Decision uncertainty in multi-attribute stated preference studies

Abstract

Econometric modelling of decision uncertainty has received extensive attention in the contingent valuation literature, but these methods are not directly transferable to the realm of multi-attribute stated preference studies. In this paper, an integrated choice and latent variable model tracing the impact of decision uncertainty on the valuation of flood risks reductions in the Netherlands is developed. The proposed model structure is not subject to the potential endogeneity bias and measurement error issues associated with most applied methods. The driving factors of decision uncertainty are identified through stated choices and a set of self-reported decision uncertainty follow-up questions. The model simultaneously accounts for the impact of decision uncertainty on individual choices and welfare estimates. In the presented case study, uncertain respondents are found to make more random choices and select the opt out option more often. Willingness-to-pay for flood risk reductions increases after accounting for these behavioural responses to decision uncertainty.

Keywords: Decision uncertainty, Stated choice, Latent variable, Scale heterogeneity, Flood risk, Bayesian analysis

JEL codes: C15, C51, D12, D80, Q51, Q54

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1. Introduction

Interest in the impact of decision uncertainty on welfare estimates obtained from stated preference (SP) surveys dates back to the period in which the contingent valuation method (CVM) was the most widely applied non-market valuation method [see 41, 44, 2, for overviews]. The capability of respondents to order alternatives in a choice set or to express their willingness-to-pay according to their preferences depends on the extent to which they are familiar with the presented trade-offs and the degree of experience they have in making such trade-offs. A bias in welfare estimates may arise when the underlying econometric model does not account for any form of decision uncertainty respondents experience throughout the decision process.

Within the CVM literature, specifically the dichotomous choice (DC) response format, various survey formats and econometric approaches have been developed to account for the impact of decision uncertainty on willingness-to-pay (WTP) estimates [e.g. 32, 36, 48, 11, 30]. The implementation of these econometric methods in the context of multi-attribute stated preference (MASP) studies is not straightforward. Several MASP studies have measured decision uncertainty by positioning a follow-up question directly after each choice task [e.g. 34, 12, 5, 26, 27, 39]. The treatment of self-reported decision uncertainty has, however, been limited from a methodological perspective. Firstly, some papers [e.g. 39] assume decision uncertainty is a result of utility differences across the alternatives in the choice set without recognising decision uncertainty itself may influence response patterns and consequently the estimated utility functions and welfare implications. Secondly, other work has used the self-reported decision certainty responses as an explanatory variable in the choice model [e.g. 34, 5] putting the analyst at risk of endogeneity bias as well as measurement error (see Section 2.2).

Integrated Choice and Latent Variable (ICLV) models [e.g. 6] offer an intuitive solution to these two problems. ICLV models treat decision uncertainty as a latent construct *simultaneously* affecting choice and the response to the follow-up question. Correlation between the implicit representation of decision uncertainty in the choice model and its explicit representation in the follow-up question is introduced by making the utility function and the measurement equation (which explains the reported degree of (un)certainty) a function of the same latent variable 'decision uncertainty'. Directional effects are therefore no longer pre-imposed in the ICLV model; endogeneity and measurement error issues are circumvented by treating the follow-up responses as a dependent variable; and the welfare implications of decision uncertainty can be traced through the impact of decision uncertainty on the choice model.

In this paper, we explore whether the conceptual benefits of ICLV models outweigh the increase in computational costs relative to the criticized approach of using self-reported decision uncertainty as an explanatory variable in the utility function. Comparisons are conducted at the level of welfare estimates given that measures of model fit are hard to compare between traditional choice models and ICLV models. Our results reveal respondents with a higher level of (latent) decision uncertainty tend to make more random decisions, and they adopt a simplifying choice heuristic making them more likely to select the status quo (i.e. opt out) option. This particular choice heuristic causes choice models not accounting for decision uncertainty to underestimate welfare effects. Models treating self-reported decision uncertainty directly as an exogenous variable, however, provide comparable welfare estimates to the more complex ICLV model. The advantage of the ICLV model is that in addition to tracing the impact of decision uncertainty on choice and welfare estimates, it also explains the driving factors of decision uncertainty across respondents.

Our MASP study is conducted in the context of flood risk exposure in the Netherlands in the face of climate change. The public nature of Dutch flood risk policy and absence of private flood risk insurance causes most people to be unfamiliar with trade-offs regarding their own flood risk exposure. This is a natural application to test our model of decision uncertainty. Many alternative applications are likely to exist in the context of resource and energy economics. MASP surveys in the context of e.g. wind turbines [31] and water quality improvements [43, 37], as published in this journal, could all be facing unfamiliar respondents adopting choice heuristics to deal with decision uncertainty.

2. Decision uncertainty in stated choice surveys

2.1. Definition

We define decision uncertainty as the combination of preference uncertainty and choice uncertainty. Preference uncertainty is the degree of uncertainty respondents experience in assigning a level of utility to an alternative. Preference uncertainty can arise as a result of i) unfamiliarity with the good itself, ii) ambiguity or difficulty in interpreting particular attributes and iii) the need to infer missing product information. Choice uncertainty arises in the process of comparing the available alternatives and evaluating the decision in light of the institutional setting. In practice, all the researcher observes is a *choice* subject to both preference and choice uncertainty. Disentangling the two sources of uncertainty is difficult (if not impossible), hence the focus of this paper is on the more generic notion of decision uncertainty.

2.2. Measurement and modelling of decision uncertainty in stated choice surveys

The standard approach to measure decision uncertainty in the MASP studies is to include a self-reported decision uncertainty follow-up question directly after each choice task [e.g 34, 12, 5, 25, 9]. Fenichel et al. [22] and Balcombe and Fraser [4] are exceptions in that they present a 'do not know' option to respondents in addition to a status quo option. The limited variability in methods measuring decision uncertainty in MASP studies highlights the field is not yet as developed as its DC-CVM counterpart.[1]

Lundhede et al. [34] use the follow-up questions to evaluate three recoding approaches rooted in DC-CVM studies to account for the impact of decision uncertainty on welfare estimates. In applying these recoding approaches arbitrary assumptions need to be made in order to define the most likely choice if the respondent would have chosen differently. In other words, it remains unclear which alternative should be considered as second best and used as the basis for recoding.[2]

To circumvent the recoding issue, self-reported decision uncertainty is usually directly incorporated as an explanatory variable in the choice model [e.g. 34, 5, 9]. Along the lines of Arentze et al. [3], Caussade et al. [13] and DeShazo and Fermo [21], the above papers explain variations in the variance (scale) of the utility function as a result of self-reported decision uncertainty. This approach is consistent with Li and Mattsson [32]'s hypothesis that uncertain respondents make more random decisions.

