Implicitly or explicitly uncertain?

Thijs Dekker, Stephane Hess, Roy Brouwer and Marjan Hofkes

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Abstract

The existence of a well-defined preference relationship can be questioned when individuals are unfamiliar with a particular trade-off. Decision uncertainty may affect actual choices and researchers run the risk of obtaining biased welfare estimates when decision (un)certainty is not properly accounted for in their model. Econometric modelling of decision certainty has received extensive attention in the contingent valuation literature, but these methods are not directly transferable to the realm of multi-alternative multi-attribute stated choice surveys. This paper develops a latent variable model suitable for stated choice surveys. The model learns about the driving factors of decision (un)certainty implicitly through the observed choices and explicitly through a set of self-reported choice certainty follow-up questions. Simultaneously, it traces the impact of decision certainty on individual choices. In a stated choice survey on willingness-to-pay for flood risk reduction in the Netherlands in the face of climate change, we find that uncertain respondents tend to make more random decisions and are more likely to select the opt out option. Not controlling for these impacts of decision uncertainty may result in an underestimation of welfare measures.

Keywords: Decision certainty, Stated choice, Latent variable, Scale heterogeneity, Flood risk

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

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Appendix: 2,282 words ; (Text 1,532 words ; Tables 750)
1 Introduction

Interest in the impact of decision uncertainty on welfare estimates obtained from stated preference (SP) studies dates back to the period in which the contingent valuation method (CVM) was thriving (see Akter et al. 2008, Samnaliev et al. 2006, Shaikh et al. 2007 for an overview). The major concern is that in SP studies respondents are generally presented with trade-offs that they are unfamiliar with or lack experience with. Consequently, the existence of a well-defined preference relationship can be questioned. A bias in welfare estimates may arise if the underlying econometric model does not appropriately take the impact of decision uncertainty into account.

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 estimates (e.g. Li and Mattsson, 1995, Vazquez et al., 2006, Kobayashi et al. 2012). The implementation of these methods in the currently more popular format of discrete choice surveys is not straightforward (see Section 2.2 for a discussion). Compared to the DC-CVM format, respondents are presented with more alternatives in each choice task and simultaneously they are requested to make trade-offs across multiple attributes. In fact, this increases the complexity of the choice task making it more likely decision uncertainty plays a role in the decision making process.

Researchers in discrete choice studies have adopted post-decisional choice certainty questions, similar to those applied in the CVM literature (e.g. Beck et al. 2011, Brouwer et al. 2010, Hensher et al. 2011, Hensher and Rose 2011, Lundhede et al. 2009, Olsen et al. 2011). Treatment of self-reported choice certainty follow-up responses has been limited from a methodological perspective. Firstly, in some work, the assumption is made of a purely one-directional impact, where self-reported choice certainty is a result of utility differences across the alternatives in the choice set, without recognising that decision uncertainty itself may influence utility (e.g. Olsen et al. 2011). Secondly, and more gravely, other work has used self-reported choice certainty as an explanatory variable in the utility functions (e.g. Beck et al. 2011, Lundhede et al. 2009) putting the analyst at risk of endogeneity bias as well as measurement error (see Section 2.4 for a discussion).

In this paper, we put forward a model treating the degree of decision certainty as a latent variable which simultaneously affects the response to the choice task and the response to the follow-up question. Thereby, we learn about (observed and unobserved) factors affecting decision certainty, while simultaneously controlling for its impact on decisions and welfare measures. The proposed simultaneous model structure introduces correlation between the implicit representation of decision certainty in the choice model and the explicit representation in the follow-up question. As such, there is no longer a specific directional effect present in the model. Moreover, by also treating the follow-up responses as a dependent variable the endogeneity and measurement error issues are circumvented.

The paper is structured as follows. Section 2 provides more background on the definition of decision uncertainty, on existing modelling approaches in the CVM and stated choice survey literature, and it discusses the associated issues. Section 3 describes an improved modelling approach and embodies two specific working hypotheses. In Section 4 the case study on flood risk valuation in the Netherlands is introduced. Section 5 contrasts existing approaches with the proposed model and shows that controlling for decision uncertainty may prevent researchers from obtaining underestimated welfare measures. Section 6 concludes.
2 Decision uncertainty in stated choice surveys

2.1 Definition

We explicitly make a distinction between preference (un)certainty and choice (un)certainty. The former is the uncertainty respondents experience in assigning a utility level to each alternative in the choice task. 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. The latter, choice uncertainty, arises in the process of comparing the available alternatives and evaluating the decision in light of the institutional settings. Choice (un)certainty is therefore closely related to the complexity of choice tasks. The more information respondents need to process, the more complex a choice task becomes, which may influence the certainty by which respondents make their decision.\footnote{We thank an anonymous reviewer to point out this important distinction.}

Preference uncertainty and choice uncertainty are confounded with each other. Effectively, all the researcher observes is a choice which can be affected by both preference and choice uncertainty. More specifically, utility remains a latent concept during the analysis since choice probabilities are derived using utility differences across the alternatives. Disentangling the two sources of uncertainty is therefore not the purpose of this paper. In the rest of this paper, this joint uncertainty factor is therefore labelled as decision uncertainty. It will be explicitly measured using follow-up questions after each choice task and implicitly modelled in the utility functions.

2.2 Methods for decision uncertainty developed in CVM studies

Li and Mattson (1995) treat decision uncertainty as part of a composite error term in the valuation function. In other words, they assume responses have a lower informational content because uncertain respondents are more likely to randomly respond with 'yes' or 'no'. Decision uncertainty thereby adds additional uncertainty (or error) to the model specification and flattens the likelihood function compared to the true distribution of preferences.\footnote{Li and Mattsson (1995) assume that a true underlying preference relation exists.} Although consistent estimates of the parameter estimates will be obtained without controlling for decision uncertainty, this leads to an overestimation of the true variance which may result to value inference bias. This is particularly the case for a log-linear specification of the value (or willingness-to-pay) function. Li and Mattson (1995) correct for this potential bias by integrating a post decisional confidence measure into the likelihood function to disentangle decision uncertainty from the standard random utility error component. Effectively, they replace the original dependent variable ('Yes' or 'No') with a recoded certainty response on a 0-100% certainty scale.

Since then, alternative approaches to account for the impact of decision uncertainty have been developed in the DC-CVM literature. The first group of studies applies an adjusted response format such that respondents can express their decision uncertainty directly, e.g. by including a 'Don't Know' (Wang, 1997), 'Probably Yes' or 'Probably No' option (Alberini et al. 2003). The second group presents the respondents with the standard DC-CVM binary response format ('Yes' or 'No'), which is then followed by a post decision certainty question in the form of a numerical scale (e.g. Loomis and Ekstrand, 1998) or text statements (e.g. Blomquist et al. 2009). Both formats result in an explicit measure of decision uncertainty after observing the
actual choice. Kobayashi et al. (2012) argue that in most cases the observed impact of decision uncertainty on welfare estimates is a direct consequence of the selected econometric approach.

This paper differs in two aspects from the DC-CVM literature. First, decision uncertainty is studied in the context of a multi-alternative multi-attribute stated choice survey (SCS). The methods developed in the DC-CVM literature and their interpretations are not directly transferable to the SCS response format (Section 2.3). Second, the use of follow-up responses for recoding purposes or direct use in the utility or value function may be associated with endogeneity and measurement issues (Section 2.4). An alternative approach for SCS methods is therefore presented in Section 3. This paper maintains the assumption of Li and Mattson (1995) that uncertain respondents are more likely to provide random responses with lower informational content.

