A new approach for analyzing multiple bounded WTP data
- Certainty dependent payment card intervals

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Abstract
In this paper we analyze the multiple-bounded (MB) format in which uncertainty is directly incorporated into the WTP question. We introduce a new approach to estimate mean and median willingness to pay (WTP) using MB data by allowing respondents to expand their WTP intervals by shifting their upper bound. Thus, less certain respondents will state a wider WTP interval. This differs from the Welsh and Poe (1998) approach (WP) which shifts the entire WTP interval and likely overestimates mean and median WTP when uncertainty is introduced. To compare empirically our expansion approach to the WP-approach, we use survey data from 2004 that elicited WTP for implementation of a predator protection policy in Sweden. In addition to its more intuitive appeal, our results indicate that the interval expansion approach better fits the data and provides a smaller range of estimated WTP. It also with better precision estimates the mean and median WTP when preference uncertainty is considered, and its estimates are less sensitive to alternative distributional assumptions.

Keywords*: contingent valuation, preference uncertainty, elicitation format, multiple-bounded, payment card, willingness to pay, predators*

JEL-Codes: C81, Q20, Q26, Q28

1. Introduction

The method of contingent valuation has become one of the dominating non-market valuation methods, presumably due to its ability to capture passive-use values (Carson et al., 2001). In spite of its popularity it is often under attack from critics who suggest that the estimated values are flawed due to hypothetical and strategic bias (Kahneman and Knetsch, 1992; Diamond and Hausman, 1994). The former bias refers to the fact that contingent valuation is based on individuals' behavior on constructed markets rather than on real market behavior.

Independent of the elicitation format applied, respondents answering a hypothetical willingness to pay question face a difficult task. This difficulty presumably increases the rate of non-response, or "I don't know" answers (when offered as an alternative). The underlying problem is that respondents often are unfamiliar with the good being valued, or the valuation situation itself. Thus, the challenge for researchers is to provide sufficient information to the respondents so they may familiarize themselves with the valuation scenario, but to avoid imposing a time-consuming burden that overwhelms or discourages respondents. The lack of information, time, or interest causes preference uncertainty, which makes the valuation task difficult.

During the last fifteen years several articles have examined preference uncertainty. The purpose of these efforts was to develop approaches that capture the inevitable preference uncertainty that respondents face in answering a question with which they are not familiar. In this paper we analyze methodological issues concerning one of those approaches, the multiple-bounded (MB) format introduced by Welsh and Poe (1998). We introduce a new technique for analyzing MB data, which is not only more intuitive compared to the conventional techniques, but also more precise in its estimate of mean and median WTP. Before describing this new approach, we provide an overview of the MB format and previous applications.

A MB question is a combination of an ordinary payment card and a polychotomous choice question introduced by Ready et al. (1995). In the MB format respondents face multiple bids rather than one bid, as in a polychotomous choice question. The respondents are asked how likely an actual "yes-vote" would be by marking one of the multiple verbal probability statements (e.g. "definitely yes", "probably yes", "unsure" "probably no" or "definitely no") associated with each bid amount.

In previous studies concerning the MB format three different empirical approaches for analyzing such data have been suggested. First, the seminal approach taken in Welsh and Poe (1998), where the probabilistic answers (e.g., "probably yes" or "probably no" etc.) are re-coded into certainty answers ("yes" or "no"). Underlying such re-coding is an assumption concerning the real meaning of the probability statements (e.g. "probably yes" means "yes" and "unsure" means "no"). After re-coding, the MB data converts to double-bounded WTP data which can be estimated with a discrete probability model. The second approach, suggested by Evans et al. (2003), assigns numerical probabilities to the verbal probability statements (e.g., "probably yes" means 75% chance of saying yes), and then creates an estimator that accommodates uncertainty on behalf of both the respondent and the researcher. Finally, Alberini et al. (2003) argue that an individual's response to each specific bid in the questionnaire emerges from a separate (independent) draw from each individual's own willingness to pay distribution rather than being driven by a single true value. From this assumption it follows that several panel modeling options become possible. For example, a simple "pooling" approach can be employed, essentially assuming complete independence between the responses to different bids. Alternatively a random (or fixed) effects model could be estimated which takes into account possible correlation among responses to bids. Besides revealing information about response-uncertainty, Alberini et al. (2003) suggest that the MB format increases the efficiency of the willingness to pay estimates compared to the dichotomous choice and the payment card format. Indeed, such efficiency improvement will be present *if* the responses on successive bids for each individual are not perfectly dependent, i.e. if the correlation is less than one. If the correlation is less than one, the implication is that an individual's willingness to pay changes throughout the "bidding process" (i.e. it is not obvious that respondents who answered "no" to \$10 also will answer "no" to \$100). As a consequence there is information not only in the switch from "yes" to "no" as in a payment card setting, but also in the response to all other bids. Alberini et al. (2003) find that the correlation is close to zero and estimates a random valuation function similar to Wang (1995).[1]

Vossler and Poe (2005) argue against the result in Alberini et al. (2003) on both theoretical and empirical grounds. Theoretically, they argue that the correlation between responses to successive bids ought to be close to one. That is, there are no theoretical justifications for assuming that individuals "change their mind" through the bidding process. Empirically, they analyzed data from Alberini et al. (2003) and found that the correlation coefficient was close to one, indicating dependence and, therefore, no efficiency improvement.

