Respondent uncertainty and willingness-to-accept estimates: a comparative analysis of different approaches

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Abstract
This research investigates the issue of preference uncertainty using data from a willingness-to-accept scenario aimed to measure the social costs borne by local residents in Valencia (Spain) resulting from the expansion of its port area. Both a "Don't know" option as a follow-up numerical certainty scale were used, hence several adjusted willingness to accept estimates were obtained as a result of following different strategies when incorporating information about uncertainty. The effect on estimation efficiency of each alternative was also addressed. Finally, in order to provide more insight into the factors underlying uncertainty in a willingness-to-accept scenario, a logistic regression with "certainty" as the dependent variable was estimated.

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1. Introduction

Contingent Valuation (CV), although controversial, still remains the most widely used method for valuing non-market goods. Carson (2011) has compiled over 7,500 studies and papers that have applied this methodology to different areas of research, now commonplace in decision-making. Nevertheless, like any other economic methodology, CV is not entirely a flawless technique, and critics argue that this method is unable to generate reliable estimates of value (Hausman 2012) or that money appears to be a poor scale for summarizing environmental values (Ryan and Spash, 2011). Preference uncertainty, defined as any factor conducting to unsure responses by respondents when facing a CV question, is a potential source of error that has been the focus of attention in recent CV literature. Preference uncertainty arises as a consequence of different factors (Shaikh, et al., 2007). First, survey respondents may have incomplete knowledge of the valuation scenario due to a lack of previous experience, thus being uncertain about what they are valuing. Second, the hypothetical nature of the CV method may induce respondents to be unable to make a trade-off between the non-market good under valuation and the payment offered to them. Third, respondents may not understand the valuation scenario or even the way of implementing the environmental change proposed to them. And fourth, the value that an individual assigns to a good is influenced by prices of both substitutes and complementary goods whose markets may behave in an unpredictable way for the individual (Wang, 1997).

The presence of preference uncertainty, and other sources of error, can hinder the role of CV as a key factor in informing decision-making. Hence CV researchers have developed a variety of approaches aimed at addressing this problem. Firstly, the recognition that a sizable portion of respondents are uncertain about their answers, led the NOAA Panel on CV (Arrow et al. 1993) to recommend the inclusion of a "Don't now" or "No answer" option in dichotomous choice CV questions in addition to the "Yes" and "No" options. Secondly, the use of a follow-up certainty question, asking respondents to rate on a numerical certainty scale (NCS) how certain they are of their responses, is a second way of treating preference uncertainty (Champ et al., 1997). This approach has proved to be relatively helpful in mitigating the hypothetical bias that can be defined as the potential divergence between stated and actual or true values (Cummings et al., 1995). Under this approach, a common recoding scheme is to recode as "No" responses only those "Yes" responses from respondents whose level of certainty falls below some specific threshold or cut-off point. Not surprisingly, more "no" responses in the recoded data set will imply lower values of WTP estimates. And thirdly, another way of allowing respondents to express uncertainty is using a multiple-bounded (Welsh and Poe, 1998) question format or a polytochomous choice (PC) format (Ready et al., 2001; Logar and van den Bergh, 2012). In both cases the information about respondent uncertainty is embedded directly into the options of this multiple WTP question.

In this study, we explore and compare the results from several approaches used to address the issue of respondent uncertainty in an application aimed to value the negative externalities stemming from the expansion of Valencia Port in Spain. Considering the perceived property rights on the environment, a WTA scenario was applied instead of a more common WTP approach. Thus, this study adds to the paucity of previous works that have addressed the issue of preference uncertainty on a WTA framework in comparison with the plethora of WTP studies. To date, only three previous studies (to the authors' knowledge) have addressed this issue on a WTA scenario (Groothuis et al., 1998; Caudill and Groothuis, 2002, and Groothuis and Whitehead 2002). As the survey instrument included both a "Don't know" option as well as a NCS for those respondents that gave a "Yes" response to the offered payment, this allowed us to investigate how the treatment of respondent uncertainty affects WTA estimates. In particular, two general treatments were considered. On the one hand, we recoded "Don't know" responses as both "No" responses and "Yes" responses; and on the other hand, we used a NCS that allowed us to use different cut-off points as well as converting the respondent uncertainty rates into estimates of the probability of paying. Hence, five different adjusted WTA estimates were obtained. In addition, in order to provide more insight into the differences between respondents who we consider as certain of their responses and those who are uncertain, we estimated a logistic regression with "certainty" as the dependent variable. In this way we hope to shed light on the factors underlying uncertain responses in a WTA scenario.

The remaining part of the paper is outlined as follows. Section 2 reviews the key literature on preference uncertainty in Contingent Valuation. Section 3 presents the case study and the data collection procedure. The estimated models and their corresponding WTA estimates appear in section 4. Section 5 includes the discussion of the results obtained followed by some concluding remarks.

