Comparing the validity of single versus double-bound dichotomous choice questions in a willingness to pay survey

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Abstract
Willingness to pay (WTP) can be elicited in a variety of ways and the format has an impact on the choice, construction and findings from estimations. In this paper one- and two-stage bidding processes are compared with respect to the model structure, mean and median WTP, explanators of variance and actual purchase decisions. The first dataset consists of 1196 respondents from rural Surat, India who stated their WTP for a treated mosquito net along with a wide range of socio-economic, demographic and malaria/mosquito-related information and the second dataset, of actual purchase decisions, reflects a follow-up visit to 300 households. Results show that starting point bias exists and continues through the second stage bid. The explanatory variables indicate both models are valid but that the second is more efficient and therefore has additional variables, all of which follow the expected sign. The estimated mean and median WTP values from both bidding stages are very close, although mean values from the first bid are significantly higher and the median values indicate the second stage bid more accurately reflected a positive skew in the distribution. Actual purchase decisions were marginally more accurately predicted using the second stage bid. The results provide evidence both for an against a move from single to double bound WTP questions.

Keywords: *willingness to pay, malaria, contingent valuation, dichotomous choice, double bound, spike model, India*

1.0 Introduction

As willingness to pay surveys are intended to inform government decisions about whether to adopt particular policies or, as in the United States of America (USA), the levels of settlements following damage to the environment (Alberini, 1995), it is important that the estimates of welfare change are efficient and unbiased. Questions to elicit an individual's willingness to pay (WTP) can be asked in a variety of ways (Frew et al., 2003). The format influences the choice of models for estimating central tendencies of WTP and explanations of its variance, all of which are the subject of continuing debate and research as investigators seek to provide more reliable and valid estimates.

Each elicitation mechanism is subject to potential biases or other disadvantages. Criticisms of open-ended questions have focussed on concerns that significant proportions of responders give unfeasibly high values (Green et al 1998) and don't mimic the market (Smith, 2000) whereas payment cards have been shown to be subject to range bias (Whynes et al 2004). The decision, in 1993, by the National Oceanic and Atmospheric Administration (NOAA) of the USA to recommend dichotomous choice questions accelerated both the use of and research into these alternative types of questions. Single-bound dichotomous choice questions (DC1) ask whether a respondent would or would not be willing to pay a specified amount (also known as the 'referendum', 'take-or-leave-it', binary choice or closed-ended method) and double- (DC2) or multiple-bound dichotomous choice questions (DCm) ask one or more follow-up questions by offering a new price that is usually dependent on the first answer - a higher bidding price is given if the first bid value is accepted or a lower bid price given otherwise (also known as 'iterative bidding' or 'bidding game').

Compared with other methods, dichotomous choice questions are argued to better reflect market decisions as well as political referendums that are used to guide social policy (Green et al 1998). Questions are less likely to be misinterpreted because there is a clearer relationship between payments by subjects and the good that would be delivered if the referendum was 'passed' (Green et al 1998). As the questions are easier to understand (Alberini 2004; Ready et al 1996) and respondents are not usually asked about very high values, the unfeasibly high values and high proportion of non-responses often attributed to open-ended questions are avoided (Green et al, 1998; Ready et al, 1996) which could reduce incentives for bias (Bateman et al 2001).

The disadvantages of dichotomous choice questions are that much larger sample sizes are needed as it is a relatively inefficient way to produce estimates of mean WTP. Not only are the analytic demands greater (Bateman et al 2001; Green et al, 1998) but the estimations of mean WTP rely on the choice of functional form as well as assumptions about the underlying distribution of values, which is itself sensitive to assumptions about the tails of distributions (Bateman et al 2001). There are also concerns that dichotomous choice questions may produce biased estimates as mean values are often higher than other valuation techniques (Ready et al 1996) even though Kealy and Turner (1993) showed that this was not consistent between public and private goods. Dichotomous choice has been criticised for producing too high estimates of mean WTP and a potential reason could be the link between the occurrence of starting-point bias or 'anchoring effects' (Calia and Strazzera 2000) which Green et al (1998) felt "invites manipulation of result by choice of design (as) high numbers can be obtained by selecting a design with high anchors".

The impact of NOAA's recommendations and growing concern about some of the problems of dichotomous choice methods led to research on the gains and losses in moving from single to multiple-bound questions. Early research compared the variance-covariance matrix and information matrix of both DC1 and DC2 ML estimators and proved theoretically and empirically that DCm is more efficient than DC1 (Hanemann et al., 1991). DCm yields more precise estimates of structural parameters and associated welfare benefits (Carson et al., 1986; Finn et al., 2001, Bateman et al, 2001; Cooper et al 2002; Calia and Strazzera 2000) for little additional cost (Cooper et al 2002), except that DCm is less amenable to mail surveys and does actually cost more per interviewer (Calia & Strazzera 2000). However, as DCm gathers more information per respondent, sample sizes can be reduced (Bateman et al, 2001). Researchers also posited that DCm methods might give time to allow preferences to unfold (Green et al 1998) and could help protect against poor selection of initial bid values (Cooper et al 2002) which is important as the best results are gained when the researcher knows at least the mean and standard deviation prior to setting bid values (Alberini 1995)! Greene et al (1998) also cited claims that DCm reduces opportunities for strategic misrepresentation.

As testing of DCm continues researchers have questioned its seeming advantages. Response rates can drop with follow-up questions (Calia & Strazzera 2000) perhaps because second questions can be unexpected, causing respondents surprise or annoyance (Cooper et al 2002), and a lack of time to think may still have an impact on DC2 question formats (Calia & Strazzera 2000). Bateman et al (2001) have highlighted the increased analytical demands of DCm over DC1. There are also concerns that normally distributed DC2 models may produce biased estimates of the mean and standard deviation of WTP when anchoring is present with the bias increasing with the degree of anchoring (Alberini et al 2005). However, a complex picture emerges that depends on the underlying distribution of WTP – and the underlying distribution needs to be know before an appropriate ‘correction’ mechanism can be adopted (Alberini et al 2005).