[1] Wang (1997) argues that uncertainty might be one reason for answering "don't know" (DK) to a dichotomous choice (DC) question. In such cases it is incorrect to treat the DK answers as a "no", or to delete them from the sample. To take advantage of some DK answers, a random valuation function could be estimated, assuming that each respondent's answer to a DC question reflects an implicit valuation distribution rather than one true value.

The Evans et al. (2003) approach is potentially useful, but its weakness is its subjective translation of verbal statements into probabilities. To confront this problem, they utilize behavioral research to interpret what an individual means when they say “probably” or “maybe.” However, the precise meaning of such words likely differs between individuals and over time, which would require continuously updated interpretations. One alternative might be to ask the respondents themselves to translate the statements into probabilities, but this works against the main purpose and strength of the MB format, which is to simplify the valuation task.

The Welsh and Poe (WP) approach is perhaps the easiest one, but its usefulness in cost benefit analysis is questionable. In our opinion, the only relevant information contained in MB data is the bids corresponding to the two probability statements that are easily translated into probabilities: “definitely yes” and “definitely no.” Using the WP-approach two specific re-codings are possible: (1) “definitely yes” means “yes” and all other statements mean “no”; and (2) all probability statements mean “yes” except “definitely no.” Estimating the mean or the median WTP conditioned on these two re-codings will produce a low and a high bound for the WTP. However, it could be useful to include uncertainty levels for cognitive reasons, i.e. middle responses may serve as means of reaching the final destination.

In this paper we introduce a new approach for analyzing MB data that is similar to the WP-approach. However, the approaches differ fundamentally in their re-coding procedure as we explain in the next section. We use data from a contingent valuation survey concerning protection of the four large predators in the Swedish fauna and show that the two approaches differ significantly in their influence on the estimated central values of the WTP distribution. Furthermore, our new approach estimates the higher bounds of mean and median WTP with better precision and is less sensitive toward distributional assumptions.

The rest of the paper is structured as follows. In section 2 we explain preference uncertainty and how it relates to the MB format. In section 3 we give a brief description of the underlying economic models, as well as the econometric specifications of the willingness to pay models. In section 4 we describe the data collection procedure and provide a descriptive analysis of the data. In section 5 we present the results from our econometric analysis. Section 6 is devoted to concluding comments and a discussion.

2. Treatment of observations elicited from a multiple-bounded question

When willingness to pay is elicited from a MB question, the respondents are allowed to express uncertainty. Figure 1 illustrates the typical assumption that respondents are expected to be certain about paying relatively small amounts, but become less certain as the amount increases (the X's is an example of an expected answer).

Amount (SEK)	"Definitely yes" (DY)	"Probably yes" (PY)	"Unsure" (U)	"Probably no" (PN)	"Definitely no" (DN)
10	*X*				
50	*X*				
100		*X*			
200		*X*			
400			*X*		
800				*X*	
1500				*X*	
3000					*X*
5000					*X*

Figure 1: Illustration of the MB format. The X's is an example of an expected answer to the MB question.

Figure 2 illustrates the trade-off facing a respondent between income and the quantity of the studied environmental amenity. The income level M_0 and amenity level z_0 represents the status quo. If we assume that the respondent is unfamiliar with this type of trade-off between money and the environmental amenity, or for some other reason feel uncertain about her WTP, it means that she is not certain about the precise location of her indifference curve. Given that the increase in the amenity level is perceived as a good, it is possible to derive logical bounds for the utility space where the respondent's indifference curve must lie. First, increasing the amenity level while holding income constant would certainly be preferable to the status quo situation because it corresponds to a higher utility level. Second, if the income level decreases while the amenity level is held constant, then this would certainly not be preferable to the status quo situation. Hence, the respondent knows for certain that the indifference curve is located in the utility space bounded by the dashed lines in Figure 2. It could also be argued that the respondent knows for certain that she would trade a relatively small amount of money for a relatively large increase in the amenity level. This type of preferable trade-off is illustrated by the area between the DY-line and the horizontal dashed line. This means that the respondent would at least be willing to pay M_0-M_L for the increase of the amenity level to z_1.[2] By a similar reasoning the respondent is certain that she does not want to trade a relatively large sum of money for a relatively small increase in the amenity level. This undesired trade-off is indicated

[2] The lower bound could be understood as an implicit contract between the respondent and the researcher where the respondent agrees to pay "definitely" a specific amount (the highest "definitely yes" amount). Interpretation of payment card data is discussed in Harrison and Kriström (1995).

by the area between the DN-line and the vertical dashed line. This means that the respondent would not be willing to pay any amount over M_0-M_U.

Thus, for a respondent to give a good guess about the precise location of her true indifference curve, she would logically want to state an interval with a lower bound equal to M_0-M_L and a higher bound equal to M_0-M_U. At some point within this interval the indifference curve has to cross the z_1 line. If we ask the respondent to state a narrower WTP interval, the respondent would be less certain that the indifference curve would fall within that interval and hence would answer in terms of probabilistic statements like "probably" and "unsure."

