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Pierre-Alexandre Mahieu - François-Charles Wolff – Jason Shogren

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Interval Bidding in a Distribution Elicitation Format[#]

Pierre-Alexandre Mahieu[*], François-Charles Wolff[**] and Jason F. Shogren[***]

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Abstract: Interval bidding allows people to report a range of values for a non-market good. Herein we allow people to choose their distribution over this range endogenously. Using elephant protection as our motivating example, our results suggest the shape of the distribution greatly varies across people and the degree of uncertainty is proportional to their willingness to pay. We also find that both the expected willingness to pay and the degree of uncertainty differ when the valuation exercise is real versus hypothetical.

Keywords: Contingent Valuation; Uncertainty; Distribution format

JEL Classification: C5; Q51

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[*] Corresponding author. LEMNA, University of Nantes, France, pamahieu@gmail.com
[**] LEMNA, University of Nantes and INED, Paris, France, francois.wolff@univ-nantes.fr
[***] Department of Economics and Finance, University of Wyoming, Unites States, jramses@uwyo.edu

1. Introduction

Interval bidding captures the idea that some people prefer to state a range of values in a stated-preference survey rather than a point estimate (see e.g., Hanley et al. 2009, Banerjee and Shogren 2014). The bidding interval reflects a longstanding idea in stated preference work that some people are uncertain about their own values for unfamiliar non-market goods, and might find it challenging to state one precise number (see for example the early work by Li and Mattsson 1995, Ready et al. 1995). A bidder might find it computationally easier to bid a range of values given time constraints or inexperience.[1]

As researchers begin to explore interval bidding, an open question that has emerged is how to treat the bidder's underlying distribution of values. The initial approaches treated the distribution of interval values as one homogenous probability density functions across the population of bidders (see Hanley et al. 2009, Banerjee and Shogren 2014). More recent attempts have relaxed this presumption and have examined several alternative distributions (uniform, triangle, see for instance Ranneby and Yu 2011).

Herein we design an interval bidding format which allows each respondent to choose his or her own distribution over the range of values (see Figure 1). By allowing the choice of value distribution to be endogenous, our approach allows for a more precise measure of willingness to pay (WTP) in the interval. Our distribution format design works in two steps: (1) people choose between stating their WTP value as either a point estimate or a range, (2) those who select a range choose one of four distributions that best captures their distribution of values (see Figure 1).

[1] Recent work in behavioral economics has rediscovered and relabeled this preference uncertainty phenomenon as *coherent arbitrariness*: a person has a range of values and might select one value within this range arbitrarily given some unknown or unexpected cue (Ariely et al. 2003).

We run this survey on both real and hypothetical bidding to protect African elephants. We find three main results. First, the choice of distribution substantially varies between participants. Second, the degree of uncertainty is proportional to the WTP value. Third, we find evidence that both the expected WTP and the degree of uncertainty differ when the valuation exercise is real versus hypothetical.

2. A model of heterogeneity in the shape of the Interval bidding distribution

Our distribution format is in two steps. In step 1, each subject states his or her WTP value as either an interval or a point estimate. In step 2, subjects who selected the interval are now asked to choose a distribution over this interval. People might choose different distributions for at least two reasons. First, a person may have personal doubts about the degree of effectiveness of an environmental programme and will assign a probability to each of the possible outcomes he or she considers. Second, a person who is uncertain about his or her preferences for an unfamiliar good could have in mind several indifference curves and assign a probability to each of them.[2]

Let us now formalize our story. Let Q be a public good and Y a private good. A person consumes the quantities Q_0^* and Y_0^* which lie on the indifference curve I^*. Let W^* represent the maximum the person will pay for a change from Q_0^* to Q_1^* (see Figure 2). When the person is uncertain about Q_1^* and consider different values of Q, in which Q_{1L} is the highest value and Q_{1R} the highest value, he or she will state a range $[L; R]$ rather than a point W^* in step 1, where L denotes the lower bound of the WTP distribution (which corresponds to the WTP for a change from Q_0^* to Q_{1L}) and R the upper bound (WTP to change from Q_0^* to Q_{1R}).

[2] In a recent article, Czajkowski et al. (2013) find that additional experience with a good will make consumers more certain over their preferences.

The choice of the distribution in step 2 depends on the shape of the outcome distribution, i.e., the probability he or she assigned to the other levels of provision of the good.

Now consider our model in the context of preference elicitation for the elephant conservation programme. If two people think the programme will save between A and B elephants (Q_0 = A and Q_0 = B), the shape of their valuation distribution differs if they have different outcome distributions in mind. For example, if one person is an optimist about the effectiveness of the program, he or she will pick the right triangular distribution, and if the other person is a pessimist, he or she will choose the left triangular distribution. If a person is uncertain about I^*, the same reasoning applies. He or she will declare a range in the first step and the choice of distribution will depend on the probability he or she assigns to each of the possible level of satisfactions.

3. Econometric specification

We now develop our econometric model that accounts for interval bidding and our distribution elicitation design. The model supposes the degree of uncertainty is proportional to WTP and the shape of the WTP distribution can vary across respondents. In addition, we drop two assumptions implicitly made in a related paper by Ranneby and Yu (2011): the shape of the value distribution is identical across individuals, and it uses an additive measurement error.[3] In contrast, our specification assumes the shape of the distribution varies across individuals, and we assume a multiplicative measurement error.[4]

[3] Our approach does builds on Ranneby and Yu (2011), who asked participants to state their WTP either as a range or as an exact value to improve water quality in Bollnas river, Sweden. They proposed an additive measurement error model based on the idea that respondents opting for a range do not know their true WTP. They consider four probability density functions (pdf) for the measurement error (see Figure 1): left triangular, symmetric triangular, right triangular and uniform. They calculate the expected WTP for each pdf.

