Environ Resource Econ (2011) 49:491–510
DOI 10.1007/s10640-010-9443-9

Tough and Easy Choices: Testing the Influence of Utility Difference on Stated Certainty-in-Choice in Choice Experiments

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Accepted: 11 December 2010 / Published online: 21 January 2011

Abstract Respondents in Stated Preference studies may be uncertain about their preferences for the good presented to them. Inspired by Wang (J Environ Econ Manag 32:219–232, 1997) we hypothesize that respondents' stated certainty in choice increases with the utility difference between the alternative chosen and the best alternative to that. We test this hypothesis using data from two independent Choice Experiments both focusing on nature values. In modelling respondents' self-reported certainty in choice, we find evidence that the stated level of certainty increases significantly as utility difference in choice sets increases. In addition, stated certainty increases with income. Furthermore, there is some evidence that male respondents are inherently more certain in their choices than females, and a learning effect may increase stated certainty. We find evidence of this in the first study where the good is described in rather broad and generic terms, but not in the second study where a more specific description of the good is used.

Keywords Choice experiment · Environmental valuation · Learning effect · Respondent uncertainty · Stated preferences · Utility balance

1 Introduction

It is a common assumption in the application of stated preference methods that the respondents know their own true preferences and that they are able to assess the exact utility they derive from the good presented to them. Respondents are therefore assumed to answer valuation questions in a way that precisely reflects their true preferences for the good being assessed

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(Hanemann 1984). However, responding to a hypothetical question about willingness to pay (WTP) for a non-market good is a difficult task for most people. They may be uncertain as to the exact value of the good for them, about the meaning of words and sentences applied in the survey instrument, or simply unfamiliar with relating to the good in monetary terms. This gives rise to preference uncertainty as formalized by Li and Mattsson (1995). Throughout the last two decades, preference uncertainty has been recognized as a problem when conducting stated preference studies. The presence of preference uncertainty may pose several problems for the estimation of welfare measures from stated preference studies. As pointed out by Li and Mattsson (1995), even if parameter estimates are consistent and unbiased, faulty estimates on variance may lead to biased value inference. Different approaches have been taken, primarily in Contingent Valuation studies, to take account of such uncertainty as stated by respondents (e.g. Loomis and Ekstrand 1998; Alberini et al. 2003), whatever the causes. However, approaches to handling respondent uncertainty may be improved if we can increase our knowledge of the underlying causes of stated uncertainty.

In this paper we focus on a particular intriguing potential cause for post-decisional stated uncertainty in Choice Experiments, and that is the utility difference between the best alternatives in a choice set. We are inspired by the argument of Wang (1997), who hypothesized that in Contingent Valuation studies, one would expect uncertainty to be high for indicated payments close to the individual's true WTP, and low for payments distinctly smaller or larger than the true WTP. Wang's point remains a hypothesis which has only tentatively been examined in the literature (e.g. Samnaliev et al. 2006), whereas other factors affecting uncertainty like prior knowledge and environmental attitude have been examined more thoroughly (Berrens et al. 2006; Jorgensen et al. 2006; Samnaliev et al. 2006). Thus, there seems to have been little attention devoted to analysing the effects of survey instrument and survey design on respondent uncertainty in a Choice Experiment context, even if e.g. the Wang-hypothesis suggest that such factors may be important.

The hypothesis formulated by Wang (1997) targeted respondent uncertainty in a Contingent Valuation setting. In a Choice Experiment setting, the respondent does not face the choice between 'Yes', 'No' and 'Don't Know', but the choice between two or more alternatives. Inspired by Wang, we hypothesize that respondents' stated certainty in choice increases with the utility difference between the alternative chosen and the best alternative to that.

In our empirical test of the hypothesis, we used two independent Choice Experiment studies where respondents reported their perceived certainty in choice following *each* choice set evaluated. The test proceeded as a two-step analysis. In the first step we estimated a mixed logit error component model with a panel structure for each individual, based on each respondent's choices without taking into account their stated uncertainty. This produced an estimated indirect utility function, which was then utilized to assign an aggregate utility measure to each alternative in the choice sets for each individual. We then calculated a measure of utility difference, defined as the difference in utility between the chosen alternative and the best alternative to that. In the second step of the analysis we estimated an ordered probit model with the self-reported certainty level serving as the response variable. We included the utility difference variable created in the first step as an explanatory variable, in order to enable an explicit test of the hypothesis that respondent certainty increases with utility difference. Furthermore, we evaluated other survey design factors as well as respondent characteristics which might affect the perceived certainty in choice.

We found that the utility difference did indeed explain a significant part of respondent certainty, and hence we found support for our hypothesis in a rather subtle test compared to earlier work. We did, however, also find that other design related and respondent specific factors had significant impact on respondent certainty and we provide interpretations of these findings too.

The paper is organised as follows. First, in Sect. 2, we take a closer look at the theoretical and empirical works on respondents' certainty, and we outline the econometric models and theory applied. In Sect. 3 we give a brief introduction to the two Choice Experiments studies, which provided the data for this study. The results of our two step analysis are presented in Sect. 4. In Sect. 5 we discuss the results and we conclude in Sect. 6.

2 Theory and Methods

2.1 Respondent Uncertainty About Own Stated Preferences

It is a common assumption in the application of stated preference methods that respondents are able to precisely assess the utility they derive from the good presented to them. Hence, respondents can answer any given valuation question with absolute certainty (Hanemann 1984). There are numerous arguments why this assumption may not be valid. In recognition of this, several Contingent Valuation studies have tried to obtain a measure of, or an expression for, the degree of certainty perceived by the respondent when answering valuation questions, and take account of this in estimations. The approaches taken to that end can roughly be split into two groups. The first approach is to have respondents choose among different answers to the payment question, which explicitly incorporate some level of certainty, e.g. 'Don't Know' (Wang 1997), 'I will definitely pay' or 'I most probably will not pay' (Alberini et al. 2003; Ready et al. 1995; Welsh and Poe 1998). The second approach is to have respondents first answer the payment question ('Yes'/'No'), and then state their degree of certainty regarding the answer just provided (Champ et al. 1997; Li and Mattsson 1995; Loomis and Ekstrand 1998), either in the form of a numeric scale or text statements. The latter approach has the advantage that it does not interfere directly with the valuation task, yet it too hinges on some degree of researcher interpretation concerning the stated certainty in order to incorporate it in estimations.