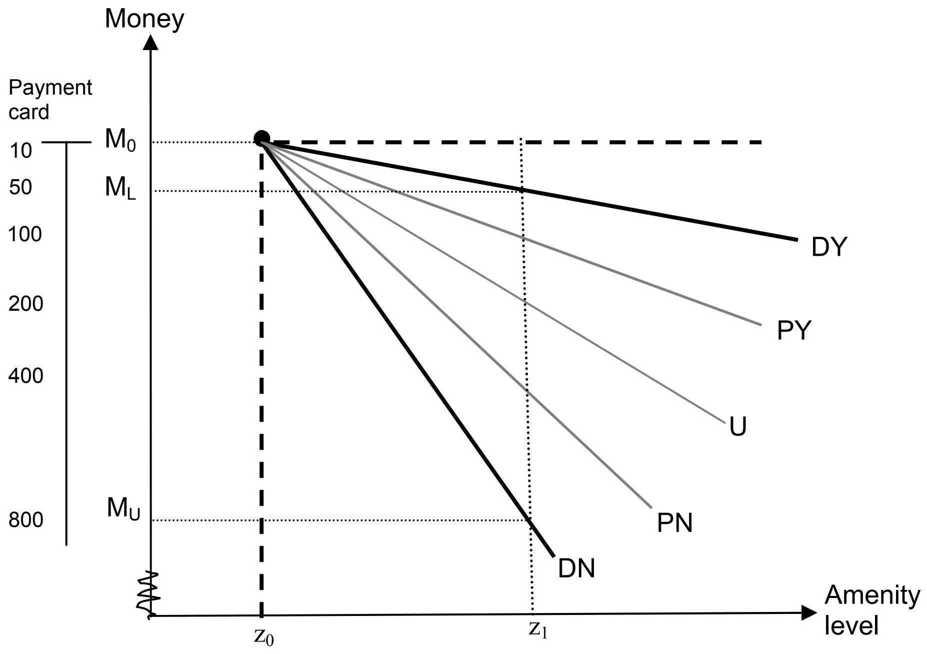

Figure 2: Preference uncertainty in a two dimensional utility space.

As mentioned above, the WP-approach is based on an arbitrary re-coding procedure that translates the data into "yes" and "no." Based on the example in Figure 1, four different re-codings are possible: (1) DY = "yes"; (2) DY and PY = "yes"; (3) DY, PY and U = "yes"; or (4) DY, PY, U and PN = "yes." This implies that both the upper and lower bounds of the WTP interval will move upwards as the accepted certainty level decreases. For example, assume that only DY = "yes", then WTP in Figure 1 will be in the interval [50, 100]. If both DY and PY = "yes", then WTP will be in the interval [200, 400]. Thus, allowing for uncertainty shifts the interval upwards.

The results in Welsh and Poe (1998) showed, not surprisingly, that the median and mean WTP increased as lower certainty levels where accepted as a "yes." Further, by comparing the results from a MB question to the results from other elicitation formats based on the same valuation scenario, it was found that the results from the *probably yes* model[3] produced similar results as the payment card and the open-ended format, whereas the results from the *unsure model* were similar to the results elicited from the dichotomous choice question. The authors concluded that, given that the choice of elicitation format significantly influences the estimates of mean and median WTP, the MB format has a practical advantage because it is possible to perform a sensitivity analysis of WTP with respect to uncertainty.

One obvious drawback with the WP-approach is that there is no obvious interpretation of the estimates to the middle responses and, therefore, their use in policy-analysis is questionable. The meaning of "probably yes," "unsure" and "probably no" is heterogeneous among individuals and has to be decided by the researcher. The only certainty levels that have a clear interpretation are "definitely yes" and "definitely no". [4] This information can be used to derive a higher and a lower bound for either the mean or median WTP. However, by using the WP-approach the researcher does not utilize all of the "certainty information" when estimating the higher bound because the certain information given by the "definitely yes" level is exchanged for the uncertain information given by the "probably no" level.

The WP re-coding implies that the respondent states a WTP interval, conditioned on a probabilistic statement, which will include her true WTP. Or, put differently, the corresponding utility space will contain her indifference curve with some probability. The weaker the probabilistic statement, the lower the probability that the corresponding interval will include the indifference curve. Therefore, the higher bound of WTP will be overestimated. It is therefore necessary for the researcher to translate the probabilistic statement "probably no" into a real probability in order to scale down the estimate.

Our alternative to the WP-approach of moving the respondents WTP intervals is to expand them. Applying this method to the example in Figure 1 and assuming that DY and PY = "yes" implies that the true WTP lies within the interval [50-400]. One fundamental difference is that the expansion approach considers uncertainty without discarding the most reliable information about each respondent's WTP (i.e., the "certain" response).

In the expansion approach the respondent becomes more certain that the stated interval includes her indifference curve because the stated interval becomes wider. Hence, when giving less of a

[3] The *probably yes* model means that both "Definitely yes" and "Probably yes" have been interpreted as a "yes" and all other options as a "no." In the *unsure model* "unsure" is also interpreted as a "yes."