[4] Rowe et al. (1996) argue the width of the range might be proportional to WTP. Håkansson (2007) find some empirical support for this hypothesis in a study dealing with a Baltic river in Sweden that allowed for point or range responses. In the marketing literature, Dost (2012) claims that the width of the WTP range might be proportional to WTP. Furthermore, it has been shown that consumers tend to evaluate differences in price

We define the relationship between the true WTP W_i^* and the expected WTP W_i of a respondent i as:

$$W_i^* = W_i * \varepsilon_i \tag{1}$$

where the distribution of ε_i depends on the responses of individual i in steps 1 and 2. When the respondent selects a point estimate value, there is no uncertainty and $\varepsilon_i = 1$. We suppose n_p respondents report an exact amount. When a person selects an interval, he or she selects a distribution. Denote L_i and R_i as the lower and upper bounds of the range in which stands the exact amount W_i^* ($W_i^* \in [L_i; R_i]$). Four possibilities exist for the distribution of ε_i:

- ε_i is a left triangular distribution (n_{T_L} respondents) in step 2 such that $\varepsilon_i \sim T\left(\frac{L_i}{W_i}, \frac{R_i}{W_i}, \frac{L_i}{W_i}\right)$, where $T(.)$ is the triangular distribution with the mode as last parameter;
- ε_i is a symmetric triangular distribution (n_{T_S} respondents) in step 2 such that $\varepsilon_i \sim T\left(\frac{L_i}{W_i}, \frac{R_i}{W_i}, \frac{L_i+R_i}{2W_i}\right)$;
- ε_i is a right triangular distribution (n_{T_R} respondents) in step 2 such that $\varepsilon_i \sim T\left(\frac{L_i}{W_i}, \frac{R_i}{W_i}, \frac{R_i}{W_i}\right)$;
- ε_i is a uniform distribution (n_U respondents) in step 2 such that $\varepsilon_i \sim U\left(\frac{L_i}{W_i}, \frac{R_i}{W_i}\right)$ where $U(.)$ is the uniform distribution.

We now explain how to estimate (a) the mean WTP, (b) the valuation function and (c) the uncertainty function based on our model specification.

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levels in relative terms rather than in absolute terms (Kahneman and Tversky 1979, Janiszewski and Lichtenstein 1999).

3.1. Mean WTP

First, we define the mean WTP. We use the properties of the four statistical distributions which are summarized in Table 1. The mean WTP corresponds to the sum of W_i divided by the total number of respondents N, with $N = n_P + n_U + n_{T_L} + n_{T_R} + n_{T_S}$:

$$E(W_i^*) = \frac{1}{N} * \left[\sum_{i \in n_P} W_i + \sum_{i \in n_U, i \in n_{T_S}} \left(\frac{L_i + R_i}{2} \right) + \sum_{i \in n_{T_L}} \left(\frac{2 * L_i + R_i}{3} \right) + \sum_{i \in n_{T_R}} \left(\frac{L_i + 2 * R_i}{3} \right) \right] \quad (2)$$

Expression (2) shows the mean WTP depends on the type of WTP distribution chosen in step 1. We calculate the variance of the mean WTP as:

$$V(W_i^*) = \frac{S_W^2}{N} + \frac{1}{N^2} * \left[\sum_{i \in n_U} \frac{(R_i - L_i)^2}{12} + \sum_{i \in n_{T_L}, i \in n_{T_R}} \frac{(R_i - L_i)^2}{18} + \sum_{i \in n_{T_S}} \frac{(R_i - L_i)^2}{24} \right] \quad (3)$$

where S_W^2 is the sample variance of expected WTP W_i. The variance depends on the variance of W_i, the width of the various ranges $R_i - L_i$ and the number of range respondents in each of distributional case. The variance $V(W_i^*)$ is included in the computation of the confidence interval: $E(W_i^*) \pm z_{\alpha/2}\sqrt{V(W_i^*)/N}$ with $z_{\alpha/2} = 1.96$ for a 95% confidence interval.

3.2 WTP function

We now define the valuation function. Let X_i be a set of characteristics describing respondent i. Assuming the unobserved WTP W_i^* is strictly positive, we consider the following linear specification:[5]

$$\ln W_i^* = X_i\beta + \xi_i \quad (4)$$

[5] Given the logarithm transformation of the dependent variable, a simple transformation to account for the case of respondents reporting a zero value is to consider $\ln(W_i^* + 1)$. Such transformation is common in the WTP literature (see Basu 2013 for a recent example).

where β is a vector of coefficients to estimate and ξ_i is a random perturbation capturing the influence of the unobserved individual covariates. Assume $E(\xi_i) = 0$ and $V(\xi_i) = \sigma^2$. Since $\ln \mathrm{W_i^*} = \ln W_i + \ln \varepsilon_i$ from (1), we have $\ln W_i = X_i\beta + \xi_i - \ln \varepsilon_i$ which we can write as:

$$\ln W_i = X_i\beta + \eta_i \tag{5}$$

The residual term $\eta_i = \xi_i - \ln \varepsilon_i$ is composed of two perturbations: ξ_i is the error term related to missing variables, and $\ln \varepsilon_i$ is the respondent's uncertainty on his or her WTP. This second error term is assumed to be uncorrelated with both X_i and ξ_i. In most studies, the error term η_i is only composed of ξ_i because each respondent is assumed to know his or her exact WTP.

Since the range width or the WTP distribution shape (or both) vary across the respondents, this implies the residual η_i is heteroskedastic. Let $\eta = (\eta_1, \dots, \eta_N)'$. The variance covariance matrix $E[\eta\eta']$ is:

$$E[\eta\eta'] = \left[\begin{pmatrix} \sigma^2 + \omega_1^2 & 0 & \dots & 0 \\ 0 & \sigma^2 + \omega_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sigma^2 + \omega_N^2 \end{pmatrix}\right] \tag{6}$$

with $V(\ln \varepsilon_i) = \omega_i^2$. We denote by $\Omega = E[\eta\eta']$ this variance covariance matrix, which may also be expressed as $\Omega = \sigma^2 I + \Psi$ with I the $n \times n$ identity matrix and Ψ a $n \times n$ diagonal matrix comprising the various terms ω_i^2 as diagonal elements.

