow up is of course contingent upon their response to the initial bid: a lower bid is offered if the respondents say no to the offered price and similarly an yes response is followed by a higher bid than the initial one. Thus, Double Bounded Dichotomous Choice questions expand the information base of the WTP estimates and may provide efficient assessment than SBDC in three ways (Haab and McConnell, 2002). Firstly, the number of responses is increased so that a given function is fitted with more data points. Second, the sequential bid offers for yes-no and no-yes responses yields clear bounds on WTP. Finally, for the no-no and yes-yes combinations, efficiency gain comes from the fact that they truncate the distributions where the respondent’s WTP are likely to reside. Hanneman et. al (1991) uses a double bounded logit model to compare the DBDC and SBDC estimates of WTP. They find that the double bounded model reduces the variance of

\(^{5}\) In 1992, the National Oceanic and Atmospheric Administration (NOAA) convened a panel of prominent social scientists to assess the reliability of natural resource damage estimates derived from contingent valuation (CV). The product of the panel's deliberations was a report that laid out a set of recommended guidelines for CV survey design, administration, and data analysis.

\(^{6}\) The implied bounds on WTP in this case are wide as it is only known whether WTP is above the assigned bid and below income (for a yes response), or below the threshold bid and above zero for a no response.
the estimated parameters several times and there is a corresponding decline in covariance term as well. This immediately translates in a tighter confidence interval around the median WTP. The efficiency of the DBDC format lies in the fact that it defines more precise boundaries for the WTP in closer neighborhood of the TVC curve than that permitted by the SBDC type questions.

Unfortunately, the increase in efficiency brought about by the DBDC is juxtaposed with biases that prevented the use of follow up responses for estimating the true WTP. The first arises from incentive (in)-compatibility bias\(^7\) that manifests in the failure of DBDC responses to satisfy conditional probability properties like Baye’s Theorem. Since the follow up bid is contingent on the response to the opening bid the probability of follow up response must equal the product of conditional probability of follow up response given the response to the first bid and the probability of initial response\(^8\). Hanemann et.al. (1999) notes that greater preponderance of yes-no responses in reported CV studies bears testimony to the fact that DBDC survey responses fails this test of consistency. The second problem arises typically as a response effect where the individual uses the first bid as an “anchor” to revise his true WTP that is estimated from the first response. This implies that when the market is properly framed (i.e. free from all framing biases) then for a proposed level of non-market good the WTP of an individual locates on a “pseudo” TVC curve lying lower than the true TVC if the first bid is lower than the true WTP and vice-versa. In this case, the initial perceived TVC is revised downwards following a cue to the notional value provided by the asked bid in the first instance. Thus, the first bid acts as a reference value around which the maximum WTP adjust.

To avoid these criticisms, even in case of DBDC models the estimate of WTP is generally carried out by using first responses only. The follow up responses are utilized to estimate the extent of bias in the follow up responses (Whitehead, 2002; Herriges and Shogren, 1996). Among the two response effects incentive incompatibility bias arises due to the public good

---

\(^7\) Elicitation questions are incentive compatible when agents find it in their best interest to respond truthfully.

\(^8\) More formally, suppose the response to the first bid \(B_i\) is yes so that a higher bid \(B_k\) is offered as a follow up. The probability that the respondent shall also agree to it is given by Baye’s Theorem such as

\[
p(ytoB_k) = p(ytoB_k \mid ytoB_i)p(ytoB_i)
\]

where \(y\) denotes yes response.
nature of the non-market good in question. Any follow up involving upward revision of bids would make the respondents suspicious about the enhanced free riding tendencies of the other group members and the probability of negative responses increase. Since the purpose of the modeling is to come up with as reliable an estimate of WTP as possible, the anchoring bias discussed earlier could be moderated by taking care to propose the first bid as close to the actual but unobserved WTP as possible.