[4] Groothuis and Whitehead (2002) argue on empirical grounds that "I don't know" responses to dichotomous choice questions would turn to "no" if the respondents where pushed to give a definite answer, simply because they dislike expenditures. The same could be argued for the different uncertainty levels in our study. On the other hand, if pushed to give a definite answer respondents may in general pay amounts they answered "probably yes" to (which is not equivalent to "I don´t know").

commitment the respondent should feel more certain about her answer. Determining the appropriate approach –moving or expanding the interval – depends primarily on how we characterize uncertainty. Given the trade-off illustrated in Figure 2, the WP-approach of moving the entire WTP interval does not seem intuitive.

3. Econometric specifications

The main objective of this paper is to study how to utilize MB data properly when estimating mean and median WTP. We begin by comparing two different econometric specifications that originate from different assumptions concerning the data generating process. In the first specification, it is assumed that a single willingness to pay amount drives the respondent's answer to each bid amount. As a consequence, the only interesting information lies between the highest "yes" and the lowest "no" bid. For example, if the respondent says "no" to $10 she will also say "no" to all higher amounts. Thus, the response to all other bids does not contain any additional information. Under this assumption, the MB format becomes equivalent to the payment card format. In the second specification, an individual's response to each bid is no longer driven by a specific value but instead emerges from a separate (independent) draw from each individual's own willingness to pay distribution. As a consequence there is information not only in the switch from "yes" to "no," but also in the response to all other bids.

The theoretical foundation of these models is based on the assumption that individuals derive utility from consumption of private goods, **q**, and an environmental public good, *z*. In this analysis only two levels of *z* are studied: z^0 is the initial level and z^1 is reached after implementation of the studied project. Individuals are assumed to be heterogeneous with respect to some characteristics, **X**. Furthermore they are assumed to maximize their utility, *u*, given income and commodity prices.

Let $e_i(\mathbf{p}, z, u_i)$ denote individual *i*'s expenditure function, where *u* denotes a specific utility level and **p** is a price-vector. Individual *i*'s WTP for a given change of the public good is equal to:

$$WTP_i = e_i^1\left(\mathbf{p}, z^1, u_i^0 \mid \mathbf{X}\right) - e_i^0\left(\mathbf{p}, z^0, u_i^0 \mid \mathbf{X}\right) \tag{1}$$

The probability that the respondents WTP is higher than the bid amount A_i is given by:

$$\Pr("yes_i") = 1 - \Pr("no_i") = 1 - \Pr(WTP_i < A_i) \tag{2}$$

Assume that WTP is an exponential function of a linear combination of observable characteristics and an additive stochastic term, ε, with zero mean and standard deviation σ. Under these assumptions the probability that a respondent will accept a specific bid, A_i, is[5]:

$$\Pr("yes_i") = 1 - \Pr(\ln(A_i) - \mathbf{BX_i} < \varepsilon_i) \quad (3)$$

Normalizing with the unknown standard deviation we get:

$$\Pr("no") = \Pr(\beta \ln(A_i) - \boldsymbol{\delta}\mathbf{X_i} < \eta_i) \quad (4)$$

Where $\eta_i = \frac{\varepsilon_i}{\sigma}$,$\boldsymbol{\delta} = \frac{\mathbf{B}}{\sigma}$ and $\beta = \frac{1}{\sigma}$.

Payment card approach

We utilize a double-bounded format: each respondent's WTP is bounded by the highest bid the respondent accepts and the lowest bid she does not accept. Hence, if we define A^L to be the highest "yes" bid, and A^U to be the lowest "no" bid, then the maximum WTP is $A^L \leq WTP < A^U$. We denote the cumulative distribution function of η as F, and let $F(A)$ be the probability for saying "yes" to bid A, and 1-$F(A)$ the probability for saying "no." The probability that the WTP lies between A^L and A^U can then be written as: $P(WTP > A^L) - P(WTP > A^U) = F(A^U) - F(A^L)$. The log likelihood is then:

$$L^{PC} = \sum_{i=1}^{N} \ln\left[F(A_i^U) - F(A_i^L)\right] \quad (5)$$

where N is the number of individuals. Under the assumption that the stochastic term is normally distributed, the parameter vector $\boldsymbol{\delta}$ and β can be estimated and then used to calculate the mean and median willingness to pay according to:

$$E[WTP] = e^{\left(\frac{\boldsymbol{\delta}\mathbf{X}}{\beta} + \frac{\sigma^2}{2}\right)} \quad (6)$$

$$Median = e^{\left(\frac{\boldsymbol{\delta}\mathbf{X}}{\beta}\right)} \quad (7)$$

The panel approach

It is straightforward to derive the likelihood function under the assumption that the response to each bid is a separate draw from the WTP distribution. This opens for several panel modeling

[5] The exponential WTP model suggests that the distribution of WTP is skewed to the right. This model was popularized by Cameron and James (1987).

options. For example we can employ a simple "pooling" approach, which assumes complete independence between the different bids. Thus, we can view the response to each bid amount as a new independent observation. This implies that we can model it as a dichotomous choice question where the number of observations equals the number of individuals times the number of bids. Following the notation above, we can then write the likelihood function as:

$$\ln L^{MB} = \sum_{i=1}^{N \cdot T} \left[S_i \cdot \ln\left((F(A_i)) \right) + (1 - S_i) \ln\left(1 - (F(A_i)) \right) \right], \tag{8}$$

where T is the number of bids and S an indicator variable that equals 1 if the respondent answers "yes" to the bid and "0" otherwise.