The self-reported decision uncertainty responses are likely to be associated with measurement error, an issue Lundhede et al. [34] control for using an Instrumental Variable (IV) approach. The IV-approach also circumvents possible endogeneity issues. Namely, when the alternatives in the choice task are close to each other in terms of their utility levels, then the choice task is likely to be perceived as complex and respondents will report this in the follow-up questions. Using the self-reported decision uncertainty as an explanatory factor in the utility function is likely to introduce correlation between the error term of the utility function and the explanatory variables.

Manski [36] and Scarpa et al. [42] introduce an alternative perspective on decision

[1]Kobayashi et al. [30] discuss the strengths and weaknesses of alternative econometric models and response formats accounting for decision uncertainty applied throughout the DC-CVM literature. The direct elicitation of choice probabilities, interpreted as a measure of decision uncertainty due to incomplete future scenarios, as proposed by Manski [36] and implemented by Blass et al. [7] is not included in the respective overview. The method has also not (yet) been implemented in the MASP literature.

[2]Beck et al. [5] work with similar arbitrary calibration and weighting approaches.

uncertainty arising in MASP studies. Respondents in MASP studies tend to be more unfamiliar with the presented hypothetical alternatives than with the status quo option, which is actually experienced by respondents. Scarpa et al. [42] recommend the inclusion of a common error component to deal with this type of uncertainty. In the remainder of this paper, we focus on the econometric treatment of the self-reported decision uncertainty follow-up responses whilst including the recommended error component.

2.3. The need for a simultaneous modelling approach

Two alternative sequential econometric modelling approaches exist in the context of self-reported decision uncertainty. First, the IV-approach discussed in the previous section finds explanatory variables for self-reported decision uncertainty and subsequently includes the measurement equation in the choice model. Second, Brouwer et al. [12] and Olsen et al. [39] reverse the process by first estimating a choice model without controlling for decision uncertainty. Expected utility differences are then directly implemented to explain the decision uncertainty responses. Although in line with the order of presentation in the actual survey, the latter approach does not allow us to trace the impact of decision uncertainty on the choice model and corresponding welfare measures.

The above discussion illustrates our critique on current approaches. A model taking a one-directional view on decision uncertainty is incomplete. It should take into account the impact of decision uncertainty on both the response to the choice task and the self-reported decision uncertainty question. We therefore propose an Integrated Choice and Latent Variable (ICLV) model in Section 3 which treats decision uncertainty as a latent variable. Latent decision uncertainty *simultaneously* affects the choice model and the decision uncertainty responses without imposing a directional effect. In making a decision, respondents experience a degree of decision (un)certainty, which is implicitly reflected in their decision (e.g. more random decisions) and explicitly in answering the self-reported decision uncertainty follow-up question. Accordingly, the ICLV model provides a more natural representation to the problem at hand.

Like in the IV-approach, the ICLV model uses a set of control variables to explain the (latent) decision uncertainty. The use of such a structural equation avoids measurement error by recognizing self-reported decision uncertainty responses are an imperfect measure of underlying latent decision uncertainty. Similarly, endogeneity issues are avoided by the inclusion of appropriate instrumental variables.

2.4. Two hypotheses

Given our interest in the impact of decision uncertainty on choice and related welfare measures we form two specific working hypotheses tracing the impact of decision uncertainty on the utility function. First, we maintain the Li and Mattsson [32] hypothesis that uncertain respondents tend to have higher variance in the error term of their utility function. Accordingly, their choices will have lower informational content. This hypothesis predicts an increase (decrease) in the variance (scale) of utility as respondents become more uncertain. This hypothesis is operationalised by introducing heteroscedasticity in the error term across choice tasks [3, 13, 21].

Alternative hypotheses exist arguing uncertain respondents adopt simplifying choice heuristics affecting the structural part of the utility function. For example, Loomes et al. [33] develop a model in which uncertain respondents are more likely to pick the status quo alternative than is the case for certain respondents. This heuristic finds empirical support in Balcombe and Fraser [4] and Swait and Adamowicz [46] and embodies our second hypothesis. The hypotheses are tested jointly in the ICLV model.

3. The ICLV model

In this section, we provide a formal description of the ICLV model and its components, i.e. the structural equation, the choice model and the measurement model, [c.f. 6]. Figure 1

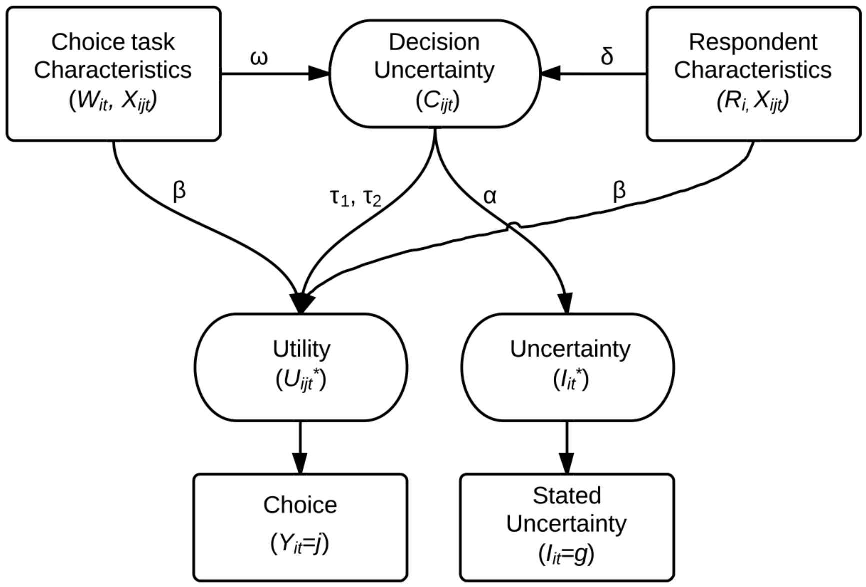


Figure 1: The ICLV model

provides a graphical representation. Rectangles represent directly observable variables and ellipses latent constructs. The structural equation describes latent decision uncertainty as a function of respondent and choice task characteristics. The choice model explains the observed choices conditional on the level of latent decision uncertainty as well as respondent and choice task characteristics. Note that the researcher only observes a choice, while we use the latent notion of utility to explain choice behaviour. Similarly, the measurement model explains 'stated uncertainty' which is measured on an ordinal scale. Like any ordered probit (or logit) model, we map these responses on a continuous uncertainty scale and use latent decision uncertainty as the only explanatory variable.[3]