Samnaliev et al. (2006) summarizes four assumptions or hypotheses regarding stated certainty, which we briefly present and discuss here. One hypothesis, adapted from Schwarz and Sudman (1996), is that certainty levels indicated by respondents will reflect only their attempt to appear consistent in answers: Once they have chosen 'Yes' or 'No', they indicate some degree of certainty to signal consistency. If such behaviour dominates, we should find a fairly constant level of certainty across alternatives and questions—but in fact stated certainty varies systematically with the bid (Loomis and Ekstrand 1998; Wang 1997). A second and related hypothesis is that certainty levels may be susceptible to strategic behaviour, e.g. respondents may exaggerate certainty along with stated WTP (Samnaliev et al. 2006). However, any strategic behaviour in relation to stated WTP should usually be screened for, and consequently most strategic answers should be excluded from further analysis on that account. Thus, while it may be a source of noise, it should not be dominant. A third hypothesis concerning preference uncertainty is that when respondents are allowed to state uncertainty, they use this option to scale down their stated WTP, i.e. an asymmetric effect reducing hypothetical bias is assumed (Champ et al. 1997). A fourth hypothesis is formulated by Wang (1997) and implied in Li and Mattsson (1995). Wang hypothesizes that rather than a single true value, each respondent holds a value distribution due to uncertainty about their own true utility function. Therefore, respondents may be quite uncertain as to their answer ('Yes'/'No') in a referendum Contingent Valuation study when the offered bid price is close to their maximum WTP, as measured by the mean of the value distributions—but quite certain when very different from their maximum WTP. In other words, the choice becomes tough when the utilities associated with the 'Yes' and the 'No' option are close to each other, but when the difference in utility increases, the choice becomes relatively easier. Thus, the difference in utility between the alternatives implied by 'Yes' and 'No' is assumed to determine stated certainty in choice. While Loomis and Ekstrand (1998), Samnaliev et al. (2006) and Wang (1997)find indications that support this hypothesis, a formal test has yet to be made.

All of the above literature exclusively treats the issue of certainty in a Contingent Valuation context. In Choice Experiments, respondents usually evaluate two alternative versions of the environmental change, potentially up against a status quo alternative. In both of the two surveys used in the present paper, respondents are faced with the status quo alternative along with two experimentally designed alternatives. Thus, when respondents are asked to state their uncertainty about the choice of alternative *ex post*, we interpret variations in this statement across choice sets as relating to the choice between the alternative they chose and the best alternative to that.[1] Thus, we define the utility difference between these two alternatives as a relevant measure for testing our hypothesis, which is heavily inspired by Wang (1997). The implication is that if the alternative chosen has the highest utility, the utility difference is positive, but if the chosen alternative is not the one with the highest utility in the choice set, it will be negative.

As the respondents make repeated choices in the Choice Experiment studies investigated here, there may be a learning effect through the sequence of choice sets, which may influence respondents' stated certainty in choice. For example, initial instability of preferences may decrease (Bateman et al. 2008; Brown et al. 2008; Carlsson and Martinsson 2001; Hanley and Shogren 2005), preferences may be constructed or at least completed (Braga and Starmer 2005), and starting point bias could decrease (Ladenburg and Olsen 2008). It is found in Flachaire and Hollard (2007) and in Luchini and Watson (2008) that respondents who are certain in their choices are less susceptible to starting point bias than less certain respondents. These observations suggest that the choice set number could be an important predictor of respondents' stated certainty in choice. Brouwer et al. (2010) do indeed find decreasing stated certainty with increasing choice set number, but do not find that reflected in a model where learning is included.

2.2 Handling Respondent Uncertainty in Estimation

The focus of this study is on testing a very specific and theoretically well-founded potential cause for respondent uncertainty in choice. The insights revealed is of interest to the more general task of handling respondent uncertainty in choice to improve model estimation, inference and welfare economic analysis based on stated preference models. While this task is beyond the scope of the present paper, we will briefly mention the perspectives of this paper and a companion paper (Lundhede et al. 2009) to those concerned with this task.

In stated preference studies, an ongoing concern is the potential hypothetical bias that estimated welfare economic measures may suffer from. Recent research have documented

[1] One could of course imagine that the self-reported uncertainty also embedded several other issues, e.g. the general uncertainty relating to the task, the instrument as such, knowledge of the environmental good or other issues. In support of our more narrow interpretation here, we point out two things: As the respondents stated their certainty after every choice set, it seems reasonable to assume that *variation* in stated certainty across choice sets relate to the specific choice task in each choice set. Secondly, a slightly circular argument, if our interpretation is very of the mark, we should not expect utility difference to play a role in stated certainty.

that also the Choice Experiment method is susceptible to this, although perhaps less so (List et al. 2006; Johansson-Stenman and Svedsäter 2008). One of the many different approaches that have been investigated with the aim to reduce this bias is to use respondents' self-reported certainty. Under the explicit or sometimes implicit assumption, that stated uncertainty reflects a degree of hypothetical bias, several Contingent Valuation studies have applied some sort of asymmetric recoding method to correct for this. A direct recoding of answers from 'Yes' to 'No' has been applied by several authors (e.g. Champ et al. 1997; Welsh and Poe 1998), whereas Loomis and Ekstrand (1998) propose an asymmetric uncertainty model incorporating stated uncertainty levels of 'Yes' answers into the likelihood function. Not surprisingly, the first approach implies an often dramatic downward adjustment of WTP estimates, whereas the effect on WTP is somewhat less with the second approach. More recently, Morrison and Brown (2009), attempts to reduce hypothetical bias by searching for a cut-off point for stated uncertainty—discarding all choices with stated uncertainty above some level.