2.3 Transferring CVM methods to stated choice surveys

The dichotomous nature of the DC-CVM response format enables the researcher to directly interpret the expressed decision uncertainty in terms of WTP uncertainty. In contrast, the multi-alternative multi-attribute nature of SCS studies forces respondents to make multiple trade-offs at the same time. The levels of multiple attributes, not just price, vary across two or more alternatives. An observed choice summarizes the balance across these trade-offs. Modifications of the response format, similar to the DC-CVM literature, are therefore insufficient to interpret the expressed decision uncertainty in terms of WTP uncertainty. Measures of relative preference strength would need to be expressed across all alternatives in the choice set to obtain information about the preference order. Additional modifications would still be required to assign these uncertainties to specific attributes, including price. Adjusted response formats are therefore not commonly applied in the SCS literature. The 'standard' approach is to include a post-decisional choice certainty question (e.g. Beck et al. 2011, Brouwer et al. 2010, Lundhede et al. 2009). Still, the follow-up question only identifies the extent to which the respondent is uncertain about his preference order amongst the available alternatives. Recoding approaches underlying the DC-CVM models become problematic in this setting. It is unclear which alternative should be considered as second best and should be used as the basis for recoding. Recoding approaches are not considered to be suitable for the SCS framework.

2.4 Direct inclusion of follow-up responses in the utility function

An alternative method to trace the impact of decision uncertainty on choices has been to directly include the follow-up responses as an exogenous explanatory variable in the utility function (e.g. Beck et al. 2011, Lundhede et al. 2009). Although appealing, this may cause endogeneity issues. 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 more complex and respondents will report this in the follow-up questions. Using the self-reported choice certainty as an explanatory factor in the utility function is likely to introduce correlation between error term of the utility function and the explanatory variables. In addition, the self-reported choice certainty measures are likely to be associated with measurement error. To our knowledge, both issues of endogeneity and

\footnote{Fenichel et al. (2009) and Balcombe and Fraser (2011) are exceptions in that they present a dont know option to respondents in addition to a status quo option.}

\footnote{Lundhede et al. (2009) propose three recoding approaches rooted in the DC-CVM literature, but do not pay specific attention to the potential issues associated with the recoding approaches.}
measurement error have received limited attention within the DV-CVM as well as in the SCS literature, despite the fact that the certainty responses have been directly implemented in the recoding approaches. Our model adopts the appealing logic of tracing the impact of decision uncertainty through the utility function, but does not suffer from these two limitations.

There are various ways to work around the issue of endogeneity and measurement error (see Train, 2009), with IV-estimation being the most widely implemented approach. IV-estimation, however, requires a sequential line of thought.³ This sequential line of thought is closely related to our first critique on the one-directional modelling approach currently used in the discrete choice modelling literature and discussed in more detail in the next subsection. The proposed Integrated Choice and Latent Variable (ICLV) model therefore proposes a simultaneous approach.

2.5 Sequential and simultaneous modelling

Sequential estimation within the IV-estimation procedure starts with regressing the responses to the self-reported choice certainty questions on a set of explanatory variables, after which the predicted values are used as explanatory factors in the actual choice model. Implicitly this approach assumes that the self-reported choice certainty question is answered before the actual choice task, while it is usually placed after the actual choice task. More problematic is the fact that self-reported choice certainty is likely to be affected by the choice task itself. Measures like utility differences are therefore suitable control variables in the first stage. For example, the well-known Shannon (1948) entropy measure can be used as an explanatory factor of self-reported choice certainty (e.g. Swait and Adamowicz 2001; Balcombe and Fraser 2011).⁶ The problem that arises is that choice probabilities are a result of utility differences, which are dependent on the IV-estimator for decision uncertainty. The latter, however, depends again on the choice probabilities creating a vicious circle.

There are three ways to prevent this vicious circle. First, one can use alternative measures of decision uncertainty not dependent on utility, but correlated with the alternatives and their attributes of the choice task itself. For example, DeShazo and Fermo (2002) use various measures based on differences in attribute levels across alternatives as explanatory factors of the scale parameter in their heteroscedastic multinomial logit model. Second, entropy can be approximated prior to estimation using a set of parameter estimates for the utility function derived from pre-tests or alternative but closely related studies. Third, an iterative procedure can be implemented where during the estimation process the intermediate values for the utility parameters are used to approximate entropy before calculating the actual choice probabilities. It is unclear whether this iterative procedure converges to a set of consistent parameter estimates. In this paper, the second approaches will be applied.

Overall, the sequential IV-estimation approach can be applied and it solves endogeneity and measurement error, because a set of exogeneous control variables is used to approximate decision uncertainty. The positioning of the follow-up question after the choice task and the close relation between the two, however, makes the sequence of modelling rather counter-intuitive. The sequential line of thought can also be reversed (e.g. Olsen et al. 2011). In this approach, the choice model is first estimated without controlling for the potential impact of decision uncertainty.

³The actual estimation procedure can also be applied in a simultaneous Full-Information Maximum Likelihood approach, which explains the choice of wording for 'line of thought'.

⁶The entropy measure quantifies the informational content of a choice task using an index of choice probabilities and is at its maximum when all alternatives have an equal probability of being chosen.
after which expected utility differences are directly used in the explaining the self-reported choice certainty responses. Although in line with the order of presenting the relevant questions, this approach does not allow to trace the impact of decision uncertainty on the choice model and related welfare measures.

In this paper, we develop an ICLV model as an alternative to the sequential IV-estimation approach. By treating decision uncertainty as a latent variable which simultaneously affects the choice model and the self-reported choice certainty responses, we believe a more natural representation of the problem is developed. In making a decision, respondents experience a degree of uncertainty, which is implicitly reflected in their decision (e.g., more random decisions) and in their expression of decision certainty. The simultaneous modelling approach thereby alleviates the incomplete relationships present in the sequential approach. Like the IV-estimation approach, a set of control variables is used to explain the latent variable decision uncertainty. By treating both the observed choices and responses as dependent variable, endogeneity and measurement error issues are taken into account.

2.6 Two hypotheses

Similar to Li and Mattson (1995), we interpret decision uncertainty as an important element of the composite error term. When respondents are uncertain about their preference order over the alternatives in the choice task, it can be hypothesized that the choice probabilities are more evenly distributed. This conjecture can be realized by introducing heteroscedasticity in the error term across choice tasks in the choice model as described by DeShazo and Fermo (2002), Arentze et al. (2003), and Caussade et al. (2005). Specifically, our model will treat the error variance of utility in a specific choice task a function of (latent) decision uncertainty. Decision uncertainty is allowed to vary across respondents and choice tasks.

Alternative hypotheses also exist arguing that uncertain respondents adopt simplifying choice heuristics affecting the structural part of the utility function. For example, Loomes et al. (2009) 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 by Balcombe and Fraser (2011) and Swait and Adamowicz (2001) and embodies our second hypotheses in the model specification. Our model will trace the possible impact of decision uncertainty on the structural and stochastic part of the utility function, thus capturing both hypotheses. By implicitly controlling for the impact of decision uncertainty on decisions, potential biases in welfare estimates can be eliminated. A formal description of the model is provided in Section 3.