More recently concerns have turned to whether responses to the 1st bid value are (in) consistent with the following bid levels. This contrasts with analytic approaches tend to assume that respondents behave identically and independently across bid stages, and therefore that responses are independent of the bound at which they were collected within an experiment (Park, 2003). For example, it might be argued that it should make no difference to any individual respondent whether they are asked to pay the same amount £X at either the first stage or the second stage of a dichotomous choice experiment. However, experimental studies have reported that two subsequent answers are not made independently, but that the second answer depends on the first and that WTP for DC2 is often lower than DC1 (Cooper et al 2002, Whitehead et al 2001). For example, Cameron and Quiggin (1994) showed the dependence of two subsequent answers by using the full information bivariate probit model although Haab (1998) later showed that they had overestimated the poor performance of the interval level model.

Recent findings of differences in bid-acceptance probabilities between each level of questionnaire indicate inconsistent behaviour of respondents’ during the course of responding to questions and therefore a potential source of bias emanating from within the DCm bidding tree. Bateman et al (2001) provide a useful basis for categorising potential causes of difference in terms of whether or not they are signs of bias. Some causes of variation may be entirely consistent with economic theory. For example: weariness or the expectation of weariness may cause respondents to expect that saying ‘yes’ may generate more research questions and hence say ‘no’; respondents may believe that a higher bid value means the government might be wasting their money (Bateman et al 2001); a respondent may attribute different characteristics to the same good when an second price is offered (Cooper et al 2002, Bateman et al 2001); or alternatively respondents may experience loss aversion to the first price as set out in prospect theory (Cooper et al 2002). Perhaps of more concern to the validity of DCm are those arguments considered to be inconsistent with rational utility theory where; respondents on a bid decreasing path may induce bargaining, thus driving down their stated WTP down in the second bid (Cooper et al 2002); free riders more likely to be concentrated in bid decreasing path (Bateman et al 2001); respondents are ‘Yea sayers’ and have an increasing probability of saying yes to higher amounts (Bateman et al 2001) or, conversely, ‘no-sayers’ (Alberini 2004); or respondents suffer guilt or indignation at the follow up bids (Bateman et al 2001).

Comparative studies of DC1 and DCm are therefore needed to determine validity. If DCm models are internally inconsistent, then it may be better to take the estimates from DC1 with larger confidence intervals. As both Bateman et al (2001) and Calia and Strazerra (2000) indicated, this needs empirical testing. Within the health care literature we are not aware of any work that addresses these issues and few outside the health care literature that use the wide variety of methods in this paper for investigating validity of DC1 versus DC2 question formats.

We derive WTP models for both bid stages. The paper first outlines the theoretical approach adopted followed by a description of the data, choice of model and impact of DCm approach on the estimation techniques used. The results show pathways of bid values, model results, estimation of mean and median WTP and a comparison of predictions with actual purchase decisions. The discussion compares and contrasts the impact of DC1 and 2-stage bid models (DC-2) and reflects on the value of further probing of WTP values.

2.0 Data

We use two related data sets. The first data was constructed from interviews with a randomly sample of 1200 households from 80 villages in the rural area of Surat district in Gujurat, India. Interviewers visited homes at least three times to gain an interview with the main earner before asking another adult (preferably the spouse or parent) to respond instead. Three quarters of the selected sample was participating in one of three arms of a community randomised trial comparing a control arm of active case detection and treatment (ACDT) with ACDT plus insecticide treated mosquito nets or ACDT plus insecticide residual spraying. A description of these interventions and their cost-effectiveness is given in Bhatia et al (2004). The fourth group of 20 villages was randomly selected from those villages outside the trial (OTA) with the same parasitic index as those selected for the trial that were <5 km from a trial village. The probabilities of households being sampled are described fully in Mistry et al (submitted).

The interview comprised five sections: household socio-economic and demographic profile; use of preventive measures; treatment seeking behaviour; WTP; income and expenditure patterns. The design and development of the questionnaire is described and justified in Bhatia and Fox-Rushby (2002).

The respondents were first asked whether they were willing to buy a TMN at all. Those who were not willing to buy a TMN were then asked if they are willing to do so if the option of paying in instalments was available. Those who said ‘yes’ or ‘don’t know’ to either of the two questions were then asked about positive WTP values using a double-bound dichotomous choice format. After the second bid, all respondents were asked about their maximum WTP. Three starting bids (50, 75, and 100 Rupees) were randomly allocated across households. As recommended by Harris et al. (1989) and NOAA (1993), respondents were also offered a ‘don’t know’ choice in addition to ‘yes/no’ options.

The second set of data was a follow-up study that involved a simulated market experiment. The 300 households in the OTA group were revisited within 2-4 weeks after the first interview in order to sell TMNs at a fixed price of Rs 75. The detailed methods are given in Bhatia and Fox-Rushby (2003).

3.0 Methods

We use four methods to assess and compare the validity of DC1 and DC2 question formats by examining the:

- response patterns and probabilities of accepting bid values, with a particular focus on the same bids values offered at different stages of the bidding process;
- regressions, to test for internal validity by checking the stability of explanators of variance;
- various estimates of mean and median, with tests for significant differences; and,
- sensitivity and specificity of DC1 and DC2 in predicting the actual purchase decision.

3.1 Assumptions and structure of the regression

As pointed out by Goldstein (1995), any dichotomous choice survey which elicits responses for several individuals at a smaller number of discrete bid amounts is essentially a hierarchical, or multilevel, model, with responses nested within individuals because data emanates from a (usually small) number of bid amounts are offered to a large number of individuals (Langford et al., 1998). Therefore, it is reasonable to expect the existence of extra-binomial variation which means there will be a two-level hierarchical model with errors associated both with individual responses and with bid amounts. In other words, the possibility that there is more uncertainty associated with some bid amounts than with others should be allowed for. For example, how people respond to a bid of, say, Rs 25 compared to a bid of Rs 200 may not simply due to individual differences or other explanatory variables. For this reason, the random effects model is adopted by some researchers (Langford et al., 1998) to contain both bid amounts and individuals effects. In our data, there is a second reasoning to account for hierarchical data as the trial followed a cluster design, where households were sampled once villages had been selected (and because villages may have specific characteristics that are not accounted for by analysing data at a household level). In this paper both characteristics of individuals and bid amounts will be accounted for and a cluster effect at village level is accounted for using robust standard errors.