In another group of papers from the contingent valuation literature, the explicit assumption is that respondents can also be uncertain about voting 'No'. This calls for a symmetric approach and several studies have suggested ways to incorporate uncertainty statements for all responses directly into the random utility model and the likelihood function. Such uncertainty statements can be implied by the chosen answer (as in Wang 1997 and in Alberini et al. 2003), or stated on some sort of scale, *post* decision (Li and Mattsson 1995; Loomis and Ekstrand 1998). As noted by both Loomis and Ekstrand (1998) and Alberini et al. (2003) the symmetric approach tends to increase the estimated WTP, even if it also provides a better performing model and improved inference.

Studies analysing these and new different approaches to handling respondent uncertainty in Choice Experiments are now called for. Based in part on the results of this paper, we have in another paper (Lundhede et al. 2009) evaluated several recoding approaches along with approaches where the stated uncertainty is explicitly included in the estimation procedure through a parameterisation of the scale parameter.[2] This latter approach increased model efficiency and performance, but did not change mean WTP much compared to a benchmark model ignoring respondents' uncertainty. This is only a small set of the possible further research paths to take on this issue. Other types of extensions and developments of the random utility model and estimation may be made, e.g. the fuzzy random utility model suggested by Sun and van Kooten (2009) in a contingent valuation setting.

2.3 The Random Parameter Error Component Logit Model

The random parameter error component logit model relies on McFadden (1974) random utility model, where the utility of a good is described as a function of its attributes, and people choose among complex goods by evaluating their attributes. Since utility can only be observed imperfectly, the random utility model is the basis for estimation. For a choice between a status quo alternative and two experimentally designed alternatives the utility model can formally be described as:

$$U\,(kin) = \begin{cases} V\left(ASC, x_{kin}, \beta_i, \beta_{fix}\right) + \varepsilon_{kin} & \text{if } k = 1; \quad (status\ quo\ \ alternative) \\ V\left(x_{kin}, \beta_i, \beta_{fix}, \sigma_i\right) + \varepsilon_{kin} & \text{if } k = 2, 3; \quad (designed\ \ alternatives) \end{cases} \tag{1}$$

[2] This approach was suggested by Riccardo Scarpa, also see Scarpa et al. (2003).

The term *U(kin)* is the i'th individual's true utility function for the good described by alternative k in choice situation n. V is the observed indirect utility function, which is a function of x_{kin}, the vector of variables that we can observe, as well as the vector of individual-specific random parameters β_i and fixed parameters β_{fix}. Following e.g. Scarpa et al. (2005) an Alternative Specific Constant (ASC) is specified for the status quo alternative. An error component, σ_i, additional to the usual Gumbel-distributed error term, ε_{kin}, is assigned exclusively to the two experimentally designed alternatives to capture any remaining status quo effects in the stochastic part of utility (Greene and Hensher 2007; Scarpa et al. 2007; Ferrini and Scarpa 2007; Scarpa et al. 2008).

Assuming that ε_{kin} is IID extreme value distributed, the Mixed Logit probabilities of individual i choosing alternative k in choice set n can be described as integrals of the standard conditional logit function evaluated at different β's with a density function as the mixing distribution. If the utility coefficients vary over people but are constant over the N choice occasions for each individual, the resulting probabilities can be specified as:

$$\Pr(kin) = \int \left(\prod_{n=1}^{N} \left[\frac{\exp\left(\beta_i' x_{kin}\right)}{\sum_j^J \exp\left(\beta_i' x_{jin}\right)} \right] \right) \varphi\left(\beta \,|b, W\right) d\beta \tag{2}$$

where $\varphi(\beta\,|b, W)$ is the distribution function for β with mean b and covariance W (Train 2003). The analyst chooses the appropriate distribution for each parameter in β. This standard setup is applied to the Choice Experiment data analysed here. Note that we deliberately ignore respondent uncertainty in this model, as our concern is the question if in conventional modelling approaches respondent uncertainty depends on estimated mean utility differences in the choice set. The further handling of such dependence in the modelling approach is dealt with elsewhere and calls for much further work, cf. Sect. 2.2.

2.4 An Ordered Probit Model of Certainty in Choice Incorporating Utility Difference

In this second step, we use the estimated model in (2), to calculate the expected aggregate utility of each alternative in each choice set for each individual and then calculate the expected utility difference, *UD*, between the alternative chosen, *k*, and the best alternative to that (either *l* or *m*), i.e. for each choice set:

$$\begin{aligned} UD &= E\left(u_{ki}\left(x_{ki}, \varepsilon_{ki}\right)\right) - \max\left\{E\left(u_{li}\left(x_{li}, \varepsilon_{li}\right)\right); E\left(u_{mi}\left(x_{mi}, \varepsilon_{mi}\right)\right)\right\} \\ &= \hat{\beta}'_i x_{ki} - \max\left\{\hat{\beta}'_i x_{li}; \hat{\beta}'_i x_{mi}\right\} \end{aligned} \tag{3}$$

That is, the utility of each alternative is calculated by multiplying the estimated utility weights with the corresponding attribute levels. This utility difference is used as an explanatory variable in a random effects ordered probit model of the self-reported level of certainty in choice. The basic notion underlying the model is the existence of a latent or unobserved continuous variable, y^*, ranging from $-\infty$ to $+\infty$, indicating the degree of certainty of a respondent i. This latent variable is related to a set of explanatory variables by the standard linear relationship:

$$y^*_{ik} = \gamma' z_{ik} + \eta_{ik} + \mu_i \tag{4}$$

where, z_{ik} is the vector of explanatory variables for respondent i in choice situation k, all chosen on account of a priori expectations of their potential impact on certainty in choice. The term η_{ik} is distributed as $N[0,1]$ and μ_i is $N[0,\sigma^2]$ distributed, and is the same for every stated certainty made by the same respondent. The latent variable y^* is not observed but is assumed to be linked to the stated ordinal certainty level with discrete values 1,…,H by an ordered probit type of relationship (McKelvey and Zavoina 1975). The respondent's stated certainty level varies from 'very uncertain' to 'very certain' where no presumption of cardinality is made.