3 The ICLV model

In this section we describe the distinct components of the proposed ICLV model, i.e., the structural equation, the choice model and the measurement model (Ben-Akiva et al. 1999). The structural equation describes (latent) decision certainty as a function of respondent and choice task characteristics. The choice model explains the responses to the choice tasks conditional on the level of latent decision (un)certainty. Similarly, the measurement equation explains the responses to the self-reported choice certainty question conditional on the degree of latent

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7 In our case, there is no need to disentangle the composite error term into decision uncertainty and measurement error, because the linear-in-parameters utility function will not lead to a value inference bias. In fact, because SCSs rely on marginal WTP estimates the estimation of consistent parameter estimates is sufficient.
decision (un)certainty. As such, the structural equation introduces correlation between the choice model and measurement equation. Thereby we learn about observed and unobserved factors affecting decision uncertainty, whilst controlling for its impact on decisions and welfare measures. Figure 1 provides a graphical representation of the hybrid choice model.

### 3.1 The structural equation

Equation 1 denotes latent decision certainty $C_{it}$ for respondent $i$ in choice task $t$ as a linear function of respondent characteristics $R_i$ and a set of choice task specific characteristics $W_{it}$. The structural differences in decision certainty across socio-economic groups are measured by $\delta$. For example, differences in gender and education may result in different degrees of decision (un)certainty. The impact of specific choice task characteristics on decision certainty are measured through $\omega W_{it}$, where $\omega$ traces the marginal impact of $W_{it}$. Some choices are more difficult than others, because the alternatives in the choice set are comparable to each other. As discussed in Section 2.5, factors included in $W_{it}$ can be an exogenous approximation of utility differences or other factors describing the complexity of the choice task at hand.

Since $\delta R_i$ is unlikely to capture all variation in decision certainty across respondents, a respondent specific term $\rho_i$ is included in the structural equation. The latter is added in the form of normally distributed random parameter with zero mean and variance $\sigma^2_\rho$. One reason for adding $\rho_i$ to the structural equation is to capture the correlation in decision uncertainty across the choice tasks presented to the same respondent. Finally, $\varepsilon_{it}$ represents an i.i.d. normally distributed error term.

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8In order to prevent a level effect arising from $R_i$ and $W_{it}$, we subtract the mean of the included continuous variables in the structural equation and work with a base level of 0 for categorical variables.

9Recent applications of latent variable models in the choice modelling literature (e.g. Abou-Zeid et al. 2011, Daly et al. 2011, Daziano and Bolduc 2011, Hess and Beharry-Borg 2011, Yanez et al. 2010) have focused on underlying attitudes at the level of the respondent, and have used attitudinal questions at the level of the respondent.
distributed error term capturing measurement error on the latent variable $C_{it}$. For normalization purposes, we set the variance of $\varepsilon_{it}$ to 1, i.e. $\sigma_\varepsilon^2 = 1$.

$$
C_{it} = \delta R_{it} + \omega W_{it} + \rho_i + \varepsilon_{it}
$$

(1)

### 3.2 The choice model

Respondents are assumed to select the alternative generating the highest level of (latent) utility. Let utility $U_{ijt} = V_{ijt} + \epsilon_{ijt}$ be specified as a linear in parameters utility function typically applied in random utility models. $V_{ijt}$ represents the deterministic part of the utility function and $\epsilon_{ijt}$ the stochastic term. It is assumed that $\epsilon_{ijt}$ follows a type I extreme value distribution with $\text{var}(\epsilon_{ijt}) = \frac{\pi^2}{6\lambda_{ijt}^2}$. The inverse relation between the scale $\lambda_{it}$ and variance of utility becomes directly clear from this expression. In estimation, we rescale the stochastic and deterministic part of the utility function by $\lambda_{it}$ such that $\epsilon_{ijt}$ follows an i.i.d distribution with variance $\text{var}(\epsilon_{ijt}) = \frac{\pi^2}{6}$. Equation 2 describes the rescaled utility function $U_{ijt}^*$. 

$$
U_{ijt}^* = \lambda_{it} V_{ijt} + \lambda_{it} \epsilon_{ijt} = V_{ijt}^* + \epsilon_{ijt}^*
\quad U_{ijt}^* = \exp(\tau_1 C_{it}) \cdot (\tau_2 C_{it} + \beta_1i) ASC_{ijt} + \beta_i X_{ijt}) + \epsilon_{ijt}^*
$$

(2)

The second line of Equation 2 describes the implemented utility function which embodies two hypotheses regarding the impact of latent decision certainty $C_{it}$ on the choices made by the respondents. First, the scale $\lambda_{it}$ of the utility function $U_{ijt}$ is expected to be increasing in decision certainty $C_{it}$. More certain respondents and easier choice tasks are expected to display a lower decisional variance, i.e. a higher scale. This is modelled by $\lambda_{it} = \exp(\tau_1 C_{it})$, where $\tau_1$ traces the impact of decision certainty on the scale of utility. $\tau_1$ is expected to be positive.\(^\text{10}\) Second, an alternative decision heuristic is implemented. Here, we follow Loomes et al. (2009) by assuming that uncertain respondents are more likely to select the status quo (or opt out) option. Alternative heuristics can be easily implemented by similar modifications of the utility function. The impact of $C_{it}$ on selecting the status quo alternative is modelled by means of an interaction with the alternative specific constant (ASC), i.e. $(\tau_2 C_{it} + \beta_1i) ASC_{ijt}$. ASC$_{ijt}$ has a value of one when the alternative is not the status quo and zero otherwise. $\beta_1i$ measures the individual specific marginal utility associated with the ASC unrelated to decision certainty. Now, $\tau_2$ traces the impact of decision certainty on deterministic utility. We expect a positive coefficient for $\tau_2$, since more certain respondents are hypothesized to be more willing to trade and therefore more likely to select one of the non-status quo alternatives.

Apart from the ASC, the deterministic part of the 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 $\beta_i$ measures the marginal utility associated with each 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 choice certainty after each choice task $t = 1, \ldots, T$.\(^\text{10}\) Given that $C_{it}$ follows a normal distribution with variance 1, the scale of utility follows a log-normal distribution with expected value $\exp(\tau_1(\delta R_{it} + \omega W_{it}) + \frac{\omega^2}{2})$. For normalization purposes the means of $R_{it}$ and $W_{it}$ are adjusted to zero and $-\frac{\omega^2}{2}$ is added to the specification of $\lambda_{it}$, i.e $\lambda_{it} = \exp(\tau_1 C_{it} - \frac{\omega^2}{2})$. As such, the expected value of $\lambda_{it}$ becomes unity. This normalization is discussed in Fiebig et al. (2010) and Greene and Hensher (2010).
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 $\theta$ represents the set of hyper-parameters. Alternatively, these random parameters can be replaced by fixed coefficients. Conditional on the individual specific parameters, this results in the following multinomial logit choice probability where respondent $i$ selects alternative $j$ from choice set $J_{it}$ in choice task $t$, i.e. $Y_{it} = j$:

$$
P(Y_{it} = j|X_{it}, ASC_{it}, C_{it}, \beta_1, \beta_2, \tau_1, \tau_2) = \frac{\exp(\exp(\tau_1 C_{it}) ((\tau_2 C_{it} + \beta_1) ASC_{ijt} + \beta_i X_{ijt}))}{\sum_{k=1}^{J_{it}} \exp(\exp(\tau_1 C_{it}) ((\tau_2 C_{it} + \beta_1) ASC_{ikt} + \beta_i X_{ikt}))}
$$

(3)

### 3.3 The measurement model

Simultaneously, $C_{it}$ also affects the response to the choice task specific follow-up question $I_{it}$. The translation of the follow-up question is the following: How certain are you about your decision? The response format comprised a rating scale with the following five levels: 'very uncertain', 'uncertain', 'neutral', 'certain' and 'very certain'. Daly et al. (2011) put forward the use of an ordered logit model as an appropriate specification of the measurement model given the ordered nature of $I_{it}$. In the present paper, an ordered probit specification of the measurement model is applied to facilitate estimation in a Bayesian framework.