Before formulating an estimable model, we should first choose an appropriate probability distribution to model WTP. The distributional assumption depends on a large degree on two considerations: (1) Whether the distribution accounts for limits that should be applied to permissible values of WTP; (2) How well the distribution fits the data (Bateman et al., 2002). Several possible parametric families of distributions could be used including normal, lognormal, logistic, log-logistic, exponential, Weibull, gamma and beta. The normal and logistic specifications have been particularly popular because of their relative simplicity. However, since they are defined across the support $-\infty$ to $+\infty$, they will predict positive probabilities for WTP for taking a negative value, which implies that the model will be mis-specified. An alternative, therefore, is to adopt a distribution that is naturally non-negative, such as, lognormal or log-logistic distribution. In this paper, a log-logistic model will be adopted for the distribution of WTP.

Assuming a distribution of WTP, which is only defined for positive values, rules out the possibility of zero WTP. However, zero values can form a high proportion of responses in WTP surveys and may occur because of corner solutions of the utility-maximisation, when goods do not contribute at all to the individual's utility (Kristrom, 1997) or due to protest responses (Donaldson et al 1998). Thus, the model must account for the possibility of a zero WTP value. One solution is to consider the model as representing two separate groups: one group of respondents who do not value the non-market goods and have a WTP of zero, with these people considered to be 'out of the market' for the TMN; and a second group that are 'in' the market with a positive WTP for a TMN. This amounts to introducing a spike that represents the probability of respondents having zero WTP. The two groups are drawn from two different distributions, which makes it a mixture model consisting of a spike and a positive WTP distribution that accounts for the theoretical restrictions that WTP must be greater than zero. The initial screening question asked before the first bid separates respondents who are in and out of the market and therefore allows generation of a spike for both first bid and second bid. Two models are to be established according to the data in the two bidding stages, which are the response to bid 1 and the response to bid 2.

Suppose there is a continuum of individuals with different valuations of a TMN. The probability that an individual's WTP does not exceed a given bid B is given by:

$$prob(WTP \le B) = F_{WTP}(B) \quad (1)$$

where $F_{WTP}(B)$ is a right, continuous, non-decreasing function.

In the spike model, it is assumed that the distribution function of WTP has the following form:

$$F_{WTP}(B) = \begin{cases} \rho & if\ B = 0 \\ G_{WTP}(B) & if\ B > 0 \end{cases} \quad (2)$$

where ρ belongs to (0, 1) and $G_{WTP}(B)$ is a continuous and increasing function such that $G_{WTP}(0) = \rho$ and $\lim B \to \infty, G_{WTP}(B) = 1$. Thus, there is a jump-discontinuity: a spike at zero. The log-likelihood function for the sample is given by:

$$l = \sum_{i}^{N} \{S_i T_i \ln[1 - F_{WTP}(B)] + S_i (1 - T_i) \ln[F_{WTP}(B) - F_{WTP}(0)] + (1 - S_i) \ln[F_{WTP}(0)]\} \quad (3)$$

The spike model basically requires information from two questions. The first stage of the questioning process: whether the respondent is willing to pay for one TMN at all, can generate the spike part. That is: if the answer is 'yes', WTP_i>0 which means the individual is in-the-market, and if the answer is 'no', then WTP_i=0 which implies the individual is out-of-the-market. We define an indicator S_i that tells if the individual is in-the-market or not:

$$S_i = \begin{cases} 1 & if\ WTP_i > 0 \\ 0 & if\ WTP_i = 0 \end{cases} \quad (4)$$

Followed by the market entrance choice, we define T_i to indicate if the respondent is willing to accept the suggested price:

$$T_i = \begin{cases} 1 & if \quad WTP_i > B \\ 0 & if\ 0 < WTP_i < B \end{cases} \quad (5)$$

As the individual characteristics could very possibly explain why an individual is in the market or not, it is plausible to assume covariate information which means individual characteristics may affect both the parameters in the distribution of $G_{WTP}(B)$ and ρ. Therefore, the estimation of ρ depends on a set of explanatory variables of individual characteristics and a logit model is used based on 1196 observations according to respondents' answer to the first screening question.

After the screening question the sample size is reduced to 939, with the 257 respondents out-of-the-market excluded in the following models for the double-bound bidding game. In the stage of the first bid, there are only two outcomes: 'yes' and 'no'. As the model for the first bid is a binary choice, we use WTPBID1 to indicate whether the respondent accepts the first bid:

WTPBID1=1, if the first bid was accepted

WTPBID1=0, if the first bid was rejected

For each individual i, we denote the initial bid as B_i. The probability of obtaining a 'no' or a 'yes' response can be presented as π^n and π^y, respectively.