2. Contingent Valuation and preference uncertainty

The empirical evidence on CV has challenged the traditional view that respondents know their preferences with complete certainty. Thus it is not surprising that the treatment of preference uncertainty, and its impact on CV estimates, has been a recurrent theme in the CV literature over the last twenty years, although there is not yet an explicit theoretical model to explain variations in preference uncertainty (Atker et al., 2008). In the following lines we provide a short review of the different approaches carried out to address respondent uncertainty.

2.1 Uncertainty and Random Utility Models

Hanemann (1984), using a Radom Utility Model (RUM), addressed this issue on the part of the investigator and not on the part of the respondent. Under the RUM the individual's utility function contains a deterministic component and an unobservable random error term. This uncertainty is expected to manifest itself in the error term of the estimated value function, so the higher the respondent uncertainty, the higher the error and the higher the probability of obtaining biased welfare estimates. However, from a respondent's perspective, Li and Mattsson (1995) argued that respondents have a true valuation of the resource but they do not know it with certainty, thus individuals' preferences are assumed to be uncertain due to their random determinants. A follow-up certainty question is used to elicit further information about the respondent uncertainty. In this way, this certainty measure is integrated into the standard dichotomous choice CV model providing more efficient value estimates.

Wang (1997) extends the traditional concept of value of a good assuming that there is a valuation distribution or a range, rather than a single value for each individual, therefore the individual's valuation of any good is best characterized as a random variable with an associated probability distribution. Since there will inevitably be many uncertain factors involved in a respondent's valuation, then WTP is shown as a continuous random variable. Thus, a CV study offering respondents only "Yes" and "No" options to choose from, would be inappropriate specially when there are factors leading respondents to make an uncertain choice. Therefore, providing an explicit "Don't know" option seems more appropriate as it increases the information obtained.

2.2 Uncertainty and the use of a numerical certainty scale format

The NCS method has been widely used for measuring preference uncertainty in CV studies. Under this approach, after the dichotomous-choice (DC) question, respondents are asked to indicate their level of certainty by selecting a score within the NCS. For example, Li and Mattsson (1995) asked the respondents to rate their certainty on a scale from 0% to 100%, while Champ et al. (1997) used a 10-point scale where "1" means "very uncertain" and "10" means "very certain". However, while Li and Mattsson (1995) used the resulting certainty percentage to recode both the "Yes" as the "No" responses, Champ et al. (1997), Polasky et al. (1996) and Johannesson et al. (1998) only recoded as “No” responses those “Yes” responses that fell under a specific threshold or cut-off point. Usually a cut-off point of seven or eight is used.

In order to make fuller use of the preference uncertainty data, whether the NCS is 1-10 or 1-100%, Loomis and Ekstrand (1998) propose to convert the respondent’s uncertainty rate into an estimate of the probability of paying their bid amount. Since within the DC CV question format “Yes” responses are coded as “1” and “No” responses as “0”, if we multiply these responses by the certainty level (P), then the “Yes” responses would be recoded with a range 1-0.1 while the “No” responses would be recoded as zero regardless of their certainty level.

This approach is labeled as Asymmetric Uncertainty Model (ASUM) since only the “Yes” responses are recoded after the follow-up certainty question. As expected, the asymmetric recoding of uncertain “Yes” responses as certain “No” responses reduces the estimated WTP values below the values from the standard DC model (Atker et al., 2009). For example, Loomis and Ekstrand (1998) found that incorporating uncertainty only for the “Yes” responses resulted in a dramatic drop in the mean WTP estimates.

When both “Yes” and “No” responses are coded with their certainty level the treatment applied is known as Symmetric Uncertainty Model (SUM) (Loomis and Ekstrand, 1998). The recoding converts the original DC dependent variable into a continuous variable, taking on values over the interval [0 1] while the original variable was of discrete nature taking only two possible values (one and zero).

2.3 Uncertainty and the use of a polychotomous choice format

Preference uncertainty can be also addressed using a PC method. Under this alternative approach, respondents are asked to express their uncertainty by choosing from a set of responses (e.g. “definitely yes”, “probably yes”, “maybe yes”, “maybe no”, “probably no” and “definitely no”). In this case, as the respondent is facing a set of different alternatives with their corresponding degree of certainty, the information about respondent uncertainty is embedded directly into the options of this polytochomous WTP question. The difficulty with this PC method with regard to the representation of value uncertainty is that the researcher must interpret how different respondents think about concepts such as “probably yes”, “maybe yes” and so on (Hanley et al., 2009). This problem is known as a “framing effect”, which arises when the distinction between these middle responses is not very clear to the respondents, since no one would expect all respondents to “frame” the CV scenario in exactly the same manner.