Let $I_{it}^+$ represent a mapping of $I_{it}$ on a continuous scale, such that a respondent will select $I_{it} = g$ if $I_{it}^+$ falls between thresholds $\psi_{g-1}$ and $\psi_g$. Given that there are five response categories to $I_{it}$, only four threshold parameters, i.e. $\psi$’s, can be identified. We therefore impose $\psi_g > \psi_{g-1}$ and set $\psi_0 = -\infty$ and $\psi_5 = \infty$. Equation 4 describes the impact of $C_{it}$ on the measurement model, where for normalization purposes $\alpha = 1$ during estimation. $\nu_{it}$ 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 choice certainty $g$, where $\phi$ is the standard normal density function following from the normal distribution imposed on $\nu_{it}$, and $\Phi$ represents its cumulative density equivalent.

$$
I_{it}^+ = \alpha C_{it} + \nu_{it}
$$

(4)

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

(5)

### 3.4 Joint likelihood function

The hybrid choice model combines the three model parts into a single likelihood function, where the conditionality on $C_{it}$ in the choice model and the measurement model allow to break the likelihood function down into three parts.\footnote{g refers to the response categories of the follow-up question. $g = 1$ represents the least certain option 'very uncertain'. $g = 2, \ldots, 5$ complies with the order of appearance and $g = 5$ ends with 'very certain'.} The first term refers to the choice probabilities, \footnote{For notational convenience we suppress the other conditionalities already presented in the individual model parts.}
the second term to the probability of the choice task specific follow-up responses and \( h(C_{it} | \ldots) \) treats the structural equation as a mixing density. Finally, \( q(\Delta_{i} | \ldots) \) represents the other random parameters in the model that control for preference heterogeneity in the choice model, i.e. \( \beta_{i} \) in the choice model, and \( \rho_{i} \) in the structural equation.

\[
L(Y, I) = \prod_{i=1}^{n} \int_{C_{it}} \prod_{t=1}^{T} P(Y_{it} = j | C_{it}) P(I_{it} = g(C_{it}|\delta, \omega, \rho_{i}) h(C_{it}|\delta, \omega, \rho_{i}) dC_{it} q(\Delta_{i}|\theta_{\Delta}) d\Delta_{i} \tag{6}
\]

Estimation of this likelihood function using classical maximum simulated likelihood methods requires simulation at the choice task specific and individual level. Hess and Train (2011) and Hess and Rose (2011) applied a similar structure, but note that it is very computational intensive and results in long run times. Therefore, we estimate the model in a Bayesian framework which works around the integrals by evaluating a set of conditional densities and using the principles of data augmentation (Tanner and Wong, 1987). The details of the Gibbs Sampler are provided in the appendix.

### 3.5 Model specifications

Section 5 will present the results from six alternative model specifications. The first model presents a standard random parameters logit model where the responses to the SCS are analysed in isolation without controlling for decision uncertainty. Model 2 again only covers the choice model, but is potentially subject to endogeneity and measurement error due using the self-reported choice certainty responses as direct measurements of \( C_{it} \). Model 3 corrects for these issues by running a sequential model. First an ordered probit model is estimated to obtain parameter estimates for \( \delta \) and \( \omega \) such that the expected values for \( \hat{C}_{it} \) can be obtained. Then a choice model is estimated based on these expected values. Models 4-6 present results for the full ICLV model. Model 4 only controls for uncertain respondents adopting an alternative decision heuristic and sets \( \tau_{1} = 0 \). Model 5 assumes uncertain respondents make more random decisions and therefore sets \( \tau_{2} = 0 \). Model 6 allows for both effects of decision uncertainty and estimates both \( \tau_{1} \) and \( \tau_{2} \).

### 4 The Case Study

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

The empirical illustration is based on data from a Dutch stated choice survey concerning flood risk valuation in the face of climate change. Large parts of the Netherlands are situated below sea level and are threatened by an increase in (coastal) flood risks due to climate change. Even though most of the Dutch know they live below sea level, they are not accustomed to making trade-offs regarding their flood safety. Water boards and other public institutions are primarily responsible for providing and monitoring flood safety levels. Furthermore, flood risk insurance is not (yet) available in the Netherlands (Botzen et al. 2009). The Dutch government is attempting to make a shift from public to private flood risk responsibilities in order to make the country ‘climate proof’ (Kabat et al. 2005). Currently, there are no incentives at the individual level to reduce exposure and vulnerability to flood risks. Decision uncertainty is therefore likely to be present in this case study. Decision uncertainty may be further amplified by the small...
probabilities and high impacts of floods - e.g. there is a risk of coastal flooding of once every 10,000 years in the study area - and consequently the fact that most people never experienced a flood themselves.

A stated preference survey was conducted in the provinces of North- and South-Holland between February and March 2010. These heavily populated provinces include the major cities of Amsterdam, Den Haag and Rotterdam. The social and economic impacts of a coastal flood are expected to be large as various parts of the land are situated below sea level. 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 (Maaskant et al. 2009).

4.2 The stated choice survey

In this study, we were interested in the extent to which people 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 stated choice survey was embedded in an on-line survey. Before facing the stated choice scenarios, respondents were gradually informed about their vulnerability and familiarized with the difficult concept of flood risks. In total, five alternative groups of approximately 250 respondents each were sampled and presented with an alternative set-up of the stated choice scenarios. Respondents within each sample were obtained independently from an on-line panel of the survey company Multiscope. In this paper, we focus on one of these five versions. 224 respondents were presented with a self-reported choice certainty follow-up question directly after each choice scenario. 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 1792 observations.

In each choice task, two different public programs and a status quo option were presented to the respondent. Each public program is described by four attributes being: (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 organize 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. The experimental design for the sample used here is based on a d-efficient design for an attributes only MNL model, including an ASC. Local non-zero priors in the design were derived from an earlier pre-test sample (Rose and Bliemer, 2009). The design consists of 24 choice cards, is blocked into three groups of eight cards and is generated by Ngene (2010). Each respondent was presented with one one of these blocks of eight choice scenarios. In order to be able to estimate the choice model at each moment of the choice sequence, we systematically varied the order of appearance of the choice cards across respondents. This resulted in 24 versions of the design and respondents were assigned randomly to a version. The sample of interest is characterized

13For example, small flood risk probabilities are explained by means of a relative risk ladder and local elevation levels are presented via an interactive link using the individual specific postal code.

14Two alternative samples are used to exogenously approximate the choice probabilities required to derive the entropy measure (Balcombe and Fraser 2011).