In this paper we show that for a systematic choice of bid vectors efficiency gains from using follow up responses may outweigh the biases using a DBDC survey data of 570 households in Bally Municipality in the district of Howrah, West Bengal. To establish the relative efficiency of our framework we estimated the WTP for proper management of solid waste in Bally Municipality applying Seemingly Unrelated Bivariate Probit (SUBVP), Random Effect Probit (RE) and Recursive Probit (RP) methods and compared the estimates obtained there from in terms of 95 percent confidence intervals using Non-parametric bootstrap method. The rest of the paper is organized as follows: section II presents a methodological overview of existing literature and section III discusses the relative merits of recursive probit one. Section IV talks about the survey design and data, section V reports the empirical estimates and section VI concludes the paper by commenting on the overall comparisons.

II. Estimation of Average WTP: A Brief Overview

As the good to be valued is purely hypothetical the estimation of average WTP starts from assuming a TVC depicting Hicksian compensating variation as a measure of welfare change. The responses to the value elicitation questions are then used to estimate the bid curve or the TVC. Given preference and income, a yes response to the offered bid implies that the compensation range is either on or below the TVC of the respondent household. Similarly for the no response the range supposedly falls in the area above the TVC (See Fig. 1). The follow up bids in the DBDC further adds to this iteration process and responses to the second set of bids narrows down the range even closer to the actual TVC. This intuition

---

9 The free riding tendency can be explained by psychological factors where the respondents perceive the follow up as crude bargaining (Altaf and Deshazo, 1994) or as possible cost overrun.
derives from the basic choice theoretic framework. However, due to the public good nature of the benefits biases in response format like anchoring effect may actually prevent correct guessing of the TVC from the final set of responses. Thus, if his true WTP were $WTP_t$, anchoring effect induced WTP ($WTP_F$) would be given by $WTP_F = (1 - \gamma)WTP_t + \gamma FB$ where $0 \leq \gamma \leq 1$ is the extent of anchoring bias and $FB$ is the initial bid offered (Herriges and Shogren, 1996). As the WTP obtained from second bid is a weighted average of the actual WTP in the first instance and the first (asked) bid hence the magnitude of the downward revision of the final WTP would be lower, smaller is the difference between the original WTP and the first bid. To see this note that $WTP_F - WTP_t = \gamma (FB - WTP_t)$, so that, given $\gamma$, closer the first bid to the actual WTP lower will be the difference between the WTP estimated from follow up and the true amount.

Figure 1: Estimation of TVC using dichotomous choice questions

![Figure 1: Estimation of TVC using dichotomous choice questions](image-url)
To prepare the setting, consider the most general formulation of WTP for a DBDC-CV survey:

\[ WTP_{ij} = \mu_i + \varepsilon_{ij} \ldots (1)^{10} \]

where \( WTP_{ij} \) is the \( j \)th respondent’s willingness to pay that is unobservable, and \( i=1,2 \) represents the response to the initial and follow up bids respectively. Let \( B_i \) be the initial bid and denote the follow up bid by \( B_F \). The follow up bid is contingent upon the response to the initial bid: a lower bid is offered if the response to the initial bid is no \( \left( B_F < B_i \right) \) and a higher bid follows after a yes response \( \left( B_F > B_i \right) \). Thus, the DBDC survey generates four sets of responses yielding both upper and lower bounds on the respondent’s WTP (See Table 1).

\[ \begin{array}{|c|c|c|} 
\hline 
\text{Response to DBDC questions} & \text{Bounds on WTP implied by responses} \\
\hline 
\text{Yes-Yes (YY)} & \text{\( B_F \)} & \text{Disposable Income (or + \( \infty \))} \\
\text{Yes-No (YN)} & \text{\( B_i \)} & \text{\( B_F \)} \\
\text{No-Yes (NY)} & \text{\( B_F \)} & \text{\( B_i \)} \\
\text{No-No (NN)} & \text{0 (or - \( \infty \))} & \text{\( B_F \)} \\
\hline 
\end{array} \]

The binary response categories admit themselves to a probabilistic definition of WTP and distributional specifications of WTP allows one to calculate the probability that sample responses falls within any of this four set described above. To illustrate, suppose the WTP distribution is characterized as \( G_c(B;\theta) \) where \( B \) is the bid amount and \( \theta \) is the vector of