$\pi^n(B_i)$ = Pr (B_i >max WTP) = $G_{WTP}(B_i, \beta)$

$\pi^y(B_i)$ = Pr ($B_i \le$ max WTP) = 1 – $G_{WTP}(B_i, \beta)$,

where $G_{WTP}(B_i, \beta)$ is the log-logistic distribution function with parameter vector β, so $G_{WTP} = \{1 + \exp[\beta_0 - \beta_1(\ln B)]\}^{-1}$

Thus, the log-likelihood function is:

$$\ln L(\beta) = \sum_{i=1}^{N} \{ d_i^n \ln \pi^n (B_i) + d_i^y \ln \pi^y (B_i) \} \qquad (6)$$

where d_i^n and d_i^y are binary-valued indicator variables

In the stage of the second bid (represented by WTPBID2), the four possible outcomes, due to the double-bound dichotomous choice format, are ordered as follows:

- WTPBID2 = 1, if both the first bid and the second bid were rejected
- WTPBID2 = 2, if the first bid was rejected and the second bid was accepted
- WTPBID2 = 3, if the first bid was accepted and the second bid was rejected
- WTPBID2 = 4, if both the first bid and the second bid were accepted

The likelihoods of obtaining these outcomes can be represented, respectively, by $\pi^{yy}, \pi^{nn}, \pi^{yn}, \pi^{ny}$ with a second higher bid is denoted as B_i^h and second lower bid as B_i^l for each individual. Under the assumption of utility maximising respondent, the formulas of these likelihoods are as follows. When both answers are 'yes', we have $B_i^h > B_i$, then

$\pi^{yy}(B_i, B_i^h)$ = Pr ($B_i \leq$ max WTP and $B_i^h \leq$ max WTP) = Pr ($B_i \leq$ max WTP $B_i^h \leq$ max WTP) * Pr ($B_i^h \leq$ max WTP) = Pr ($B_i^h \leq$ max WTP)[1] = 1 – $G_{WTP}(B_i^h, \beta)$

$\pi^{nn}(B_i, B_i^l)$ = Pr (B_i >max WTP and B_i^l >max WTP) = $G_{WTP}(B_i^l, \beta)$

When a 'yes' is followed by a 'no', we have $B_i^h > B_i$, then

$\pi^{yn}(B_i, B_i^h)$ = Pr ($B_i \leq$ max WTP $\leq B_i^h$) = $G_{WTP}(B_i^h, \beta) - G_{WTP}(B_i, \beta)$

When a 'no' is followed by a 'yes', we have $B_i^l < B_i$, then

$\pi^{ny}(B_i, B_i^l)$ = Pr ($B_i \geq$ max WTP $\geq B_i^l$) = $G_{WTP}(B_i, \beta) - G_{WTP}(B_i^l, \beta)$

Thus, the log-likelihood function takes the form:

$$\ln L(\beta) = \sum_{i=1}^{N} \{ d_i^{yy} \ln \pi^{yy}(B_i, B_i^h) + d_i^{nn} \ln \pi^{nn}(B_i, B_i^l) + d_i^{yn} \ln \pi^{yn}(B_i, B_i^h) + d_i^{ny} \ln \pi^{ny}(B_i, B_i^l) \}$$

(7)

(*where* $d_i^{yy}, d_i^{nn}, d_i^{yn}, d_i^{ny}$ are binary-valued indicators).

Different from the usual ordered model in which the cut points that specify whether a respondent belongs to which outcome group are unknown, all the three cut points are known (three levels of bid values). Therefore, the ordered model is not needed, and instead an interval regression model was used. STATA version 8.0 was used to estimate all the three models using maximum likelihood.

In the interests of space, Box 1 provides a brief summary of the expected relationships based on a review of current evidence on the WTP for TMNs and the use of WTP studies in India.

Box 1: Selected variables and direction of expected effect

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[1] With $B_i^h > B_i^1$, Pr ($B_i^1 \leq$ max WTP | $B_i^h \leq$ max WTP) $\equiv$ 1, similarly, with $B_i^l < B_i^1$, Pr ($B_i^l \leq$ max WTP | $B_i^1 \leq$ max WTP) $\equiv$ 1

Variables with stronger evidence

1. Expenditure and income variables (+ve) [Onwujekwe et al., 2001; Onwujekwe, 2001]
2. Education (+ve). Mixed evidence for TMNs (Onwujekwe, 2001) but WTP always positive in WTP studies in India.
3. Higher occupations (+ve): (Onwujekwe et al., 2003, 2004)
4. Household size (+ve) [Onwujekwe et al., 2001, 2004]

Variables with weaker evidence

1. Higher caste (+ve)
2. Male gender (+ve) [mixed results in TMNs (Onwujekwe. et al., 2001, Onwujekwe, 2001; (Onwujekwe et al., 2003 Onwujekwe and Neagbo, D, 2002) but WTP of males positive in WTP studies in India
3. 'Pucca' (higher quality) houses (+ve due to wealth but –ve due to lower need and substitution to electric fans) relative to semi-pucca and kacha houses
4. ownership of cows (+ve)

Variables with no evidence

1. Alternative methods used to prevent malaria (coils, mats, smoke, fans, odomos, applying oil to the body and using a sheet to cover the body)

3.2 Mean and median estimation of WTP

Two bidding stages will be combined with the spike separately to estimate mean and median WTP. Generally, the mean is the area under the survival function, i.e.,

$$E(WTP) = \int_{0}^{\infty} 1 - F_{WTP}(B)dB - \int_{-\infty}^{0} F_{WTP}(B)dB \tag{8}$$

The latter part vanishes when negative WTP is ruled out and the spike at zero has zero contribution. As the distribution is log-logistic, mean and median WTP for the spike model are then obtained as:

$$WTP_{mean} = (1-\rho_i)\pi_i \frac{\exp(-\beta_0 + \sum \lambda_j X_{ij} / \beta_1)}{\beta_1 \sin(\pi_i / \beta_1)} \tag{9}$$

$$WTP_{median} \begin{cases} (1-\rho_i)\exp(-\beta_0 + \sum \lambda_j X_{ij} / \beta_1), & \rho_i < 1/2 \\ 0, & \rho_i \geq 1/2 \end{cases} \tag{10}$$

3.0 Results

The survey response rate in the first data set was 100% due to the number of return visits made interviewers to households and the replacement of main earner with spouse or parent at the 3rd visit. The response rate in the second data set was 99%.