As an alternative to the pooling approach a random (or fixed) effects model could be estimated, taking into account possible correlation among responses to bids.

4. The survey and descriptive statistics

The empirical analysis below is based on survey data from 2004. The objective of the survey was to gather information about attitudes toward the four large predators in the Swedish fauna.[6] Of the 4,050 randomly selected individuals that received the mail survey, approximately 61 percent returned their answers after two reminders. To ensure that individuals living in regions of specific interest were selected we used a stratified random sample. In total, 10 strata were defined, including four wolf area strata.

Successful implementation of the Swedish government's predator policy means that the number of wolves and wolverines will increase significantly in the Swedish fauna, which can be seen as a good or a bad development, depending on one's perspective. Unfortunately, the survey did not include a question about the magnitude of the compensation needed to make respondents with negative preferences indifferent to the policy. However, since our interest in this paper concerns methodological issues regarding response uncertainty we will only focus on the respondents who are in favor of implementation.[7] A more complete policy-analysis of the predator policy is provided in Broberg and Brännlund (2007).

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[6] The four large predators are wolf (*Canis lupus*), bear (*Ursus arctos*), wolverine (*Gulo gulo*), and lynx *(Lynx lynx)*.

[7] The fact that the empirical analysis only includes respondents with WTP>0 is the main argument for applying the exponential WTP model described in section 3.

In addition to studying attitudes toward predators, the survey also included a two-part willingness to pay question regarding implementation of the predator policy. First, respondents were asked: *"Imagine that the predator policy package is important for securing survival of the Swedish predators in the long run. Implementation of the policy costs money. Would you be willing to contribute financially to such a project?"* Those who answered yes were asked a MB question as follows: "*Below, we list several amounts of an annual tax that you will have to pay for the next five years for implementation of the predator policy package, which covers wolves, bears, lynx and wolverines. Mark for each amount how certain you are about paying that amount*." Nine bids were presented in the payment card ranging from SEK 10 to SEK 5000.[8]

Table 1 summarizes the first WTP question and indicates that approximately 39 percent of the respondents were willing to contribute financially to the implementation of the predator policy. After adjusting with sample weights corresponding to the stratification, the number rises to 49 percent.

Table 1: Willingness to contribute to implementation of the predator policy (frequencies and percent)

	Frequency strata sample	Percent strata sample	Frequency population	Percent population
Yes	890	38.7	3 099 839	49.0
No	1 408	61.3	3 223 177	51.0
Total	2 298	100.0	6 323 016	100.0
Missing	144		383 986	
Total	2 442		6 720 381	

Only six respondents favoring implementation of the predator policy did not answer the MB question. However, those who did fill out the MB matrix did so in various ways. In Table 2 the responses to the MB question have been divided into different categories depending (primarily) on their uncertainty status and (secondarily) on whether or not their responses could be used directly in our empirical analysis or required individual interpretation. As shown, the majority of respondents filled out the MB matrix diagonally as expected. However, a large fraction of the respondents did not state any uncertainty, stating only "definitely yes" to one specific amount. We interpret such observations as if the WTP interval bounded by the highest amount they definitely would pay and the next amount on the payment card includes all the uncertainty levels. Other respondents expressed uncertainty but not diagonally (e.g. marked "probably yes" on one amount but left all else blank). The remaining respondents answered the MB question in an inconsistent or nonsensical way. In total, seven observations were assessed as being non-usable and deleted from the sample (e.g. two respondents stated "unsure" to all nine bids).

[8] One $US approximately equals seven SEK

Table 2: MB question response quality

Response quality	Percent
Uncertainty	
1. Diagonal	54.2
2. Diagonal after being individually analyzed	2.2
3. Uncertainty indicated but not diagonal	5.5
4. Non-usable	0.8
No uncertainty	
5. Only “definitely yes”	34.3
6. Both “definitely yes” and “definitely no”	2.6

In Table 3, we present descriptive statistics on the variables that are used in the empirical analysis for both our studied sub-sample and the total sample. The empirical analysis is carried out on a sub-sample of the 872 respondents that stated a positive WTP, had a non-zero household income, and answered the MB question consistently and interpretable.