---

10 The derivation of this reduced form equation from random utility models is fairly standard (See Hanemann et. al. 1999). In short, suppose the deterministic component of random utility model is \( V_i = \alpha_i + \beta_i y \), where \( y \) denotes the income of the respondents. Then, the probability that the offered bid vector \( B \) bounds the individual true willingness to pay is given by \( P(\Delta V \geq \Delta \theta) \) where \( \Delta V \) denotes the income compensating change in utility corresponding to the provision of non-market good in question. This is interpreted as the Cumulative Distribution Function (cdf) of WTP of the representative individual. Invoking different distributional assumptions for this cdf one can estimate the expressions for WTP.
parameters. Then the probability of YY response is given by $1 - G_c(B_f; \theta)$, that of YN response is $G_c(B_f; \theta) - G_c(B_i; \theta)$ and so on. Linking up (1) with the sample characteristics such that $\mu_i = X'\beta$ and assuming that $\varepsilon_i$ is IID with mean zero and variance $\sigma_i^2$, WTP can be completely estimated by recovering these parameter estimates by method of Maximum Likelihood.

However, for the initial and follow up questions (1) is realized as a simultaneous system of equations having different parameters for each equation. If respondents refer to the same valuation function for both the initial and follow up questions then the difference between parameter estimates and hence the mean WTP will not be statistically significant across two response equations. In the “Interval Data Model” introduced by Hanneman et. al. (1991) this restriction is exogenously imposed by constraining the mean to be identical across responses and assuming zero covariance to assure independence of the response equations. In some cases the interdependence is obviated by pooling the responses from the first and second question and estimating the model as independent probit (Alberini 1995, Shyamsundar and Kramer 1996). Here the second set of responses is simply considered as additional observations generated on the same TVC.

An alternative modeling approach initiated by Cameron and Quiggin (1994) incorporates this independence as a special case. In this approach the initial and follow up responses are modeled as latent regression introducing “index functions” for the unobservable WTP. More formally the model is specified as:

$$y_1 = \beta'_1 x_1 + \varepsilon_1, \quad y_1 = 1 \text{ if } WTP_1 \geq B_f, 0 \text{ otherwise.}$$

$$y_2 = \beta'_2 x_2 + \varepsilon_2, \quad y_2 = 1 \text{ if } WTP_2 \geq B_f, 0 \text{ otherwise.}$$

$$\text{Var}[\varepsilon_1] = \sigma_1, \text{Var}[\varepsilon_2] = \sigma_2, \text{Cov}[\varepsilon_1, \varepsilon_2] = \rho$$

11 Here the WTP for the $j^{th}$ individual is specified as $WTP_j = \mu + \varepsilon_j$ so that both the mean and variance are constant across initial and follow up response equations.
If the error terms in (2) are assumed to follow normal distributions with zero mean then the system of equations can be estimated as Seemingly Unrelated Bivariate Probit (SUBVP) model. Note that in this model if the parameters are restricted to be equal and the estimated correlation co-efficient is statistically indistinguishable from zero one reverts back to the interval data model. Thus, the latter is a special case of SUBVP model. When the estimated correlation coefficient is statistically significant but the parameters are not statistically different then the model is termed as Random Effects Probit model (RE) in the literature and is an application of the restricted SUBVP model (Haab & McConnell, 2002).

In case of both Interval Data Model and Random Effect Probit Model once the parameters are estimated it is relatively straightforward to calculate the average WTP for the target population. For a single regressor \( x_i \), the asked bid, depending on whether the WTP is assumed to follow a normal or log-normal distribution the mean WTP is estimated as \( -\frac{\beta_0}{\beta_1} \) and \( \ln(1 + e^{\beta_0})/\beta_1 \). However, in the unrestricted SUBVP model two sets of parameter estimates are available from two rounds of bidding game. Here, parameter estimates from the first equation are generally used in the computation of Mean WTP. The reason being the fact that the second equation parameters are likely to contain more noise in terms of anchoring bias where the respondents is assumed to take the cue from the first bid while forming his WTP for the second question.