[3] Choice task and respondent characteristics have a direct impact on individual preferences U^*_{ijt}, and possibly indirect through latent decision uncertainty C_{it}. We do, however, not believe they also bear a direct relation with uncertainty I^*_{it}. If that were the case there would be a structural mismatch between C_{it} and I^*_{it} and the way we measure decision uncertainty. Violations of this assumption would possibly bias the model parameters. Empirical identification of both the direct and indirect effect is, however, hard and not common practice in the ICLV literature.

3.1. *The structural equation*

Equation (1) denotes latent decision uncertainty C_{it} for respondent i in choice task t as a linear function of respondent characteristics R_i and a set of choice task specific characteristics W_{it}. Let δ and ω denote the marginal effects associated with respectively R_i and W_{it}. For example, differences in gender and education may result in different degrees of decision (un)certainty, while some choice tasks are more difficult than others, because the alternatives in the choice set are more comparable to each other.

$$C_{it} = \delta R_i + \omega W_{it} + \rho_i + \varepsilon_{it} \tag{1}$$

Since δR_i is unlikely to capture all respondent specific variation in decision uncertainty across respondents, a respondent specific term ρ_i is included in the structural equation. The latter is added in the form of a normally distributed random parameter with zero mean and variance σ_ρ^2.[4]. Finally, ε_{it} represents an i.i.d. standard normally distributed error term capturing remaining (unexplained) variations in latent decision uncertainty. In accordance with the Bolduc et al. [8] normalisation the variance of ε_{it} is restricted to unity. C_{it} remains unobserved and takes the form of a continuous variable where higher values represent higher degrees of decision uncertainty.

A critical factor to include in the structural equation is a summary of choice task complexity. Shannon [45]'s entropy measure $H(J_{it}) = -\sum_{j \in J_{it}} P_{ijt} ln(P_{ijt})$ provides a natural candidate reaching its maximum when all alternatives in the choice set have the same choice probability P_{ijt}. Its dependence on choice probabilities, however, complicates

[4]Recent applications of latent variable models in the choice modelling literature (e.g. Abou-Zeid et al. [1], Daly et al. [17], Daziano and Bolduc [18], Hess and Beharry-Borg [28], Yanez et al. [49]) have focused on underlying attitudes at the level of the respondent, and have used attitudinal questions at the level of the respondent as an indicator of these latent attitudes. Note that these responses have been captured only once per respondent. In contrast, we obtain a degree of self-reported decision uncertainty after *each* choice task $t = 1, \ldots, T$.

operationalising the proposed ICLV model due to endogeneity. One option is to adopt an iterative approach where at intermediate parameter values choice probabilities and entropy are iteratively updated until the likelihood stabilises. It is not clear whether such an iterative approach generates consistent parameter estimates. An easy and often available alternative, adopted in this paper, is to estimate a basic choice model on a different sub-sample (or pre-test sample) of the survey. The obtained choice probabilities then enable researchers to approximate the entropy measure. Other options are to replace entropy by alternative measures of complexity not depending on choice probabilities [e.g. 21].

3.2. The choice model

Respondents are assumed to select the alternative generating the highest level of (latent) utility. The utility function $U_{ijt} = V_{ijt} + \epsilon_{ijt}$ is specified in the standard linear-additive form. V_{ijt} represents the deterministic part of the utility function and ϵ_{ijt} the stochastic term. It is assumed that ϵ_{ijt} follows a Type I Extreme Value distribution with $var(\epsilon_{ijt}) = \frac{\pi^2}{6\lambda_{it}^2}$. The inverse relation between the scale λ_{it} and variance of utility becomes directly clear from this expression. In estimation, we rescale the stochastic and deterministic part of the utility function by λ_{it} such that ϵ^*_{ijt} follows an i.i.d distribution with variance $var(\epsilon^*_{ijt}) = \frac{\pi^2}{6}$. Equation (2) describes the rescaled utility function U^*_{ijt}.

$$\begin{aligned} U^*_{ijt} &= V^*_{ijt} + \epsilon^*_{ijt} = \lambda_{it} V_{ijt} + \lambda_{it}\epsilon_{ijt} \\ &= \exp(\tau_1 C_{it}) \cdot ((\tau_2 C_{it} + \beta_1 + \zeta_i) ASC_{ijt} + \beta_i X_{ijt}) + \epsilon^*_{ijt} \end{aligned} \tag{2}$$

The second line of Equation (2) describes the implemented utility function which embodies the two working hypotheses and Scarpa et al. [42]'s error component. First, the scale parameter $\lambda_{it} = \exp(\tau_1 C_{it})$ is expected to be decreasing in decision uncertainty C_{it}. Uncertain respondents are expected to display a higher decisional variance, i.e. a lower scale. Accordingly, τ_1 is hypothesize to be negative.[5] Second, $\tau_2 C_{it}$ represents the alternative decision heuristic that uncertain respondents are more likely to select the status quo (or opt out) option. We model this by interacting C_{it} with the alternative specific constant (ASC). Here, ASC_{ijt} has a value of one when the alternative is not the status quo. Hence, τ_2 is hypothesized to take a negative value. β_1 measures the average utility associated with the ASC unrelated to decision uncertainty. Third, the interaction between ζ_i and the ASC captures the additional variance associated with the hypothetical alternatives. ζ_i takes the form of a normally distributed error component with zero mean and variance σ_ζ^2. Like in Scarpa et al. [42] the error component is introduced at the panel level.