3.1 Sample description

89% of respondents were the main earners of the household. Of the main earners, 93.7% (1000/1067) were male, and of those non-main-earner respondents, 31.6% (42/133) were male. Respondents with no education at all comprised nearly half of the sample population (47.8%), although a large percentage (32.8%) only had primary education, and few (15.5%) had secondary education or higher (4%). As the survey was carried out in a rural area of India, a large proportion of the sample (58.8%) population engaged in agriculture, with the remainder in labouring (17.2%) and other occupations (public service, private service, housemaid, business, housewife, etc.) that sum to 23.9%.

3.2 Response pattern and acceptance rate

Figure 1 depicts the pattern of responses to the three WTP questions. Group 1 refers to the sub-sample given the starting bid of Rs 100, Group 2 Rs 75 start and Group 3 Rs 50 (with number of respondents are in brackets).

Figure 1: Pattern of responses to WTP questions, by initial bid value

$$\begin{array}{c} Group\ 1 \\ (399) \end{array} \left\{ \begin{array}{ll} N(97) & instalment \\ & Y(302) \end{array} \right. \left\{ \begin{array}{c} N(91) \\ Y(6) \end{array} \right\} \xrightarrow[Y(308)]{bid\ 100} \left\{ \begin{array}{l} Y(110) \xrightarrow{bid\ 200} \left\{ \begin{array}{l} Y(9) \\ N(101) \\ DK(0) \end{array} \right. \\ \left\{ \begin{array}{l} DK(1) \\ N(197) \end{array} \right\} \xrightarrow{bid\ 75} \left\{ \begin{array}{l} Y(122) \\ N(75) \\ DK(1) \end{array} \right. \end{array} \right.$$

$$\begin{array}{c} Group\ 2 \\ (403) \end{array} \left\{ \begin{array}{ll} N(92) & instalment \\ & Y(311) \end{array} \right. \left\{ \begin{array}{c} N(90) \\ Y(2) \end{array} \right\} \xrightarrow[Y(313)]{bid\ 75} \left\{ \begin{array}{l} Y(206) \xrightarrow{bid\ 150} \left\{ \begin{array}{l} Y(8) \\ N(198) \\ DK(0) \end{array} \right. \\ \left\{ \begin{array}{l} DK(2) \\ N(105) \end{array} \right\} \xrightarrow{bid\ 50} \left\{ \begin{array}{l} Y(89) \\ N(16) \\ DK(2) \end{array} \right. \end{array} \right.$$

$$\begin{array}{c} Group\ 3 \\ (398) \end{array} \left\{ \begin{array}{ll} N(82) & instalment \\ & Y(316) \end{array} \right. \left\{ \begin{array}{c} N(76) \\ Y(6) \end{array} \right\} \xrightarrow[Y(322)]{bid\ 50} \left\{ \begin{array}{l} Y(291) \xrightarrow{bid\ 100} \left\{ \begin{array}{l} Y(56) \\ N(235) \\ DK(0) \end{array} \right. \\ \left\{ \begin{array}{l} DK(1) \\ N(30) \end{array} \right\} \xrightarrow{bid\ 25} \left\{ \begin{array}{l} Y(28) \\ N(2) \\ DK(1) \end{array} \right. \end{array} \right.$$

In the dataset 4/1200 respondents chose the 'don't know' option, kept saying 'don't know' all through the survey and did not state their maximum WTP. These responses are treated as missing. 257 respondents (21.5%) were not willing to pay anything for a TMN. Therefore 939 is the sample size used in the two models for each stage of the double-bound bid questioning process.

To give a clear overview of the data, the cumulative bid acceptance response rates are presented in Table 2. The columns of Table 2 separate the respondents according to which initial bid faced, while the rows are ordered according to the amount, which each response rate[2] refers to. Inspection of Table 2 shows the expected negative relationship between the initial DC1 bid amount and the probability of its acceptance (see bold type). Within any column, reading up from the DC1 amount shows the acceptance probabilities for the bid-decreasing path, while reading down from the DC1 amount shows the bid-increasing path. Again, within any column (initial bid) the expected negative relationship between bid amount and acceptance probability is obtained. However, reading across the rows of Table 2 it is evident that there is a positive relationship between probability of bid acceptance and the initial bid amount such that given any bid amount the probability of accepting the bid amount is greater for the respondents with relatively high initial bid amounts than for those with relatively low initial bid amounts. For example, considering the bid amount

[2] These are cumulative bid-acceptance response rates (aggregating from highest bid down to lowest bid), i.e., a respondent who accepts a bid of Rs 200 in Group 1 is assumed to accept the bid of Rs 75.

of Rs 75 (the fifth row in Table 2), the rate of positive responses rises from approximately P=0.66 where the initial bid amount was Rs75, to approximately P=0.76 with an initial bid amount of Rs 100.

Table 2: Cumulative bid acceptance response rates for three initial bid amounts and corresponding double-bound bidding trees

Response amount	Initial bid amount		
	Rs 50	Rs 75	Rs 100
Rs 25	0.993769		
Rs 50	**0.906542** [a]	0.948553 [b]	
Rs 75		**0.662379** [a]	0.755700 [b]
Rs 100	0.174455 [a]		**0.358306** [b]
Rs 150		0.025723	
Rs 200			0.029316

The rows of Table 2 show that three bid amounts have more than one observed response rate (denoted ‘a’ and ‘b’). Two-tailed Z-tests[3] assessed the significance of differences between each pair of the response rates in such rows, and the results are presented in Table 3. Based on the significance level, higher DC1 amounts generate significantly higher probabilities of acceptance in their subsequent DC2 bidding trees than do lower initial bid amounts.

