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The Effect of Uncertainty on Contingent Valuation Estimates: A Comparison

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The Effect of Uncertainty on Contingent Valuation Estimates: A Comparison

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Abstract

We examine the impact of uncertainty on contingent valuation responses using (1) a survey of Canadian landowners about willingness to accept compensation for converting cropland to forestry and (2) a survey of Swedish residents about willingness to pay for forest conservation. Five approaches from the literature for incorporating respondent uncertainty are used and compared to the traditional RUM model with assumed certainty. The results indicate that incorporating uncertainty has the potential to increase fit, but could introduce additional variance. While some methods for uncertainty are an improvement over traditional approaches, we caution against systematic judgments about the effect of uncertainty on contingent valuation responses.

Keywords: respondent uncertainty; willingness to accept; contingent valuation

1. Introduction

The impact of uncertainty on contingent valuation estimates has been discussed in the literature on both a theoretical and empirical level. McFadden (1973) first incorporated observer uncertainty about individuals' preferences using a random utility maximization (RUM) framework. The RUM model postulates that, from the point of view of the analyst, an individual's utility consists of a deterministic component plus an unobservable random error term. Hanemann (1984) applied this idea to the valuation of non-market amenities using a contingent valuation device where a respondent is faced with a choice to accept or reject an offered 'bid' for an improvement in the level of the amenity. However, this approach addresses uncertainty on the part of the investigator, not uncertainty on the part of the respondent.

Hanemann and Kriström (1995) argue that, if respondents truly know their valuation of a contingency, an open-ended question format should be used to elicit this information. Yet, the dichotomous-choice format is generally preferred because it better simulates a 'take it or leave it' marketplace situation, and results in lower variance than estimates from an open-ended format. But there is also, in our view, an implicit recognition with dichotomous choice that the random component of the respondent's utility function is the result of preference uncertainty, or perhaps more appropriately, respondent uncertainty about the answer provided. In this paper, we use the term preference uncertainty to denote this uncertainty. As noted below, uncertainty about the answer provided to a valuation question implies uncertainty about the tradeoff between the amenity in question and the monetary good.

Uncertainty arises in a number of different ways. It might originate with the public good or contingency that is to be valued. Respondents may be uncertain about what it is that they are valuing, having no experience with it and perhaps never having seen it. The value an individual assigns to the specified non-market amenity is influenced by prices of both substitutes and complements, if they even exist, and markets for these goods may behave in ways that are unpredictable to the individual (Wang 1997). Uncertainty can also originate with the questionnaire used to elicit information, although this problem can be overcome to some extent by improved survey design. Nonetheless, it is generally accepted that the contingent valuation method (CVM) contributes to potential measurement error, because it relies on hypothetical scenarios (Loomis and Ekstrand 1998). Over and above the hypothetical nature of the CVM, individuals may simply be unable to make a tradeoff between the amenity in question and monetary value. They may also not understand the contingency in question and the manner in which it would be achieved, perhaps being hesitant about the policy (tax, subsidy, etc.) proposed for addressing the environmental spillover. Additionally, uncertainty may be prevalent in programs related to climate change, say, because of the scientific uncertainty and perceived non-immediacy of its effects.

While some uncertainty can be resolved by better informing respondents, or working with them one-on-one, some uncertainty can never be resolved. This is why some prefer situations where a facilitator helps stakeholders identify their preferences and/or enables disparate groups of stakeholders to make a decision concerning environmental amenities (Gregory, Lichtenstein and Slovic 1993).

A number of methods have developed for incorporating preference uncertainty in empirical applications while maintaining the RUM framework. The first to do so were Li and Mattsson (1995) who used a follow-up question to a dichotomous-choice valuation question that asked respondents how certain or confident they were of their previous ‘yes’/‘no’ answer. A similar ‘follow-up’ strategy for addressing preference uncertainty was employed by a number of other researchers (Champ et al. 1997; Blumenschein et al. 1998; Johannesson, Liljas and Johansson 1998; Loomis and Ekstrand 1998; Ekstrand and Loomis 1998; van Kooten, Krcmar and Bulte 2001).[1] Ready, Whitehead and Blomquist (1995), Wang (1997), Welsh and Poe (1998), Ready, Navrud and Dubourg (2001), and Alberini, Boyle and Welsh (2003) did not use a follow-up strategy, but instead imbedded information about preference uncertainty directly in the response options to the valuation question, thereby jettisoning the straightforward 'yes'/'no' choice. The methods used by researchers to deal with respondent uncertainty vary considerably, but they all appear somewhat ad-hoc in their approach.

While these disparate approaches for treating respondent uncertainty have evolved, there has been no consensus over the appropriate treatment and there have been few attempts to compare approaches using independent data. The current study seeks to fill this gap in the empirical literature using data from two very different surveys: (1) a survey of landowners in western Canada that asked about willingness to accept (WTA) compensation for converting marginal agricultural land to forestry for carbon uptake purposes, and (2) a Swedish survey that asked people their willingness to pay for forest protection. The data are analyzed using five different methods of addressing preference uncertainty, and comparing these to the standard RUM approach with assumed respondent certainty. The research presented here does not develop the methods for treating uncertainty and therefore does not discuss the theoretical appropriateness of each method. The objective of this study is to compare methods in the literature using two independent datasets in order to assess and compare the performance of each suggested method. While economic intuition and previous studies suggest that the inclusion of uncertainty will lower WTP and raise WTA, results indicate that estimates of average WTA or

[1] Note that the follow-up questions used in this literature are not designed to increase the confidence of the estimated welfare measure, as with the double-bounded approach (see Kanninen 1993).