15Inconsistent decision makers were not removed from the dataset since this will have an impact on the scale parameter and is therefore already taken into account (partially) by $\rho_i$. 

11
<table>
<thead>
<tr>
<th>Attribute</th>
<th>Possible attribute levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>1 in 4,000 1 in 6,000 1 in 8,000 1 in 10,000 years years years years</td>
</tr>
<tr>
<td></td>
<td>(1.5x smaller) (2x smaller) (2.5x smaller)</td>
</tr>
<tr>
<td>Compensation</td>
<td>0% 50% 75% 100%</td>
</tr>
<tr>
<td>Evacuation time</td>
<td>6 hours 9 hours 12 hours 18 hours</td>
</tr>
<tr>
<td>Increase in annual tax</td>
<td>€40 €80 €120 €160</td>
</tr>
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</table>

| Status quo alternative  | Probability  Compensation  Evacuation  Tax |
|-------------------------|---------------------------|----------------|--------------|
|                         | 1 in 4,000                0%             6 hours        €0           |

Table 1: Attributes and attribute levels

by an added choice certainty follow-up question to each choice task. The follow-up question was already defined in Section 3.3.

5 Results

Despite their lack of experience with floods, most respondents report a relatively high level of choice certainty in the follow-up question. Responses concentrate around the 'neutral' and 'certain' levels, respectively 36% and 43%. In approximately 10% of the observations respondents reported that they were 'very certain' and in another 10% they were 'uncertain' about their decision. Only in 1% of the observations respondents did select the 'very uncertain' response option. Closer investigation of dynamics in response patterns over the choice sequence reveals that 80 respondents did not alter their choice certainty responses across the choice tasks. Three respondents changed their certainty responses after almost every choice task (seven out of eight times) and nineteen did this only once. Most respondents revealed both increases and decreases in choice certainty over the choice sequence. These patterns suggest that decision certainty is perhaps more related to the complexity of the choice task, rather than the position in the choice sequence. Indeed, average choice certainty peaks in choice task four (closest to the ‘certain’ level) and shows a gradual decline afterwards to the ninth choice task. The $\chi^2$-test, however, fails to reject the null hypothesis of an identical distribution in self-reported choice certainty over the choice sequence at the 5% significance level. In the remaining of this section, the responses to the follow-up questions are used to (i) trace the impact of decision uncertainty on the responses to the stated choice scenarios and related welfare effects; and (ii) identify the drivers of decision uncertainty.
Table 2: Results choice models

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<tr>
<td></td>
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<td>Std. COST</td>
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<td>0.09</td>
</tr>
<tr>
<td>(\tau_2)</td>
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<td>1792</td>
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<td>0.56</td>
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</table>

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

5.1 The choice model

Table 2 presents the results for the first three model specifications. Model 1 can be characterized as an attributes only choice model where the probability, compensation and cost attribute follow a log-normal distribution to ensure a strictly positive (negative impact for cost) on utility. The ASC and the evacuation attribute follow a normal distribution. The choice model included in models 2-6 are all based on model 1 with additional control factors for decision uncertainty in the form of the parameters \(\tau_1\) and \(\tau_2\).

Indeed, the parameter and welfare estimates for model 1 confirm expectations. Respondents experience a positive utility from reductions in flood probability, additional compensation, and increased availability of evacuation time. Respondents are less likely to select an attribute with higher costs. The marginal WTP estimates at the bottom reveal that households are willing to pay €7,77 per year to increase the denominator of the flood probability by 1,000 years, i.e. from 1/4,000 to 1/5,000. Similarly, an additional percentage of compensation is worth €0,69 per household per year and an extra hour of evacuation time is worth €1,93 per household per

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16 Estimations are conducted in Matlab. The Gibbs Sampler is available upon request.
17 Model results are more stable using a normal distribution for the evacuation attribute, but our overall conclusions also apply to other specifications, including one with a fixed parameter for evacuation.
Model 2 controls for the impact of decision uncertainty on the choice model by using the follow-up responses as direct measures of $C_{it}$. As expected, both $\tau_1$ and $\tau_2$ have a positive coefficient. The former highlights that more certain respondents are subject to a lower decisional variance. The latter provides evidence that certain respondents are more willing to trade and have a lower tendency to select the status quo alternative. Treating the follow-up responses as an exogenous explanatory variable also translates into an improvement in model fit as highlighted by the Bayes Factor of 9.41 relative to model 1. Median WTP estimates for model 2 are all higher compared to model 1. However, no significant differences in welfare estimates can be detected across specifications.

Although the results for model 2 confirm our expectations on the impact of decision uncertainty on choice behaviour, the model specification may be subject to endogeneity and measurement error, possibly resulting in biased estimates. Model 3 therefore presents the results for an instrumental variable specification. In the first stage (results not reported) self-reported certainty is regressed on a set of eight explanatory variables. The expected value of $C_{it}$ is accordingly used as an explanatory variable in model 3. In contrast to model 2, a scale effect of decision certainty is no longer observed as highlighted by the standard deviation on $\tau_1$. More specifically, 65% of the draws of the Gibbs Sampler show a value of $\tau_1 < 0$. We still find evidence for a potential choice heuristic effect given the positive coefficient for $\tau_2$. Only 5% of the maintained draws for $\tau_2$ have a negative value. Model 3 results in a lower marginal likelihood compared to model 1. The additional coefficients indeed increase the likelihood, but the improvement in fit is insufficient to overcome the penalty for additional parameters in the model introduced through the priors. The WTP estimates obtained from model 3 are close to the estimates obtained from model 1. Accordingly, the results highlight that the direct use of self-reported choice certainty in model 2 may result in an overestimation of median WTP. Although the size of the standard errors preclude direct support of this conclusion, the results warrant the empirical application of the proposed ICLV model.

### 5.2 The ICLV model

Table 5.2 presents the results for the three alternative ICLV model specifications. For all model specifications we find a positive impact of latent decision certainty on the choice model. In fact, for models 4 and 5 the Gibbs Sampler finds no draws for respectively $\tau_2$ and $\tau_1$ with a negative value. For model 6 this is the case in less than one percent of the draws. Latent decision uncertainty thus has an impact on choice behaviour and induces respondents to make more random decisions and (or) make respondents more likely to select the opt out option. The model fits across all three specifications are nearly identical. Thus it cannot be identified which of the two effects is the strongest.

---

18 During each iteration of the Gibbs Sampler, the median WTP for an attribute is calculated using the hyper parameters of the associated (log-)normal distribution and those of the cost attribute. The ratio of log-normals is used for the probability and compensation attribute. Krinsky and Robb (1986,1990) is applied to approximate median WTP for the evacuation attribute at each draw of the Gibbs Sampler.

19 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. This is new in the choice modelling literature.