Table 3: Two-tailed Z scores for differences in bid acceptance response rates for respondents facing different initial bid

Response amount	Z score a vs. b
Rs 50	2.047856**
Rs 75	2.568149**
Rs 100	5.312656***

Significant levels: ** $p<0.05$; *** $p<0.001$

3.3 Regression Models

Table 4 shows that, in addition to the constant, five variables and the 5% level and on (cow) at the 10% significant level explain variation in WTP. With the exception of the negative natural log of bid value, showing that as price rises demand falls, all variable are positive. Each sign is as expected. However, it is interesting that the degree of mosquito nuisance is not as important an influence as their simply being considered some degree of nuisance. Total household income has a significant effect on whether the in-the-market consumers will accept the first bid, though the magnitude of the effect is very small. It also appears that respondents who know the market price of a 6*4 net are more likely to accept the first bid than the reference respondent, perhaps indicating an interest in a similar product. We note that two variables in this model also explain variation in those who decide to enter the market, as depicted in Appendix 1; household income and whether the respondent knows the price of an untreated net.

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[3] The equation for the test is: $Z = (P_b - P_a) / \sqrt{P_b(\frac{1-P_b}{n_b}) + P_a(\frac{1-P_a}{n_a})}$ where P is the cumulative bid acceptance response rate for a group of size n.

Table 4: Logit regression models of WTP for TMNs from first bidding stage: base and reduced models

	Base Model Coefficient (Robust standard errors)	Reduced Model Coefficient (Robust standard errors)
Respondents education		
No education and primary	Base	
Further education	.12 (.235)	
Does the respondent consider mosquitoes to be a nuisance? Major	1.52 (.61)**	1.35 (0.63)**
Minor	1.91 (.64)***	1.78 (0.65)***
None	Base	
Preferred method (smoke) Yes	.18 (.24)	
No	Base	
Prefers mosquito net Yes	.48 (.30)	
No	Base	
Preferred method (using a sheet) Yes	.19 (.25)	
No	Base	
Use mosquito coils Yes	.64 (.70)	
No	Base	
Apply oil to body Yes	1.87 (1.21)	
No	Base	
Use fan Yes	-.10 (.34)	
No	Base	
Does the respondent know the cost of a 6*4 net in the market? Yes	.46 (.20)**	.55 (.19)***
No	Base	
Household size	-.04 (.04)	
Irrigate land (in acres)	.13 (.05)***	
cow	.06 (.04)	.08 (.04)*
Total number of anti-mosquito methods used	-.04 (.15)	
Number of nets the household owns	.12 (.07)	
Members of the family suffering from Malaria last year	.08 (.06)	
Number of nets you would buy at this price	.04 (.09)	
Total income	3.47e-06 (4.57e-06)	.0000107 (3.17e-06)***
Ln of the first bid values	-4.47 (.44)***	-4.47 (.42)***
Wealth index	.17 (.20)	
Household own transport index	.04 (.20)	
cons	17.35 (1.99)***	17.78 (1.93)***
Goodness of fit: Pearson chi2 (821)		801.63
Prob > chi2		0.6791
Correctly classified		75.29%
n	939	939
Log pseudolikelihood	-455.99	-465.10
Wald χ^2 (degrees of freedom)	198.40	168.07
Probability > χ^2	0.0000	0.0000

***** $p \leq 0.01$, ** $p \leq 0.05$, *$p \leq 0.1$**

In the second bidding stage (see Table 5), none of the significant variables from the first bid drop out of the model of the second bid value and all but one remain with the same sign. However the change in sign of the natural log of the first bid values from negative to positive suggests that, controlling for other factors, the higher bid the respondent faced in the first bidding stage, the more likely he or she would accept the second bid. Five additional statistically significant variables enter the second-bid model, four at the 5% level and 1 (oiling the body to deter mosquitoes) at the 10% level. Three of these variables increase WTP; oiling the body, the total number of anti-mosquito methods used and a wealth index. The within household wealth index has a relatively large positive effect on the probability of accepting the second bid value. Two variables decrease WTP; using a fan to deter mosquitoes and household size. The least expected is household size but larger households having less money per head to spend on purchasing a TMN might explain it.

Table 5: Interval regression models of WTP for TMNs from second bidding stage: base and reduced models

	Base Model	Reduced Model
	Coefficient (Robust standard errors)	Coefficient (Robust standard errors)
Respondents education		
No education or primary	Base	
Further education	4.37 (2.95)	
Type of House: Kaccha	Base	
Semi pucca	-.230 (4.03)	
Pucca	-1.866 (4.64)	
Does the respondent consider mosquitoes to be a nuisance? Major	16.31 (6.37)**	15.33 (6.27)**
Minor	20.66 (6.62)***	20.77 (6.43)***
None	Base	Base
Prefers mosquito net: Yes	5.08 (3.21)	
No	Base	
Preferred method (using a sheet): Yes	3.23 (2.64)	
No	Base	
Use mosquito coils: Yes	12.47 (7.92)	
No	Base	
Use odomos: Yes	7.60 (23.92)	
No	Base	
Apply oil to body: Yes	17.88 (9.57)*	16.38 (9.78)*
No	Base	
Use fan: Yes	-6.70 (3.80)	-7.96 (3.60)**
No	Base	
Does the respondent know the cost of a 6*4 net in the market? Yes	7.39 (2.43)***	8.25 (2.34)***
No	Base	Base
Household size	-1.08 (.57)*	-1.31 (.55)**
Irrigate land (in acres)	.53 (.46)	
cow	1.39 (.57)**	1.49 (.55)***
Total number of anti-mosquito methods used	2.06 (2.12)	3.61 (1.61)**
Number of nets the household owns	.46 (1.02)	
Number of nets you would buy at this price	-.79 (1.07)	
Total income	.0000666 (.000)	.0001243

		(.0000408)***
Ln of the first bid values	23.26 (3.85)***	22.77 (3.79)***
Wealth index	4.62 (2.35)**	5.28 (2.23)**
Household own transport index	1.45 (2.59)	
cons	-37.70 (18.61)*	-34.49 (17.42)**
/lnsigma	3.27 (.06)***	3.28 (.06)***
sigma	26.30 (1.54)	26.55 (1.57)
RESET Test: Chi2 Prob > chi2		 0.02 0.8750
n Log pseudolikelihood Wald χ^2 (degrees of freedom) Probability > χ^2	939 -894.837 155.22 0.0000	939 -900.732 100.40 0.0000