Table 3: Descriptive statistics for sub-sample WTP>0 and whole sample. Mean values are presented with standard deviations in parenthesis

Variable	Mean sub-sample WTP>0	Mean total sample
Age	49 (15.25)	51 (16.78)
Share of retirees	0.14 (0.35)	0.28 (0.45)
Male (Yes=1)	0.46 (0.5)	0.51 (0,5)
Number of children in household	0.62 (0.94)	0.53 (0.94)
Number of adults in household	1.85 (0.81)	1.88 (0.77)
Member of green NGO (Yes=1)	0.15 (0.36)	0.08 (0.28)
Hunter (Yes=1)	0.07 (0.26)	0.15 (0.35)
Someone else in the household hunts (Yes=1)	0.09 (0.28)	0.14 (0.35)
Owner of dog (Yes=1)	0.27 (0.44)	0.22 (0.41)
Household income (SEK)	302 239 (175 145)	285 351 (166 482)
Lower bound WTP[a]	312.56 (21.03)	
WTP[a] NOBS	872	2442

[a] The lower bound is the mean of the highest amount the respondents agreed to definitely pay.

An illustration of how uncertainty may influence the WTP distribution is given in Figure 3, where we have drawn non-parametric survival functions for each certainty level.[9] As expected, when lower certainty levels are interpreted as "yes" answers, respondents are willing to pay higher amounts for implementing the predator policy. Hence, more probability mass is moved towards the middle and the right tail of the corresponding probability density function.

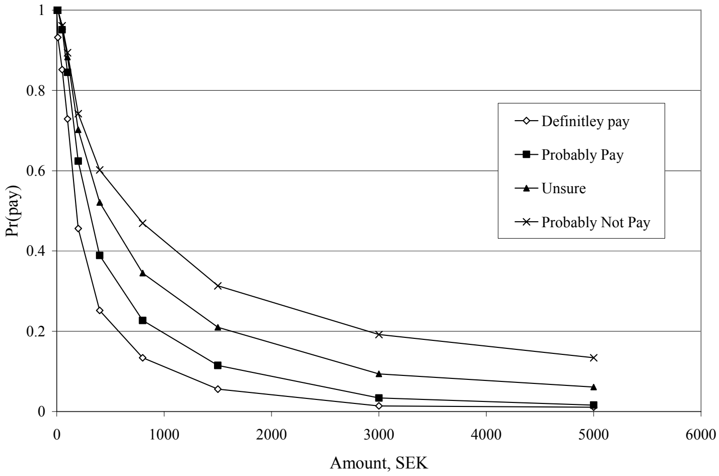

Figure 3: Survival functions corresponding to different certainty levels derived by linear interpolation.

5. Results

In this section we present the results from two different approaches (with brief consideration to a third approach) that utilize the uncertainty information elicited from the MB question. In order to get an idea about the degree of "independence" between the responses to the successive amounts presented in the MB matrix, we estimate a random effects probit model.[10] The correlation between the successive choices from the same individual is approximately 0.99, suggesting that that an individual's response to each bid is driven by an underlying single WTP amount. The results support the conclusion in Vossler and Poe (2005) that there are no efficiency gains to be made from applying a panel approach. Therefore, we do not present any further results for the panel model. Instead we focus the results on the two payment card approaches available: the WP-approach and our suggested "expansion" approach.

[9] These functions were derived by linear interpolation between the different amounts on the payment card.

[10] The random effects probit means that the error term is specified as: $\varepsilon_{iq} = u_i + v_{iq}$, where i refers to an individual and q to the choice (q = 1,..., 9). The correlation coefficient between successive choices can now be written as $\rho = \sigma^2_u/(\sigma^2_u + \sigma^2_v)$.

The only interesting estimates for policy analysis are those conditioned on the certainty levels giving the lower and the higher bound for mean and median WTP (i.e. “definitely yes” and “definitely no”). Including any other certainty level (“probably yes” “unsure” or “probably no”) implies that we exchange *certain* information for *less certain* information. For this reason we have highlighted the estimates of the WTP bounds in Table 4. The table confirms our expectation that the estimates of mean and median WTP increases as lower certainty levels are accepted as a “yes” response. However, the increase is much smaller for the expansion approach. This follows from the fact that the former approach accounts for uncertainty by shifting each individual’s WTP interval rather than expanding them.

The lower bounds of the mean and median WTP are the same for the WP and the expansion approach. A non-parametric estimate for the lower bound mean WTP is given by the sample mean of the highest amount the respondents agreed to pay with certainty.[11] As shown in Table 3 this is equal to SEK 313. However, by applying the double-bounded approach described in the previous section we can estimate a less conservative measure of mean (and median) WTP. In the fourth column in Table 4 we present parametric estimates of the lower bound for WTP following from estimation of equation (5). The estimates of the lower bound mean and median are equal to SEK 467 and 169, respectively, for both the WP and expansion approach

The estimates of the higher bound for both the mean and the median differ substantially between the two approaches. The WP estimate of the mean and the median are approximately 3.5 and 2 times higher than the estimates from the expansion approach. The estimates of the higher bound mean are SEK 2027 (WP) and 583 (expansion approach), respectively.

In addition to producing a narrower interval between the bounds for both the mean and median WTP, the expansion approach also estimates the higher bound with better precision. By studying the confidence intervals in Table 4 it is evident that the expansion approach produces narrower confidence intervals both in absolute size and in relation to the estimated mean (i.e., the width of interval divided by the corresponding mean or median).

In order to discriminate between the non-nested models under scrutiny we apply the Akaike information criteria (AIC). Since all models include the same numbers of free parameters, the criterion reduces to a simple comparison of the log-likelihood (LL) values corresponding to each model.[12] This test indicates that the expansion approach fits the data better than the WP-approach. It can be verified in Table 4 that the LL-value increases as the intervals expand.

