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# Decision uncertainty in multi-attribute stated preference studies

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## 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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## 29 1. Introduction

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

39 Within the CVM literature, specifically the dichotomous choice (DC) response for-  
40 mat, various survey formats and econometric approaches have been developed to ac-  
41 count for the impact of decision uncertainty on willingness-to-pay (WTP) estimates [e.g.  
42 32, 36, 48, 11, 30]. The implementation of these econometric methods in the context of  
43 multi-attribute stated preference (MASP) studies is not straightforward. Several MASP  
44 studies have measured decision uncertainty by positioning a follow-up question directly  
45 after each choice task [e.g. 34, 12, 5, 26, 27, 39]. The treatment of self-reported deci-  
46 sion uncertainty has, however, been limited from a methodological perspective. Firstly,  
47 some papers [e.g. 39] assume decision uncertainty is a result of utility differences across  
48 the alternatives in the choice set without recognising decision uncertainty itself may in-  
49 fluence response patterns and consequently the estimated utility functions and welfare  
50 implications. Secondly, other work has used the self-reported decision certainty responses  
51 as an explanatory variable in the choice model [e.g. 34, 5] putting the analyst at risk of  
52 endogeneity bias as well as measurement error (see Section 2.2).

53 Integrated Choice and Latent Variable (ICLV) models [e.g. 6] offer an intuitive solu-  
54 tion to these two problems. ICLV models treat decision uncertainty as a latent construct

55 *simultaneously* affecting choice and the response to the follow-up question. Correlation  
56 between the implicit representation of decision uncertainty in the choice model and its  
57 explicit representation in the follow-up question is introduced by making the utility func-  
58 tion and the measurement equation (which explains the reported degree of (un)certainty)  
59 a function of the same latent variable ‘decision uncertainty’. Directional effects are there-  
60 fore no longer pre-imposed in the ICLV model; endogeneity and measurement error issues  
61 are circumvented by treating the follow-up responses as a dependent variable; and the  
62 welfare implications of decision uncertainty can be traced through the impact of decision  
63 uncertainty on the choice model.

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

78 Our MASP study is conducted in the context of flood risk exposure in the Netherlands  
79 in the face of climate change. The public nature of Dutch flood risk policy and absence of  
80 private flood risk insurance causes most people to be unfamiliar with trade-offs regarding

81 their own flood risk exposure. This is a natural application to test our model of decision  
82 uncertainty. Many alternative applications are likely to exist in the context of resource  
83 and energy economics. MASP surveys in the context of e.g. wind turbines [31] and water  
84 quality improvements [43, 37], as published in this journal, could all be facing unfamiliar  
85 respondents adopting choice heuristics to deal with decision uncertainty.

## 86 **2. Decision uncertainty in stated choice surveys**

### 87 *2.1. Definition*

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

### 98 *2.2. Measurement and modelling of decision uncertainty in stated choice surveys*

99 The standard approach to measure decision uncertainty in the MASP studies is to include  
100 a self-reported decision uncertainty follow-up question directly after each choice task [e.g.  
101 34, 12, 5, 25, 9]. Fenichel et al. [22] and Balcombe and Fraser [4] are exceptions in that  
102 they present a ‘do not know’ option to respondents in addition to a status quo option. The  
103 limited variability in methods measuring decision uncertainty in MASP studies highlights

104 the field is not yet as developed as its DC-CVM counterpart.<sup>1</sup>

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

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

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

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

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<sup>1</sup>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.

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

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

### 132 *2.3. The need for a simultaneous modelling approach*

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

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

151 decision uncertainty follow-up question. Accordingly, the ICLV model provides a more  
152 natural representation to the problem at hand.

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

#### 158 *2.4. Two hypotheses*

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

167 Alternative hypotheses exist arguing uncertain respondents adopt simplifying choice  
168 heuristics affecting the structural part of the utility function. For example, Loomes et al.  
169 [33] develop a model in which uncertain respondents are more likely to pick the status  
170 quo alternative than is the case for certain respondents. This heuristic finds empirical  
171 support in Balcombe and Fraser [4] and Swait and Adamowicz [46] and embodies our  
172 second hypothesis. The hypotheses are tested jointly in the ICLV model.