Instead of attempting a direct estimation of unobservable \( \gamma \), we are proposing a strategy for bid design that would minimize the probability of difference between the initial asked bid (FB) and the true WTP (WTP). For this the population distribution of mean WTP is obtained from the pilot survey and the start bids are proposed accordingly. If the second set of responses can be generated as a follow-up to this practice, then the additional observations are not likely to deviate significantly from the original TVC. If now the anchoring effect is modeled explicitly by running a Recursive Probit (RP) model then the estimated WTP is expected to be both statistically efficient and robust.

12 This restriction also implies that the marginal distributions of WTP responses are identical across two equations but the responses are not independent.
13 Another source of bias is the Starting Point Effect where the response to the second bid is sensitive to the initial bid offered.
In the following section we describe such attempt as a formulation of Recursive Probit (RP) models where the estimated WTP from the initial response is inserted in the second response equation as an additional covariate. We then compare the point estimates of WTP from the unrestricted SUBVP, RE and RP models by constructing confidence intervals using both finite sample and asymptotic methods. Previously interval estimation of WTP took place in the context of SBDC (Cameron 1991) or for interval data models in isolation (Welsh and Poe, 1998). We extend this work to compare the efficiency and robustness of estimates of average WTP for all the three models described above.

III. Recursive Probit Model: Estimation of WTP from Follow Up

If anchoring effect is assumed to be present in the follow up responses then one must account for the endogeneity of the WTP derived from the first response equation. Since, \( WTP_f \) is a weighted average of \( WTP_1 \) and \( FB \), hence, in the estimation of \( WTP_f \) the estimated \( WTP_1(FB) \) should enter the second response equation as an independent variable. Thus, the recursive system can be derived from (2) where the first equation is the usual reduced form equation

\[
y_1 = \beta'_1 x_1 + \epsilon_1 \ldots \quad (3a)
\]

but the second equation is replaced by the structural equation

\[
y_2 = \beta'_2 x_2 + \beta_3 WTP_{1j} + \epsilon_2 \ldots \quad (3b)
\]

where \( WTP_{1j} \) is the WTP estimated from the first response equation for the \( j \)th respondent. Following Maddala (1983) the system of equations defined by (3a) & (b) can be estimated by a two-stage maximum likelihood procedure. The parameters from (3a) are recovered up to a scale parameter say \( \lambda_i, i=1,2 \) where \( \lambda_i \) is the error variance of the reduced form equation. Thus, in case of a single regressor \( x_i \) in the first equation only \( \beta_1 / \lambda_1 \) can be estimated. For equation (3b), the parameter estimates for the exogenous and pre-determined variables are \( \beta_2 / \lambda_2 \) and \( \beta_3 \lambda_1 / \lambda_2 \) respectively. For brevity assume a linear WTP model so that the average WTP from the estimated parameters of (3b) is derived as
\[
\left( \frac{\beta_{02}}{-\beta_2} + \frac{\beta_3 \lambda_1}{-\beta_2} \sum_{i}^{n} \frac{WTP_{ij}}{n} \right) \ldots 3(c)
\]

where \( n \) is the number of respondents.

Assume further that the structural form disturbances for 3(a) & (b) have a variance \( \sigma_1 \) and \( \sigma_2 \) respectively. Since the structural form equations coincides with reduced form equation in 3(a), \( \lambda_1 = \sigma_1 \). Thus, WTP estimate from the second response equation is sensitive to both mean and variance of the estimated WTP from the initial question.

For comparing the alternative point estimates from the SUBVP, RE and RP models we opted for construction of interval estimates around the mean WTP. However, one problem with applying the symmetric intervals with normality assumption is that no exact form of the WTP distribution is known to us. Mean WTP is a non-linear combination of the estimated parameters so even if individual co-efficient are normally distributed we cannot say so for the Expected WTP statistic. To address the comparability issue we resort to simulating confidence intervals with the Krinsky Robb procedure. For all the three models the Krinsky Robb method uses random draws from assumed multivariate normal distribution to generate new parameter vectors. WTP is then calculated for each of these parameter estimates and they are used to construct the WTP distribution for the complete set of replications\(^{14}\).