WTP vary substantially across approaches.

The paper is organized as follows. Models incorporating uncertainty into dichotomous choice CVM are reviewed in Section 2, while the two surveys employed in the analysis are described in Section 3. The empirical results are provided in Section 4, followed by a discussion of policy implications and considerations for further research.

2. Models Incorporating Uncertainty

This paper analyzes dichotomous-choice CVM surveys that rely on a certainty follow-up question to address respondent uncertainty. Five econometric methods for incorporating respondent uncertainty into the RUM framework are examined, as is the fuzzy method proposed by van Kooten, Krcmar and Bulte (2001). The various approaches are reviewed in this section.

Weighted Likelihood Function Model (WLFM)

Li and Mattson (1995) were the first to implement an empirical framework for addressing preference uncertainty within the RUM model. They retain the assumption that individuals have a true value for the amenity, v_i, but they have incomplete knowledge about that value. Survey respondents arrive at some value, $\tilde{v}_i = v_i + \xi_i + \varepsilon_i$, where v_i is the individual's true valuation of the resource and ξ_i and ε_i are stochastic disturbances arising from uncertainty related to the respondent and the observer, respectively. Observer uncertainty is treated the same as it is in the standard RUM model, but a post-valuation question is used to elicit information about the respondent's preference uncertainty. The standard certainty model likelihood function for the dichotomous-choice RUM model is modified generally for the uncertain case as:

(1) $$L = \sum_{i=1}^{N} w_i \left\{ \left(y_i \ln(1 - \Phi_{wtp}) \right) + (1 - y_i) \ln(\Phi_{wtp}) \right\}$$

where N is the number of survey respondents. The initial dichotomous choice is given as y=1 for a 'yes' and y=0 for a 'no' answer, and Φ is the cumulative distribution function of the maximum WTP. The weights, w_i, are used as a measure of certainty determined by the response to the follow-up question.

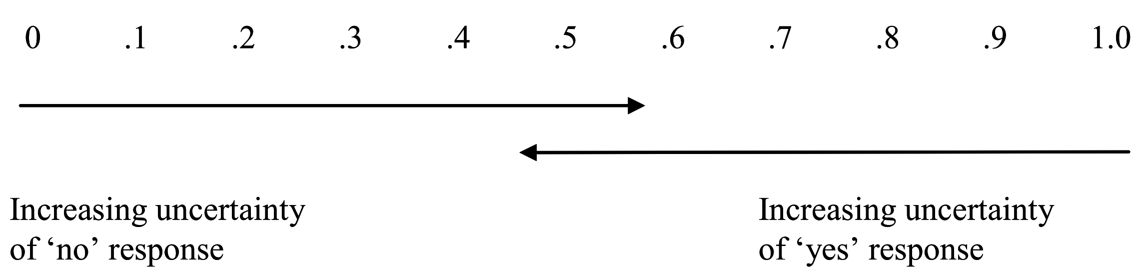
Li and Mattson constructed a post-decisional confidence rating for assessments of the preservation value of forests in northern Sweden using a follow-up question that elicited a respondent's certainty on a scale ranging from 0% to 100% (with 5% intervals). The certainty percentages were used to weight the individual dichotomous-choice responses directly in the likelihood function. Before doing so, however, certainty responses were recoded so that, for example, a 'yes' ('no') response with 40% certainty was recoded to a 'no' ('yes') response with 60% certainty. A 'yes' or 'no' with absolute certainty in this case results in the standard dichotomous-choice model with certainty.

Asymmetric Uncertainty Model (ASUM)

Champ et al. (1997) developed an alternative approach for incorporating the certainty follow-up response. Using a scale of 0 (very uncertain) to 10 (very certain), they elicited responses to the follow-up rating question: "How certain are you that you would donate the requested amount [in the valuation question]?" All 'yes' responses were recoded as a 'no' if the respondent was not completely certain (providing a rating of 10). Ready, Navrud and Dubourg (2001) estimated the value of avoiding episodes of respiratory illness using both dichotomous-choice and payment-card survey techniques. In both cases, the WTP question was posed using the following choices: (1) 'almost certainly yes' (95% sure 'yes'), (2) 'most likely yes', (3) 'equally likely yes and no', (4) 'more likely no', and (5) 'almost certainly no' (95% sure 'no'). Like Champ et al., responses were recoded so that only an 'almost certainly yes' (choice 1) was treated as a ‘yes’, but the other four categories were considered ‘no’ responses. In both of these studies, the initial ‘yes’ response is only considered a valid ‘yes’ if it is with near perfect certainty. As a result, Loomis and Ekstrand (1998) refer to this type of model as an ‘asymmetric uncertainty model’ (ASUM). This model would be most appropriate if respondents answering ‘no’ are quite certain they would not pay, but those answering ‘yes’ are more uncertain about their response. As discussed below, evidence of asymmetry exists in the willingness to accept a tree planting program data (Figure 1), suggesting that the ASUM will perform well in this case.