A review of the literature shows that the treatment of these responses varies considerably, and is subject to a high degree of subjectivity on the part of the researcher. For example, Vossler et al. (2003) using a three-option PC format (“yes”, “no” and “undecided”) treat “undecided” responses as a “separate response” category, as “no” responses or even exclude them from the sample altogether. In the case of a multiple-choice PC format, recoding can be applied in different ways (Akter et al., 2008), e.g. calibrating the two bipolar endpoints “definitively yes” and “definitively no” as “1” and “0” respectively, and the rest of options as missing, or calibrating “definitely yes” as 1 and the rest as 0, or even calibrating all “yes” responses (“definitely yes”, “probably yes”, and “maybe yes”) as 1 and the rest as 0.

2.4 Uncertainty and “don’t know” responses

Before the generalization of the use of NCS and PC formats to address respondent’s uncertainty, the NOAA Panel on Contingent Valuation suggested the use of a “Don’t know” or “middle” option to the DC CV format. Thus, uncertain respondents could choose this option instead of giving either a “Yes” or “No” response which does not reflect meaningful preferences with regard to the good that is being valued. However, the interpretation of these “middle” responses is not straightforward since several possibilities arise. One possibility is that uncertain respondents are not in the market for the good being valued at the particular bid amount (Carson et al., 1998), while an alternative interpretation, suggested by Alberini et al. (2003), is that these respondents have not yet made up their minds, and so cannot provide a meaningful response.

A practical issue arises of what to do with these “middle” responses. If they are dropped from the data set, there is a cost in terms of lost information or even a problem of sample selection bias if these uncertain respondents are systematically different from the rest of respondents (Wang, 1997). A conservative and popular strategy is to treat these “Don’t-know” responses as “No” responses (Carson et al., 1998; Groothuis and Whitehead, 2002). However, recently Balcombe and Fraser (2009) state that the selection of “Don’t know” responses represents a failure of the individuals to recognize their own preferences, which in turn constitutes a form of misreporting. Therefore, in contrast to previous work, they found that a “Don’t know” response is more similar to a ”Yes” response than to a “No” response since “Don’t know” responses are more likely to be from respondents predicted to have a positive utility for the bid. On the other hand, Carson et al. (1994) recommended treating these “middle” responses as missing since respondents who choose this option would say “No” if they were forced to choose. Wang (1997) points out that deleting “Don’t know” responses can never be theoretically justified.

2.5 Preference uncertainty within a WTA framework

Carson et al. (2003) point out that CV is a survey approach mainly used to measure what people would be willing to pay for specific changes in the quality or quantity of public goods or, more rarely, what they would be willing to accept in compensation for well-specified degradations in the provision of these goods. Considering this statement, along with the guidelines proposed by the Blue Ribbon Panel on CV, which recommended the use of WTP questions as a more conservative choice, it is not surprising that a vast majority of CV studies have addressed the issue of preference uncertainty using a WTP framework instead of a WTA one. We are aware of the existence of only three previous studies that have tackled this problem within a WTA framework.

Groothuis et al. (1998) measured WTA for estimating the compensation needed to site a hazardous waste disposal facility in Pennsylvania (USA). Respondents were given three alternatives: “Yes”, “No” and “Don’t know”. They addressed the issue of preference uncertainty allowing uncertain respondents to choose the “Don’t know” or “middle” response option. Later, in the empirical analysis carried out, the “Don’t know” responses were treated as “Yes” responses to provide a conservative estimate of WTA.

In a later study, Groothuis and Whitehead (2002) found that “Don’t know” responses were similar to “No” responses in the WTP scenario, while in the WTA scenario they were similar to a “middle” response. In this latter scenario, 28% of respondents gave a “Don’t know” response. The main reason for this type of response was that the respondents needed more information, thus indicating that respondents had uncertainty in their preferences. As in the previous work, the initial assumption was that the “Don’t know” responses were more closely related to a “Yes” response resulting in more conservative WTA estimates. Nevertheless, the results obtained suggested again that “Don’t know” answers were found to be “middle” responses, therefore in this case researchers should estimate ambivalence bounds, using a two- threshold ordered logit model, instead of providing a single-point estimate.

Finally, Caudill and Groothuis (2005) developed a multinomial logit model to statistically determine whether any of the “Don’t know” responses in CV studies are more likely “Yes”, or more likely “No” replies , or whether some are distinct as “Don’t know” responses. This new approach calculated the probability that the “Don’t know” response is actually a “Yes”, a “No” or a “Don’t know” response. Thus, all observations in the “Don’t know” category are reassigned to another category or remain a “Don’t know”. They find that with the “Don’t know” responses assigned to the “Yes” conservative category the estimated WTA is lower than when the “Don’t know” are omitted.