20 The control variables included in the structural equation are equivalent to those used in first stage of model 3.
<table>
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<th>Post StDev</th>
<th>Post Mean</th>
<th>Post StDev</th>
<th>Post Mean</th>
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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

Table 3: Results ICLV models
Given the interactions of $\tau_1$ and $\tau_2$ with the ASC, it is not surprising that the parameter estimates for the ASC and its associated standard deviations are affected compared to model 1. The estimates for the hyper parameters of the policy attributes are also affected. In particular the mean of the log-normal distributions in models 5 and 6 reveal a higher marginal impact of the policy attributes on utility compared to models 1 and 3. A lower cost sensitivity in model 2 caused an increase in marginal WTP estimates, here it is the higher marginal impact of the policy attributes that results in higher marginal WTP estimates compared to models 1 and 3. This also holds for model 4, but for this model WTP estimates are more comparable to the base model. In contrast to model 3, the ICLV model specifications stipulate that not controlling for decision uncertainty in the choice model may indeed lead to an underestimation of the welfare implications. WTP estimates for model 6 are close to those obtained for model 2. The proposed ICLV model structure, however, offers a more natural model specifications and deals with the issues of endogeneity and measurement error. By learning simultaneously about decision uncertainty through the choices and the responses to the follow-up questions, a better understanding of the connections in the model are obtained than by using the responses to the follow-up directly as an exogenous explanatory variable.

The ICLV model also provides additional insight into the drivers of decision uncertainty. Decision certainty is decreasing in the informational content of the choice task at hand as reflected by the Shannon entropy measure (Shannon, 1948). The dummy variables Block1 and Block3 indicate that splitting up the design into three blocks resulted in Block2 being slightly more difficult for respondents compared to the two blocks. Indeed, correlating the blocks with the entropy measure revealed that Block2 contained two relatively easy choice tasks. Decision uncertainty may also increase with the length of the stated choice survey as reflected by the parameter for Cardnr. By altering the order of appearance of the choice tasks across respondents, this effect is more likely to be related to fatigue or boredom effects, than to choice task specific effects.

Like Olsen et al. (2011), we barely find impacts of respondent characteristics on decision certainty. Both Olsen et al. (2011) and Brouwer et al. (2010) find that males are more certain about their decision than females. Our ICLV model supports this finding. Respondents who stated that the proposed policy scenarios are credible tend to reflect higher levels of decision certainty, a finding also reported in Brouwer et al. (2010). The estimate for $\sigma^2$ indicates there is substantial heterogeneity in decision certainty across respondents. Part of this can be explained by The lack of respondent characteristics reflecting the impact of respondent characteristics can be explained by the 80 out of the 224 respondents did not change their certainty responses over the choice sequence. In particular, when respondents have different interpretations of the five point rating scale of the follow-up questions the inclusion of $\rho_i$ in the structural model is likely to pick up most of the variation in decision certainty across respondents. Finally, the threshold parameters for the measurement model confirm that only a limited number of respondents is very uncertain ($\psi_1$) and that most responses to the follow-up question fall between the ‘neutral’ and ‘certain’ response ($\psi_3$ and $\psi_4$). The fact that the responses to the follow-up questions can still be related to the structural equation illustrates that researchers can learn about decision

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21 For an exact definition see Balcombe and Fraser (2011).
22 An attempt to relate these coefficients to the choice task factors defined by DeShazo and Fermo (2002) was unsuccessful.
23 The credibility measure is obtained from a single follow-up question where respondents could indicate on a five point scale how credible the presented scenarios were.
uncertainty from both the choice model and the measurement model.

6 Conclusions

In this paper we have put forward a modelling approach accounting for decision (un)certainty in stated choice surveys. The proposed model simultaneously takes into account the implicit and explicit modelling strategies of decision (un)certainty adopted in, for example, Brouwer et al. (2010) and Lundhede et al. (2009). By treating preference certainty as a latent variable which simultaneously affects the stated choices and responses to the (follow-up) choice certainty questions, our model works around potential endogeneity and measurement error issues likely to arise when using the follow-up responses as direct measurements of decision uncertainty. The model we applied our model to data from a stated choice survey on flood risk valuation in the Netherlands, a case study which is likely to suffer from decision uncertainty due to a lack of experience and familiarity as a result of the public provision of flood protection and small flood probabilities.

We (jointly) tested two sets of hypotheses in the empirical model. The first hypothesis represented the conjecture that uncertain respondents make more random decisions than certain respondents. The second hypothesis controlled for uncertain respondents adopting alternative decision heuristics to simplify the choice task. The decision heuristic adopted here accounted for uncertain respondents being more likely to select the status quo (or opt out) option. Evidence for both hypotheses was found in the form of significant interactions of latent decision certainty with respectively the scale of the utility function, and the alternative specific constant associated with the status quo option.

The results highlight two important conclusions. First, not controlling for decision uncertainty in the choice model may result in biased welfare estimates. In our case study, we find that a basic choice model underestimates median marginal willingness to pay values. By being a single case study in combination with the size of the current standard errors, this conclusion still requires additional empirical support by applying the same model structure to alternative datasets. Second, the presented integrated choice and latent variable model provides a more intuitive approach to treating decision uncertainty compared to existing methods. Directly using the responses of the follow-up choice certainty questions as direct (exogenous) measures of decision uncertainty does not necessarily lead to biased welfare estimates, but it limits the researcher in explaining the factors driving latent decision uncertainty and tracing its impact on the choice model. In our case study, we indeed find that there exists a correlation between the implicit and explicit measurement of decision uncertainty. The integrated choice and latent variable model thereby showed a different impact of decision uncertainty compared to the more simplistic exogenous and sequential approaches. The proposed model thereby offers potential for future research, including the testing of alternative decision heuristics possibly in the form of latent class models where latent decision uncertainty is associated with the probability of belonging to a particular class.

Still significant work remains to be done. The joint modelling framework opens the road for improved welfare estimates, and a renewed focus on the driving factors of decision uncertainty. For example, we find that decision certainty increases when respondents are presented with easier choice tasks. Choice task complexity was quantified through the Shannon (1948) entropy measure. 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 survey. The implications of decision uncertainty can thereby already be reduced in the design stage rather than correcting for it during the eventual analysis.

7 References


A The Gibbs Sampler

The appendix is structured in the following way. Section A.1 starts with a brief note on the notation used in this appendix. It differs slightly from the main text to facilitate the presentation of the conditional posteriors. Section A.2 provides the overall structure of the Gibbs Sampler. The conditional posteriors used to take draws from in the Gibbs Sampler are discussed in Sections A.3 and A.4. The former describes the specification of the required prior distributions. The latter discusses the resulting conditional posteriors.

A.1 Notation

Prior parameter values are denoted by underlining parameters, e.g. \( \mu_{\delta, \omega} \) represents the prior mean on the joint vector \([\delta, \omega]\). Similarly, bars represent posterior parameter values, e.g. \( \bar{V}_{\delta, \omega} \) denotes the posterior variance on the joint vector \([\delta, \omega]\). We discuss these specific examples in more detail below.

The conditional posteriors derived in this appendix can be either observation specific, respondent specific or affect all observations in the database. These different levels of aggregation are denoted by means of the subscripts \(i\) and \(t\) and the use of the * symbol. Let \(C_{it}\) represent an observation specific value for the latent variable choice certainty. Similarly, \(C_i\) captures all
(augmented) observations of C for respondent i, i.e. \( C_i \) is of size T by 1. Finally, C is the obs by 1 vector containing all observations of C in the database. For some parameters and explanatory variables, we have only a single observation per respondent. In these cases we use the * symbol. Let \( \rho^* \) represent the (n by 1) vector with all the respondent specific augmented parameters for \( \rho_i \) defined in Equation 1. For consistency, let \( \rho^*_i \) represent a specific element from \( \rho^* \). By using the * symbol the notation differs slightly from the equations used in the main text.