### 173 **3. The ICLV model**

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

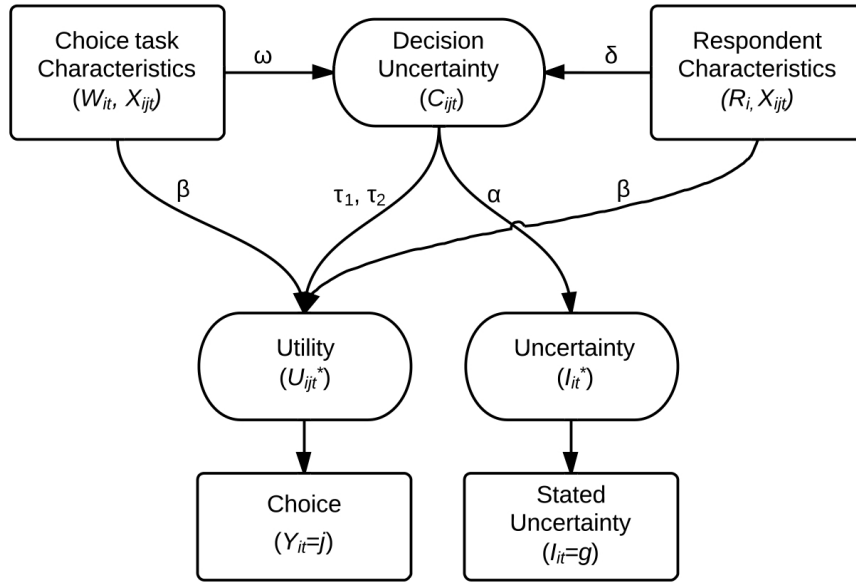


Figure 1: The ICLV model

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

<sup>3</sup>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.

185 *3.1. The structural equation*

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

$$C_{it} = \delta R_i + \omega W_{it} + \rho_i + \varepsilon_{it} \quad (1)$$

192 Since  $\delta R_i$  is unlikely to capture all respondent specific variation in decision uncertainty  
 193 across respondents, a respondent specific term  $\rho_i$  is included in the structural equation.  
 194 The latter is added in the form of a normally distributed random parameter with zero  
 195 mean and variance  $\sigma_\rho^2$ .<sup>4</sup> Finally,  $\varepsilon_{it}$  represents an i.i.d. standard normally distributed  
 196 error term capturing remaining (unexplained) variations in latent decision uncertainty.  
 197 In accordance with the Bolduc et al. [8] normalisation the variance of  $\varepsilon_{it}$  is restricted to  
 198 unity.  $C_{it}$  remains unobserved and takes the form of a continuous variable where higher  
 199 values represent higher degrees of decision uncertainty.

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

---

<sup>4</sup>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  $t = 1, \dots, T$ .

204 operationalising the proposed ICLV model due to endogeneity. One option is to adopt  
 205 an iterative approach where at intermediate parameter values choice probabilities and  
 206 entropy are iteratively updated until the likelihood stabilises. It is not clear whether  
 207 such an iterative approach generates consistent parameter estimates. An easy and often  
 208 available alternative, adopted in this paper, is to estimate a basic choice model on a  
 209 different sub-sample (or pre-test sample) of the survey. The obtained choice probabilities  
 210 then enable researchers to approximate the entropy measure. Other options are to replace  
 211 entropy by alternative measures of complexity not depending on choice probabilities [e.g.  
 212 21].

### 213 3.2. The choice model

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

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

222 The second line of Equation (2) describes the implemented utility function which embod-  
 223 ies the two working hypotheses and Scarpa et al. [42]’s error component. First, the scale  
 224 parameter  $\lambda_{it} = \exp(\tau_1 C_{it})$  is expected to be decreasing in decision uncertainty  $C_{it}$ . Un-