An Ordinary Least Squares (OLS) estimation of (5) would give efficient estimates of the regression parameters only in the case of a constant variance across the observations for $V(\ln \varepsilon_i)$, which is not the case given our distributional assumptions on ε_i. A first approach to account for heteroskedasticity is to use the OLS estimator and compute robust standard errors following the procedure described in White (1980). This approach, however, is inefficient since the information about the nature of the heteroskedasticity, which is given by the knowledge of $V(\ln \varepsilon_i)$, is ignored. An alternative estimation technique is to use the Feasible Generalized Least Squares (FGLS). This estimator is used when the dependent variable is estimated, which is the case when the dependent variable includes sample means (Lewis and Linzer 2005).

While the calculation of $V(\varepsilon_i)$ is straightforward for respondents choosing an interval along with a distribution (see Table 1), it is more complicated to obtain $V(\ln \varepsilon_i)$ since the term $\ln \varepsilon_i$ follows an exponential distribution. Detailed calculations of $\omega_i^2 = V(\ln \varepsilon_i)$ are presented in Apppendix A. Contrary to the perturbations ω_i^2 $(i = 1, \dots, N)$ which are known for all respondents, we have no information about the variance σ^2 of ξ. To obtain an estimate of the variance σ^2, we follow the solution described in Hanushek (1974). Let $tr(.)$ the trace matrix operator. From the OLS regression $\ln W_i = X_i\beta + \eta_i$, the expectation of the sum of squared residuals is:

$$E\left(\sum_i \hat{\eta}_i^2\right) = E[\eta\eta'] - tr((X'X)^{-1}X'\,\Omega\,X)) \tag{7}$$

Using $E(\sum_i \eta_i^2) = N\sigma^2 + \sum_i \omega_i^2$ and after some manipulations, we have:

$$\hat{\sigma}^2 = \frac{\sum_i \hat{\eta}_i^2 - \sum_i \omega_i^2 + tr((X'X)^{-1}X'\,\Psi\,X))}{N-k} \tag{8}$$

with k being the number of columns in X which is equal to the number of covariates plus one when a constant is included in the regression. It can be shown that $\hat{\sigma}^2$ is an unbiased estimator for σ^2 (Hanushek 1974, Lewis and Linzer 2005). Once this estimator is obtained, we calculate the following weight for each respondent:

$$\vartheta_i = \frac{1}{\hat{\sigma}^2 + \omega_i^2} \tag{9}$$

Finally, a Weighted Least Squares (WLS) estimator of (5) with ϑ_i as weights provides asymptotically efficient estimates of β and standard errors are consistent regardless of the relative size of ω_i^2 and $\hat{\sigma}^2$.[6] Implementation of the FGLS estimator is straightforward using standard econometric software.

3.3. Uncertainty function

Our measure of uncertainty at the individual level is $V(\varepsilon_i) = \tau_i^2$. As shown in Table 1, the value of $V(\varepsilon_i)$ depends on the distribution selected by the respondent. We consider the person who selects the uniform distribution as more uncertain about his or her WTP than a person who chooses a triangular distribution. Also, stating a WTP between 5 and 10 EUR or between 5*k* and 10*k* EUR leads to the same value of τ_i^2 (regardless of the value of *k*) as long as the shape of the distributions is identical.[7]

We estimate the following model to explain the role of individual characteristics on the uncertainty associated to WTP:

$$\tau_i^2 = Z_i\delta + \kappa_i \quad (10)$$

with Z_i a set of explanatory variables, δ a vector of parameters to estimate and κ_i an error term such that $E(\kappa_i) = 0$ and $V(\kappa_i) = \pi^2$. We use a Tobit model because a mass point exists in the distribution of τ_i^2 given some subjects report an exact amount.[8]

4. Survey

We now describe the design of the survey — the subject pool, the real and hypothetical treatments, the description of the good, the interval bidding mechanism, treatments, and the actual procedures. First, our subjects were undergraduate economics students from University of Nantes, France. Group interviews were organized, with all of the

[6] Lewis and Linzer (2005) compare the FGLS and OLS (with robust standard errors) estimates in both a Monte Carlo application and a case study concerning political leaders. They show that FGLS ought to be used when reliable information about ω_i^2 is available.

[7] In addition, our measure of uncertainty is insensitive to the currency: converting WTP statements (from EUR to USD for instance) has no effect on τ_i^2.

[8] For point respondents, the uncertainty value is zero by definition.

instructions being read aloud by the interviewer and displayed on a board using a video projector. The students were divided into ten groups of 25 and were interviewed by the same monitor. Each student wrote down his or her answers on private response sheet.

Second, in each group, students were randomly divided into two sub-groups—real payments and hypothetical payments. Each student in the real payment group was informed that he or she would make a real donation when the experiment was complete (the donation would be made online using the classroom computers). The monitor checked that the students paid the amount they had written on their response sheet. In contrast, each subject in the hypothetical group was told that his or her bid was just hypothetical and no payment would have to be made at the end of the experiment. Otherwise, the protocol was identical between the two sub-groups.[9]

Third, the subjects valued an elephant conservation programme supported by the WWF (World Wildlife Foundation).[10] Using information from the official WWF website, we provided subjects with general information on African elephants. They were told that each year hunters illegally kill approximately 12,000 African elephants for the tusks and skins. We showed a video describing the WWF protection programme (http://trafic.wwf.fr/elephants/). The video describes the three measures undertaken by the organization: (1) the creation of protected area to prevent illegal hunting; (2) the training of guards working in the protected areas and (3) the training of employees ensuring that ivory is not sold in local markets. The video also stresses the need to collect donations to pursue this conservation programme. The WWF website was briefly shown to the respondents, including the online donation

[9] In addition, "will" was replaced by "would" in the valuation task instruction.

[10] Several real and hypothetical valuation studies have used conservation programmes by the WWF. For instance, Jacquemet et al. (2013) conducted a CV study in France on dolphins based on a sample of 72 students and Svedsater (2007) carried out a CV study in the United Kingdom on African elephants based on a sample of 111 students.

webpage. Using this webpage, a one-time donation could be made for this specific program, with the possibility of stipulating the exact amount to donate.