3. Case study, data collection and survey instrument

The current case study takes place in the context of port expansion and negative environmental externalities. Over the last few decades the intensification of the current globalization process has brought about major technological changes in the shipping industry. Thus, seaports have been forced to readapt to these new circumstances relocating their cargo terminals to urban peripheral sites more suitable to meeting the current standard of space and transport links (Saz-Salazar and García-Menéndez, 2003; Huang et al., 2011). Not surprisingly, community opposition to port expansion is a growing concern in many port cities since people, particularly those living in the nearby areas, are more aware of the port’s negative environmental impact.

In this particular context, a 29-question survey was designed to investigate people’s preferences for a potential monetary compensation for those negatively affected by the expansion of the Valencia Port (VP) in Spain over the last 30 years. As a consequence of its economic success, VP has become one of the leading seaports in the Western Mediterranean basin in terms of containerized cargo volume, which has multiplied by thirty-five over this period (ESPO, 2011). However, land reclamation from the sea, in order to accommodate new quays protruding into the sea, is the main environmental issue related to this expansion process along with some other minor problems (such as odors, noise, wind-borne dust, and so forth).

Although a WTP framework is the preferred question format to value both gains and losses, since it provides more conservative welfare estimates, in this case it was deemed more convenient to use a WTA framework considering the perceived property rights of nearby residents who have lived in this area for a long time before this expansion process took place. A WTP scenario would have contradicted residents' perceived property rights; moreover it would be quite unrealistic given that the expansion process in favor of the general interest is indeed unstoppable in the current circumstances.

After the pre-testing, and several focus groups, 400 face-to-face interviews were carried out in July 2010 in the six neighborhoods of the city closest to the port area. To keep respondent's attention, and to facilitate understanding of the valuation scenario, visual aids showing the port's area before and after the expansion process were used, as well as charts explaining the main environmental impact following the port's growth. Using a DC question, respondents were asked to agree or disagree with a specific annual amount of compensation. A five-bid vector was identified (€10, €30, €60, €120 and €270) using data from the two pilot studies conducted and following the procedures adopted by Cooper (1993). In order to address the issue of respondent uncertainty, a double approach was adopted. On the one hand, when offering the payment there were three possible replies: "Yes", "No" and "Don't know". And, on the other hand, following Champ et al. (1997; 2009), Champ and Bishop (2001) and Moore et al. (2010), those respondents that gave a "Yes" answer were asked to indicate on a 10-point scale how certain they were of their response. In particular, the framework used took the following form in the survey instrument:

Question 1: In the case that you would feel negatively affected by the externalities derived from this growth process as previously explained, would you be willing to accept an annual reduction of € ... in the real estate tax annually paid as a compensation for the damage caused? Yes - No - Don't Know

Question 2: If you answered Yes to the previous question, on a scale of 1 to 10, where 1 means "very uncertain" and 10 means "very certain", how certain are you that you would pay € ... if you had an opportunity to actually do so?

Although payment vehicles based on taxation face more opposition that those based on donations, in this case an annual reduction in the local property taxes currently paid by respondents was considered the most appropriate payment vehicle since it was very familiar to the population surveyed and incentive compatible. Respondents were also informed that the payment received would reduce the availability of funds for other public policies, thus encouraging them to give realistic responses.

The final section of the survey, as usual, included several socio-economic questions regarding age, education, personal and family income, environmental awareness and so on. These allowed us to explain both the WTA determinants as well as explaining respondents' uncertainty determinants.

4. Results

4.1 General survey results

Table 1 shows the percentage distribution of the follow-up numerical certainty scale asked only to those respondents who gave a "Yes" answer to the offered compensation. Most respondents (31.5%) chose to state a value of "10" regardless of the bid amount; nevertheless it seems that for the lower bids this same percentage is even larger than for the two highest bids. In any case, as Samnaliev et al. (2006) point out, certainty represents a general attitude toward the program being valued rather than an economic value. Hence respondents indicating high levels of certainty to a "Yes" response may be expressing their support to this program. On the other hand, in many studies the value "5" may act as a focal point for those respondents who want to express a moderate level of uncertainty (Martínez-Espiñeira and Lyssenko, 2012), although this is not our case since the respondents that chose the value "5" were between 5 to 15% of the sample depending on the bid offered to them. Finally the data show a skewed distribution towards the higher values (8 to 10) since the values of less than

“5” are very infrequent or in fact do not exist, as in the case of the levels “1” and “2”. In addition, the mean and median values for the whole sample are 7.9 and 8.0 respectively, a result that is almost identical to that reported by Champ et al. (2009).