Symmetric Uncertainty Model (SUM)

The symmetric uncertainty model (SUM) of Loomis and Ekstrand (1998) provides an alternative to the ASUM by attempting to preserve the initial ‘yes’ or ‘no’ response to the dichotomous-choice question. To estimate the benefits of preserving Mexican spotted owl habitat, they pose a dichotomous-choice referendum question with a certainty scale follow-up rating question: “On a scale of 1 to 10, how certain are you of your answer to the previous [valuation] question?” Respondents are instructed to answer 1 for ‘not certain’ to 10 for ‘very certain’. As in the other cases, responses are recoded for estimation purposes, but in this case the recoding converts the dichotomous-choice dependent variable into a ‘continuous’ variable taking on values over the closed interval [0 1]. The symmetric nature of the recoding is illustrated in the following graph:



A ‘no’ response with perfect certainty takes on the usual value of 0, while a ‘yes’ with perfect certainty equals 1. For a ‘no’ response, the dependent variable takes on the value associated with the expressed uncertainty; thus, a ‘no’ response with a follow-up uncertainty response of 60% is coded 0.6, while a ‘no’ with uncertainty 40% is coded 0.4. For ‘yes’ responses, the dependent variable takes on the value of 100% minus the expressed uncertainty; thus, a ‘yes’ response with a follow-up uncertainty response of 60% is coded 1–0.6=0.4, while a ‘yes’ with uncertainty 40% is coded 0.6. If a ‘yes’ or ‘no’ answer to the dichotomous-choice valuation question has an associated uncertainty of 50%, it is assigned a value of 0.5. In this respect, the recoding is similar to that used by Li and Mattson, but while their method retains the two-step response in the likelihood function, the SUM model does not. Following Loomis and Ekstrand, the SUM can be estimated directly using a maximum-likelihood procedure.

Random Valuation Model (RVM)

Wang (1997) views the value that an individual attaches to any amenity (including market traded goods) to be a random variable with an unspecified probability distribution. He assumes that each respondent has in mind an implicit distribution of values rather than a single true value. A respondent will accept to pay a particular amount for an increase in the level of the amenity only if the latent compensating surplus (CS) is ‘sufficiently large’ relative to the bid, and reject the proposed payment if latent CS is ‘sufficiently small’. A ‘don’t know’ (DK) response occurs if latent CS lies in a ‘grey area’ where CS is either not sufficiently large or sufficiently small relative to the proposed payment. Since the valuation question permits a DK response, no follow-up question is needed to elicit the uncertainty of the response. Then, defining the WTP function as $v_i = x_i\beta + \varepsilon_i$, and assuming ε_i is normally distributed, the log likelihood function for the three response categories and a proposed one-time payment is:

$$(2) \qquad \log L = \sum_{i \in yes} \log\left[1 - \Phi(\frac{t_i + a_i - x_i\beta}{\sigma})\right] + \sum_{i \in no} \log\left[\Phi(\frac{t_i - b_i - x_i\beta}{\sigma})\right]$$

$$+ \sum_{i \in DK} \log\left[\Phi(\frac{t_i + a_i - x_i\beta}{\sigma}) - \Phi(\frac{t_i - b_i - x_i\beta}{\sigma})\right],$$

where t_i is the bid level assigned to respondent *i,* and $a_i = v_i - S1_i$ and $b_i = S2_i - v_i$, where S1 and S2 are the lower and upper bounds of the DK region, respectively. If S1 and S2 are constants, maximization of (2) effectively amounts to estimating an ordered Probit model. The assumptions can be relaxed to allow *a* and *b* to be functions of the variables thought to affect individual variations. Wang also estimated the model by treating the DKs as 'no' responses, similar to the approaches of Ready, Navrud and Dubourg (2001) and Champ et al. (1997), and also by deleting them from the sample. Not surprisingly, Wang found estimated WTP to be significantly lower when all DKs were recoded as 'no' responses.

Multiple-bounded Discrete Choice (MBDC)

Although not implemented in the current study, an extension of Wang's approach was implemented by Welsh and Poe (1998), and Alberini, Boyle and Welsh (2003). They adopt a 'multiple-bounded discrete choice' (MBDC) approach that directly incorporates certainty levels through a two-dimensional decision matrix: One dimension specifies dollar amounts that individuals would be required to pay on implementation of the policy, and the second dimension allows individuals to express their level of voting certainty via four response options – 'definitely no', 'probably no', 'not sure', and 'definitely yes'. This expands to four the three options available in Wang (1997). A multiple-bounded logit model is used to estimate separate WTP functions for each certainty level.

Fuzzy Model (FM)

Like Wang, van Kooten, Krcmar and Bulte (2001) also assume that an individual does not know the amenity's precise ('crisp') value, and will never know it with certainty. A respondent only knows the level above which she will certainly reject the proposed payment and the level below which she will certainly accept it. In between these levels, the preferences of the respondent are 'vague', so that the respondent's WTP and willingness not to pay (WNTP) are best viewed as fuzzy sets (Jang, Sun and Mizutani 1997). That is, rather than assuming the individuals know the distribution of the true value, but not the precise value itself, the researchers assumed that CS can be a member of both the WTP and WNTP fuzzy sets at the same time (which is a characteristic of fuzzy set theory). In their application, follow-up information about how confident or certain the respondent is about her response to the valuation question is used to estimate both WTP and WNTP fuzzy membership functions.