$$y_{ik} = h \quad \text{if} \quad \delta_{h-1} < y_{ik}^{*} \leq \delta_h \tag{5}$$

where δ_h are the unobserved thresholds defining the boundaries between the different certainty levels. The threshold δ_0 is taken as $-\infty$ and δ_h is taken as $+\infty$, and the remaining threshold parameters δ_1 to δ_{h-1} are freely estimated together with γ with no significance to the unit distance between the different observed levels of certainty. The probability function for a single observation of the dependent variable that enters the likelihood function can be written as:

$$P\left(y_{ik} = h\right) = \varphi\left(\delta_h - \gamma' z_{ik} - \mu_i\right) - \varphi\left(\delta_{h-1} - \gamma' z_{ik} - \mu_i\right) \tag{6}$$

where $\varphi(f)$ represents the cumulative standard normal density distribution. The estimates are obtained by maximum likelihood.

3 Data Description

3.1 The Motorway Survey

The hypothetical scenario shown to respondents was based on the assumption that 100 km of new motorways were to be built in Denmark during the next ten years. The scenario described that the exact location of these stretches of motorway through the countryside can be decided upon with more or less consideration for different nature areas.

Three different types of nature were chosen as attributes in the Choice Experiment design: 'forest', 'wetland', and 'heath'. A price attribute was defined in terms of an extra annual income tax for the household. In Denmark, the building of motorways is financed through taxes, lending credibility to this payment vehicle. The attributes and their levels are summed up in Table 1.

Table 1 Attribute levels used in the motorway survey

Attribute (type of nature)	Level (km new motorway through nature area)
Forest	0, 5, and 10 km
Wetland	0, 2.5, and 5 km
Heath/pastoral area	0, 2.5, and 5 km
Arable land[a]	80, 82.5, 85, 87.5, 90, 92.5, 95, 97.5, and 100 km
Annual extra tax payment per household[b]	(0 DKK), 100 DKK, 200 DKK, 400 DKK, 700 DKK, 1100 DKK, 1600 DKK

[a] As the total stretch of motorway was fixed at 100 km, a fourth supplementary attribute, 'arable land', was introduced to account for the location of the remaining 80 km. This attribute functioned as an accumulation attribute, its level being determined by the other attribute levels. Thus, due to perfect correlation, it was not included in the experimental choice set design and it is not included in the parametric modelling of preferences
[b] 100 DKK ≈ 13.4 €

The attribute levels were assigned to alternatives using an experimental design and paired into choice sets of 3 alternatives. As a full factorial design comprised 162 alternatives, a D-optimal fractional factorial design consisting of 18 choice sets was identified (Louviere et al. 2000). To minimize the number of dominating and non-causal alternatives, the initially identified efficient design was subjected to the manual swapping procedure suggested by Huber and Zwerina (1996). The sample was split into three groups, so each respondent answered six choice sets consisting of three alternatives: The zero-priced status quo alternative and two experimentally designed improvement alternatives with an associated price.[3] Following each choice set, they were asked to state how certain they were of the choice just made. An example of a choice set is displayed in Appendix A. Initially, 1,293 potential respondents participating in an internet panel were contacted, and out of these 702 (54.3%) chose to answer the questionnaire. After expunging protest zero bidders and irrational responses, the final dataset consists of 595 responses resulting in a total of 3,570 choice observations.[4] In a total of 66.1% of the choices, respondents state that they are certain or very certain. Looking at demographic characteristics, the gender distribution in the obtained sample of respondents is found to be representative of the target population which is Danes in general. However, age-groups below 25 and above 55, groups with relatively low income, and groups with short educations are all slightly under-represented in the sample.

3.2 The National Park Survey

Following a long political process and ongoing public debate, Denmark is currently establishing its first national parks. As part of the policy process surrounding this, a valuation study was performed to evaluate preferences for different environmental attributes of national parks as well as seven potential sites. Respondents were asked to evaluate choice sets in which the ‘Location’ of the new national park was one attribute along with four generic attributes of the parks, namely ‘Extra initiatives for special plant and animals’, ‘Extra effort for general nature protection’, ‘Increased amount of walking and biking paths’. The establishment, nature protection efforts and management of the national parks will be paid for over the general taxes in Denmark, and thus ‘Extra income tax per year and household’ was added as a price variable to trade against. The attributes are shown in Table 2. Each respondent was only presented with four of the seven locations, allocated by a cyclic design of four groups. The attribute levels were assigned to alternatives by a fractional factorial design and resulted in an orthogonal, balanced experimental design of 32 choice sets consisting of two alternatives and a status quo (no national park). The choice sets were blocked into 4 blocks of 8. No choice sets were eliminated from the design, i.e. also alternatives with zero payment for a national park occurred. An example of a choice set is shown in Appendix B. Each respondent replied to 8 choice sets. The response rate was 49.3% and out of these 32% were zero

[3] In the status quo, the motorway was projected to be placed through 10 km of forest, 5 km of wetland, 5 km of heath, and 80 km of agricultural areas.

[4] Protest bidders were identified as respondents who chose the status quo alternative in all six choice sets and in a follow-up question revealed protest reasons for doing so. A total of 17 irrational respondents were identified using a perfectly dominated choice set in the end of the choice set sequence. For a more thorough description of the survey and a full version of the used questionnaire, see Olsen et al. (2005). Not surprisingly, the protest bidders were found to state significantly higher levels of certainty in choice than the valid responses obtained from other respondents. In similar accordance with a priori expectations, the irrational respondents were generally less certain about their choices in the sense that this rather small group of respondents had a higher propensity than other respondents to answer “neither certain nor uncertain” or “don’t know”. As these respondents have not made the assumed trade-offs when choosing alternatives, they are not included in the following analysis of preferences.