Fourth, we described the interval bidding mechanism.[11] The interviewer first explained (in French) the two steps:

> *I am going to ask you how much you would be willing to donate to the conservation program. You will be given the opportunity to state a range of values. Then, I will randomly draw a single amount from your stated range using Excel, and you would have to pay this amount before the end of the survey using the webpage I have just shown you*.

The instructions displayed on the board after the oral explanations were:

> *Please, complete these two statements:*
>
> - *I would accept donating AT LEAST ____ EUR* (amount A) *to the programme*
>
> - *I would accept donating NO MORE THAN____ EUR* (amount B) *to the programme*

The participants could state a point by reporting the same amount twice. Next the interviewer described the second step:

> *A single amount will be randomly drawn between amounts A and B before the end of the survey. There are different "ways" to draw a random amount. You will have to choose one of them*.

Figure 3 illustrates how we presented the four distributions densities to the respondents. For each respondent, the interviewer drew a random number in Excel based on his or her responses and wrote this random amount on the front page of the response sheet. If the

[11] We ran two focus groups of 15 subjects. In the first group, two students found it somewhat difficult to understand the density graphs. In the second group, we added a verbal expression to each of distribution: "close to A", "close to B", "in the middle", "anywhere". The verbal expressions were fully understood by all the participants and were therefore used in the final survey.

respondent stated a point WTP, the interviewer reported this point value on the front page. Then, the interviewer returned the response sheets to the respondents.

Finally, each subject answered a set of questions on socio-economic (gender, age, income), and risk aversion. We asked each subject to choose one of three hypothetical lotteries: (1) a 10% chance to win 100 EUR, a 90% chance to win 0 EUR, (2) a 50% chance to win 20 EUR, a 50% chance to win 0 EUR, and (3) a 90% chance to win 11 EUR, a 10% chance to win 0 EUR.

The final sample size is 223 participants. We removed 24 questionnaires due to protest responses (like "I would need more time") or incomplete questionnaires, and 6 extreme responses in the hypothetical payment group in the following ranges: [50;500]; [30;300], [200;500], [100;200], [100;300] and [1;100]. Protest answers were detected by means of the open-ended follow-up question that was asked to those refusing to pay. Table 2 summarizes the respondents and their repartition between the hypothetical and actual payment groups.

5. Results

We now present and support our three key results. Consider each in turn.

Result 1*: The choice of the valuation distribution substantially varies between people.*

Support: In Table 3, we report the proportion of point and range respondents choosing the different distributions. We see 149 of 223 respondents state an interval bid: 28.9% have chosen the left triangular distribution ($n_{T_L} = 43$), 27.5% the symmetric triangular distribution ($n_{T_S} = 41$), 7.4% the right triangular distribution ($n_{T_R} = 11$) and 36.2% the uniform distribution ($n_U = 54$). The shape of the WTP distribution is not identical across people as commonly presumed in previous studies (e.g., Flachaire and Hollard 2007, Hanley et al. 2009, Ranneby and Yu 2011).

Interestingly, 30 of 149 interval respondents reported zero as a lower bound ($L = 0$ and $R > 0$). Among the point respondents ($n_P = 74$), most did not want to donate money ($L = R = 0$). Only five bidders stated a strictly positive value, with the following amounts: 1, 10, 20, 20 and 50 euros.

Result 2: *The width of the range tends to be proportional to the expected WTP.*

Support: The correlation between $\log(R_i - L_i)$ and $\log(W_i)$ is positive and close to one $(r = 0.88)$, which provides some support for the use of multiplicative measurement error rather than additive measurement error. Figure 4 illustrates the strong link between $\log(R_i - L_i)$ and $\log(W_i)$ with a scatter plot and a fitted line.

As a consequence, assuming the same distribution for all the participants will be critical when the stated ranges are large. Intuitively, the larger the width of the ranges, the larger the impact of distributional assumption on the mean WTP. It follows that the benefits of using our approach are expected to be higher when the level of WTP is high or when people are uncertain about their WTP.[12]

Result 3: *The nature of the payment — real versus hypothetical — affected both the expected willingness to pay and the degree of value uncertainty.*

Support: Table 3 illustrates that the expected WTP is lower in the real payment group. The mean WTP is 3.808 EUR in the real payment group, and 16.472 EUR in the hypothetical payment group (p-value = 0.00). This result is in line with Jacquemet et al. (2013) who conducted a Vickrey auction on a WWF dolphin programme. They found that the mean WTP

[12] Participants may feel it easier to choose a distribution when the stated range is wide.

values were 3.33 EUR and 14.61 EUR in the real and hypothetical groups. In addition, we observe that the proportion of respondents choosing the left triangular distribution is greater in the hypothetical payment group (p = 0.36) than in the real payment group (p = 0.26), although the difference fails to be statistically significant at conventional levels (p-value = 0.184). The proportion of point respondents is higher in the real payment group (p = 0.552) than in the hypothetical group (p = 0.136). The high number of participants refusing to pay in the real payment group (n = 57) contributes to it.

Results related to the mean WTP indicate that the mean WTP based on our approach (10.509) leads to a mean WTP which is close to assuming a symmetric distribution for all the participants (10.853). This result does not mean that a symmetrical distribution should be used when only the two endpoints of the range are elicited (e.g., classic and interval opened-question). The midpoint of the range might have been represent biased proxy of the true WTP in other studies since the shape of the distribution may be case dependent, i.e., the choice of distributions may differ between surveys.

Table 4 presents the FGLS estimates of the WTP function. These results show a negative association between the expected WTP and being in the real payment group. Also, we find the measurement error is higher when the payment is hypothetical relative to real payments. This result is consistent with Dost and Wilken (2012) who consider interval bids for a private good. They found people bidding over coffee in a real setting were more certain about their value than those in the hypothetical setting. Our results are also consistent with studies which assume that people who are uncertain about preferences can narrow their uncertainty with efforts (see Shogren et al. 2000, Guzman and Kolstad 2007).

6. Conclusion

We conclude with two observations and two caveats. First, the endogenous distribution approach can work for interval bidding — it is straightforward to implement given verbal instructions, and we find significant behavioral differences emerge when we allow people to choose the distribution that defines their own preference uncertainty. Second, testing the procedure on a national population is next on the research agenda. The key here will be to make sure people understand what their choice of a distribution implies for their uncertainty.