Van Kooten, Krcmar and Bulte (2001) employ the same data as Li and Mattsson (1995). The latter assume that an individual *k* who is 40% certain of a 'yes' response is also 60% certain of a 'no' response, so w_k=0.6 and y_k=0 in (1) or w_k=0.4 and y_k=1, but not both. The former assume, however, that *k*'s response is a member of the WTP fuzzy set with membership value 0.4 and a member of the WNTP fuzzy set with value 0.6. That is, the post-decisional confidence of a response is used to determine the membership values of the WTP and WNTP fuzzy sets. The intersection of the estimated WTP and WNTP membership functions corresponds to the 'comfort' level of the associated welfare estimate. Fuzzy estimates of WTP to protect forests in northern Sweden were well below those estimated using the WLFM approach of Li and Mattson.

3. Survey Data

For our empirical application, we employ data from two surveys, one of which elicited WTA compensation for planting trees on marginal agricultural land and the other WTP for preservation of forest ecosystems. We chose to use two different surveys—one with WTA and the other with WTP—in order to observe any consistent patterns across the various treatments of uncertainty. The surveys are briefly discussed in the following paragraphs.

Tree Planting in Western Canada

A survey of landowners in Canada's Prairie region elicited willingness to accept compensation for a tree planning program on marginal agricultural land. A questionnaire was mailed in July 2000 to randomly selected landowners in the grain belt region of Manitoba, Saskatchewan, Alberta and northeastern British Columbia. The survey included a cover letter explaining the role of tree planting and carbon credits in mitigating climate change. It elicited detailed information on farmers' agricultural operations (including activities on marginal fields), opinions about and awareness of climate change issues and carbon credits, and personal characteristics and demographics. Initial questions were meant to reduce information biases by familiarizing respondents with the topic and issues under investigation before asking about willingness to accept compensation for planting trees. More information on the survey design and descriptive variables can be found in Shaikh, Sun and van Kooten (2005).

Summary statistics for the explanatory variables are provided in Table 1. The choice of explanatory variables is based on previous research (van Kooten, Shaikh and Suchánek 2002; Shaikh, Sun and van Kooten 2005). Not all returned surveys were used in the estimation as the survey design did not permit those respondents who were unwilling to consider a tree planting program to answer the valuation questions. Landowners might have rejected the option to plant trees because they were located in a dry area (southern grain belt) where trees are less likely to survive or grow large, or in a region where land clearing for agricultural purposes is still ongoing (northern grain belt). While these responses could be construed as a ‘no’ response for any bid amount, they are not included in this analysis because we are primarily interested in those indicting a potential willingness to convert their land. Research to examine this issue further is important but outside the scope of the current study. After excluding those who did not proceed to answer the valuation question or failed to provide other information required for the current analysis (failed to answer the follow-up question, did not provide data on marginal fields, etc.), 122 questionnaires were available for estimating WTA.

<Insert Table 1 about here>

In the survey, landowners were presented a hypothetical 10-year contract to plant trees on their most marginal land. The contract would pay up-front planting costs and provide an annual payment to compensate for lost agricultural production. The contingent contract indicated that farmers had no right to harvest the trees before the contract expired, but trees became their property at the end of the contract period. No compensation was provided for conversion of land back to agriculture; instead, it was explicitly noted in the survey that a market for selling carbon credits might have developed by that time or landowners could simply sell the trees thereby covering the cost of converting land back to agriculture if necessary. In the absence of *a priori* valuation information, the compensation offers were selected on the basis of results from a pilot study, and ranged from \$1 to \$60 per acre per year. The distribution of these bids is skewed towards the lower end of the range in order to provide more efficient estimates of WTA (Cooper 1993). In a follow-up to the dichotomous-choice valuation question, the respondent was asked to rate the certainty of her response on a scale of '1' for not certain to '10' for very certain. Both questions are provided in the Appendix.

As indicated in Figure 1, around 50% of those answering 'no' were very certain of their answers, compared to only 15% of those responding 'yes'. As was the case for Welsh and Poe (1998), if respondents to a one-shot dichotomous-choice question are unsure whether they would pay the dollar threshold, they are most likely to report they would vote 'yes' – an indicator of 'yea saying'.

<Insert Figure 1 about here>

Forest Conservation in Northern Sweden

Li and Mattsson (1995) used a contingent valuation survey to assess the preservation value of forests. The survey asked respondents what they would be willing to pay to continue to visit, use and experience the forest environment in northern Sweden. Bid amounts took one of the following values: 50, 100, 200, 700, 1000, 2000, 4000, 8000 and 16000 SEK. A follow-up question asked how certain the respondent was about her 'yes'/'no' answer on a 0-100 percent scale with 5% intervals. About 14% of the 'yes' respondents and 11% of the 'no' respondents reported confidence levels below 50%. Similar to the Canadian survey, some 35% of the 'yes' and 16% of the 'no' respondents indicated that they had complete confidence in their response to the valuation question.

The Swedish survey also collected data on respondents' age, gender, number of forest visits, education and household income. The sample made available to us by Li and Mattsson consisted of 389 usable surveys, which, following their lead, was reduced to 344 observations by excluding observations with reported income levels below 11,000 SEK and above 300,000 SEK, and with education levels below 1 year and above 25 years.

4. Comparing Uncertainty Models

In this section, we compare the results of five approaches for addressing preference uncertainty, beginning with the survey of western Canadian landowners. The ASUM of Champ et al., Li and Mattson's WLFM, Loomis and Ekstrand's SUM, and Wang's RVM are all estimated as described earlier. (Lack of information prevents the use of the MBDC approach.) However, we expand on the estimation procedure of the fuzzy model because it is likely the least familiar and it involves a distinct estimation procedure.