Table 2 Attributes presented in the national park survey

Attribute	Levels
Location	None, Læsø, Møn, Thy, Nordsjælland, Mols Bjerge, Lille Vildmose, Vadehavet
Nature preservation	No extra effort, Little extra effort, Some extra effort, Large extra effort
Extra effort for specific animals and plants	No, Yes (with indication of which species for the given location)
Walking and biking path	No. increased amount of path, Increased amount of path
Extra income tax per year per household	DKK 0, 50, 100, 200, 400, 700, 1500, 2000

bidders or protest bidders, and they were treated outside the present modelling (cf. Jacobsen and Thorsen 2010). Consequently the data for the present analysis consists of 636 responses resulting in 4,866 choice observations.[5] In a total of 74.5% of the choices, respondents state that they are certain or very certain. Compared to the target population (Danes), the sample is a little under-represented in age-groups below 35 and above 65, and also in short educations, whereas both the lowest and the highest income groups are under-represented. There is no significant difference on gender.

4 Results and Analyses

4.1 The Estimated Mixed Logit Error Component Models

4.1.1 The Motorway Survey

Table 3 displays the results obtained from the random parameter error component logit model. All attribute parameters, except income tax and the ASC, are assumed to be normally distributed in the population. This choice is based on past experience with considerable preference heterogeneity concerning related environmental goods in similar studies in Denmark (Jacobsen et al. 2008; Jacobsen and Thorsen 2010; Ladenburg and Olsen 2008; Olsen 2009). All parameter estimates are significant except for the coefficient of the ASC. The significant error component, σ_{23}, indicates that utilities across the two experimentally designed alternatives are correlated. Furthermore, this result suggests a difference between the perception of the status quo alternative and that of the two experimentally designed alternatives. Even though the insignificant ASC would reject a status quo effect, the significant error component supports the presence of a status quo effect, but in the stochastic rather than the deterministic component of utility. As expected, the nature attributes' mean estimates are all of a negative sign indicating that on average respondents experience a decrease in utility when one km of motorway is placed through the specific types of nature. Likewise, the income tax parameter estimate has a negative sign as would be expected. The estimated standard deviations of the random parameters are highly significant, revealing a considerable degree of heterogeneity in

[5] In the National Park data, respondents were asked prior to the choice sets if they would at all be willing to pay over their taxes for forthcoming national parks. People that answered 'No' were not requested to answer the choice sets, and that effectively avoided further protest answers from choice sets—and therefore also protest respondents answering the uncertainty questions. Among the 303 people answering 'No' a proportion of 65% gave protest reasons. See Jacobsen et al. (2006) for further details of this survey.

Table 3 The basic model of step 1 for the motorway data: the random parameter error component logit model

Attribute	Estimate	Std. err.	*t*-value		WTP in DKK (95%CI)
ASC					
Mean (fixed)	−0.3356	0.210	−1.60	NS	169 (−35–373)
Forest					
Mean	−0.1641	0.015	−11.31	***	82 (69–96)
Standard deviation	0.2200	0.017	13.12	***	
Wetland					
Mean	−0.2161	0.023	−9.50	***	109 (86–131)
Standard deviation	0.2473	0.030	8.14	***	
Heath					
Mean	−0.0923	0.019	−4.88	***	46 (28–65)
Standard deviation	0.1824	0.031	5.96	***	
Additional income tax					
Mean fixed	−0.0020	> 0.001	−27.17	***	
σ_{23}	3.1437	0.213	14.73	***	
# Observations	3570				
# Respondents	595				
LL at convergence	−2756.0				
Adj. McF pseudo-R^2	0.297				

Simulations are based on 1,000 Halton draws. *** indicates significance at the 0.001 level; *NS* non-significance at the 0.05 level. 95% confidence intervals for WTP are estimated using the Krinsky-Robb method with 10,000 draws. By questionnaire construction and data coding, the nature type parameter estimates are negative, thus in the calculation of WTP these estimates are multiplied by −1

the respondents' preferences for the three types of nature attributes. The adjusted pseudo-R^2 value as well as the likelihood ratio test reveals that the model fits the data well (Domencich and McFadden 1975; Louviere et al. 2000).

4.1.2 The National Parks

Table 4 displays the results for the national parks data as obtained from the random parameter error component logit model. Like in the previous estimation all parameters except the income tax and the ASC are assumed to be normally distributed around their mean—and for the same reasons. Most of the parameter estimates are significant at the 0.05 level or less except the mean location dummy for the national park Nordsjælland and the mean parameter for increased amount of walking and biking paths. The error component, σ_{12}, is significant, indicating correlation between the two experimentally designed alternatives.[6] The dummy for the national park Læsø is excluded and is confounded with the ASC. Notice that the negative ASC can be interpreted as a WTP for a benchmark national park and thus the WTP for each of the other location attributes as add-ons hereto (Jacobsen and Thorsen 2010). The location of a national park in Lille Vildmose offers the highest WTP among locations although none

[6] For the National Park data model we use the notation σ^{12}, because the experimentally designed alternatives were the first and second alternatives in the National Park data, whereas the status quo was the third.

Table 4 The basic model of step 1 for the national park data: The random parameter error component logit model

Attribute	Estimate	Std. err.	*t*-value		WTP in DKK (95%CI)
ASC/Læsø					
Mean (fixed)	−2.1833	0.199	−10.99	***	−1078 (−1256 to −899)
Location møn					
Mean	0.3555	0.143	2.49	**	175 (39–312)
Standard deviation	1.3458	0.187	7.20	***	
Location thy					
Mean	0.2978	0.147	2.02	*	147 (5–289)
Standard deviation	1.1871	0.172	6.91	***	
Location Nordsjælland					
Mean	-0.1146	0.173	−0.66	NS	−57 (−226–113)
Standard deviation	1.8776	0.185	10.16	***	
Location Mols Bjerge					
Mean	0.4415	0.160	2.76	**	218 (63–373)
Standard deviation	1.5742	0.191	8.26	***	
Location Lille Vildmose					
Mean	0.8141	0.138	5.92	***	402 (269–534)
Standard deviation	1.3630	0.167	8.17	***	
Location Vadehavet					
Mean	0.6014	0.152	3.95	***	297 (151–442)
Standard deviation	1.6092	0.160	10.09	***	
Nature preservation					
Mean	0.1216	0.032	3.77	***	60 (29–91)
Standard deviation	0.2835	0.058	4.89	***	
Effort for animal/plants					
Mean	1.1291	0.081	14.02	***	557 (486–628)
Standard deviation	0.8242	0.110	7.46	***	
Walking and biking paths					
Mean	0.1615	0.087	1.85	NS	80 (−5–164)
Standard deviation	0.8086	0.138	5.85	***	
Price					
Mean (fixed)	−0.0020	$>$ 0.001	−33.49	***	
σ_{12}	2.7036	0.184	14.68	***	
# Observations	4866				
# Respondents	636				
LL at convergence	−3742.96				
Adj. McF pseudo-R^2	0.298				