The models and the alternative estimates of mean WTP are tested on a DBDC data set of 570 households of Bally Municipality in West Bengal. In the next section we provide a description of the data set and the survey design.

\(^{14}\) Park et. al. (1991), Cameron (1991) are some of the initial application of the Krinsky Robb procedure.
IV. Data Description and Survey Design

4.1 Questionnaire and Sampling

The provisioning of Waste Management system in the Municipality of Bally in the district of Howrah, displays all the traits that are typical of an urban agglomerate of developing countries. According to official estimate 150 tonnes of waste are generated per day in the Bally area most of which comes from the resident households. The collection activity is irregular and the uncollected waste putrefies in roadside vats imposing severe health and aesthetic cost on the inhabitants. On the disposal side the local body is fast running out of its existing dumping ground and given the fact that Bally has the highest decadal urbanization rate in the district\(^{15}\) the cost of siting new grounds are bound to escalate in future. On the other hand promulgation of Municipal Solid Waste Management and Handling Rules (2000) now requires the local bodies to improve their waste management services within a stipulated time frame. Two major thrust of the new regulation is to upgrade the existing open dumping grounds to sanitary landfills and in response to potential scarcity of land adoption of alternative disposal practices like composting. However, successful adoption of composting is largely contingent on the level of community participation, as this requires daily waste to be separated at source. To mobilize the community, information regarding citizen’s perceived demand for the proposed system would be a vital input for the local planners. Keeping this in mind we designed a CVM survey for the households in the Bally Municipal area regarding their preference for an improved system of waste management compared to the status quo. The CV questionnaire was divided into seven sections. The first section consisted of questions regarding information about the respondents and the household. The next section dealt with the present practice of waste disposal by the households. The third section focused on household’s knowledge about recycling and source separation. The fourth section sought information about household’s willingness to pay for an improved system. The next two sections were designed to extract information about household’s socio economic status and their attitude with environmental problems both at the global level and at the local level. The last section asked the households to provide

\(^{15}\) Municipal population in the Bally area grew at a rate of more than 40 percent between 1991-2001.
information about the extent of individual social capital like inclusion in groups, level of trust and reciprocity.

To select the sample we employed a two stage sampling procedure: the primary sampling unit that is the wards were chosen on the basis of ratio of slum population to total population. The 29 wards of Bally Municipal area are divided into three administrative zones Bally, Belur and Liluah. From there wards 2, 8 & 9 from Bally, 22 & 24 from Liluah and 12 from Belur are selected, where 2 & 24 represents high slum concentration, 8 & 22 represents moderate concentration and 9 & 12 represents low concentration. Our second stage-sampling units were the households and they were chosen randomly from the GIS listing provided by the Bally municipality.

4.2 Bid Design

An important issue in the implementation of the CV survey and especially the DBDC one is the choice of initial and follow up bid vectors. Bid design is important from the point of view of the efficiency of the estimators because they determine the variance-covariance matrix when they are the only regressors. To obtain a preliminary guess about the WTP distribution we conducted a pilot study with open-ended questions that directly asked the individuals the maximum amount they are willing to pay for the improved garbage disposal services. Our range of response varied between 0 and 100 with high concentration at the lower end. To fit the observed data points to an underlying probability distribution we used nonparametric kernel density estimation. The bandwidth for the estimated epanechnikov kernel is determined at 3.223. For observations greater than 50 the bid values are associated with a probability density value that is close to zero (See Figure 2). In view of this, three