Tree Planting in Western Canada

The results of the standard certainty RUM model and the four non-fuzzy methods for addressing uncertainty (WLFM, ASUM, SUM and RVM) are provided in Table 2. The conversion of our data and estimation methods are straightforward for the WLFM, ASUM and SUM models as they exploit information from the follow-up question in straightforward fashion. For the RVM method, the certainty information is exploited in a less direct fashion. Two approaches are possible: Wang (1997) provided three choice options, while Welsh and Poe (1998), and Alberini, Boyle and Welsh (2003), provided four options. The difference had to do with the intensity of the 'yes'/'no' response. We could best mimic the RVM approach of Wang (1997) by recoding a 'yes' response followed by an expressed certainty greater than 7 (see Appendix) as a 'certain yes', a 'no' followed by an expressed certainty greater than 7 as a 'certain no', and any in-between response as 'don't know'. We do not consider the alternative

RVM scaling associated with the MBDC approach.

<Insert Table 2 about here>

The coefficients on the bid are statistically significant with the expected positive signs at the 0.05 level or better in all models (Table 2). By more fully incorporating information about respondent uncertainty according to the WLFM approach of Li and Mattsson, we obtain the highest pseudo R^2 (=0.356), although pseudo R^2 in the certainty model is only slightly lower (=0.301). For the asymmetric uncertainty, random valuation and symmetric uncertainty models pseudo R^2s are substantially lower – 0.193, 0.157 and 0.153, respectively. WLFM also performs best based on mean absolute error (MAE), while the certainty model performs best on the basis of Root MSE. They both have the same number of correct predictions.

For fuzzy CVM, membership functions for aggregated WTA and WNTA are estimated from available survey data of western Canadian landowners using a statistical approach, as opposed to aggregating individually-constructed WTA and WNTA membership functions. The follow-up certainty data (see Appendix) are interpreted as the degree of membership in the fuzzy sets WTA and WNTA. Linear and exponential specifications for the fuzzy WTA and WNTA membership functions were chosen to cover a broad range of applications. To obtain the membership functions, we regress the respondents' post-decisional certainty ('comfort') levels for the respective 'yes' and 'no' responses on the relative bid. For the exponential and linear membership functions, we employed MLE and OLS estimation to obtain the following membership functions for WTA and WNTA:

Exponential:

$$\mu_{wta}(w) = \frac{1}{1+\exp(0.0816-0.0168w)}$$

$$\mu_{wnta}(w) = \frac{1}{1+\exp(-1.6661+0.0186w)}.$$

Linear:

$$\mu_{wta}(w) = 0.4936+0.0037w$$

$$\mu_{wnta}(w) = 0.8380-0.0029w.$$

A membership value of 0 in the fuzzy set WTA ($\mu_{\text{WTA}} = 0$) indicates that the respondent is completely certain that the bid is unacceptable, while $\mu_{\text{WTA}} = 1$ indicates complete certainty that it is acceptable. A similar (but opposite) explanation holds with respect to fuzzy WNTA.

A crisp representation of the *minimum* value of the willingness of landowners to accept a tree planting program is determined at the point where the membership functions of WTA and WNTA intersect. At this point, membership in the fuzzy sets 'WTA the bid' and 'WNTA the bid' is identical.[2] If the bid is lower, μ_{WNTA} is higher while μ_{WTA} is less. Of course, the minimum WTA where both μ_{WNTA}=0 and μ_{WTA}=1 occur can also be considered a crisp representation of the landowners' WTA, but it could be infinite. Rather, using the fuzzy choice rule of van Kooten, Krcmar and Bulte (2001), the crisp value that is found at the point of intersection between the fuzzy sets WTA and WNTA provides a minimum welfare measure that has the greatest comfort level. In this application, for the exponential functional form, the intersection occurs at a value of \$49.38 per acre and comfort level (membership) of 0.679; for the linear model, it occurs at a value of \$52.28/ac and comfort level of 0.685. The comfort level conveys information about the remaining uncertainty, which can never be completely removed except at unreasonably high levels of compensation.

[2] This interpretation can be considered as similar to the use of median WTA as a welfare measure.

The estimated median WTAs for each of the 'standard' statistical models are reported in Table 3. Monte Carlo simulation over the parameter estimates was used to calculate the distribution of WTA at the means. The fuzzy results are also reported in the table for comparison. The median compensation needed to get farmers to plant blocks of trees in the preference certainty case is $32.83 per acre (or $33.07/ac if estimated parameter values are random and Monte Carlo simulation is used). The estimated median willingness to accept is $59.51 (or $61.92/ac based on simulation) for the ASUM and $34.45/ac ($34.78/ac) for the WLFM. The results for the SUM and RVM approaches are much lower at $7.89/ac ($7.48/ac) and $14.78 /ac ($14.71 /ac), respectively. As will be described below, the estimates of WTA using the fuzzy approach are not sensitive to functional form and range from $49.38/ac to $52.28/ac. In summary, the estimated WTA ranges from $7.48 to $61.92 per acre.

<Insert Table 3 about here>

One expects that the inclusion of preference uncertainty will lower WTP estimates, but raise WTA results. This is unambiguously the case only in the ASUM and fuzzy models, while the WLFM yields estimates of WTA that are not statistically different from those of the certainty RUM model.