The remaining part of the deterministic utility function comprises a set of exogenous variables X_{ijt} describing the attribute levels of each alternative and possibly other socio-economic characteristics. The vector β_i measures the marginal utility associated with each of these variables, where the subscript i denotes that marginal utility may vary across respondents. Heterogeneity in preferences is described by means of a random parameter specification using the mixing density $f(\beta_i|\theta)$, where θ represents the set of hyper-parameters. Conditional on the individual specific parameters and C_{it}, the choice probability of respondent i selecting alternative j from choice set J_{it} in choice task t, i.e. $Y_{it} = j$, is described by:

$$P(Y_{it} = j|X_{it}, C_{it}, \beta_i, \tau_1, \tau_2) = \frac{exp\left(\exp(\tau_1 C_{it})\left((\tau_2 C_{it} + \beta_{1i})ASC_{ijt} + \beta_i X_{ijt}\right)\right)}{\sum_{k=1}^{J_{it}} exp\left(\exp(\tau_1 C_{it})\left((\tau_2 C_{it} + \beta_{1i})ASC_{ikt} + \beta_i X_{ikt}\right)\right)} \quad (3)$$

[5] Given that C_{it} follows a normal distribution with variance 1, the scale of utility follows a log-normal distribution with expected value $\exp\left(\tau_1(\delta R_i + \omega W_{it}) + \frac{\tau_1^2}{2}\right)$. For normalisation purposes $-\frac{\tau_1^2}{2}$ is added to the specification of λ_{it}, i.e $\lambda_{it} = \exp(\tau_1 C_{it} - \frac{\tau_1^2}{2})$. As such, the expected value of λ_{it} reduces to unity for a base group. See also Fiebig et al. [23], Greene and Hensher [24].

3.3. The measurement model

Latent decision uncertainty is measured by the choice task specific follow-up question I_{it}. The translation of the follow-up question is: '*How certain are you of your choice?*', where the response format comprised a rating scale with five levels: '*very certain*', '*certain*', '*neither certain nor uncertain*', '*uncertain*' and '*very uncertain*', respectively coded as [0,1,2,3,4]. Daly et al. [17] put forward the use of an ordered logit model as an appropriate specification of the measurement model given the ordered nature of I_{it}. We prefer to use an ordered probit specification to facilitate estimation in a Bayesian framework.[6]

Let I^+_{it} represent a mapping of I_{it} on a continuous scale, such that a respondent selects $I_{it} = g$ if I^+_{it} falls between thresholds ψ_{g-1} and ψ_g.[7] Given that there are five response categories to I_{it}, only four threshold parameters can be identified. We impose $\psi_g > \psi_{g-1}$ and respectively set $\psi_0 = -\infty$ and $\psi_5 = \infty$. Equation (4) then links latent decision uncertainty C_{it} to the responses, where for normalisation purposes we impose $\alpha = 1$. ν_{it} represents a zero mean i.i.d. normally distributed stochastic term with variance restricted to unity to comply with the ordered probit specification. Accordingly, Equation (5) describes the probability that the respondent will indicate the degree of decision uncertainty g, where ϕ denotes the standard normal density function and Φ its cumulative density equivalent.

$$I^+_{it} = \alpha C_{it} + \nu_{it} \tag{4}$$

$$P(I_{it} = g|C_{it}) = \int_{\psi_{g-1}}^{\psi_g} \phi\left(I^+_{it} - \alpha C_{it}\right) dI^+_{it} = \Phi\left(\psi_g - \alpha C_{it}\right) - \Phi\left(\psi_{g-1} - \alpha C_{it}\right) \tag{5}$$

[6] Effectively, in estimation we use a re-parameterised version of the ordered probit model similar to Nandram and Chen [38] reducing autocorrelation in the Gibbs Sampler.

[7] g refers to the response categories of the follow-up question. $g = 1$ represents the most certain option 'very certain'. $g = 2, \ldots, 5$ complies with the order of appearance and $g = 5$ ends with 'very uncertain'.

3.4. Joint likelihood function and complexity of estimation

When the two sets of dependent variables, namely the observed choices Y and self-reported decision uncertainty I, are analysed separately, the researcher estimates a discrete choice model and an ordered probit model. The ICLV simultaneously estimates these two models, and links them through the latent factor decision uncertainty. The conditional expressions $P(Y_{it} = j|C_{it})$ and $P(I_{it} = g|C_{it})$ in the joint likelihood function in Equation (6) therefore refer to the choice probabilities and the probability of the choice task specific follow-up responses. $h(C_{it}|\cdot)$ describes the structural equation linking the two models. The latent nature of C_{it} in combination with the parameters (β_i,ρ_i; captured in (6) by Δ_i) controlling for unobserved heterogeneity across respondents requires integration at two levels.

$$L(Y, I) = \prod_{i=1}^{n} \int_{\Delta_i} \prod_{t=1}^{T} \int_{C_{it}} P(Y_{it} = j|C_{it}) P(I_{it} = g|C_{it}) h(C_{it}|\delta, \omega, \rho_i) dC_{it} q(\Delta_i|\theta_\Delta) d\Delta_i \quad (6)$$

Hess and Train [29] note that ICLV models are computationally intensive when using frequentist estimation approaches. Therefore, we estimate the model using Bayesian methods and work around the integrals by evaluating a set of conditional densities using the principles of data augmentation [47].[8] Relative to existing sequential approaches to decision uncertainty, the ICLV model introduces additional estimation complexity, but allows to trace the impact of decision uncertainty on the choice model without imposing directional relationships between choices and self-reported decision uncertainty as discussed in Section 2.3.

[8]The details of the Gibbs Sampler are available from the corresponding author.

4. The Case Study

4.1. Valuation of flood risks in the Netherlands

The case study is based on a Dutch MASP survey concerning flood risk valuation in the face of climate change. An online survey was conducted in the provinces of North- and South-Holland between February and March 2010. The cities of Amsterdam, The Hague and Rotterdam are situated in these densely populated provinces. The Dutch government and regional water boards attempt to maintain a flood probability of once every 10,000 years in the study area. Without additional investments, flood probabilities are expected to increase to once every 4,000 years by 2040 due to climate change [35]. Even though most of the Dutch are aware that they live below sea level, they are not accustomed to making trade-offs regarding their personal flood safety. Water boards and other public institutions are primarily responsible for providing and monitoring flood safety levels. Decision uncertainty is therefore likely to play a role in this case study.