---

16 Slum population constitutes nearly one third of the total population in Bally Municipal area.
17 If the objective of estimation is to quantify the location & scale of the sample WTP distributions inclusion of covariates other than bids may not be much useful. However, covariate effects can help in benefit transfer exercises and can even correct for non-representative samples (Cameron & Quiggin, 1994, Haab & McConnell, 2002).
18 The pilot study interviewed 38 respondents from ward 2 and ward 9. The former has a higher concentration of slums than the latter. Apart from providing information about the distribution of WTP the pilot study results also gave an indication about the covariates that significantly affects WTP and helped to validate the survey questionnaire.
19 The kernel is estimated using STATA 10.1. Unless otherwise specified the bandwidth is estimated as the “width” that minimizes Mean Integrated Square Error (MISE).
starting bids of Rs.5, 10 and 20 were randomly allotted to 570 sampled households in the final survey. If the respondents agreed to pay the offered bid the follow up bid is doubled and in case of a no response the respondents are offered a bid that is half of its initial value. For instance, when offered a bid of Rs. 5 a follow up bid of Rs. 10 is offered if the response is yes and in case of a no response a bid offer of Rs. 2.5 is given to the household. Thus, the range of bid vectors in the follow up i.e. Rs 2.5, Rs.5 Rs.10 Rs.20 and Rs.40, spanned the relevant left tail of the kernel density where most of the observations are concentrated.

Figure 2: Kernel Density Estimates of Stated WTP from the Pilot Study

V. Alternative Estimates of Mean WTP

To find out whether utilizing follow up responses provides more efficient and robust estimates of WTP this section reports the point estimates of WTP from SUBVP, RE and RP
models. In fact, both the Interval Data model and Random Effects Probit models (RE) can be obtained as a special case of SUBVP models. The initial formulation of Interval Data Model in Hanneman et. al (1999) utilizes a double bounded logit model. But as Cameron and Quiggin (1994) note this does not allow for the non-zero correlation across response equations. So we chose to accommodate the possibility of Interval Data structure within the RE model by explicitly estimating the correlation coefficient even when the mean and variance of the WTP from first and second equations are constrained to be equal. Given the sample responses if the chi-square value of the estimated correlation coefficient falls short of the critical value we can reject the null hypothesis of endogeneity of the estimated WTP. Note that WTP is estimated from the first response equation in the SUBVP to facilitate comparison of WTP estimates from the RP model. Moreover, to show that the switch from SBDC to DBDC is indeed more efficient we report the point and interval estimates of WTP from first response equation only. If SBDC interval estimates are not tighter than any of the three DBDC methods the claim for improved efficiency of DBDC format will be reiterated for our sample observations.

It is problematic to indulge in a direct comparison of RP estimates with that of the other bivariate competing models discussed earlier. This is because the earlier models viz. RE, Interval Data Models and SBDC are all nested within SUBVP but RP is not. But given the fact that Mean WTP in this case is also a non-linear combination of estimated parameters we can still resort to constructing the confidence interval around mean by means of Krinsky Robb procedure. Then, at least we can attempt some qualitative comparisons in terms of the precisions of the relative estimates.

In the RP model we included household income as an additional covariate other than the initial bid in the reduced form equation 3(a). This is necessary to estimate the first stage WTP for the individual sample households and this WTP enters the structural form equation in 3(b) as an additional covariate along with the follow up bid. The WTP from the follow up

---

20 All the analysis is performed using statistical package STATA 10.1.
21 By the same argument accounting for possible endogeneity in WTP precludes estimation by way of pooling the responses from the initial and follow up questions.
is then estimated at the mean WTP from the first response equation as shown in 3(c)\textsuperscript{22}. The alternative point and interval estimates of Mean WTP for the SUBVP, RE and RP models are shown in Table 2.