Forest Conservation in Northern Sweden

We also compare the results of the standard certainty RUM model and the five approaches for addressing preference uncertainty in the case of forest preservation in northern Sweden. The estimation results are reported in Table 4. Consistently, the WLFM approach of Li and Mattsson results in the highest pseudo R^2 (=0.283), with pseudo R^2 for the certainty, asymmetric uncertainty, random valuation and symmetric uncertainty models equaling 0.203, 0.237, 0.167 and 0.121, respectively. WLFM also performs best on the basis of MAE, Root MSE and number of correct predictions.

<Insert Table 4 about here>

For the fuzzy model, we employed MLE and OLS estimation to obtain the following membership functions for WTP and WNTP:

Exponential:

$$\mu_{wtp}(w) = \frac{1}{1+\exp(-0.8805-0.00006w)}$$

$$\mu_{wntp}(w) = \frac{1}{1+\exp(-1.5614+0.00014w)}.$$

Linear:

$$\mu_{wtp}(w) = 0.8367 - 0.00003w$$

$$\mu_{wnta}(w) = 0.7118 + 0.00001w.$$

A crisp representation of the <u>maximum</u> value of the willingness to pay for forest protection is determined at the point where the membership functions of WTP and WNTP intersect. At this point, membership in the fuzzy sets 'WTP the bid' and 'WNTP the bid' is identical. In this application, for the exponential functional form, the intersection occurs at a value of 3385.81 SEK and comfort level (membership) of 0.749; for the linear model, it occurs at a value of 3112.06 SEK and comfort level of 0.743.

For each of the 'standard' models, the estimated median willingness to pay is reported in Table 5. Again, bootstrapping was used to calculate the distribution of WTP at the means. The median WTP in the preference certainty case is 3899 SEK (or 3915 SEK if bootstrapped). The estimated median WTP is 814 SEK (772 SEK) for the ASUM and 3643 SEK (3640 SEK) for the WLFM. The result from SUM is much higher at 11,598 SEK (11,882 SEK), as it is for the RVM at 2719 SEK (6801 SEK). As indicated above, the estimates of WTP using the fuzzy approach are not sensitive to functional form and range from 3112 to 3386 SEK. In summary, the estimated WTP for forest preservation ranges considerably from 772 to 11,882 SEK.

<Insert Table 5 about here>

Again, the literature indicates that WTP estimates are likely biased upwards if uncertainty is not taken into account. The inclusion of uncertainty lowers WTP estimates, as expected, for the ASUM, WLFM and fuzzy models, although the difference between the certain estimates and those of the WLFM cannot be considered to be different. These same approaches led to expected higher WTA estimates when preference uncertainty was included in the tree-planting survey.

5. Discussion

Differences clearly exist between valuation estimates based on a model that assumes preference certainty and preference uncertainty models that exploit additional information available from certainty ratings. Nonetheless, as Loomis and Ekstrand (1998) point out, there are two conditions that need to be satisfied if the predictive accuracy of intended behavior is to be improved when uncertainty information is taken into account. First, respondents must be able to assess the certainty of their valuation with some degree of accuracy, but this may be difficult due to general lack of cognitive ability in responding to dichotomous-choice valuation questions. Second, respondents must all interpret the certainty scale equivalently – those who provide a rating of four, say, must all have the same level of preference uncertainty. This is unlikely the case, with the incomparability of rating responses across individuals potentially adding more noise than signal. Thus, the approach adopted to reflect respondent uncertainty could potentially introduce additional variance into the analysis.

Our results show that the inclusion of preference uncertainty information can improve welfare measures. However, the means used to incorporate uncertainty information is crucial. Evidence from the two surveys presented here supports the WLFM approach of Li and Mattsson, because WLFM outperforms the other statistical methods for incorporating preference uncertainty on the basis of several goodness-of-fit criteria. On this basis, it also outperforms the traditional RUM certainty model. However, the WLFM results are also closest to those of the certainty model (in both cases welfare measures are not statistically different), which suggests that the inclusion of preference uncertainty has only a minimal impact on welfare estimates.

The fuzzy approach leads to welfare estimates that are 'close' to those of the WFLM method (at least closer than other approaches for addressing preference uncertainty), and, by interpreting a respondent's certainty level as a membership value in both the WTA (WTP) and WNTA (WNTP) fuzzy sets, it addresses the points raised by Loomis and Ekstrand. The problem with the fuzzy method, however, is that there is no means for comparing it with the other approaches. Even though the estimated fuzzy WTA (WTP) falls within the range of values derived from the other models and is closest to those from the WLFM, which also has the best goodness-of-fit, there are no grounds to judge it relative to the other approaches.

6. Summary and Further Research

Manski (1995) recommends directly eliciting the percent or likelihood of some action, arguing that even if expectations are not rational, probabilistic intentions data may have greater predictive power than binary data. Evidence in favor of incorporating respondents' preference uncertainty into CVM surveys is increasingly found in empirical studies. Beginning with Li and Mattson (1995), studies show that mean estimates of willingness to pay are seriously biased upwards if preference uncertainty is ignored. Champ et al. (1997) found that WTP estimates were quite similar to actual cash WTP if all 'yes' responses where the individual was not very certain were recoded to 'no' responses, while Ready, Nvrud and Dubourg (2001) found convergence of dichotomous choice and payment card formats using a similar approach. The results of this study show that incorporating preference uncertainty does have the potential to increase goodness of fit, but, depending on the empirical method used to incorporate the uncertainty follow-up, it could introduce additional variance into the analysis.