The first caveat is that we did not use an incentive compatible auction mechanism to elicit values or the distribution. For instance, the monitor could follow a Becker–DeGroot–Marschak (BDM) procedure and show the price to the subject after he or she has completed the survey. If the price exceeds the amount drawn from the distribution, the person would buy the product at this price. The Vickrey auction approach, which has been employed by Banerjee and Shogren (2014), could also be used. The provision point mechanism could also be explored. We did not use Vickrey or BDM because we did not want to complicate the current testbed experiment. Likewise, we did not use voluntary payment because it was unrealistic: NGO never refunds the collected money.

Second, we used classic and interval open-ended question to elicit the two endpoints of the range. Future work can explore the many elicitation formats that could be used in the first stage of our approach, such as the payment ladder (Hanley et al. 2009), the rotated disc (Dubourg et al. 1994), the randomised card sorting (Carthy et al. 1998) or the traffic lights (Cook et al. 2012).

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Table 1. Characterization of the selected distributions

Parameters	Left triangular distribution	Symmetric triangular distribution	Right triangular distribution	Uniform distribution
Support	$x \in [L_i, R_i]$	$x \in [L_i, R_i]$	$x \in [L_i, R_i]$	$x \in [L_i, R_i]$
Density function on support	$\frac{2 * (R_i - x)}{(R_i - L_i)^2}$	$\frac{4*(x-L_i)}{(R_i-L_i)^2}$ for $x \leq \frac{L_i+R_i}{2}$ $\frac{4*(R_i-x)}{(R_i-L_i)^2}$ for $x \geq \frac{L_i+R_i}{2}$	$\frac{2 * (x - L_i)}{(R_i - L_i)^2}$	$\frac{1}{R_i - L_i}$
Mode	L_i	$\frac{L_i + R_i}{2}$	R_i	Any value in $[L_i, R_i]$
$E(W_i^*)$	$\frac{2 * L_i + R_i}{3}$	$\frac{L_i + R_i}{2}$	$\frac{L_i + 2 * R_i}{3}$	$\frac{L_i + R_i}{2}$
$V(W_i^*)$	$\frac{(R_i - L_i)^2}{18}$	$\frac{(R_i - L_i)^2}{24}$	$\frac{(R_i - L_i)^2}{18}$	$\frac{(R_i - L_i)^2}{12}$
$E(\varepsilon_i)$	$\frac{2 * \frac{L_i}{W_i} + \frac{R_i}{W_i}}{3}$	$\frac{\frac{L_i}{W_i} + \frac{R_i}{W_i}}{2}$	$\frac{\frac{L_i}{W_i} + 2 * \frac{R_i}{W_i}}{3}$	$\frac{\frac{L_i}{W_i} + \frac{R_i}{W_i}}{2}$
$V(\varepsilon_i)$	$\frac{\left(\frac{R_i}{W_i} - \frac{L_i}{W_i}\right)^2}{18}$	$\frac{\left(\frac{R_i}{W_i} - \frac{L_i}{W_i}\right)^2}{24}$	$\frac{\left(\frac{R_i}{W_i} - \frac{L_i}{W_i}\right)^2}{18}$	$\frac{\left(\frac{R_i}{W_i} - \frac{L_i}{W_i}\right)^2}{12}$

Source: author's calculations

Table 2. Descriptive statistics of the sample (N=223)

Variable	Description	Mean	St. dev.
Real payment	1 if the respondent is in the real payment group, 0 otherwise	0.47	0.50
Age	Age of respondent in years	20.12	1.01
Male	1 if the respondent is a male, 0 otherwise	0.39	0.49
Income	The midpoint of the income range expressed in hundreds of euro per month	2.49	2.24
Self-confidence	Score ranging from 1 *I do not agree at all* to 5 *I fully agree* to the following statement: *I am a self-confident person*	2.99	0.96
Effectiveness	Score ranging from 1 *I do not agree at all* to 5 *I fully agree* to the following statement: *the programme will be effective at saving African elephants*	2.97	0.88
Risk aversion	Lottery (1) is coded 1 (10% chance to win 100 EUR, 90% chance to win 0 EUR), lottery (2) is coded 2 (50% chance to win 20 EUR; 50% chance to win 0 EUR) and lottery (3) is coded 3 (90% chance to win 11 EUR and 10% chance to win 0 EUR)	2.38	0.81

Source: authors' calculations.

Table 3. Mean comparisons using t-test

Variables	All (1)	Real payment group (2)	Hypothetical payment group (3)	Difference (2) – (3)
Point respondents	0.332	0.552	0.136	0.416***
Range respondents	0.668	0.448	0.864	-0.416***
Selected distribution (for range respondents)				
Left triangular	0.289	0.362	0.255	0.107
Symmetric triangular	0.275	0.213	0.304	-0.091
Right triangular	0.074	0.085	0.069	0.016
Uniform	0.362	0.340	0.372	-0.032
Expected WTP				
Mix of distribution	10.509	3.808	16.472	-12.664***
Left triangular	9.178	3.400	14.319	-10.919***
Symmetric triangular	10.835	3.948	16.964	-13.016***
Right triangular	12.493	4.495	19.609	-15.114***
Uniform	10.835	3.948	16.964	-13.016***

Source: authors' calculations.

Note: Significance levels are 1% (***), 5% (**) and 10% (*).

Table 4. Estimation of the WTP and uncertainty functions (N=223)

Variable	(1) WTP function	(2) Uncertainty function
Real payment	-1.404***	-0.078***
	(0.153)	(0.013)
Risk aversion	-0.026	-0.014*
	(0.098)	(0.008)
Age	0.186**	0.001
	(0.077)	(0.006)
Income	0.007	0.002
	(0.037)	(0.004)
Male	-0.055	0.016
	(0.169)	(0.014)
Self confidence	-0.133	0.019***
	(0.088)	(0.007)
Effectiveness	0.226**	0.004
	(0.088)	(0.008)
Constant	-1.698	0.102
	(1.624)	(0.126)

Source: authors' calculations.