225 certain respondents are expected to display a higher decisional variance, i.e. a lower scale.  
 226 Accordingly,  $\tau_1$  is hypothesized to be negative.<sup>5</sup> Second,  $\tau_2 C_{it}$  represents the alternative  
 227 decision heuristic that uncertain respondents are more likely to select the status quo (or  
 228 opt out) option. We model this by interacting  $C_{it}$  with the alternative specific constant  
 229 (ASC). Here,  $ASC_{ijt}$  has a value of one when the alternative is not the status quo. Hence,  
 230  $\tau_2$  is hypothesized to take a negative value.  $\beta_1$  measures the average utility associated  
 231 with the ASC unrelated to decision uncertainty. Third, the interaction between  $\zeta_i$  and  
 232 the ASC captures the additional variance associated with the hypothetical alternatives.  
 233  $\zeta_i$  takes the form of a normally distributed error component with zero mean and variance  
 234  $\sigma_\zeta^2$ . Like in Scarpa et al. [42] the error component is introduced at the panel level.

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

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

---

<sup>5</sup>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  $\lambda_{it}$ , i.e.  $\lambda_{it} = \exp(\tau_1 C_{it} - \frac{\tau_1^2}{2})$ . As such, the expected value of  $\lambda_{it}$  reduces to unity for a base group. See also Fiebig et al. [23], Greene and Hensher [24].

244 3.3. The measurement model

245 Latent decision uncertainty is measured by the choice task specific follow-up question  $I_{it}$ .  
 246 The translation of the follow-up question is: ‘*How certain are you of your choice?*’, where  
 247 the response format comprised a rating scale with five levels: ‘*very certain*’, ‘*certain*’,  
 248 ‘*neither certain nor uncertain*’, ‘*uncertain*’ and ‘*very uncertain*’, respectively coded as  
 249 [0,1,2,3,4]. Daly et al. [17] put forward the use of an ordered logit model as an appropriate  
 250 specification of the measurement model given the ordered nature of  $I_{it}$ . We prefer to use  
 251 an ordered probit specification to facilitate estimation in a Bayesian framework.<sup>6</sup>

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

$$I_{it}^+ = \alpha C_{it} + \nu_{it} \quad (4)$$

$$P(I_{it} = g | C_{it}) = \int_{\psi_{g-1}}^{\psi_g} \phi(I_{it}^+ - \alpha C_{it}) dI_{it}^+ = \Phi(\psi_g - \alpha C_{it}) - \Phi(\psi_{g-1} - \alpha C_{it}) \quad (5)$$

---

<sup>6</sup>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.

<sup>7</sup> $g$  refers to the response categories of the follow-up question.  $g = 1$  represents the most certain option ‘very certain’.  $g = 2, \dots, 5$  complies with the order of appearance and  $g = 5$  ends with ‘very uncertain’.

262 *3.4. Joint likelihood function and complexity of estimation*

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

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

272 Hess and Train [29] note that ICLV models are computationally intensive when using fre-  
 273 quentist estimation approaches. Therefore, we estimate the model using Bayesian meth-  
 274 ods and work around the integrals by evaluating a set of conditional densities using the  
 275 principles of data augmentation [47].<sup>8</sup> Relative to existing sequential approaches to deci-  
 276 sion uncertainty, the ICLV model introduces additional estimation complexity, but allows  
 277 to trace the impact of decision uncertainty on the choice model without imposing direc-  
 278 tional relationships between choices and self-reported decision uncertainty as discussed in  
 279 Section 2.3.

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<sup>8</sup>The details of the Gibbs Sampler are available from the corresponding author.

## 280 4. The Case Study

### 281 4.1. Valuation of flood risks in the Netherlands

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

### 293 4.2. The stated choice experiment

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

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

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





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

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

## 325 5. Results

326 We present results from five alternative model specifications. The first model presents a  
327 random parameters logit model where the choices in the SC are analysed without con-  
328 trolling for decision uncertainty. Model 2 treats the self-reported decision uncertainty  
329 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

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

346 *5.1. Choice models and simple IV-estimation*

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

354 The parameter and welfare estimates for Model 1 confirm expectations. Respondents  
355 experience a positive utility from reductions in flood probability, additional compensation,  
356 and increases in available evacuation time, while they are less likely to select a policy  
357 alternative with higher costs. The marginal WTP estimates reveal households are willing  
358 to pay €7.08 per year to reduce flood probabilities by 1,000 years, i.e. from 1/4,000 to  
359 1/5,000 year. Similarly, an additional percentage of compensation is worth €0.71 per  
360 household per year and an extra hour of evacuation time €1.90.<sup>9</sup>  $\sigma_\zeta$  confirms that the  
361 hypothetical alternatives are associated with additional error variance.