<table>
<thead>
<tr>
<th>Models</th>
<th>Mean WTP</th>
<th>Confidence Intervals (95%)</th>
<th>Range (UB-LB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBDC(Eq (1) only)</td>
<td>33.09</td>
<td>25.43-59.24</td>
<td>33.81</td>
</tr>
<tr>
<td>Bivariate Probit (SUBVP)</td>
<td>32.93</td>
<td>25.38-58.28</td>
<td>32.90</td>
</tr>
<tr>
<td>Random Effects Probit (RE)</td>
<td>33.09</td>
<td>27.58-44.69</td>
<td>17.11</td>
</tr>
<tr>
<td>Recursive Bivariate Probit (RP)</td>
<td>22.98</td>
<td>17.79-31.60</td>
<td>13.81</td>
</tr>
</tbody>
</table>

a: 5000 replications

As can be seen that the Mean WTP for the SBDC compares well with SUBVP and RE models. However, the interval estimates are certainly tighter for the SUBVP and even more for RE models compared to estimates based on first response only in SBDC. Thus, we find support for the claim of improved efficiency of DBDC over SBDC models. As is quite evident the RP model is relatively more efficient than the SUBVP and the RE models as it has tighter confidence intervals around the point estimate. Between SUBVP and RE, the latter gives tighter confidence interval and hence is more efficient. Though, it is not possible to compare RP estimates directly with that of RE, it can be noted that the range of variation in case of the latter is minimal indicating strong influence of correlation between the first and the follow up response in the estimated value of the average WTP. When both the initial and final responses from the sample are used to estimate Mean WTP it comes out to be equal to 43.58. When only final responses are taken the value becomes 40.08. However, in the RP model when the dependence of the follow up response on the initial asked bid is explicitly taken into account the estimated mean WTP becomes almost half (See Table 2). So this interdependence has strong influence on the WTP which when ignored, will make the

\textsuperscript{22} The mean sample household income and the mean of the first stage WTP are Rs. 7948.66 and Rs.30.00 respectively.
basis of estimation statistically weaker. On a different note estimated mean value in the RP model also comes closer to the real situation where some local bodies like Kanchrapada and North Dumdum are charging a fee of Rs. 10-15 per household for providing door step collection of daily refuse.

VI. Conclusion

The claim of increased efficiency of DBDC over SBDC Contingent valuation surveys relied on achieving tighter bounds on mean WTP estimated from the first response equation. The information regarding WTP in the follow up was neglected owing to bias arising from the possible endogeneity of anchoring effects. Attempts to model this endogeneity is present in the literature (See Herriges & Shogren, 1996, Watson & Ryan, 2007) but comparison of mean WTP with explicitly accounting for the independence is scarce. In this paper we propose a Recursive Bivariate Probit model that uses the follow up responses to arrive at mean WTP estimates using data from a Contingent Valuation Survey of 570 households for improved waste management in Bally Municipality, West Bengal. Our exercise suggests that when the bid design is carefully done the observation from both initial and the follow up bid would refer to the same TVC and hence, the use of follow up response would help in generating better estimates of mean WTP because of its higher information content. The estimated mean WTP is more efficient and robust than those obtained from unrestricted Bivariate Probit Models and Random Effects Probit model. To control the inherent biases of second bid, we have randomized the first bid around the spikes of the kernel density obtained from the pilot survey. Under this control the incorporation of second response in the assessment of WTP expands the information base of the estimation. Since recursive models most successfully utilized the information related to $FB$ and $WTP_1$ in evaluating $WTP_f$, hence, as expected, here the result is most efficient and robust.

On a closing note it is useful to consider the desirability of the DBDC type of survey in setting of typically developing country like India. Much of the criticisms against using the second response is based on the structure of agent belief where offered a follow up the respondent feels that “something is going on”. This can lead to downward biases in WTP
estimates as there can be higher uncertainty around the second price because the agent might feel that there is a further scope of bargain that he may lose by answering yes to the final bid. Also, the posting of follow up might signal a change in the quality of the offered commodity and he might shift his WTP distribution to the right especially if his answer to the first bid is no. While much of this can be true in a fully integrated market economy with well differentiated products the same may not be true for places like India where most of the trading in daily commodity is informal and is guided by a custom of bargaining. We feel this fact could be used to our advantage once we successfully design “consequential survey questions” and minimize the variances of the offered bids around a well-guessed population mean WTP. Further probe into the relation between agent’s belief structure and the variation in expected WTP could help clarify this.

References


---

23 Here agents believe that the survey results could actually influence the agency’s action and thus treat the survey questions as an opportunity to influence such actions.