Note: (1) are FGLS estimates of the transformed dependent variable $\ln(W_i + 1)$, (2) are Tobit estimates of $V(\varepsilon_i)$ with robust standard errors. The R^2 associated with the WTP function regression is 0.318. Standard errors are displayed in brackets below the coefficients. Significance levels are 1% (***), 5% (**) and 10% (*).

Figure 1. Possible distributions of ε_i for range respondents

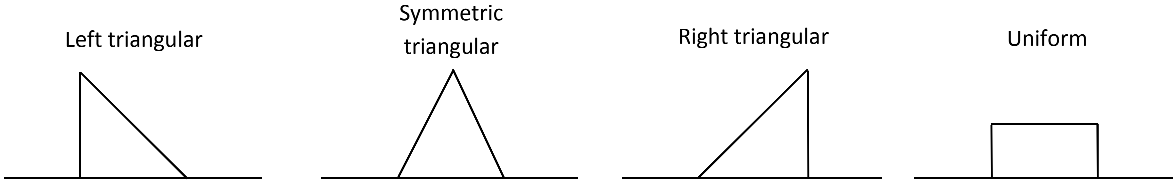
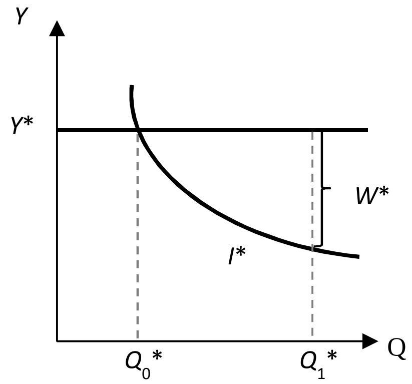


Figure 2. Graphical representation of the valuation responses

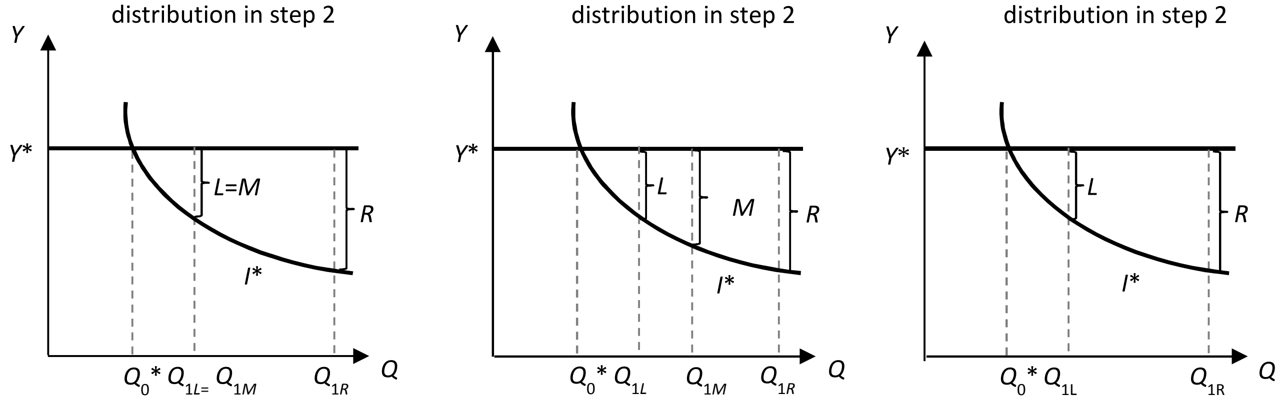
-Point response in step 1: no uncertainty



-Range response in step 1

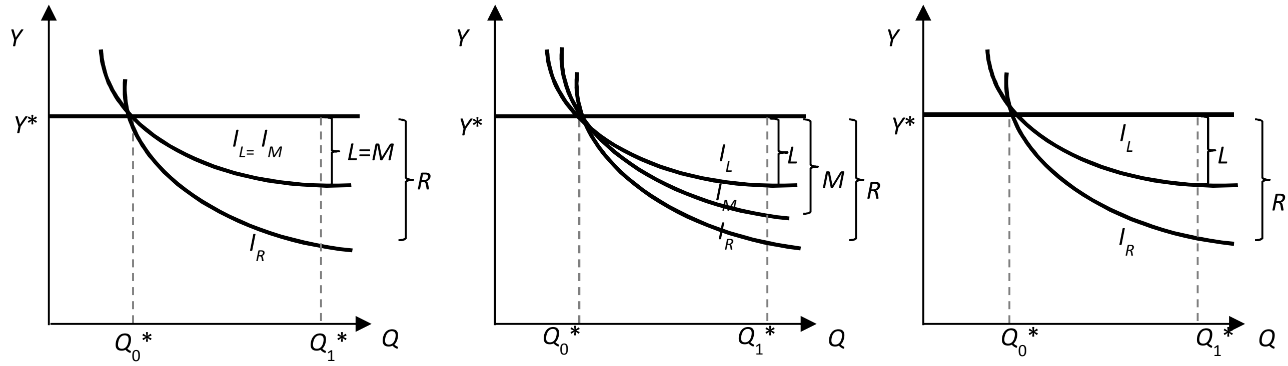
-Uncertainty over the good to be valued (Q_1*)

Left triangular distribution in step 2 | Symmetric triangular distribution in step 2 | Uniform distribution distribution in step 2



-Uncertainty over preferences (I*)

Left triangular distribution in step 2 | Symmetric triangular distribution in step 2 | Uniform distribution distribution in step 2

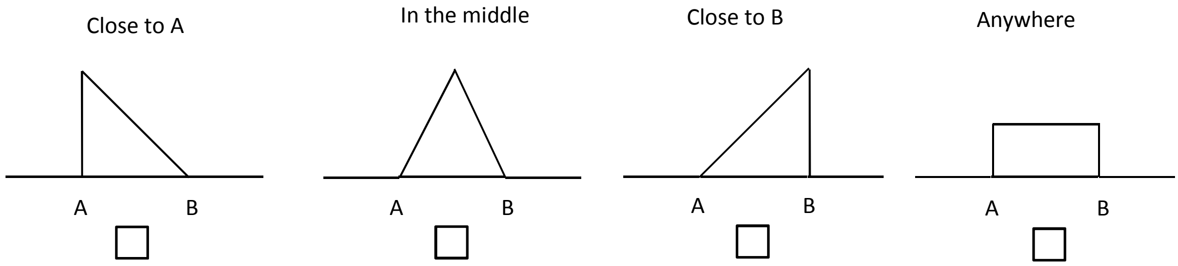


Note: M denotes the mode of the WTP distribution. For the ease of the presentation, we discard the right triangular distribution because it is very similar to the left triangular distribution.