[11] Harrison and Kriström (1995)

[12] $AIC = -2LL + 2k$, where k = the number of free parameters.

However, in the WP case there is no clear pattern for the LL-values ("probably yes" model has the highest LL-value).

To further discuss the relative validity of the two approaches under scrutiny, we study the effects of the covariates included in the estimated function. It can be seen in Table 4 that the influence of specific covariates differs between different uncertainty models (e.g. the negative age effect gets larger as the certainty level decreases regardless of re-coding approach[13]). However, the expansion approach leads to relatively stable effects of specific covariates. The difference between the approaches is most obvious for the age, gender, income and $\beta=1/\sigma$ parameters.[14]

All of the estimates above were derived under the assumption that the WTP is distributed log-normally. In order to check the robustness of our estimation with respect to the distributional assumption, we estimate a regression assuming a log-logistic distribution and find that the Welsh and Poe estimates are relatively more sensitive.[15] The higher bound of the mean and median WTP increases to SEK 5,335 and 582 respectively, which are significantly different from the estimates derived under the assumption of a log-normal distribution. Applying the log-logistic assumption to the expansion approach results in mean and median estimates of SEK 684 and 305, which are not significantly different from the estimates derived under the log-normal assumption. Hence, in this respect the expansion approach produces relatively robust estimates.

[13] The age effect indicates that younger respondents tend to be more uncertain than older respondents.
[14] The standard deviation is the shape parameter of the log-normal distribution and hence determines how much probability mass is found in the tails of the WTP distribution, i.e. the larger the standard deviation, the more mass in the tails.

[15]Model selection of non-nested models can be based on the Akaike information criteria. Since the number of free parameter is the same regardless of the distributional assumption made this turns out to be the same as comparing the LL-values. Based on this criterion the log-normal assumption is preferred to the log-logistic assumption when estimating the higher bound. However, the LL-values are close to each other.

Table 4: Estimates of the WTP function for the Welsh and Poe (WP) and the expansion approach (Exp). Within parenthesis T-values for each parameter and 90% confidence intervals for mean and median WTP (derived by Krinsky and Robb simulation).

	Welsh and Poe approach			Lower	*Expansion approach*		
	Higher bound[a]	*Unsure*[b]	*Prob.yes*[c]	**Bound**[d]	*Prob.yes*[c]	*Unsure*[b]	**Higher bound**[a]
Constant	4.65*** (23.38)	*4.78*** (23.55)*	*3.75*** (23.42)*	**3.38*** (19.46)**	*4.63*** (22.07)*	*4.96*** (21.93)*	5.18*** (22.08)
Age (1-pensioner)	-0.01*** (-4.85)	*-0.01*** (-3.14)*	*-0.004 (-1.14)*	**-0.002 (-0.77)**	*-0.002 (-0.65)*	*-0.007** (-1.96)*	-0.01*** (-3.09)
Pensioner	-1.34*** (-8.3)	*-1.06*** (-6.5)*	*-0.61*** (-3.77)*	**-0.36** (-2.2)**	*-0.48*** (-2.83)*	*-0.79*** (-4.48)*	-1.07*** (-5.88)
Male	0.08 (1.08)	*0.14** (1.99)*	*0.19*** (2.65)*	**0.17** (2.41)**	*0.21*** (2.76)*	*0.2*** (2.59)*	0.19** (2.42)
Green NGO	0.52*** (5.01)	*0.61*** (6.16)*	*0.58*** (5.91)*	**0.46*** (4.89)**	*0.6*** (6.01)*	*0.65*** (6.22)*	0.67*** (6.04)
Wolf area	0.02 (0.28)	*-0.005 (-0.06)*	*-0.03 (-0.4)*	**-0.06 (-0.76)**	*-0.05 (-0.59)*	*-0.04 (-0.42)*	0.02 (0.22)
Stockholm	0.06 (0.41)	*-0.02 (-0.13)*	*-0.02 (-0.16)*	**-0.02 (-0.43)**	*-0.05 (-0.37)*	*-0.03 (-0.2)*	0.01 (0.06)
Dog owner	0.17** (2.18)	*0.2** (2.56)*	*0.23*** (2.94)*	**0.22*** (2.78)**	*0.27*** (3.3)*	*0.26*** (3.14)*	0.26*** (2.96)
Hunter	0.07 (0.34)	*0.11 (0.61)*	*0.13 (0.78)*	**0.17 (1.12)**	*0.2 (1.21)*	*0.22 (1.26)*	0.23 (1.24)
Hunter in wolf area	-0.21 (-0.54)	*-0.18 (-0.47)*	*-0.04 (-0.1)*	**0.20 (0.44)**	*-0.03 (-0.08)*	*-0.06 (-0.14)*	-0.11 (-0.27)
Household income[e]	0.001 (1.14)	*0.002* (1.75)*	*0.002** (2.14)*	**0.0013 (1.47)**	*0.002** (2.47)*	*0.002** (2.44)*	0.002** (2.29)
(Household income)^2	-(0.00004) (-0.22)	*-(0.00006) (-0.42)*	*-(0.0001) (-0.62)*	**-(0.00007) (-0.5)**	*-(0.0001) (-0.8)*	*-(0.0001) (-0.78)*	-(0.0001) (-0.67)
(1/σ)	0.65*** (34.33)	*0.76*** (37.2)*	*0.87*** (38.49)*	**0.70*** (42.73)**	*0.91*** (36.13)*	*0.91*** (33.97)*	0.89*** (32.24)
Mean WTP	2026.94 [1766-2331]	*1048.79 [943-1165]*	*601.60 [552-657]*	**466.66 [406-539]**	*449.67 [413-491]*	*515.86 [471-566]*	583.29 [528-646]
Median WTP	616.01 [554-681]	*438.48 [401-478]*	*311.77 [288-337]*	**169 [154-186]**	*245.77 [227-266]*	*280.58 [259-303*	311.11 [287-338]
NOBS	872	*872*	*872*	**872**	*872*	*872*	872
LL	-1814.39	*-1759.18*	*-1666.80*	**-1771.23**	*-1270.87*	*-1109.03*	-1013.36
Chi^2	-3628.79	*-3518.36*	*-3333.60*	**-3542.46**	*-2541.74*	*-2218.06*	-2026.72