Table 1
Distribution of certainty levels from the NCS follow-up question (percentages)

Certainty level	All	€10	€30	€60	€120	€270
1	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0
3	2.1	0.0	7.1	0.0	0.0	3.3
4	2.1	0.0	3.6	3.0	0.0	3.3
5	12.2	11.8	10.7	12.1	15.6	10.0
6	10.7	17.6	7.1	9.1	15.6	6.7
7	10.7	17.6	14.3	12.1	6.3	6.7
8	16.4	11.8	3.6	15.2	28.1	10.0
9	14.3	5.9	14.3	9.1	12.5	26.7
10	31.5	35.3	39.3	39.4	21.9	23.3
Mean	7.89	7.88	7.87	8.09	7.72	7.93
Median	8.00	8.00	9.00	8.00	8.00	8.50

4.2 Exploring uncertainty: a comparison of different approaches

In this section different Logit models are estimated in order to explain the determinants of agreeing or not to the proposed compensation. In table 2 the set of explanatory variables used are described with their respective mean values and standard errors, while the estimated models with their variables and coefficients are shown in table 3. Each model treats the information about response uncertainty in a different way, thus we have six different models. In particular, we compare the results of the standard DC model, in which no adjustment for uncertainty has been made, with the results from the other five models in which different adjustment criteria have been adopted. These latter models can be grouped into two categories. In the first category, following a conservative strategy we firstly recoded the “Don’t know” responses as “No” responses (model DKNo), and secondly these responses were recoded as “Yes” responses (model DKYes) following Balcombe and Fraser (2009) that consider “Don’t know” replies to be more similar to a “Yes” than to a “No” response. In the second category, using the rates from the NCS and following Champ et al. (1997), we have recoded the "Yes" responses as "No" if they have certainty levels of six or less (model Yes7) and of seven or less (model Yes8). Finally, the last column of table 3 presents the model that uses the procedure proposed by Loomis and Ekstrand (1998) to convert the respondent uncertainty rate into an estimate of the probability of paying their bid amount (model ASUM).

Table 2
Summary and description of the variables used in the analysis

Variable	Description	Mean	Standard error
Bid	Offered compensation (WTA) in € a year	99.036	0.0014
Income	Respondent's household monthly income after taxes coded in eleven categories (from 0€ to > €3,000)	4.943	0.0674
Crisis	Respondent's opinion about how the current economic crisis affects them from a financial point of view ("very affected" or "quite affected" =1; other cases = 0)	0.286	0.322
Tax	Respondent's awareness of the local property tax paid last year (if remembered = 1; other cases = 0)	0.536	0.2729
Motivation	Respondent's motivation when answering the survey (if "very motivated" or "quite motivated" = 1; rest of cases = 0)	0.650	0.3050
Cabanyal	Neighborhood where the survey was conducted (Cabanyal = 1; other cases = 0).	0.139	0.5180
Grao	Neighborhood where the survey was conducted (Grao = 1; other cases = 0).	0.168	0.4120
Betero	Neighborhood where the survey was conducted (Betero = 1; other cases = 0).	0.143	0.4271

Before comparing different approaches to the treatment of respondent uncertainty and to analyze the effect of each alternative treatment on WTA estimates, we have considered necessary to find relationships between the likelihood that the individual is going to accept the compensation for the environmental damage borne and a set of explanatory variables other than the bid. Thus it is possible to validate the results from a theoretical point of view. In all the models estimated the offered compensation (BID) has the expected sign and is significant, i.e. the higher the offer amount, the higher the probability of accepting it since we have used a WTA scenario instead of a WTP approach. INCOME also shows the expected sign indicating that individuals belonging to high-income households are less likely to accept the compensation offered to them. This result is coherent with the diminishing marginal utility of income (Groothuis et al., 1998). CRISIS is a zero-one variable that indicates the respondent's perception of how the current situation of crisis is affecting them from an economic point of view. Therefore, as expected, those respondents who were "very" or "quite" negatively affected by the crisis are more willing to accept the monetary compensation offered to them. TAX is another dummy variable that takes value "one" if the respondent was capable of remembering and stating how much they had paid the previous year in real estate taxes to the local authority. Therefore, it seems that these individuals are more likely to give a "Yes" response, since they have in mind a clear reference figure of the approximate magnitude of compensation offered to them. The results also show that respondents who were more motivated when answering the questionnaire have a higher WTA.