*** p ≤ 0.01, ** p ≤ 0.05, *p ≤ 0.1

3.4 Estimation of mean and median WTP

By substituting all the parameters estimated from the three models (including the spike model in Appendix 1) into equations (9) and (10), mean and median WTP can be calculated for each model. The predicated mean probability of saying 'yes' for the screening question is 0.7851, so average $\hat{\rho}$=1-0.7851=0.2149 < 0.5, which means the median WTP is positive. Table 6 shows that the mean predicted WTP ranges from 56.6 to 91.0 depending on whether the first bid and zero values are accounted for. The range for the mean and median values is very similar and values are relatively close for all estimations of central tendency. As expected, the spike models have lower values and these tend to be around 20 rupees different regardless of the bid stage. Table 6 also shows a switch in the placement of the mean and median values – the mean is higher than the median for the first bid, but lower than the median in the second bid with the spike model (although not for the without spike model).

Table 6: Mean and Median WTP of the first- and second-stage bids

		Mean [95% Conf. Interval]	Median [95% Conf. Interval]
1st bid	With spike	71.1 [69.3 72.9]	70.8 [69.0 72.6]
	Without spike	91.0 [89.2 92.9]	90.6 [88.8 92.5]
2nd bid	With spike	69.3 [67.8 70.8]	75.0 [72.7 76.8]
	Without spike	88.2 [87.4 89.0]	87.0 [86.2 87.6]

Table 7 reports paired T-tests of the difference between the estimated means from the first-bid and second-bid models. For the overall sample, the estimated means of with and without spike from the first-bid model are significantly higher than those from the second-bid model. However, when the T-tests are performed for different sub-samples (respondents facing a first bid of Rs50, 75, 100, separately), results become more complex; the mean values are higher than median values when the initial bid is 50 but reversed when the initial bid is 100, with differences between DC1 and DC2 being statistically significant. At Rs75 the mean and median are very similar and the difference between DC1 and DC2 models is not significantly different for the spike model but is for the without spike model.

Table 7: Paired t test of means between bid1 and bid 2 with and without spike

	With spike	Without spike

Variable	Mean	[95% Conf. Interval]	Mean	[95% Conf. Interval]
1st bid mean	71.1	69.32 72.87	91.0	89.20 92.86
2nd bid mean	69.3	67.84 70.78	88.2	87.38 88.98
difference	1.8	.90 2.67	2.8	1.47 4.23
Ho	mean(1st bid mean – 2nd bid mean) = mean(diff) = 0			
Ha	Ha: mean(diff) != 0 t = 3.97 P > |t| = 0.0001		Ha: mean(diff) != 0 t = 4.04 P > |t| = 0.0001	

3.5 Comparison of stated and actual WTP

Because the price TMNs were actually sold at was Rs75 we conducted two tests of predictive behaviour for the DC1. Table 8 combines those who said yes to Rs75 and 100 as one group, as those who said no to 100 may have been willing to pay 75 whereas Table 9 combines those who said no to Rs50 or 75 as one group to increase the accuracy of the lower value group. These tables show that stated WTP was a particularly poor predictor of purchase when people said they were WTP either Rs 50 or 75 at the DC1 stage but a fair predictor of responses when bid values were grouped as either Rs 75 or 100 results. Table 10 shows that DC2 was a little more accurate in predicting actual purchase decisions.

Table 8: Stated versus actual WTP of from DC1 (accurate upper values)

	Did not buy a TMN	Bought a TMN	Total
Stated not WTP Rs 75 or 100	121	91	212
Stated was WTP Rs 75 or 100	25	58	83
Total	146	149	295

Pearson chi2(1) = 17.3370 Pr = 0.000 Sensitivity: 69.88% Specificity 57.08% Area under ROC: 0.6348

Table 9: Stated versus actual WTP of from DC1 (accurate lower values)

	Did not buy a TMN	Bought a TMN	Total
Stated not WTP Rs 50 or 75	51	23	74
Stated was WTP Rs 50 or 75	95	126	221
Total	146	149	295

Pearson chi2(1) = 14.9140 Pr = 0.000 Sensitivity: 57.01% Specificity: 68.92% Area under ROC: 0.6297

Table 10: Stated versus actual WTP of from DC2

	Did not buy a TMN	Bought a TMN	Total*
Stated WTP Below Rs 75	79	36	115
Stated was WTP Rs 75+	43	84	127
Total	122	120	242

Pearson chi2(1) = 29.3000 Pr = 0.000 Sensitivity: 66.14% Specificity: 68.70% Area under ROC: 0.674 2

* excludes those from the bid-path who said yes to Rs50 and no to Rs100 as their answer with respect to Rs 75 is not clear

4.0 Discussion

Although the application of WTP in health care is growing rapidly (Diener, et al., 1998; Klose, 1999), there is still no consensus on the best elicitation method in health care. This study provides evidence both for and against the robustness of double-bound bidding format. Possibly the evidence of greatest concern regarding DC2 is that the second-stage of questioning does not lead to a dissipation of what is clear evidence of starting point bias, even though it does indicate the impact of starting point bias that would remain undetectable in DC1 format. We are also concerned that there was a higher probability of accepting a higher bid in one group relative to another (p=0.029 for Rs200 vs p=0.026 for Rs150). As both were on bid increasing paths and it might suggest that 'yea saying' effects are exacerbated with high starting bids. This might occur if respondents felt that Rs100 was obviously overvaluing a TMN (perhaps because they knew the price of an untreated net) and, as they had already said 'yes' to it, why not keep up the pretence. This would be worthy of further investigation as it could affect all estimates of the upper end of distributions, particularly if there are close market substitutes.

The reduced DC2 model had a larger number of variables explaining WTP, which is evidence of the greater efficiency of this question format. The additional variables were all of the expected sign[4] and included a key additional economic variable (wealth index) and indicator of felt need (total number of methods used), both of which indicate the DC2 model has greater validity.