4.2. The stated choice experiment

The choice experiment elicits the extent to which respondents are willing to increase their annual (tax) contributions to the water board in order to reduce the probability of a coastal flood and the associated consequences. A detailed description of the survey is provided in Dekker [19]. The choice experiment is distinctively different from Botzen and van den Bergh [10] who present flood risk reductions in the context of a public-private partnership where respondents can insure themselves against flood risks as a result of climate change. Flood risk insurance is, however, currently not (yet) available in the Netherlands. Accordingly, our positioning of flood risk valuation in the context of a pure public good is more in line with the current institutional setting.

In this paper, we focus on the only subsample (one of five) in which respondents were presented with a decision uncertainty follow-up question after each choice task.

Respondents were presented with ten choice tasks each. The first and tenth choice task were identical, where the first task served as an introductory question and the final choice task was included as a test for consistency. In the analysis, we focus on choice tasks 2-9, resulting in a balanced panel of eight choice tasks per respondent and a total of 1,792 observations from a sample of 224 respondents.

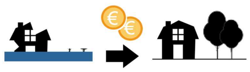
In each choice task, two different flood policy scenarios and a status quo option were presented to the respondent. Each policy scenario is characterised by four attributes: (i) reductions in flood probability; (ii) compensation of material damage to each household after a coastal flood has occurred; (iii) available time for local authorities to organise and completely evacuate the area under threat; and (iv) an increase in annual tax to the water board per household. Table 1 shows the potential levels of each attribute and defines the status quo (i.e. opt out) option. An example of a choice card, including the follow-up question is presented in Table A.5.

The experimental design for the sample used here is based on a d-efficient design for a linear attributes only MNL model, including an ASC. Local non-zero priors in the design were derived from an earlier pre-test sample on which alternative functional forms were tested. The design was generated in Ngene [16] and consists of 24 choice cards blocked into three groups of eight cards. Each respondent was randomly presented with one of these blocks. Positions of the cards within each block were systematically rotated to prevent ordering effects [see also 20].

5. Results

We present results from five alternative model specifications. The first model presents a random parameters logit model where the choices in the SC are analysed without controlling for decision uncertainty. Model 2 treats the self-reported decision uncertainty responses [0,1,2,3,4] as a correct measurement of C_{it} and includes these directly in the

Table 1: Attributes, attribute levels and definition of the Status Quo option

Attribute	**Possible attribute levels***				
Probability 	1 in 4,000 years	1 in 6,000 years (1.5x smaller)	1 in 8,000 years (2x smaller)	1 in 10,000 years (2.5x smaller)	
Compensation 	0%	50%	75%	100%	
Evacuation time 	6 hours	9 hours	12 hours	18 hours	
Increase in annual tax 	€0	€40	€80	€120	€160

* The Status Quo option takes the most left (lowest) levels on all policy attributes

choice model. Accordingly, Model 2 might be subject to endogeneity and measurement error. Model 3 corrects for these issues by running a sequential IV-model. First a random effects ordered probit model is estimated to obtain parameter estimates for δ and ω and thereby derive expected values for $\hat{I^+}_{it}$. Then a choice model is estimated using $\hat{I^+}_{it} = \hat{C}_{it}$ as a control variable. Model 4 presents the Full Information Maximum Likelihood (FIML) equivalent of Model 3. That is, the conditional posterior for the augmented variable I^+_{it} not only takes into account the boundaries set by the threshold parameters in the ordered probit model (as in Model 3), but also the subsequent impact of $\hat{I^+}_{it} = \hat{C}_{it}$ on the choice model. Model 5 presents the results of the developed ICLV model. The difference between Models 4 and 5 is that the latter treats I^+_{it} and C_{it} as separate entities. Effectively, the estimated thresholds parameters associated with the self-reported decision uncertainty questions no longer constrain the location of C_{it} and thereby alter Model 4 from a sequential into a simultaneous model structure. This subtle change accommodates the critiques mentioned in Section 2.3. All models include a separate error-component accounting for potential scale difference between the scale of the status quo and hypothetical alternatives [42].

5.1. Choice models and simple IV-estimation

Table 2 presents the results for the first three model specifications. Model 1 can be characterised as an attributes only choice model where the probability, compensation and cost attribute follow a lognormal distribution to ensure a strictly positive (negative for cost) impact on utility. The evacuation attribute follows a normal distribution in order to allow the model to converge. The specification of the choice model does not vary across models 1-5 apart from the interaction of decision uncertainty with respectively the ASC and scale parameter.

The parameter and welfare estimates for Model 1 confirm expectations. Respondents experience a positive utility from reductions in flood probability, additional compensation, and increases in available evacuation time, while they are less likely to select a policy alternative with higher costs. The marginal WTP estimates reveal households are willing to pay €7.08 per year to reduce flood probabilities by 1,000 years, i.e. from 1/4,000 to 1/5,000 year. Similarly, an additional percentage of compensation is worth €0.71 per household per year and an extra hour of evacuation time €1.90.[9] σ_ζ confirms that the hypothetical alternatives are associated with additional error variance.

As expected, both τ_1 and τ_2 have a negative coefficient in Model 2. The former highlights uncertain respondents exhibit a higher decisional variance. The latter confirms uncertain respondents have a higher tendency to select the status quo alternative. Treating the follow-up responses as an exogenous explanatory variable in the choice model translates into a decisive improvement in model fit as highlighted by the Bayes Factor of 7.07 relative to Model 1.[10] Median WTP estimates for Model 2 are all higher compared

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[9]During each iteration of the Gibbs Sampler, the median WTP for an attribute was calculated and stored using the augmented preference parameters across individuals.

[10]Balcombe et al. (2009) introduced the method of Gelfand and Dey (1994) for model comparison in the mixed logit framework. This method is not suitable due to the large number of latent variables. Accordingly, we apply the method of Chib and Jeliazkov (2001) for model comparison.