Simulations are based on 1,000 Halton draws. *** indicates significance at the 0.001 level; ** at the 0.01 level; * at the 0.05 level; *NS* non-significance at the 0.05 level. 95% confidence intervals for WTP are estimated using the Krinsky–Robb method with 10,000 draws.

of the location attributes are significantly different from each other. As expected the generic attributes all have a positive sign and the income tax parameter has the expected negative sign. The estimated standard deviations in the population of the random parameters show a higher degree of heterogeneity in respondents' preferences for the location of a national park compared to the generic attributes. This indicates a larger agreement in the population concerning what to put in a national park, as compared to where to put the national park. The test statistics indicate that the model fits the data well.

4.2 Testing the Utility Difference Hypothesis

Using the estimated utilities from Tables 3 and 4, we apply Eq. (3) to estimate the expected utility difference for each individual and for each choice set. Subsequently, this utility difference enters the ordered probit model in Eq. (4) as an explanatory variable. Note that this procedure implies that the utility difference is measured with the error implied by estimation. We ignore this inaccuracy in the following as we are only concerned with the potential of the estimated utility difference as a factor explaining the stated certainty level. We will not in this paper attempt to use the information to e.g. improve efficiency in estimating welfare measures as this is the focus of the accompanying paper by Lundhede et al. (2009) mentioned in Sect. 2.2. Table 5 displays the results obtained from estimating the ordered probit model of possible determinants of the likelihood that respondents report their certainty on an ordered scale ranging from 'very uncertain' with the value of zero to 'very certain' with the value of four. For both data sets the 'Don't know'-responses have been categorised as the medium level with the value two.

Table 5 Determinants of certainty in choices—random effect ordered probit model

Parameter	Motorway survey				National parks survey			
	Estimate	Std. err.	*t*-value		Estimate	Std. err.	*t*-value	
Utility difference	0.1553	0.0138	11.22	***	0.0833	0.0084	9.89	***
Choice set number	0.0490	0.0108	4.54	***	0.0018	0.0063	0.29	NS
Age group	0.0031	0.0497	0.06	NS	-0.0044	0.0045	−0.98	NS
Male	0.3693	0.1245	2.97	**	0.1781	0.1120	1.59	NS
Educational level	0.0797	0.0806	0.99	NS	-0.0464	0.0631	−0.74	NS
Income level	0.2259	0.0792	2.85	**	0.2114	0.0524	4.03	***
Knowledge of good	0.0896	0.1475	0.61	NS	-0.0653	0.1225	−0.53	NS
Constant	1.2503	0.0385	32.45	NS	1.9505	0.0357	54.65	NS
μ_1	2.5574	0.0428	59.72	***	2.0868	0.0361	57.88	***
μ_2	4.7249	0.0449	105.29	***	4.2247	0.0383	110.17	***
μ_3	1.5147	0.0449	33.70	***	1.3235	0.0405	32.67	***
σ	0.1553	0.0138	11.22	***	0.0833	0.0084	9.89	***
# Observations	3570				4866			
LL	−3747.1				−4683.8			
McFadden's pseudo-R^2	0.212				0.203			

*** indicates significance at the 0.001 level; ** at the 0.01 level; * at the 0.05 level; *NS* non-significance at the 0.05 level

For both surveys the goodness of fit indicates that the ordered probit model provides a reasonably good description of the dataset. Secondly, both models reveal that the utility difference variable constructed in the first step of the analysis does indeed have a highly significant impact on respondents' self-reported certainty level.[7] The positive sign of the utility difference parameter is as expected, i.e. the larger the utility difference as defined in Eq. (3), the higher the probability of observing a relatively high level of stated certainty in choice—and vice versa. We also note that in the Motorway survey other variables have a significant bearing on the likelihood that the respondent feels certain about their choice (income, gender and notably, choice set number), whereas only income level is significant in the National Park survey. The random effects parameter, σ, is also significant indicating that the stated certainty is correlated across choice sets within the individual respondent's choices.

5 Discussion

5.1 Testing Our Hypothesis: Tough Choices Cause Uncertainty

Inspired by Wang (1997) we formulate the hypothesis that respondents' stated certainty in choice increase with the utility difference between the alternative chosen and the best alternative to that. We develop a two-step procedure to test this hypothesis and apply it to datatsets from two independent Choice Experiment studies.

This hypothesis is particularly interesting for at least three reasons: First of all it is testable as we have shown here. Secondly, if the hypothesis is well-founded it may be possible to use the utility difference as a basis for capturing variance heterogeneity across choice sets *ex post*—in turn improving model performance and inference. Finally, if the researcher has an *a priori* expectation about the relative preferences for the environmental goods in question, utility difference in choice sets may also enter the choice set design consideration prior to data collection. In this paper, we focus on the first issue of interest, the test of the hypothesis, as this is a prerequisite for harvesting the benefits implied by the latter two points, which are discussed below in Sects. 5.2 and 5.3.