362 As expected, both  $\tau_1$  and  $\tau_2$  have a negative coefficient in Model 2. The former high-  
363 lights uncertain respondents exhibit a higher decisional variance. The latter confirms  
364 uncertain respondents have a higher tendency to select the status quo alternative. Treat-  
365 ing the follow-up responses as an exogenous explanatory variable in the choice model  
366 translates into a decisive improvement in model fit as highlighted by the Bayes Factor of  
367 7.07 relative to Model 1.<sup>10</sup> Median WTP estimates for Model 2 are all higher compared

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

<sup>10</sup>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
$\sigma_{\zeta}$	1.98	0.32	0	1.77	0.28	0	2.01	0.34	0
$\tau_1$	-			-0.40	0.08	100	0.04	0.15	41
$\tau_2$	-			-0.44	0.18	99	-0.83	0.43	98
<u>IV-part</u>									
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
$\sigma_{\rho}$							1.42	0.08	0
$\psi_1$							-1.78	0.24	100
$\psi_2$							0.47	0.24	2
$\psi_3$							2.48	0.24	0
$\psi_4$							4.31	0.27	0
Obs- Choice n	1792			1792			1792		
ML-Choice n	224			224			224		
BF	-1401.1			-1394.04			-1411.65		
				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

368 to Model 1, particularly for the probability attribute. The size of the posterior standard  
369 errors on the WTP estimates, however, indicate there are no significant differences in  
370 welfare estimates between Models 1 and 2. The increase in median WTP estimates can  
371 be related to the choice heuristic associated with  $\tau_2$ . Without controlling for the impact  
372 of decision uncertainty, Model 1 increases the relative importance of the cost attribute to  
373 accommodate for the fact that uncertain respondents select the status quo more often.

374 The sequential IV-estimation procedure presented by Model 3 experiences difficulties  
375 in linking expected decision uncertainty to observed choice behaviour.  $\tau_1$  on the one  
376 hand changes sign and is no longer statistically different from zero.  $\tau_2$  on the other hand  
377 suggests respondents are even more likely to select the status option due to decision  
378 uncertainty. Note, however, that the posterior standard errors on the  $\tau$  parameters have  
379 also increased substantially. It is therefore not surprising that Model 3 reveals a lower  
380 marginal likelihood than Models 1 and 2. We attribute this to the fact that Model 3 does  
381 not account for the heterogeneity in decision uncertainty represented by  $\rho_i$  given that we  
382 used a mean-based approach. Based on Model 3, we might conclude that the direct use  
383 of self-reported decision uncertainty in Model 2 results in an overestimation of median  
384 WTP. Namely, we only observe a negligible, increase in median WTP estimates relative  
385 to Model 1. The instability of the  $\tau$  parameter estimates in Model 3, however, justifies a  
386 closer examination of decision uncertainty in the context of a sequential FIML approach  
387 and the proposed ICLV model.

### 388 *5.2. Explanatory variables in the IV-approach and structural equation*

389 The explanatory variables included in the IV-part of Model 3 (and in the remaining  
390 models) are summarised in Table 3. They represent the driving factors of self-reported  
391 decision uncertainty. Tables 2 and 4 point out that males are less uncertain than females,  
392 while education does not seem to have an influence on decision uncertainty; a finding

393 confirmed by both Olsen et al. [39] and Brouwer et al. [12]. Respondents who stated  
 394 that the proposed policy scenarios are credible tend to reflect lower levels of decision  
 395 uncertainty, a finding also reported in Brouwer et al. [12]. The results, however, do not  
 396 confirm that respondent that have previously experienced a flood exhibit lower levels of  
 397 decision uncertainty.<sup>11</sup> Four variables are related to choice task characteristics.