An important result of the comparisons made here is that willingness to accept compensation and willingness to pay under uncertainty can be higher or lower than the associated measure under certainty. While previous studies have generally shown that models assuming certainty result in WTP estimates that are biased upwards, the WLFM, ASUM and fuzzy approaches are the only ones that confirm this result – inclusion of respondent uncertainty increases WTP and decreases WTA. The RVM and SUM approaches lead to the opposite result. Hence, the results of this analysis caution against systematic judgments about the directional effect of uncertainty on contingent valuation responses. Further, while several methods have been suggested in the literature for treating uncertainty, there is little evidence that one method is generally superior to another, thereby warranting additional developments in this area.

Given that the WLFM approach to the inclusion of uncertainty is associated with the 'best' performance but results in welfare measures not distinguishable from those of the certainty RUM model, several questions come to mind. Are individuals truly uncertain about the tradeoff between the money metric and the proposed contingency? If so, are current methods for treating this uncertainty in deriving welfare measures up to the task? This research treats uncertainty as an empirical question only. A full representation of preference uncertainty would require its incorporation into a utility maximization model, from which a new form of WTA (WTP) would be derived and estimated. It would also require better means for eliciting preference uncertainty in CVM-type questionnaires. To our knowledge, these issues have not been explored fully within the CVM literature and remain important concerns for further research.

7. Appendix

Valuation Question:

Suppose a block tree-planting program (planting of entire fields) is available, and at least one of your fields is identified as a potential site for tree plantations. Would you be willing to accept ANNUAL compensation of **$ <to be filled in>** per ACRE for a 10-year contract? (**Please circle**)

YES NO

Follow-up Question:

On a scale 1 to 10, how certain are you of your answer to the previous question? **Please circle** the number that best represents your answer if **1= not at all certain** and **10 very certain.**

1 2 3 4 5 6 7 8 9 10

not at all certain Somewhat certain very certain

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Figure 1: Comparison of certainty of yes and no responses.

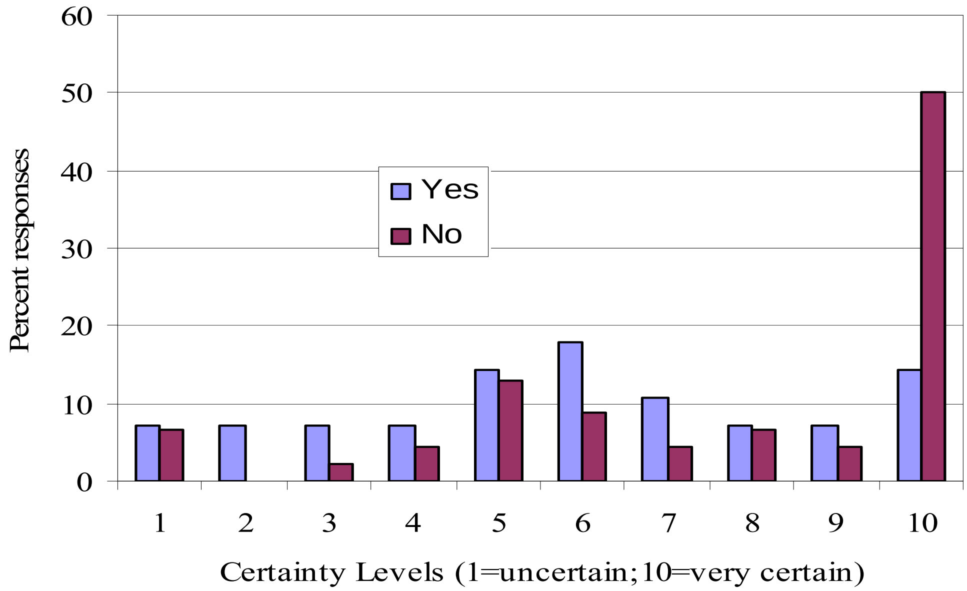

Table 1: Variable Statistics for Tree-planting Program (n=122)

Explanatory Variable	Mean	S.D.	Min	Max
Compensation offered ($ per ha)	26.090	16.860	3.00	60.00
Brown soil zone (=1, 0 otherwise)	0.156	0.364	0.00	1.00
Forest landscape thought visually unappealing (=1, 0 otherwise)	2.008	1.032	1.00	5.00
Acres of farmland covered with trees	41.861	72.901	0.000	525.00
Age (median category variable from 33 to 68 years with 5-year intervals)	55.541	9.690	33.00	68.00

Table 2: Estimation Results for Tree-planting Program (n=122)[a]

Explanatory Variable	Preference Certainty	Preference Uncertainty			
		ASUM[b]	WLFM	SUM[b]	RVM[b]
Constant	-3.663***	-3.829***	-8.489***	-1.483*	—
	(0.924)	(0.982)	(2.052)	(0.812)	
Compensation offered	0.044***	0.035***	0.098***	0.037***	0.036***
	(0.008)	(0.009)	(0.018)	(0.008)	(0.006)
Brown soil zone (=1; =0 otherwise)	1.029***	0.128	1.314**	0.462	0.291
	(0.365)	(0.398)	(0.669)	(0.367)	(0.261)
Forest landscape visually unappealing	-0.237	-0.082	-0.309	0.076	0.030
	(0.149)	(0.152)	(0.302)	(0.131)	(0.096)
Acres of farmland covered with trees	0.007***	0.004*	0.014***	0.003	0.005***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Age (median category variable from 33 to 68 years with 5-year intervals)	0.040***	0.031**	0.089***	0.015	0.030***
	(0.014)	(0.015)	(0.027)	(0.013)	(0.011)
Log likelihood	-57.992	-45.232	-36.765	-62.663	-107.218
Pseudo R^2	0.301	0.193	**0.356**	0.153	0.157
Root MSE	**0.400**	0.500	0.406	0.509	0.763
MAE	0.315	0.364	**0.302**	0.430	0.582
Correct predictions	**94**	75	**94**	73	51
	(77.05%)	(61.48%)	**(77.05%)**	(59.84%)	(41.80%)