The three last variables considered refer to the neighborhood in which the interview was conducted. Therefore, the positive coefficients for CABANYAL and GRAO indicate that respondents living in these neighborhoods are less willing to accept the compensation offered to them as a consequence of the possible welfare loss derived from the negative externalities borne. However, if we consider that these neighborhoods are very close to the port area, the result obtained is counterintuitive. In fact, we would have expected a positive sign, i.e. the closer you live to the port area, the more affected you are by its expansion process and the higher the probability of accepting any compensation. Nevertheless, in this particular case the result is justified by the fact that the vast majority of port workers live precisely in these two neighborhoods. So, they seem not to be opposed to the referred growth process and the resulting negative environmental impact because they actually make their living from the port itself. Finally, if the interview was conducted in BETERO, the probability of accepting the compensation offered is higher than in the rest of areas considered. In this case, given that it is the furthest neighborhood from the port area, we would have expected a negative sign, since they are less likely affected by the negative externalities stemming from the VP growth. However, this result might be explained by the lower education and income levels of its habitants which led them to accept any offer.

Table 3
Logit regressions of alternative models

Variable	Standard DC	DKNo	DKYes	Yes7	Yes8	ASUM
Constant	-0.7250	-0.8205*	-0.3729	-1.4034***	-1.6760***	-1.0836**
	(-1.580)	(-1.812)	(-0.871)	(-2.844)	(-3.199)	(-2.274)
Bid	0.0033**	0.0034**	0.0029**	0.0027*	0.0032**	0.0026*
	(2.179)	(2.288)	(2.022)	(1.776)	(2.025)	(1.722)
Income	-0.1455**	-0.1409**	-0.1537**	-0.1200*	-0.1201	-0.1409**
	(-2.160)	(-2.102)	(-2.374)	(-1.726)	(-1.642)	(-2.047)
Crisis	1.0879***	1.1174***	0.9572***	0.7823**	0.8994***	0.8568***
	(3.381)	(3.487)	(3.145)	(2.456)	(2.726)	(2.731)
Tax	0.6228**	0.6344**	0.5512**	0.6845**	0.5020*	0.5942**
	(2.227)	(2.280)	(2.073)	(2.300)	(1.678)	(2.110)
Motivation	0.8183***	0.8301***	0.5620***	1.0213***	1.1382***	0.8240***
	(2.683)	(2.748)	(1.973)	(3.238)	(3.420)	(2.692)
Cabanyal	-2.1261***	-1.7161***	-1.2983***	-2.3603***	-2.6731***	-1.9765***
	(-4.105)	(-3.470)	(-3.203)	(-3.615)	(-3.458)	(-3.481)
Grao	-1.3321***	-1.3107***	-1.2754***	-1.2274***	-1.3843***	-1.1562***
	(-3.234)	(-3.182)	(-3.146)	(-2.811)	(-2.925)	(-2.689)
Betero	1.3777***	1.4212***	1.2464***	0.6924*	0.5907	0.9661**
	(3.226)	(3.328)	(2.984)	(1.770)	(1.482)	(2.469)
Log Likelihood	-157.0820	-159.5143	-170.6942	-151.3267	-141.1325	-155.9245
McFadden pseudo R^2	0.186	0.195	0.146	0.150	0.159	0.197
N	280	295	295	280	280	280

Note: *t*-values are shown in parenthesis. * Statistically significant at 90% level; ** Statistically significant at 95%level; *** Statistically significant at 99% level.

4.3 The effect of uncertainty on WTA estimates

As Akter et al. (2008) point out, it is expected that the preference uncertainty adjusted WTA estimates should be lower than the standard DC WTA considering the ability of preference uncertainty treatments to remove hypothetical bias. From the coefficients of the different models estimated, mean WTA measures were calculated following Hanemann (1984; 1989):

$$\text{Mean WTA} = (1/\beta_1)\ \ln(1+\exp[\beta_0 + \beta_2 income + \beta_3 crisis + \beta_4 tax + \beta_5 motivation + \beta_6 cabanyal + \beta_7 grao + \beta_8 betero +]\ ) \qquad (1)$$

where β_1 is the estimated coefficient of the bid amount, β_0 is the estimated constant and β_2, β_3, …, β_8 are the independent variables' coefficients which in turn are multiplied by their respective means. The mean WTA estimate obtained from the standard DC model is €134.5 (see table 4) and it is used as a baseline estimate to compare the performance of the different respondent uncertainty treatments, since we do not have actual payment data, as would be desirable. When "Don't know" responses are coded as "No" responses the mean WTA estimate (€118.1) is lower by a factor of 1.14 since the number of "No" responses is higher than in the standard DC model. This same result is expected when a NCS is applied to recode as "Yes" responses only those "Yes" responses that fall over a specific threshold (models Yes7 and Yes8), thus recoding the rest as "No" responses. In this case the mean WTA estimates (€99.0 and €60.7, respectively) are lower than the baseline by a factor of 1.36 and 2.21 respectively. Under the ASUM treatment the numerical certainty categories are converted into probabilities only for the "Yes" responses, while the "No" responses are kept as zeroes. Again that implies a drop in the mean WTA estimate as was firstly demonstrated by Loomis and Ekstrand (1998). By contrast, when "Don't know" responses are coded as "Yes" responses following Balcombe and Fraser (2009), then the mean WTA estimate is higher as expected since the proportion of "Yes" responses is higher.