Loomis and Ekstrand (1998), Samnaliev et al. (2006) and Wang (1997) find indications that support Wang's hypothesis, but a formal test has to the authors' knowledge not been made so far. In our study, we addressed our much related hypothesis in a Choice Experiment context. We used data from two independent Choice Experiment surveys and found that the utility difference has a clear impact on the probability of respondents reporting that they are certain or very certain of their choice—*ex post*. Thus, the larger the utility difference between the alternative chosen and the best of the remaining alternatives, the more confident the respondents are likely to be in their choices. The intuition is straightforward and indeed the pattern found is also highly significant. The confirmation of this hypothesis allows us to reject the hypothesis that respondents use the certainty question to show consistency—rather there is a more subtle pattern in how the stated certainty varies with choice sets. This finding opens up the potential for using it in enhancing modelling efficiency and choice experiment designs.

[7] Admittedly, as we have ignored the estimation error of utility difference here, the test statistics may be slightly upward biased. On the other hand, given that the alternative hypothesis to the null is a strictly positive effect, one could argue for the use of a one-sided test here, increasing the significance of the parameter. In any case, the test statistics are so large that we feel we can safely proceed in our conclusions.

5.2 Perspective for Handling Respondent Uncertainty using Utility Differences

As pointed out by Li and Mattsson (1995), preference uncertainty in choices or answers may at the very least imply a risk of biased and invalid inference in Stated Preference studies. Furthermore, if respondent uncertainty is believed to indicate hypothetical bias, also found to be present in Choice Experiments (List et al. 2006), then that is another reason for handling respondent uncertainty. A common approach following this latter line of focus is to apply some form of recoding or truncation of respondent answers with high self-reported uncertainties. Examples abound in the Contingent Valuation literature (e.g. Champ et al. 1997; Welsh and Poe 1998), where also recent evidence suggests that the approach may have some merits in reducing hypothetical bias (Morrison and Brown 2009). The effects on WTP estimates of recoding choices in Choice Experiments have been found less convincing (Lundhede et al. 2009).

The recoding approach may be found unattractive due to the implied loss of information and meddling with the data. Therefore, another approach has been to explicitly include the stated uncertainty in the modelling, e.g. through various extensions of the random utility model. This approach has been pursued in Contingent Valuation studies by several authors, e.g. Alberini et al. (2003), Li and Mattsson (1995) and Loomis and Ekstrand (1998). Another kind of approach is the fuzzy random utility model suggested by Sun and van Kooten (2009), also applied to a Contingent Valuation study.

So far, however, too few studies have developed similar approaches for Choice Experiments. The results of this study points to the utility difference in choice sets as a potential key vehicle to model variance effects of uncertainty in choice. In our companion paper (Lundhede et al. 2009) we have evaluated several recoding approaches as well as models explicitly taking stated certainty into account in the random utility model. More precisely, we used the stated certainty to parameterize the scale parameter of the random utility model, which is usually normalised to one. We found that indeed scale varies greatly and significantly with the certainty in choice. Specifically, the higher the level of certainty in choice was, the lower was the amount of unexplained variance. Again, we found no significant differences in WTP compared with a benchmark model ignoring respondent certainty in choice. Note, that this approach essentially weighs the different responses with their scale parameter, and hence assigns less weight to the uncertain responses in the estimation. As such, it is related to other recent works, e.g. Bush et al. (2009). While noting that this approach may only be one of several options to go ahead, we stress that explicitly modelling variation in scale reduced the unexplained variance considerably and offers a structurally and intuitively appealing way of accounting for uncertainty in choices in Choice Experiment surveys.

5.3 Choice Set Designs: Balancing Utility Difference Against Utility Balance

It has long been a recommendation in Choice Experiment design to attempt to achieve utility balance in choice sets (Huber and Zwerina 1996; Kuhfeld 2004). With the current development in the design approaches, including sequential re-sampling for efficiency, this recommendation can actually be implemented. A high degree of utility balance in choice sets will indeed increase statistical efficiency of the sample based estimates, *provided* that respondents have a high degree of preference *certainty* and can in fact make the tough choices. If this is not the case, then our results suggest that a high degree of utility balance may in fact reduce the performance and inference quality. In the extreme, almost complete utility balance in choice sets will produce highly uncertain choices, at the risk of gathering little solid information even at the margin. Thus, it appears that a well-known balance needs to be handled: In order to learn anything about respondents' values on the margin, tough choices are essential. On the other hand, to allow inference on values on the margin, some degree of certainty is needed too, and hence not all choices should be equally tough. This balance is a relevant future research question.

5.4 Familiarity, Learning Effects and Respondent Certainty

It is a well-documented observation that as respondents evaluate more choice sets, initial instability of preferences may decrease (Bateman et al. 2008; Brown et al. 2008; Carlsson and Martinsson 2001; Hanley and Shogren 2005; Ladenburg and Olsen 2008). It is straightforward to formulate the hypothesis that such an effect should cause respondent certainty to increase with the choice set number. Our study provides a test of this hypothesis, but we obtain ambiguous results, cf. Table 5. In the Motorway survey, we find support of this hypothesis as increasing choice set number leads to increasing probability of reporting a higher certainty level. However, in the National Park survey, the parameter for choice set number has the congruent positive sign, but it is not significantly different from zero at any conventional significance criteria. The difference across the surveys suggests that learning is not a given thing, at least within the limits of the surveys here. One reason could be differences in respondents' familiarity with the good. List (2003) finds increased experience with a good to result in increased preference consistency; a result confirmed by Brown et al. (2008), but not by Brouwer et al. (2010) even though they do find an effect on the stated uncertainty. In our study, the Motorway case was somewhat more generic than the National park case, and indeed we find that the respondents in the former were on average more uncertain than in the latter.[8] Thus, it could be argued that the potential for (and need for) learning was simply bigger in the Motorway survey. Overall, uncertainty in the respondents assessment of own preferences of one alternative over another may be affected by several aspects of complexity of the experimental design, e.g. the amount of information provided, the number of alternatives in each choice set, the number of attributes and also levels of each attribute, and—as we found—the number of choice sets provided (Kamenica 2008; Puckett and Hensher 2008) may affect respondents' stated uncertainty.