Figure 3. Elicitation question in the hypothetical payment group (step 2)

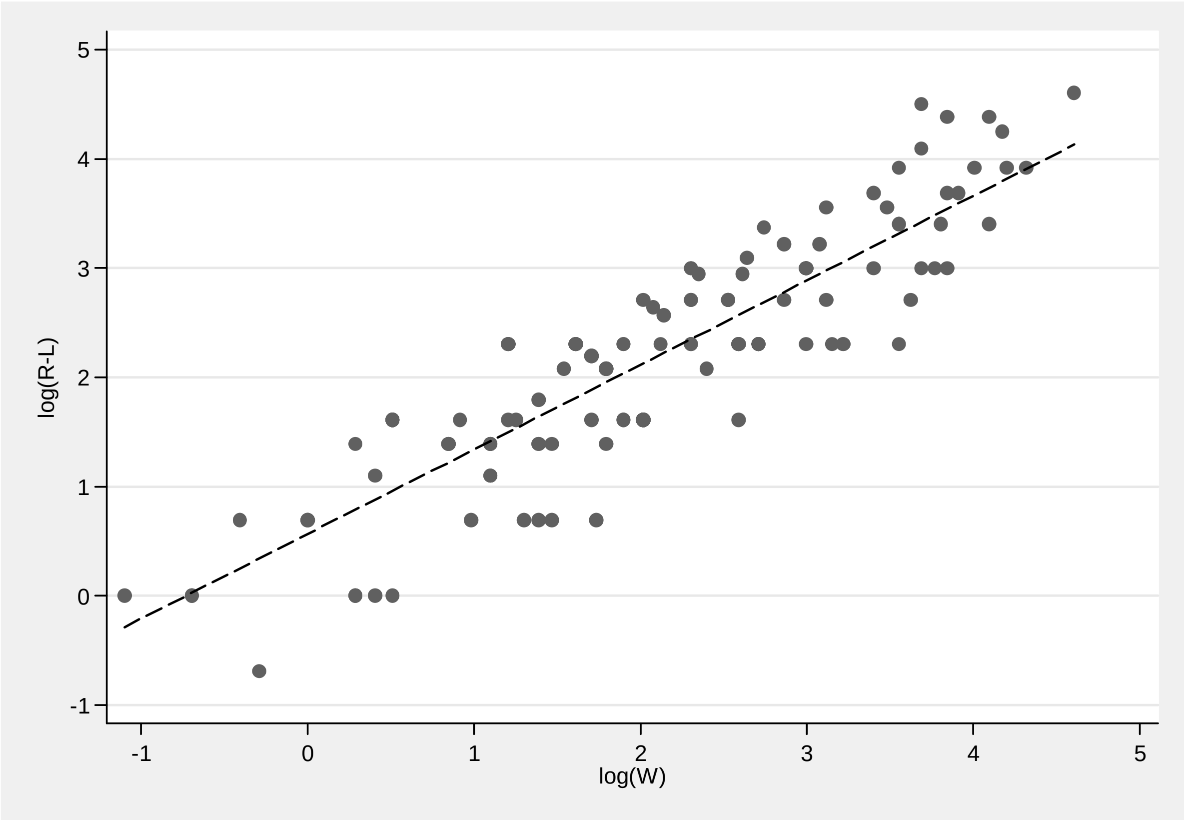
There are different ways in Excel to draw a random amount. Please, choose the way you prefer.

I would prefer the random amount to be more likely to be located (tick your preferred option on your response sheet).



Note: “would” was removed from the instructions in the real payment group

Figure 4. Illustration of the multiplicative measurement error (N=223)



Source: authors' calculations.

Appendix A. Calculation of $V(\ln \varepsilon_i)$

Let $f(x)$ a density variable for a continuous random variable x. The expected value $E(x)$ is $E(x) = \int x f(x) dx$ and the variance is $V(x) = \int \left(x - E(x)\right)^2 f(x) dx$. Denoting by $g(.)$ a possibly non-linear function, the expected value $\mathrm{E}\left(g(x)\right)$ and the variance $\mathrm{V}\left(g(x)\right)$ are:

$$E\left(g(x)\right) = \int g(x) f(x) dx \quad \text{(A1)}$$

$$V\left(g(x)\right) = \int \left(g(x) - \mathrm{E}\left(g(x)\right)\right)^2 f(x) dx \quad \text{(A2)}$$

Let $R_i' = R_i/W_i$ and $L_i' = L_i/W_i$. For the presentation, we consider the case of the uniform distribution and assume that $\varepsilon_i \sim U(L_i', R_i')$. From (A1) and using the density function of the uniform distribution, it follows:

$$E(\ln \varepsilon_i) = \int_{L_i'}^{R_i'} \ln \varepsilon_i * \frac{1}{(R_i' - L_i')} d\varepsilon_i \quad \text{(A3)}$$

By integrating by parts, $\int \ln \varepsilon_i \, d\varepsilon_i = [\varepsilon_i \ln \varepsilon_i] - \int 1 d\varepsilon_i = [\varepsilon_i(\ln \varepsilon_i - 1)]$ from which we deduce:

$$E(\ln \varepsilon_i) = \frac{1}{(R_i' - L_i')} * \left(R_i'(\ln R_i' - 1) - L_i'(\ln L_i' - 1)\right) \quad \text{(A4)}$$