A.2 The structure of the Gibbs Sampler

Model estimation proceeds by sequentially drawing from a set of conditional posteriors. We label this as updating (or augmenting) of parameters. Because this process is done sequentially, the next parameter is updated conditional on the updated value of the previous parameter(s). Hence, a loop can be constructed to repeat this conditional updating procedure a large number of times (100,000 times in our case study). The draws from the conditional posteriors will eventually converge to a stable level and represent draws from the joint posterior distribution. The converged draws provide the necessary information on the parameters of interest.\(^{24}\) This process is also known as a Gibbs Sampler, which has the following structure:

1. Assign starting values to all model parameters
2. Update the fixed coefficients \( \beta_f \) in the choice model.
3. Update the augmented (individual specific) marginal utility parameters \( \beta^*_i \).
4. Update the hyper-parameters \( \mu_\beta \) and \( \sigma^2_\beta \) associated with the mixing densities in the choice model. Draw respectively from a normal and inverse gamma density.
5. Sequentially update \( \tau_2 \) and \( \tau_1 \) in the choice model. M-H required.
6. Sequentially update the threshold parameters \( \psi \) of the measurement model. M-H required.
7. Augment the response variable \( I_{it}^+ \). Draw from a truncated normal density.
8. Simultaneously update \( \delta \) and \( \omega \), draw from a normal density
9. Update \( \rho^*_i \), draw from a normal density
10. Update \( \sigma^2_\rho \), draw from an inverse gamma density
11. Update \( C_{it} \), M-H required
12. Repeat steps 2-10 a large number of times and check convergence of the draws by examining posterior plots and using Geweke’s convergence diagnostics.
13. Store a set of converged draws and describe the mean and standard error and other elements of interest. These draws serve as informational content for posterior analysis.\(^{24}\)

\(^{24}\)We discard the first 50,000 draws and use every 5th draw of the retained 50,000 draws. As such, the draws from the posterior density covers 10,000 draws for each model parameter.
A.3 The prior densities

Construction of the conditional posterior requires a prior distribution and a likelihood function. The prior summarizes the knowledge about a specific parameter before tracing its impact on a dependent variable of interest. Every parameter in the model therefore requires the specification of a prior distribution.

The choice model is characterized by the following parameters $\beta_f, \beta^*_i, \mu_\beta, \sigma^2_\beta, \tau_1, \tau_2$. Of these parameters $\beta_f, \tau_1$ and $\tau_2$ are most comparable, because they operate as fixed parameters associated with an explanatory variable. They can take any positive and negative value, although we expect the $\tau$’s to be positive. Hence, we assign a normally distributed prior with 0 mean and variance 1000 to each of them. The variance is set relatively large to make sure the prior is inherently vague and will hardly affect the shape of the posterior density.

$\beta^*_i$ is a special case, because it is the augmented value of the random parameter $\beta_i$. Therefore, the normal mixing density $p(\beta^*_i) \sim n(\mu_\beta, \sigma^2_\beta)$ already works as the relevant prior density. The hyper-parameters of the mixing densities, however, need their own set of priors. To obtain a conditional posterior distributions with a known analytical shape, we respectively assign a normal prior and an inverse gamma prior to $\mu_\beta$ and $\sigma^2_\beta$. These are also known as conjugate priors. Again, the parameters of these prior densities are defined such that the resulting prior is relatively vague. The values are reported in Table 4.

<table>
<thead>
<tr>
<th>Choice model</th>
<th>Parameter</th>
<th>Size</th>
<th>Prior Distribution</th>
<th>Hyper Parameters</th>
<th>Prior values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_f$</td>
<td>$k_f \times 1$</td>
<td>Multivariate</td>
<td>Normal</td>
<td>$\mu_f, V_f$</td>
<td>$\mu_f = 0$ \ $V_f = 1000 \cdot I_{k_f}$</td>
</tr>
<tr>
<td>$\beta^*_i$</td>
<td>$k_r \times 1$</td>
<td>Independent</td>
<td>Normal</td>
<td>$\mu_\beta, \sigma^2_\beta$</td>
<td>Augmented</td>
</tr>
<tr>
<td>$\mu_\beta$</td>
<td>$k_r \times 1$</td>
<td>Independent</td>
<td>Normal</td>
<td>$\mu_\beta, \sigma^2_\beta$</td>
<td>$\mu_\beta = 0$ \ $\sigma^2_\beta = 1000$</td>
</tr>
<tr>
<td>$\sigma^2_\beta$</td>
<td>$k_r \times 1$</td>
<td>Independent</td>
<td>Normal</td>
<td>$\kappa$ (scale), $\eta$ (shape)</td>
<td>$\kappa = 0.5$ \ $\eta = 0.5$</td>
</tr>
<tr>
<td>$\tau_1$</td>
<td>scalar</td>
<td>Normal</td>
<td>$\mu_{\tau_1}, \sigma^2_{\tau_1}$</td>
<td>$\mu_{\tau_1} = 0$ \ $\sigma^2_{\tau_1} = 1000$</td>
<td></td>
</tr>
<tr>
<td>$\tau_2$</td>
<td>scalar</td>
<td>Normal</td>
<td>$\mu_{\tau_2}, \sigma^2_{\tau_2}$</td>
<td>$\mu_{\tau_2} = 0$ \ $\sigma^2_{\tau_2} = 1000$</td>
<td></td>
</tr>
</tbody>
</table>

$k_f$ refers to the number of fixed parameters in the choice model  
k_r refers to the number of random parameters in the choice model  
$I_k$ refers to the identity matrix of size $k$

Table 4: Priors associated with the Choice model

Table 5 summarizes the prior distributions associated with the structural model. The structural model is characterized by the parameters $\delta, \omega, \rho^*_i$ and $\sigma^2_\rho$. $\delta$ and $\omega$ operate as fixed parameters and only affect the normally distributed latent variable $C_{it}$. Similar to $\mu_{\beta_\text{eta}}$ we assign a conjugate normal prior to the joint vector $[\delta, \omega]$ in order to obtain a convenient conditional posterior.
Like $\beta_i^*$, $\rho_i^*$ acts as the augmented value of the random parameter $\rho_i$. It has a zero mean normal density with variance $\sigma^2_\rho$ that acts as its prior. Hence, only $\sigma^2_\rho$ requires a prior density of its own. Like $\sigma^2_\beta$, we assign an inverse gamma prior to $\sigma^2_\rho$.  

### Structural model

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Size</th>
<th>Prior Distribution</th>
<th>Hyper Parameters</th>
<th>Prior values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[\delta', \omega']'$</td>
<td>$k_s$ by 1</td>
<td>Multivariate Normal</td>
<td>$\mu_{\delta,\omega}, V_{\delta,\omega}$</td>
<td>$\mu_{\delta,\omega} = 0$, $V_{\delta,\omega} = 1000 \cdot I_{k_s}$</td>
</tr>
<tr>
<td>$\rho_i^*$</td>
<td>scalar</td>
<td>Normal (zero mean)</td>
<td>$\sigma^2_\rho$</td>
<td>Augmented</td>
</tr>
<tr>
<td>$\sigma^2_\rho$</td>
<td>scalar</td>
<td>Inverse gamma</td>
<td>$\kappa$ (scale), $\eta$ (shape)</td>
<td>$\kappa = 0.5$, $\eta = 0.5$</td>
</tr>
</tbody>
</table>

$k_s$ refers to the number of fixed parameters in the structural model $I_k$ refers to the identity matrix of size $k$

Table 5: Priors associated with the Structural model

The measurement model (see Table 6) is only defined by the $(G - 1)$ threshold parameters $\psi$, because $\alpha$ is normalized to unity in our specification. All the threshold parameters are assigned an independent normal prior with mean $\mu_\psi = 0$ and variance $V_\psi = 0$. Additionally, we work with the mapping of $I_d$ on a continuous scale to $I^+_d$. For the latter term the measurement model acts as its associated normal prior with mean $C_{it}$ and variance 1.