5.5 Respondent Dependent Uncertainty

As opposed to utility difference, respondent characteristics do not vary with choice sets, but may of course still have an influence on the level of stated uncertainty. We find in the

[8] It should however be noticed that none of the surveys were utterly imaginary. The timing of the Motorway survey coincided with a public debate concerning a planned new motorway through different nature and landscape types around the city of Silkeborg—areas of which some are considered unique in Denmark (Olsen et al. 2005). Similarly, the establishment of one or more new national parks in Denmark had been much debated in the media before the launch of the valuation study used here, lending credibility to the scenarios presented (Jacobsen and Thorsen 2010). In fact, five parks have been or are currently being established. Another possible explanation of the differences in average certainty could be survey mode effects (Olsen 2009). The Motorway survey was conducted as an internet panel survey where choice sets where only disclosed one at a time with no option to go back in the sequence of choice sets. In the National parks survey a traditional mail survey approach with a printed questionnaire was used. Thus, respondents in this survey could in principle look at all choice sets before answering them. If so, a learning effect, which the certainty in choice statements will not be able to capture, might actually take place prior to the respondent's actual sequence of choices.

Motorway dataset, that male respondents have a higher probability of reporting a high certainty in choice than female respondents. The same tendency is present in the National park data set, but not significant. *A priori*, we would expect that being knowledgeable would reduce preference uncertainty and hence increase certainty for all utility differences, but prior knowledge as well as educational level are found to have no significant effect on certainty in choice. In fact, the parameters even have a somewhat surprising negative sign. Thus, being knowledgeable—either of the good or in general—has no direct effect on stated certainty in the two surveys once the effect of utility difference has been accounted for.

In both data sets there is a significant effect of respondents' household income: The higher the income level, the higher the probability of a respondent stating certainty in choice. As all respondents are faced with the same payment intervals, it could be an indication that especially poorer income groups use the certainty question to scale down WTP.

5.6 A Possible Caveat and Future Research

Several possible extensions exist to this study. Here we point to one related to other ongoing research: In the present study we have not investigated the effect of attribute levels and attribute processing strategies on stated certainty. We therefore assume that respondents assess the value of each attribute with equal certainty. When these assumptions do not hold, it may lead to discontinuous preferences and thus lexicographic ordering (Campbell 2008; Hensher 2008; Sælensminde 2001). It would be interesting to analyse the impact of discontinuous preferences in relation to stated certainty, but this is beyond the scope of the present paper. Also, the possible effects of different variations in the complexity of the choice sets and alternatives themselves will deserve further attention.

6 Conclusion

Respondents in Stated Preference surveys may be uncertain about their choices, especially in non-market good cases, and such uncertainty may lead to reduced efficiency and potentially biased inference (Li and Mattsson 1995). Inspired by Wang (1997) we formulate the hypothesis that respondents' stated certainty in choice will depend on the utility difference in each choice set. We define the utility difference as the difference in utility between the alternative chosen and the best of the remaining alternatives in the choice set. We set up a two-step procedure to test this hypothesis and use data from two independent Choice Experiment surveys in an empirical test. We find that the utility difference indeed has a clear impact on the probability of respondents reporting a higher degree of certainty in choice: The larger the utility difference between the alternative chosen and the best of the remaining alternatives, the more confident the respondents are likely to be in their choice. The intuition is straightforward and indeed the pattern found is also very strong.

The result provides a potential for further improvement of Choice Experiments when valuing non-market goods. One avenue ahead is the explicit modelling of respondent uncertainty, and the results of this study points to the utility difference in choice sets as a key vehicle to model variance heterogeneity effects of uncertainty across choice sets. Another avenue ahead is that rather than aiming for perfect utility balance, our results suggest that at least some degree of utility imbalance in designs is necessary in order to increase statistical performance and inference quality when respondents are uncertain about their choices. Determining a suitable or even optimal level of utility (im-)balance in design, i.e. a proper balance between tough and easy choices, is certainly a topic worthy of further research.

Acknowledgments The authors are grateful to two anonymous reviewers and associate editor John List for helpful comments and suggestions. An earlier version of the paper was presented at the EAERE annual conference in Gothenburg, 2008. We thank participants at this conference for helpful comments and suggestions. The authors further acknowledge the financial support from the Ministry of Environment and the Environmental Assessment Institute, which made possible the data collection for the surveys used. Thomas Hedemark Lundhede and Jette Bredahl Jacobsen further acknowledge the support of the Danish Research Councils making possible further work.

Appendix A—Example of a Choice Set Question for the Motorway Data

Which of the following locations for the future motorways would you prefer?

Remember to imagine that the nature areas which you visit most often, *will* be affected.

	Alternative 0	Alternative 1	Alternative 2
Number of kilometres through:			
Forest	10 km	0 km	10 km
Wetland	5 km	0 km	5 km
Heath/common	5 km	5 km	2.5 km
Arable land	80 km	95 km	82.5 km
Annual extra payment	0 DKK	200 DKK	100 DKK
I prefer …(tick one):	☐	☐	☐

How certain are you of your choice?

It's ok to be uncertain—Your reply will be no less valuable for that reason!

	(*tick one*)
Very uncertain	☐
Uncertain	☐
Neither certain nor uncertain	☐
Certain	☐
Very certain	☐
Don't know	☐

Appendix B—Example of a Choice Set Question for the National Park Data

10. **Do you prefer Choice 1, Choice 2 or No national park?**

(Mark one)
(The money have to be taken from your normal budget, and you will therefore have less money available for other things)

	Choice I	Choice II	No national park
Location of the national park	Thy	Mols Bjerge	
Nature preservation	Little extra effort	Some extra effort	
Extra initiatives for special plants and animals	Yes (Crane and red deer)	Yes Butterflies and barn owl	
Paths	No more paths	More paths	
Yearly extra income tax for your household	700 kr.	50 kr.	0 kr.

Choose only one of the possibilities … .... ☐ ☐ ☐

How certain were you of your choice … .... *Very certain* ☐ *Certain* ☐ *Uncertain* ☐ *Very uncertain* ☐ *Don't know* ☐

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