[a] Standard errors are provided in parentheses: ***, ** and * indicate statistical significance at the 1%, 5% and 10% or better levels, respectively. The "best" model based on the criterion is indicated in bold.
[b] In the ordered logit model, the estimated coefficients of the two cuts are not reported here.

Table 3: Estimated Median Willingness to Accept a Tree-planting Program ($/acre)

Model and item	Median	Standard Deviation	Minimum	Maximum
Preference certainty				
Estimated parameter values fixed; WTA based on farmers' covariates	$32.83	$16.20	–$38.15	$65.92
Estimated parameter values random; representative farmer covariates[a]	$33.07	$3.39	$21.94	$44.98
ASUM				
Estimated parameter values fixed; WTA based on farmers' covariates	$59.51	$11.19	$9.78	$83.87
Estimated parameter values random; representative farmer covariates[a]	$61.92	$13.06	$44.23	$264.44
WLFM				
Estimated parameter values fixed; WTA based on farmers' covariates	$34.45	$13.96	–$32.61	$62.79
Estimated parameter values random; representative farmer covariates[a]	$34.78	$2.85	$25.71	$44.34
SUM				
Estimated parameter values fixed; WTA based on farmers' covariates	$7.89	$7.97	–$29.70	$20.36
Estimated parameter values random; representative farmer covariates[a]	$7.48	$5.32	–$29.36	$19.63
RVM				
Estimated parameter values fixed; WTA based on farmers' covariates	$14.78	$13.46	–$58.22	$37.30
Estimated parameter values random; representative farmer covariates[a]	$14.71	$4.51	–$11.29	$28.79
Fuzzy Method	Value	Comfort Level		
Exponential membership function	$49.38	0.679		
Linear membership function	$52.28	0.685		

[a] Except for the fuzzy model, results are based on bootstrapping with n= 10,000.

Table 4: Estimation Results for Forest Protection in Northern Sweden (n=344)[a]

Explanatory Variable	Preference Certainty	Preference Uncertainty			
		ASUM[b]	WLFM	SUM[b]	RVM[b]
Constant	-2.260***	-2.069***	-2.354***	-1.488**	—
	(0.608)	(0.643)	(0.650)	(0.635)	
Bid	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Annual number of forest visits	0.002**	0.003***	0.003***	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.227***	0.151***	0.229***	0.182***	0.177***
	(0.052)	(0.054)	(0.055)	(0.053)	(0.046)
Income	0.011***	0.008**	0.012***	0.013***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Income $\times$ Education	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-189.856	-172.484	-133.307	-176.495	-311.133
Pseudo R^2	0.203	0.237	**0.283**	0.121	0.167
Root MSE	0.430	0.456	**0.429**	0.491	0.683
MAE	0.373	0.384	**0.355**	0.409	0.472
Correct Predictions	253	237	**255**	219	180
	(73.55%)	(68.90%)	**(74.13%)**	(63.66%)	(52.33%)

[a] z-statistics are provided in parentheses: ***, ** and * indicate statistical significance at the 1%, 5% and 10% or better levels, respectively. The "best" model based on the criterion is indicated in bold.
[b] In the ordered logit model, the estimated coefficients of eliminated variables are not reported here.

Table 5: Estimated Median Willingness to Pay for Forest Protection in Sweden (SEK)

Model and item	Median	Standard Deviation	Minimum	Maximum
Preference certainty				
Estimated parameter values fixed; WTP based on respondents' covariates	3899.01	2709.68	-5335.72	15145.47
Estimated parameter values random; representative respondent covariates[a]	3915.05	601.78	1607.82	6271.53
ASUM				
Estimated parameter values fixed; WTP based on respondents' covariates	813.76	1713.09	-4007.63	6103.45
Estimated parameter values random; representative respondent covariates[a]	771.83	449.42	-1390.25	2055.18
WLFM				
Estimated parameter values fixed; WTP based on respondents' covariates	3643.10	2358.13	-3504.61	11515.67
Estimated parameter values random; representative respondent covariates[a]	3640.14	467.27	2212.35	5255.04
SUM				
Estimated parameter values fixed; WTP based on respondents' covariates	11597.50	3453.25	-1515.63	22735.89
Estimated parameter values random; representative respondent covariates[a]	11881.70	1706.68	8342.57	23530.26
RVM				
Estimated parameter values fixed; WTP based on respondents' covariates	2719.20	2446.44	-5275.69	11991.92
Estimated parameter values random; representative respondent covariates[a]	6801.26	677.42	4598.72	8945.75
Fuzzy Method	Value	Comfort Level		
Exponential membership function	3385.81	0.749		
Linear membership function	3112.06	0.743		

[a] Except for the fuzzy model, results are based on bootstrapping with *n*= 10,000.