From (A2), the variance $V(\ln \varepsilon_i)$ is $V(\ln \varepsilon_i) = \int_{L_i'}^{R_i'} \left(\ln \varepsilon_i - E(\ln \varepsilon_i)\right)^2 * \frac{1}{(R_i' - L_i')} d\varepsilon_i$ and thus:

$$V(\ln \varepsilon_i) = \frac{1}{(R_i' - L_i')} \int_{L_i'}^{R_i'} \left((\ln \varepsilon_i)^2 - 2(\ln \varepsilon_i) E(\ln \varepsilon_i) + \left(E(\ln \varepsilon_i)\right)^2\right) d\varepsilon_i \quad \text{(A5)}$$

By integrating by parts, $\int (\ln \varepsilon_i)^2 d\varepsilon_i = [\varepsilon_i (\ln \varepsilon_i)^2] - \int \varepsilon_i d(\ln \varepsilon_i)^2 = [\varepsilon_i (\ln \varepsilon_i)^2] - 2 \int \ln \varepsilon_i \, d\varepsilon_i$. Since $\int \ln \varepsilon_i \, d\varepsilon_i = [\varepsilon_i(\ln \varepsilon_i - 1)]$ and after some manipulations, we obtain the following formulae for the variance $V(\ln \varepsilon_i)$:

$$V(\ln \varepsilon_i) = \frac{R_i'(\ln R_i')^2 - L_i'(\ln L_i')^2}{(R_i' - L_i')} - 2E(\ln \varepsilon_i) - \left(E(\ln \varepsilon_i)\right)^2 \quad \text{(A6)}$$

We proceed in a similar way for the various triangular distributions and summarize our results in Table A1.

Table A1. Expected value and variance of $\ln \varepsilon_i$ for selected distributions

Distribution	Expected value $E(.)$ / variance $V(.)$
Left triangular	$E_L(\ln \varepsilon_i) = \frac{2}{(R_i' - L_i')^2} * \left(\frac{R_i'^2}{2} \ln R_i' - \frac{3R_i'^2}{4} - \left(R_i' L_i' - \frac{L_i'^2}{2} \right) \ln L_i' + R_i' L_i' - \frac{L_i'^2}{4} \right)$
	$V_L(\ln \varepsilon_i) = \frac{2}{(R_i' - L_i')^2} * \left(\begin{array}{c} \frac{R_i'^2}{2} (\ln R_i')^2 - \left(\frac{3R_i'^2}{2} + E_L R_i'^2 \right) \ln R_i' + \left(\frac{E_L^2}{2} + \frac{3E_L}{2} + \frac{7}{4} \right) R_i'^2 \\ - \left(L_i' R_i' - \frac{L_i'^2}{2} \right) (\ln L_i')^2 - \left(\frac{L_i'^2}{2} + E_L L_i'^2 - 2R_i' L_i' (1 + E_L) \right) \ln L_i' - (E_L^2 + 2E_L + 2) R_i' L_i' + \left(\frac{E_L^2}{2} + \frac{E_L}{2} + \frac{1}{4} \right) L_i'^2 \end{array} \right)$
Symmetric triangular	$E_S(\ln \varepsilon_i) = \frac{4}{(R_i' - L_i')^2} * \left(\frac{L_i'^2}{2} \ln L_i' + \frac{R_i'^2}{2} \ln R_i' - \left(\frac{L_i' + R_i'}{2} \right)^2 \ln \left(\frac{L_i' + R_i'}{2} \right) - \frac{3}{8} (R_i' - L_i')^2 \right)$
	$V_S(\ln \varepsilon_i) = \frac{4}{(R_i' - L_i')^2} * \left(\begin{array}{c} \frac{L_i'^2}{2} (\ln L_i')^2 + \frac{R_i'^2}{2} (\ln R_i')^2 - \left(\frac{L_i' + R_i'}{2} \right)^2 \left(\ln \left(\frac{L_i' + R_i'}{2} \right) \right)^2 - \left(\frac{3}{2} + E_S \right) L_i'^2 \ln L_i' - \left(\frac{3}{2} + E_S \right) R_i'^2 \ln R_i' \\ + (3 + 2E_S) \left(\frac{L_i' + R_i'}{2} \right)^2 \ln \left(\frac{L_i' + R_i'}{2} \right) + \left(\frac{7}{8} + \frac{3}{4} E_S + \frac{1}{4} E_S^2 \right) (R_i' - L_i')^2 \end{array} \right)$
Right triangular	$E_R(\ln \varepsilon_i) = \frac{2}{(R_i' - L_i')^2} * \left(\left(\frac{R_i'^2}{2} - R_i' L_i' \right) \ln R_i' + R_i' L_i' - \frac{R_i'^2}{4} + \frac{L_i'^2}{2} \ln L_i' - \frac{3}{4} L_i'^2 \right)$
	$V_R(\ln \varepsilon_i) = \frac{2}{(R_i' - L_i')^2} * \left(\begin{array}{c} \left(\frac{R_i'^2}{2} - L_i' R_i' \right) (\ln R_i')^2 - \left(\frac{R_i'^2}{2} + E_R R_i'^2 - 2R_i' L_i' (1 + E_R) \right) \ln R_i' + \left(\frac{E_R^2}{2} + \frac{E_R}{2} + \frac{1}{4} \right) R_i'^2 - (E_R^2 + 2E_R + 2) L_i' R_i' \\ + \frac{L_i'^2}{2} (\ln L_i')^2 - \left(\frac{3L_i'^2}{2} + E_R L_i'^2 \right) \ln L_i' + \left(\frac{E_R^2}{2} + \frac{3E_R}{2} + \frac{7}{4} \right) L_i'^2 \end{array} \right)$
Uniform	$E_U(\ln \varepsilon_i) = \frac{1}{(R_i' - L_i')} * \left(R_i' (\ln R_i' - 1) - L_i' (\ln L_i' - 1) \right)$
	$V_U(\ln \varepsilon_i) = \frac{R_i' (\ln R_i')^2 - L_i' (\ln L_i')^2}{(R_i' - L_i')} - 2E_U - E_U^2$

Source: authors' calculations.