398 The dummy variables *Block 1* and *Block 3* indicate that splitting up the design into  
 399 three blocks resulted in *Block 2* being slightly easier for respondents compared to the  
 400 two other blocks. Indeed, correlating the blocks with the entropy measure revealed that  
 401 *Block 2* contained two relatively easy choice tasks. Decision uncertainty is increasing in  
 402 the length of the stated choice survey as reflected by *Cardnr*. By altering the order of  
 403 appearance of choice cards across respondents, this effect is most likely related to fatigue  
 404 or boredom effects. Finally, *Entropy* summarises choice task complexity using Shannon  
 405 [45]’s entropy measure (see Section 3.1). The results confirm that decision uncertainty is  
 406 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

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<sup>11</sup>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.

407 *5.3. FIML and ICLV models*

408 Table 4 shows large consistencies between the IV-parts in Models 3 and 4. The direct con-  
409 nection between the ordered probit model and the choice model in Model 4 enables better  
410 identification of the  $\tau$  parameters, which again take the expected negative value. Decision  
411 uncertainty therefore has an impact on individual choice behaviour through making more  
412 random choices and by adopting alternative decision heuristics. The obtained marginal  
413 WTP estimates from Model 4 show close resemblance with those obtained from the cri-  
414 tiqued Model 2. In other words, there might not be too much bias in directly including  
415 the self-reported decision uncertainty responses in the choice model. Moving from the  
416 sequential FIML model (Model 4) to the proposed ICLV model (Model 5) shows that the  
417 parameters of the choice model stay fairly constant. The  $\tau$  parameters lead to the same  
418 conclusion that decision uncertainty has an impact on individual choice behaviour, even  
419 though  $\tau_1$  shows a slight drop relative to Model 4. The main difference between the two  
420 models arises in the parameters for the structural and measurement equation. The final  
421 column in Table 4 reveals estimates for Model 4 are about a factor 0.7 smaller than those  
422 for Model 5. The scaling is a direct consequence of the fact that additional variance is  
423 added around latent decision uncertainty in the ICLV model. In fact, when neglecting  
424 the influence of the choice model the variance of the ordered probit model increases to  
425 two, explaining why the parameters in the ICLV model are about a factor  $\sqrt{2} \approx \frac{1}{0.7}$  larger  
426 than those in the FIML model.

427 The ICLV model has a decisively better fit than the FIML likelihood approach. We  
428 explain this by noting that the sequential FIML puts most emphasis on explicit decision  
429 uncertainty represented in the self-reported decision uncertainty measures. Part of the  
430 224 respondents did not change their self-reported decision uncertainty over the choice  
431 sequence, while a different pattern may be revealed by the implicit representation of deci-  
432 sion uncertainty in the choice model. By using both implicit and explicit representations

Table 4: Results FIML and ICLV model

	Post	(4)	% < 0	Post	Post	% < 0	(5)
	Mean	Post		Mean	StDev		Ratio
		StDev					(4)/(5)
<u>Choice</u>							
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	
$\sigma_{\zeta}$	2.34	0.37	0	2.35	0.42	0	
$\tau_1$	-0.16	0.05	100	-0.10	0.04	100	
$\tau_2$	-0.35	0.13	100	-0.33	0.14	100	
<u>Structural</u>							
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
$\sigma_{\rho}$	1.39	0.08	0	1.87	0.50	0	0.75
<u>Measurement</u>							
$\psi_1$	-1.82	0.18	100	-2.59	0.26	100	0.70
$\psi_2$	0.46	0.18	0	0.64	0.24	0	0.72
$\psi_3$	2.48	0.19	0	3.50	0.24	0	0.71
$\psi_4$	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

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

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

## 447 **6. Conclusions**

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

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

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

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

474 The finding that WTP estimates increase when controlling for decision uncertainty can  
475 be related to the second hypothesis. When the model does not control for the adoption  
476 of an alternative choice heuristic, other model parameters correct for such behavioural  
477 patterns and become biased. In our case, the respondents either need to become more  
478 cost sensitive or assign a lower importance to the non-cost policy attributes. Both effects  
479 translate into lower WTP estimates for the policy attributes which are actually caused by  
480 uncertain respondents having a higher tendency to select the status quo option. The first  
481 hypothesis also translates into an increase in marginal WTP estimates, but the magnitude  
482 of the change is smaller. In general, the observed differences in WTP estimates relative to  
483 the base model are of minor size, a finding confirmed by Lundhede et al. [34]. Our findings