Table 2: Results choice models and basic IV-estimation

	(1)			(2)			(3)		
	Post Mean	Post StDev	% < 0	Post Mean	Post StDev	% < 0	Post Mean	Post StDev	% < 0
ASC	2.51	0.28	0	1.99	0.27	0	2.81	0.34	0
PROB	-2.10	0.23	100	-2.25	0.22	100	-2.11	0.23	100
COMP	-2.16	0.18	100	-2.34	0.17	100	-2.24	0.18	100
EVAC	0.49	0.11	0	0.40	0.09	0	0.46	0.11	0
COST	-1.79	0.13	100	-2.05	0.14	100	-1.83	0.13	100
Std. PROB	1.34	0.22	0	1.32	0.21	0	1.33	0.21	0
Std. COMP	1.19	0.18	0	1.14	0.18	0	1.24	0.18	0
Std. EVAC	0.83	0.15	0	0.65	0.12	0	0.81	0.15	0
Std. COST	1.14	0.12	0	1.22	0.13	0	1.15	0.12	0
σ_ζ	1.98	0.32	0	1.77	0.28	0	2.01	0.34	0
τ_1	-			-0.40	0.08	100	0.04	0.15	41
τ_2	-			-0.44	0.18	99	-0.83	0.43	98
IV-part									
Male							-0.54	0.20	100
Education							-0.14	0.20	75
Experience							-0.18	0.31	72
Credibility							-0.37	0.14	100
Block 1							0.24	0.25	17
Block 3							0.36	0.24	6
Cardnr							0.02	0.01	4
Entropy							1.22	0.22	0
σ_ρ							1.42	0.08	0
ψ_1							-1.78	0.24	100
ψ_2							0.47	0.24	2
ψ_3							2.48	0.24	0
ψ_4							4.31	0.27	0
Obs- Choice	1792			1792			1792		
n	224			224			224		
ML-Choice	-1401.1			-1394.04			-1411.65		
BF				7.07			-10.54		
WTP PROB	7.08	1.57	0	7.85	1.67	0	7.28	1.58	0
WTP COMP	0.71	0.11	0	0.76	0.12	0	0.69	0.11	0
WTP EVAC	1.90	0.48	0	1.91	0.49	0	1.85	0.48	0

Units:
All marginal median WTP estimates are in €per household per year
Probability - Increase in the denominator of probability by 1,000 years, i.e. from 1/4,000 to 1/5,000
Compensation - Additional percentage of compensation
Evacuation - Additional hour of available evacuation time

to Model 1, particularly for the probability attribute. The size of the posterior standard errors on the WTP estimates, however, indicate there are no significant differences in welfare estimates between Models 1 and 2. The increase in median WTP estimates can be related to the choice heuristic associated with τ_2. Without controlling for the impact of decision uncertainty, Model 1 increases the relative importance of the cost attribute to accommodate for the fact that uncertain respondents select the status quo more often.

The sequential IV-estimation procedure presented by Model 3 experiences difficulties in linking expected decision uncertainty to observed choice behaviour. τ_1 on the one hand changes sign and is no longer statistically different from zero. τ_2 on the other hand suggests respondents are even more likely to select the status option due to decision uncertainty. Note, however, that the posterior standard errors on the τ parameters have also increased substantially. It is therefore not surprising that Model 3 reveals a lower marginal likelihood than Models 1 and 2. We attribute this to the fact that Model 3 does not account for the heterogeneity in decision uncertainty represented by ρ_i given that we used a mean-based approach. Based on Model 3, we might conclude that the direct use of self-reported decision uncertainty in Model 2 results in an overestimation of median WTP. Namely, we only observe a negligible, increase in median WTP estimates relative to Model 1. The instability of the τ parameter estimates in Model 3, however, justifies a closer examination of decision uncertainty in the context of a sequential FIML approach and the proposed ICLV model.

5.2. Explanatory variables in the IV-approach and structural equation

The explanatory variables included in the IV-part of Model 3 (and in the remaining models) are summarised in Table 3. They represent the driving factors of self-reported decision uncertainty. Tables 2 and 4 point out that males are less uncertain than females, while education does not seem to have an influence on decision uncertainty; a finding confirmed by both Olsen et al. [39] and Brouwer et al. [12]. Respondents who stated that the proposed policy scenarios are credible tend to reflect lower levels of decision uncertainty, a finding also reported in Brouwer et al. [12]. The results, however, do not confirm that respondent that have previously experienced a flood exhibit lower levels of decision uncertainty.[11] Four variables are related to choice task characteristics.

The dummy variables *Block 1* and *Block 3* indicate that splitting up the design into three blocks resulted in *Block 2* being slightly easier for respondents compared to the two other blocks. Indeed, correlating the blocks with the entropy measure revealed that *Block 2* contained two relatively easy choice tasks. Decision uncertainty is increasing in the length of the stated choice survey as reflected by *Cardnr*. By altering the order of appearance of choice cards across respondents, this effect is most likely related to fatigue or boredom effects. Finally, *Entropy* summarises choice task complexity using Shannon [45]'s entropy measure (see Section 3.1). The results confirm that decision uncertainty is increasing in the complexity of the choice task.

Table 3: Overview of explanatory variables in the structural equation

Name	Type	Mean	St.dev	Min	Max
Male	Dummy	0,48	0,50	0,00	1,00
Low & Medium Education	Dummy	0,51	0,50	0,00	1,00
Experience	Dummy	0,13	0,33	0,00	1,00
Credibility	Categorical	-0,04	0,71	-2,00	2,00
Block 1	Dummy	0,29	0,45	0,00	1,00
Block 3	Dummy	0,36	0,48	0,00	1,00
Cardnr	Continuous	3,50	2,29	0,00	7,00
Entropy	Continuous	0,31	0,13	0,00	0,46

[11] The variables *Experience* and *Credibility* are related to specific questions in the survey, where the former is included as a dummy variable. Credibility is measured as a five-level categorical variable ranging from 'very incredible' (lowest) to 'very credible' (highest), which is included in a linear fashion in the model.