*, **, *** significant on 1, 5 and 10-% level respectively

[a] "Definitely yes", "Probably yes" , "Unsure" and "Probably no" = **"yes"**; "Definitely no" = **"no"**

[b] "Definitely yes" , "Probably yes" and "Unsure" = **"yes"**; "Probably no" and "Definitely no" = **"no"**

[c] "Definitely yes" and "Probably yes" = **"yes"**; "Unsure" , "Probably no" and "Definitely no" = **"no"**

[d] "Definitely yes" = **"yes"**; "Probably yes", "Unsure" , "Probably no" and "Definitely no" = **"no"**

[e] Total household income, divided by the number of members in the household.

6. Discussion and concluding remarks

In this paper we analyze the multiple-bounded format and, more specifically, we introduce a new estimation approach for such data. We use survey data from 2004 considering the WTP for implementing the predator policy in Sweden to compare empirically this new approach with two approaches used in previous applications. As with Vossler and Poe (2005), we find that each respondent's answer to sequential WTP questions are driven by one single WTP amount. This finding disqualifies the panel approach suggested in Alberini et al (2003), since it only makes sense if the responses are more or less independent.

By applying the payment card approach suggested in Welsh and Poe (1998), a lower and a higher bound can be estimated for mean and median WTP. However, other estimates of mean and median WTP are difficult to interpret because they are conditioned on verbal probability statements. As a direct consequence of the WP re-coding procedure each individuals WTP interval moves as the probability statement changes. We argue that this procedure will overestimate the higher bound of WTP because each individual's WTP interval is conditioned on the subjective meaning of a verbal probability statement.

We argue that a more intuitive approach would be to expand the WTP intervals. Preference uncertainty logically implies that the respondents would like to state an interval as opposed to a precise value. The more uncertain the respondent is, the wider the stated WTP interval. For this reason, we argue that expanding the intervals on the payment card is the proper way of accounting for uncertainty.

Using a non-parametric estimation procedure, we estimate the lower bound mean WTP to be SEK 313. A less conservative value is given by the parametric estimate of SEK 467. The size of the higher bound mean WTP depends on whether the WP or the expansion approach is applied. The former approach results in SEK 2027 while the latter approach gives SEK 583. Hence, there is a significant difference between the two approaches in their estimates of the higher bound of mean WTP.

We argue that the expansion approach: (1) is more intuitive; (2) better fits the data, as shown by our empirical analysis; (3) estimates the higher bound of mean and median WTP with better precision; and (4) is less sensitive to distributional assumption. The estimated intervals of mean and median WTP are tighter, which makes the estimates more suitable for policy-analysis. If the estimated interval is too wide, policy conclusions are more difficult to reach. Based on these results the expansion approach seems promising. In future research we plan to do a Monte-Carlo study to further compare the two approaches. This will allows us to do a more stringent comparison where we ultimately will be able to draw conclusions concerning the relative estimation efficiency of the two approaches.

By expanding the WTP intervals on the payment card the treatment of uncertainty is similar to the open-ended approach suggested by Håkansson (2007), where respondents have the option to state an interval rather than a precise value. By using the MB format, the researcher will have less precise information about the width of each respondent's true WTP interval, but may make the valuation task less cumbersome by presenting pre-specified intervals. As the number of bids included in the MB matrix approaches infinity, the MB format and the open-interval format will converge.

The usefulness of the MB format is dependent on its performance compared to other elicitation formats that account for preference uncertainty. For this reason, a comparative study could provide interesting information, especially a comparison between the MB, polychotomous choice, and the open-ended interval format. The argument in favor of the MB format is that it is a double-bounded format with a pre-specified form. Hence, it has the potential to provide a relatively high response rate and relatively efficient estimates. Future research should as well address design issues involved in creating an optimal MB matrix (e.g. how many bids and certainty levels should be included).

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