484 are, however, at stake with conclusions from the contingent valuation (CV) literature,  
485 where WTP estimates tend to decrease after controlling for decision uncertainty [e.g. 11].  
486 The controversy might be related to the recoding approaches applied in the CV literature,  
487 where uncertain ‘yes’ responses are frequently recoded as ‘no’ responses [15].<sup>12</sup>

488 Recoding approaches find their origin in real world behaviour, where uncertain respon-  
489 dents might be inclined to say ‘yes’ in stated preference studies, but in real-world decision  
490 would revert to ‘no’.<sup>13</sup> The equivalent type of reverting behaviour between stated- and  
491 real-world behaviour in MASP contexts is less clear. One of the recoding approach put  
492 forward by Lundhede et al. [34], i.e. recode uncertain responses into the status quo op-  
493 tion, is the only and probably most realistic approach available yet. Additional research  
494 on this topic, in combination with the use of alternative response formats to identify de-  
495 cision uncertainty in MASP studies [e.g. 4, 22, 36] is required. MASP studies on decision  
496 uncertainty are not as developed as their CVM counterparts in this regard.

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

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<sup>12</sup>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.

<sup>13</sup>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].

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

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

516 Researchers should question whether the additional effort of setting up a complex  
517 ICLV model is justified. When the prime interest is in obtaining unbiased welfare esti-  
518 mates, naive approaches may be sufficient. These simple approaches also do not depend  
519 on imperfect measures of choice task complexity, such as the Shannon [45] entropy mea-  
520 sure applied in this paper. The joint modelling framework, however, also opens the road  
521 for improved welfare estimates, and a renewed focus on the driving factors of decision  
522 uncertainty. For example, we find that decision uncertainty decreases when respondents  
523 are presented with easier choice tasks. This is not a call for easier choice tasks, but it  
524 highlights the delicate balance between designing choice tasks with small utility differ-  
525 ences, to accurately identify the impact of specific policy attributes, and the opposite  
526 effect it has on decision uncertainty. Moreover, the random parameter in the structural  
527 model indicates that significant heterogeneity in decision uncertainty across respondents  
528 remains unexplained. Partially, this could be related to the simplistic format of the follow-  
529 up question, but finding better drivers of decision uncertainty can also help in improving  
530 the formatting and wording of the stated choice experiment. The implications of deci-  
531 sion uncertainty can thus already be reduced in the design stage rather than correcting  
532 for it during the data analysis. One possible line of future research is to provide a split

533 sample with alternative information treatments to see whether survey descriptions (i.e.  
534 information) affects decision uncertainty.

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

544 The results of this study have no direct implications for Dutch flood risk policies.  
545 Currently, flood risk policies are evaluated in the context of social cost benefit analysis  
546 where benefits are quantified using a prevented global damage method, also known as  
547 the *HIS schade en slachtoffer module (version 2.1)* . Non-market values, such as derived  
548 through our MASP study, are not included in those procedures. In the context of climate  
549 change, Dutch policy makers are, however, looking for alternative ways to quantify policy  
550 benefits and for public-private partnerships in sharing responsibilities for flood risks [e.g.  
551 10]. Non-market valuation methods have an important role in this process. The fact that  
552 respondents lack experience with making decision regarding (future) flood risk exposure  
553 should, however, be taken into account when using MASP studies for these purposes.  
554 Similar concerns regarding the impact of decision uncertainty on welfare estimates should  
555 be taken into account when applying MASP studies to any non-market valuation study,  
556 including those in the field of energy and resource economics.

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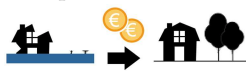


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697 Appendix A. Example of a choice card

Table A.5: Example of a choice card

	<b>Plan A</b>	<b>Plan B</b>	<b>Status Quo</b>
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:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

**How certain are you of your choice?**

Very Certain    Certain    Neither certain nor uncertain    Uncertain    Very Uncertain