5.3. FIML and ICLV models

Table 4 shows large consistencies between the IV-parts in Models 3 and 4. The direct connection between the ordered probit model and the choice model in Model 4 enables better identification of the τ parameters, which again take the expected negative value. Decision uncertainty therefore has an impact on individual choice behaviour through making more random choices and by adopting alternative decision heuristics. The obtained marginal WTP estimates from Model 4 show close resemblance with those obtained from the critiqued Model 2. In other words, there might not be too much bias in directly including the self-reported decision uncertainty responses in the choice model. Moving from the sequential FIML model (Model 4) to the proposed ICLV model (Model 5) shows that the parameters of the choice model stay fairly constant. The τ parameters lead to the same conclusion that decision uncertainty has an impact on individual choice behaviour, even though τ_1 shows a slight drop relative to Model 4. The main difference between the two models arises in the parameters for the structural and measurement equation. The final column in Table 4 reveals estimates for Model 4 are about a factor 0.7 smaller than those for Model 5. The scaling is a direct consequence of the fact that additional variance is added around latent decision uncertainty in the ICLV model. In fact, when neglecting the influence of the choice model the variance of the ordered probit model increases to two, explaining why the parameters in the ICLV model are about a factor $\sqrt{2} \approx \frac{1}{0.7}$ larger than those in the FIML model.

The ICLV model has a decisively better fit than the FIML likelihood approach. We explain this by noting that the sequential FIML puts most emphasis on explicit decision uncertainty represented in the self-reported decision uncertainty measures. Part of the 224 respondents did not change their self-reported decision uncertainty over the choice sequence, while a different pattern may be revealed by the implicit representation of decision uncertainty in the choice model. By using both implicit and explicit representations

Table 4: Results FIML and ICLV model

	(4)			(5)			
	Post Mean	Post StDev	% < 0	Post Mean	Post StDev	% < 0	Ratio (4)/(5)
Choice							
ASC	3.02	0.38	0	3.08	0.46	0	
PROB	-2.00	0.21	100	-2.01	0.23	100	
COMP	-2.10	0.17	100	-2.12	0.17	100	
EVAC	0.51	0.12	0	0.50	0.12	0	
COST	-1.80	0.14	100	-1.78	0.14	100	
Std. PROB	1.31	0.20	0	1.31	0.22	0	
Std. COMP	1.15	0.18	0	1.17	0.18	0	
Std. EVAC	0.82	0.16	0	0.82	0.15	0	
Std. COST	1.21	0.13	0	1.20	0.13	0	
σ_ζ	2.34	0.37	0	2.35	0.42	0	
τ_1	-0.16	0.05	100	-0.10	0.04	100	
τ_2	-0.35	0.13	100	-0.33	0.14	100	
Structural							
Male	-0.57	0.19	100	-0.82	0.26	100	0.70
Education	-0.16	0.19	79	-0.23	0.27	80	0.67
Experience	-0.19	0.29	75	-0.27	0.42	75	0.71
Credibility	-0.38	0.14	100	-0.52	0.19	100	0.73
Block 1	0.25	0.24	14	0.37	0.32	12	0.69
Block 3	0.39	0.22	5	0.54	0.32	4	0.71
Cardnr	0.02	0.01	3	0.03	0.02	3	0.70
Entropy	1.25	0.22	0	1.75	0.30	0	0.71
σ_ρ	1.39	0.08	0	1.87	0.50	0	0.75
Measurement							
ψ_1	-1.82	0.18	100	-2.59	0.26	100	0.70
ψ_2	0.46	0.18	0	0.64	0.24	0	0.72
ψ_3	2.48	0.19	0	3.50	0.24	0	0.71
ψ_4	4.36	0.24	0	6.14	0.32	0	0.71
Obs- Choice	1792			1792			
n	224			224			
ML	-3099.2			-3088.9			
BF				10.2			
WTP PROB	7.80	1.64	0	7.68	1.72	0	
WTP COMP	0.76	0.12	0	0.74	0.12	0	
WTP EVAC	1.91	0.49	0	1.87	0.50	0	

Units:
All marginal median WTP estimates are in €per household per year
Probability - Increase in the denominator of probability by 1,000 years, i.e. from 1/4,000 to 1/5,000
Compensation - Additional percentage of compensation
Evacuation - Additional hour of available evacuation time

of decision uncertainty, the ICLV model can work around such inconsistencies between C_{it} and I_{it}^{+} and improve model fit.

Overall, the ICLV model illustrates that there exists a correlation between the implicit and explicit representation of decision uncertainty in respectively choice behaviour and self-reported decision uncertainty. Clearly, there is not a one to one relation between the two and possibly a (non-modelled) causal relation exists. As such, the self-reported decision uncertainty variable cannot be used as a direct (and exogenous) explanatory variable in the choice model from a theoretical perspective. Remarkably, however, is that in the current case study the latter naive approach and more advanced FIML and ICLV models result in a comparable increase in median WTP estimates. The scale-free median WTP estimates highlight the potential for underestimation of welfare effects when not controlling for decision uncertainty. It should be noted that these effects are not very strong given the size of the posterior standard deviations, but concern is warranted for future research.

6. Conclusions

In this paper, we propose an Integrated Choice and Latent Variable (ICLV) model to account for decision uncertainty in multi-attribute stated preference (MASP) studies. Decision uncertainty is treated as a latent variable, which simultaneously affects stated choices and responses to a set of follow-up decision uncertainty questions. The ICLV model thereby works around potential endogeneity and measurement error issues likely to arise when using the follow-up responses as a direct measure of decision uncertainty.

The proposed ICLV model provides a more intuitive approach to treating decision uncertainty compared to existing methods in the MASP literature. The frequently adopted assumption of a one-directional impact in sequential models hampers the modelling of the complex relation between the implicit and explicit representation of decision uncertainty.

That is, the degree of decision uncertainty present in the actual choice process might not always correspond with the stated level of decision uncertainty. The simultaneous modelling approach accounts for the correlation between the decision uncertainty respondents implicitly reveal while making choices and the explicit degree of decision uncertainty stated in the follow-up questions, but does not assume they are identical.

The ICLV model is applied to a MASP experiment on flood risk valuation in the Netherlands. Two complementary hypotheses are embedded in the ICLV model. The first hypothesis represents the conjecture that uncertain respondents make more random decisions reducing the informational content of their responses. The second hypothesis controls for uncertain respondents adopting an alternative decision heuristic to simplify the choice task. The decision heuristic adopted here accounts for uncertain respondents being more likely to select the status quo (or opt out) option. Evidence for both hypotheses is found in the form of significant interactions of latent decision uncertainty with respectively the scale of the utility function, and the alternative specific constant, whilst including an error-component accounting for potential scale difference between the hypothetical and status quo alternatives.