By testing the difference of means estimated from each bidding stage, the results show that the welfare estimation from the first bidding stage is statistically significantly higher than from the second bidding stage, however, the welfare estimations of WTP from both bidding stages are very close to each other, so it could also indicate that either the double-bound bidding game provides stable estimations of sample population's WTP for TMNs or that the DC1 adequately captured the mean value. However, the estimated means from both stages are quite different from mean WTP calculated from the final open-ended question of people's maximum WTP, which gave values of Rs 73.1 (excluding zeros) and Rs 57.4 (including zeros) (Bhatia and Fox-Rushby, 2002) and suggests that the both DC1 and DC2 question formats could overestimate stated WTP.

As the estimation of mean WTP using the spike model from the DC2 is only a little lower (Rs 1.8) than from DC1 while the median WTP from the second bidding stage is a little higher (Rs 4.2) than the first stage, it suggests the second question either produces (or better captures) a positively skewed distribution. This is interesting because Alberini (1995) has argued that it does not pay to place the largest bids beyond the 97th or 98th percentile although, more recently Alberini et al (2005) stated that "with right skewed distributions of WTP the estimate of mean WTP depends crucially on 'nailing down' the upper tail of the distribution, a task that can be accomplished only by querying respondents about their WTP relatively large bid amounts". Our results suggest the second-bid question may have managed this successfully, which would provide some support for the internal validity of the DC2 model.

The comparison between stated and actual WTP for DC1 and DC2 questions is novel and appears to suggest a marginal advantage to adding in follow-up questions, although this could be an artefact of the groupings in DC1. However the movements around responses to DC1 above and below Rs75 (Section 3.4) may also be related to the varied results we had when comparing mean values between DC1 and DC2 by

[4] Except perhaps household size, which we need to investigate a little further.

initial bid value. It seems that those offered a higher initial bid have an important influence on the overall mean value (especially through the follow up bid) but that those who do say they will buy are also more likely to do so in practice. This might suggests that those in the middle of a distribution may more easily change between following their stated values and actual practice, perhaps because their preferences are not so exact as those at the tail-ends of distributions. This could be investigated further using approaches set out by Blumenschein et al (2000) and Alberini et al (2003).

The use of a spike model was designed to account for a nonzero probability of zero WTP. As expected, the estimated mean and median WTP using the spike model are lower than conventional logit model's estimation. The application of a spike model has much more effect when the population of zero WTP takes up a relatively large proportion, as in this dataset it is about 22%. Given this WTP study was done in a rural area of India, it is reasonable to expect that some of the sample population are too poor to afford a TMN, thus, the application of the spike model can improve the estimation in this case by accounting for the zero WTP. Our data also suggest that the respondents are quite stable in whether or not they are willing to pay for the TMN at all no matter whether the instalment option is offered or not, which suggests that the screening question might be useful in separating out-of-the-market consumers from in-the-market consumers.

There are some suggestions for further research. In terms of distributional assumptions for WTP, some researchers have used a lognormal distribution in the analysis of WTP data whilst others a right truncation at people's income level accounting for the possibility that some people's reported WTP might be larger than their income. There is no evidence indicating which distribution is more fit to the double-bound WTP questionnaire format with allowing the probability of zero WTP. Thus, this is a promising further research area. There are alternatives of the choice of models. For example, many double-bound bidding game experiments taken in environmental economics design have used a multi level model (MLM) to account for such study design. One of the main flexibilities of using an MLM approach is that it is not necessary for all individuals to answer all questions. (Bateman and Willis 1999), by using a MLM approach, there is no need to separate out-of-the-market consumers from in-the-market consumers. Alternatively a double-hurdle model could be used to account for the excess zero values. Further research could compare these models to explore the potential for better model for the DC2.

What is clear to us is that not only is the method of estimation key (Giraud et al, 2001) but also the methods of calculating mean and median values (Haab & McConnel 1998). However, we have not been able to determine whether the bias uncovered is the method itself or whether it is introduced as a result of having to specify the underlying distribution, or both (Ready et al 1996). Indeed, this may be impossible (Alberini et al 2005) and this leads to proposing further development of approaches that counteract starting point bias. Telling respondents there are multiple bids coming or asking questions about the follow up questions (Alberini et al 2005) may be one route.

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Appendix 1: The 'spike' model (Logistic regression of WTP for TMNs: reduced model)

		Reduced Model Odds ratio (Robust standard errors)
Intervention Village	Treated Mosquito nets	0.23 (0.12)**
	In-house spray village	1.05 (0.31)
	Active case detection	0.81 (0.26)
	Outside trial area	Base
Household size		1.156 (0.08)**
Caste	Schedule caste	0.29 (0.23)
	Schedule tribe	Base
	Other backward caste	0.31 (0.11)***
	Other caste	0.23 (0.11)**
House type	Kaccha	Base
	Semi pucca	0.47 (0.11)***
	Pucca	0.74 (0.26)
Level of mosquito nuisance	Major	4.20 (2.20)**
	Minor	4.14 (2.42)**
	None	Base
Is preferred method a mosquito net?		1.52 (0.37)*
Does respondent know cost of 6*4 net (yes)?		1.65 (0.38)**
How many nets do you own?		0.74 (0.08)**
Total expenditure incurred on treatment		1.01 (0.00)***
Who takes decision to buy in household?	Self	Base
	Other	0.00 (0.00)***
Total annual income (Rs in quartiles)		

Lower (0 – 10000)	Base
Second (10001 – 16000)	1.71 (0.48)*
Third (16001 – 30000)	1.87 (0.57)**
Upper (30001 +)	3.38 (1.38)**
n	1196
Goodness of fit (Hosmer-Lemeshow test)	χ^2 = 6.02, (df = 8), p = 0.65
Log pseudolikelihood Wald χ^2 (degrees of freedom) Probability > χ^2	-350.61 123.18 (19) < 0.001

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

Source: Mistry et al (submitted)