Li and Mattsson (1995) and Manski (1995) suggest that incorporating uncertainty into the model provides more specific information about the individual's valuation than the pure discrete yes/no response model, thereby resulting in more efficient estimates of the valuation function. This hypothesis can be tested by comparing the goodness of fit of the different models, measured by the McFadden pseudo R^2, and the precision of the WTA estimates, measured by dividing the 95% confidence interval over the mean WTA. The pseudo R^2

ranged from 0.146 to 0.197 (see table 4), and in general we did not find evidence of a substantial improvement in the goodness of fit since only for the DKNo and ASUM models there was a gain of 0.01 over the standard DC model, while for the rest of models there was a reduction between 0.03 and 0.04.

Regarding the ratio between the 95% confidence interval and the corresponding mean WTA, it can be observed that the standard DC model has a value of 0.14 while for the "Yes7", "Yes8" and ASUM models this ratio is only slightly higher. Therefore, we cannot conclude that preference uncertainty welfare estimates are more efficient than the welfare estimate obtained through the conventional DC model, i.e. there is no improvement in the precision of welfare estimates. Chang et al. (2007) found that the conventional DC model showed the greatest efficiency with regard to the rest of approaches used (PC, ASUM and SUM). In the same way, Logar and van den Bergh (2012) found no evidence that accounting for respondent uncertainty leads to gains in estimate efficiency.

Table 4
Mean WTA and 95% confidence intervals

Model	Mean WTA	95% CI	95% CI / mean WTA	Standard DC mean WTA / Version mean WTA
Standard DC	134.5	125.2 – 143.6	0.14	1.0
DKNo	118.1	110.3 – 125.9	0.13	1.14
DKYes	170.5	158.4 – 182.6	0.14	0.79
Yes7	99.0	90.6 – 107.3	0.17	1.36
Yes8	60.7	55.9 – 65.5	0.16	2.21
ASUM	120.0	109.8 – 130.3	0.17	1.12

4.4 Explaining respondent uncertainty

Empirical evidence for the underlying reasons for respondent uncertainty is still rather scarce (Akter, et al., 2008). Therefore, taking advantage of the additional information provided by the NCS used after the DC question, we estimated a logistic regression with "certainty" as the dependent variable following Champ et al. (2009). This latter variable takes value "1" for those respondents that circled “8-10” on the certainty scale and “0” value for those that circled “1-7”. Therefore, formalizing this into a testable empirical model and assuming a logistic specification we have:

$$\Pr(\text{Certainty} = 1) = 1/(1 + \exp[\beta_0 + \beta_1 bid + \beta_2 motivation + \beta_3 view + \beta_4 visited + \beta_5 familysize + \beta_6 responsibility + \beta_7 limit]) \qquad (2)$$

The results and explanatory variables used are shown in table 5. This model included only those respondents that say they would accept the compensation offered. The regression results suggest that the offer amount (BID) is positively related to certainty; therefore it seems that the higher the offer amount, the greater the certainty level stated by the respondent. Loomis and Ekstrand (1998) found a quadratic relationship between self-reported preference uncertainty and bid levels, which led them to conclude that at extremely high and low bids respondents are more certain of their responses and less certain at intermediate bid levels. In our case, introducing the bid level in a quadratic form was of no use since this variable was not significant. Lyssenko and Martínez-Espiñeira (2012) find that the higher the bid value the less certain the responses. As expected, our results also suggest that there is a positive relationship between certainty levels and the respondent’s MOTIVATION when answering the survey. The variables VIEW and VISITED are related to the prior knowledge and familiarity with the good in question. Hence respondents who enjoy a view of the port area from their dwelling places and have visited this area in the previous year are more certain of their responses than the rest of individuals who lack previous experience with the good. This result conforms to previous findings by Loomis and Ekstrand (1998) and Brouwer (2009). However, Logar and van den Bergh (2012) found that familiarity did not have a significant effect on respondent uncertainty. On the other hand, we find evidence that individuals belonging to larger families (FAMILYSIZE) are more certain of their responses. Finally, following Diekmann and Preisendörfer (2003), who used a set of "nine statements" for environmental concern, we have introduced in the regression two variables (RESPONSIBILITY and LIMIT) precisely related to environmental concern. Their negative coefficient implies that those respondents who "agree" or "strongly agree" with (i) "the great majority of people do not act in an environmentally responsible way" and with (ii) "there are limits to economic growth which the industrialized world has already reached or will reach very soon", are less certain of their responses. This result contradicts previous findings by Champ et al. (2009) being worthy of additional inquiry. So considering that they used a WTP scenario while we have used a WTA approach, it seems that in this latter case respondents self reported as more environmentally aware are less certain of their "Yes" responses to the bid because, in some way, they could consider it to be a "bribe" in return for allowing a decrease in the quality of the environment.