The finding that WTP estimates increase when controlling for decision uncertainty can be related to the second hypothesis. When the model does not control for the adoption of an alternative choice heuristic, other model parameters correct for such behavioural patterns and become biased. In our case, the respondents either need to become more cost sensitive or assign a lower importance to the non-cost policy attributes. Both effects translate into lower WTP estimates for the policy attributes which are actually caused by uncertain respondents having a higher tendency to select the status quo option. The first hypothesis also translates into an increase in marginal WTP estimates, but the magnitude of the change is smaller. In general, the observed differences in WTP estimates relative to the base model are of minor size, a finding confirmed by Lundhede et al. [34]. Our findings are, however, at stake with conclusions from the contingent valuation (CV) literature, where WTP estimates tend to decrease after controlling for decision uncertainty [e.g. 11]. The controversy might be related to the recoding approaches applied in the CV literature, where uncertain 'yes' responses are frequently recoded as 'no' responses [15].[12]

Recoding approaches find their origin in real world behaviour, where uncertain respondents might be inclined to say 'yes' in stated preference studies, but in real-world decision would revert to 'no'.[13] The equivalent type of reverting behaviour between stated- and real-world behaviour in MASP contexts is less clear. One of the recoding approach put forward by Lundhede et al. [34], i.e. recode uncertain responses into the status quo option, is the only and probably most realistic approach available yet. Additional research on this topic, in combination with the use of alternative response formats to identify decision uncertainty in MASP studies [e.g. 4, 22, 36] is required. MASP studies on decision uncertainty are not as developed as their CVM counterparts in this regard.

The approach taken in non-recoding studies, including ours, is slightly different. We are interested in the trade-offs that people are willing to make after taking away the impact of decision uncertainty on their choices. These preferences might not correspond with the choices that would be made in the real-world when individuals might still be suffering from decision uncertainty. Instead the inferred preferences get closer to the utilities and welfare effects experienced by individuals when the uncertainty disappears (e.g. when a project is actually implemented). As a result, potential discrepancies between the welfare estimates from non-recoding methods and those of recoding approaches are best attributed to a (negative) welfare effect of decision uncertainty. The latter relates to welfare effects perceived at the moment of decision making. Either way, recoding and

[12] Shaikh et al. [44] show that the directional impact on WTP is not necessarily consistent across recoding approaches. Moreover, Brouwer [11] finds a decrease in WTP without using recoding approaches.

[13] In the limited number of studies exploring at which certainty cut-off value hypothetical WTP best simulates actual market behaviour, values vary between 6 and 10 using a scale from 1 to 10 [e.g. 14, 40].

modelling approaches do suggest that not accounting for decision uncertainty at all is likely to introduce some form of bias in the welfare estimates. The size and direction of this effect needs to be determined empirically.

Despite its conceptual advantages, the ICLV model comes with additional computational costs. Comparable median WTP estimates are obtained when using more naive modelling approaches, such as the direct use of self-reported decision uncertainty in the discrete choice model. By being restricted to a single case study, the generalisability of this similarity in results is limited and can only be confirmed by applying the same model structure to alternative datasets.

Researchers should question whether the additional effort of setting up a complex ICLV model is justified. When the prime interest is in obtaining unbiased welfare estimates, naive approaches may be sufficient. These simple approaches also do not depend on imperfect measures of choice task complexity, such as the Shannon [45] entropy measure applied in this paper. The joint modelling framework, however, also opens the road for improved welfare estimates, and a renewed focus on the driving factors of decision uncertainty. For example, we find that decision uncertainty decreases when respondents are presented with easier choice tasks. This is not a call for easier choice tasks, but it highlights the delicate balance between designing choice tasks with small utility differences, to accurately identify the impact of specific policy attributes, and the opposite effect it has on decision uncertainty. Moreover, the random parameter in the structural model indicates that significant heterogeneity in decision uncertainty across respondents remains unexplained. Partially, this could be related to the simplistic format of the follow-up question, but finding better drivers of decision uncertainty can also help in improving the formatting and wording of the stated choice experiment. The implications of decision uncertainty can thus already be reduced in the design stage rather than correcting for it during the data analysis. One possible line of future research is to provide a split sample with alternative information treatments to see whether survey descriptions (i.e. information) affects decision uncertainty.

Additional lines of future research include the potential use of the iterative estimation approach to derive Shannon [45]'s entropy measure , i.e. approximate utility differences between alternatives and choice probabilities in the choice task, in the absence of pilot data, or alternative data sources. Moreover, we have solely focused on the interaction between decision uncertainty and the generic scale parameter. We have done so since our empirical study focused on future scenarios, including the status quo. In future research it might be explored whether interactions with the included error component are more apporpriate, particularly when the status quo is well-known to the respondents, but the hypothetical alternatives are relatively unfamiliar.

The results of this study have no direct implications for Dutch flood risk policies. Currently, flood risk policies are evaluated in the context of social cost benefit analysis where benefits are quantified using a prevented global damage method, also known as the *HIS schade en slachtoffer module (version 2.1)* . Non-market values, such as derived through our MASP study, are not included in those procedures. In the context of climate change, Dutch policy makers are, however, looking for alternative ways to quantify policy benefits and for public-private partnerships in sharing responsibilities for flood risks [e.g. 10]. Non-market valuation methods have an important role in this process. The fact that respondents lack experience with making decision regarding (future) flood risk exposure should, however, be taken into account when using MASP studies for these purposes. Similar concerns regarding the impact of decision uncertainty on welfare estimates should be taken into account when applying MASP studies to any non-market valuation study, including those in the field of energy and resource economics.

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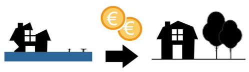
Appendix A. Example of a choice card

Table A.5: Example of a choice card

	Plan A	**Plan B**	**Status Quo**
Probability 	1 in 8,000 years (2x smaller)	1 in 10,000 years (2.5x smaller)	1 in 4,000 years
Compensation 	75%	50%	0%
Evacuation time 	9 hours	18 hours	6 hours
Increase in annual tax 	€120	€160	€0
Choice:	☐	☐	☐

How certain are you of your choice?

Very Certain	Certain	Neither certain nor uncertain	Uncertain	Very Uncertain
☐	☐	☐	☐	☐