Table 5
Logic regression of "certainty" (dependent variable=1 if certainty level is 8-10)

Variable	Description	Coefficient
Constant		-1.2188** (-2.226)
Bid	Offered compensation (WTA) in € a year	0.0038* (1.706)
Motivation	Respondent's motivation when answering the survey (if "very motivated" or "quite motivated" = 1; rest of cases = 0)	1.4833*** (3.265)
View	View of the port area from respondent's dwelling place (if she enjoys a view=1; rest of cases=0)	1.2810*** (2.406)
Visited	Visits to the port area (if she visited in the last year =1; rest of cases = 0)	0.8032** (1.949)
Familysize	Family size (if family members > 3 =1; rest of cases = 0)	1.2815*** (2.776)
Responsibility	Respondent's environmental concern ("agree" or "strongly agree" with the great majority of people do not act in an environmentally responsible way = 1; other cases =0)	-0.7608* (-1.749)
Limit	Respondent's environmental concern ("agree" or "strongly agree" with there are limits to economic growth which the industrialized world has already reached or will reach very soon = 1; other cases =0)	-.92157** (-2.266)
Log likelihood McFadden		-77.12313

pseudo R^2	0.170
N	140

Note: *t*-values are shown in parenthesis. * Statistically significant at 90% level; ** Statistically significant at 95%level; *** Statistically significant at 99% level.

5. Discussion and concluding remarks

In this research different criteria have been applied to compare the performance of alternative treatments for addressing respondent uncertainty in a WTA scenario. Considering that the vast majority of the previous studies addressing this issue used a WTP scenario, the comparison between these studies and our own research is not as straightforward as it may seem at the outset. Nevertheless, it can be said that, to some extent, our results conform to previous findings in the literature for several reasons. First, as shown by Champ et al. (1997), incorporating uncertainty regarding just the “Yes” responses has resulted in a dramatic drop in mean WTA estimates (models “Yes7” and “Yes8”) in comparison with the standard DC model. Second, treating “Don’t know” responses as “No” responses has also led us, as expected, to obtain more conservative WTA estimates; although, as Wang (1997) points out, common sense suggests that if respondents are answering truthfully, then “Don’t know” responses are not the same as “No” responses. Groothuis et al. (1998), in order to obtain a conservative estimate of WTA, proceeded in a different way to us by treating the “Don’t know” responses as “Yes” responses. Third, applying the ASUM model, proposed by Loomis and Ekstrand (1998), has also resulted in a decrease in the WTA estimates, although of a lower magnitude than the former treatments. And fourth, contrary to what is expected from a theoretical point of view, our results also confirm the empirical evidence that preference-uncertainty adjusted welfare estimates are not more efficient than the welfare estimates obtained with the standard DC model. Hence, these welfare measures should be taken cautiously when informing decision-making processes since the incorporation of uncertainty information has not resulted in a noticeable gain in estimation efficiency. This makes the comparison of the different treatments all the more difficult when choosing the most appropriate approach to tackle the issue of respondent uncertainty.

On the other hand, in order to delve further into the factors explaining respondent uncertainty, we estimated a logistic regression with “certainty” as the dependent variable. We found that familiarity and prior experience with the good in question led to higher-certainty responses from respondents. We also found a positive and significant relationship between the offer amount and the certainty rate stated by the respondent. In the same way, our results also suggested that more motivated respondents were more certain of their responses, while respondents self reported as environmentally concerned were more uncertain.

Finally, as Samnaliev et al. (2006) point out, and our results seem to confirm this, the underlying motivation for a “Don’t know” choice may differ from the motivation for choosing a low level of certainty on a 10-point scale. Hence, applying these two approaches to identical samples produces different welfare estimates, since they are capturing different types of uncertainty. In any case, despite the growing literature on preference uncertainty, the motivation behind uncertain responses is not completely understood, this would imply that a methodological problem still remains in contingent valuation studies. This problem can be exacerbated when added to the difficulties inherent to the use of a WTA scenario, as is the case with this research (lack of experience with compensation claims for environmental damage, a higher cognitive effort that can result in higher protest rates, a tendency to strategic bidding, etc.). Therefore, further research is needed before reliable conclusions can be drawn regarding the treatment of respondent uncertainty within a WTA scenario.

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