Finally, the measurement model and the choice model are affected by the augmented latent variable $C_{it}$, decision certainty. The structural equation acts as its prior. Hence, the prior on $C_{it}$ is normally distributed with mean $R_i^* \delta + W_{it} \omega + \rho_i^*$.  

### Measurement model

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Size</th>
<th>Prior Distribution</th>
<th>Hyper Parameters</th>
<th>Prior values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi$</td>
<td>$(G - 1)$ by 1</td>
<td>Independent Normals</td>
<td>$\mu_\psi, V_\psi$</td>
<td>$\mu_\psi = 0$, $V_\psi = 1000$</td>
</tr>
<tr>
<td>$I^+_it$</td>
<td>scalar</td>
<td>Normal</td>
<td>mean: $C_{it}$ variance: 1</td>
<td>Augmented</td>
</tr>
<tr>
<td>$C_{it}$</td>
<td>scalar</td>
<td>Normal</td>
<td>mean: $\delta R_i^* + \omega W_{it} + \rho_i^*$ variance: 1</td>
<td>Augmented</td>
</tr>
</tbody>
</table>

$G$ refers to the number of response categories

Table 6: Priors associated with the Measurement model

### A.4 The conditional posterior densities

#### A.4.1 The choice model

Evaluation of the parameters in the choice model is done conditional on the value of the (augmented) value for decision certainty $C_{it}$. As such, the choice model reduces to a standard Bayesian multinomial logit model with data augmentation as described in Train (2009, Chapter
12). Its likelihood is described by the the product of the conditional MNL choice probability $p(Y_{it} = j | \beta_f, \beta^*_i, \tau_1, \tau_2, C_{it})$ over all observations. Train (2009) describes that the combination of any prior with this likelihood function will not result in a conditional posterior from which a researcher can easily take draws. Hence, a Metropolis Hastings algorithm is required to take draws from respectively $\beta_f, \beta^*_i, \tau_1$ and $\tau_2$. The conditional posteriors are described in Equation 7 and note that $\beta^*_i$ is augmented and updated for every individual and every random parameter separately.

$$\begin{align*}
p(\beta_f | \beta, \tau_1, \tau_2, Y, C, X) &\propto \prod_{i=1}^{n} \prod_{t=1}^{T} p(Y_{it} = j | \beta_f, \beta^*_i, \tau_1, \tau_2, C_{it}) \exp \left( -\frac{1}{2} (\beta_f - \mu_f)^\top V_f^{-1} (\beta_f - \mu_f) \right) \\
p(\beta^*_i | \beta_f, \tau_1, \tau_2, Y, C, X) &\propto \prod_{i=1}^{n} \prod_{t=1}^{T} p(Y_{it} = j | \beta_f, \beta^*_i, \tau_1, \tau_2, C_{it}) \exp \left( -\frac{(\beta^*_i - \mu^*_i)^2}{2\sigma^2_{\beta}} \right) \\
p(\tau_1 | \beta_f, \beta, \tau_2, Y, C, X) &\propto \prod_{i=1}^{n} \prod_{t=1}^{T} p(Y_{it} = j | \beta_f, \beta^*_i, \tau_1, \tau_2, C_{it}) \exp \left( -\frac{(\tau_1 - \mu_1)^2}{2\sigma^2_{\tau_1}} \right) \\
p(\tau_2 | \beta_f, \beta, \tau_1, Y, C, X) &\propto \prod_{i=1}^{n} \prod_{t=1}^{T} p(Y_{it} = j | \beta_f, \beta^*_i, \tau_1, \tau_2, C_{it}) \exp \left( -\frac{(\tau_2 - \mu_2)^2}{2\sigma^2_{\tau_2}} \right) 
\end{align*}$$

(7)

The mixing density on the random parameters $\beta^*_i$ now acts as the likelihood on the hyper-parameters $\mu_\beta$ and $\sigma^2_{\beta}$.

Koop (2003) and Train (2009) show analytical posteriors can be derived for these two hyper-parameters. First, the conditional posterior on $\mu_\beta$ follows a normal distribution with variance $\frac{\sigma^2_\beta}{2} = \left( \frac{1}{\frac{\sigma^2_\beta}{2}} + \frac{n}{\sigma^2_\beta} \right)^{-1}$ and mean $\mu_{\beta} = \frac{\sigma^2_\beta}{2} \left( \frac{\mu_\beta}{\sigma^2_\beta} + \sum_{i=1}^{n} \frac{\beta^*_i}{\sigma^2_\beta} \right)$. The conditional posterior on $\sigma^2_\beta$ follows an inverse gamma distribution with posterior shape parameter $\eta = \frac{n}{2} + \sum_{i=1}^{n} (\frac{\beta^*_i - \mu_\beta}{2})^2$ and scale parameter $\kappa = \frac{\eta}{2}$.

### A.4.2 The structural model

Since the joint vector $[\delta', \omega']'$ affects every observation of $C_{it}$, the associated likelihood is described by $\prod_{i=1}^{n} \prod_{t=1}^{T} p(C_{it} | \delta, \omega, \rho^*_i, R^*_i, W_{it})$, which is a product of normal densities. Following Koop (2003), the conditional posterior $p(\delta, \omega | \rho, C, Z)$ follows a normal distribution with variance $\overline{V}_{\delta,\omega} = \left( \sum_{t=1}^{T} \left( \overline{V}_{\delta,\omega}^{-1} + \left( Z'C - \rho \right) \right) \right)^{-1}$. $Z$ represents the obs by $k_s$ of explanatory variables in the structural model, i.e. $[R, W]$ such that $[R, W] \cdot [\delta', \omega']'$ is of size obs by 1. The posterior mean is then described by $\overline{V}_{\delta,\omega} = \overline{V}_{\delta,\omega} \left( \overline{V}_{\delta,\omega}^{-1} + \left( Z'C - \rho \right) \right)$, where $C$ and $\rho$ are both of size obs by 1. They contain the augmented values for $C_{it}$ and $r\rho^*_i$ for each observation.

Note that $\rho^*_i$ only affects the observations $C_i$. Its associated likelihood function is then described by $\prod_{i=1}^{n} p(C_i | \delta, \omega, \rho^*_i, R^*_i, W_{it})$, a product of normal densities. The associated prior is also of normal form. The conditional posterior on $\rho^*_i$ is therefore also of normal form. Its posterior variance has value $\overline{\sigma}^2_{\rho^*_i} = \left( \frac{1}{\overline{\sigma}^2_{\rho^*_i}} + T \right)^{-1}$ and the posterior mean takes the value $\overline{\mu}_{\rho^*_i} = $
\[ \sigma^2 \sum_{t=1}^T (C_{it} - (\delta R^*_i + \omega W_{it})). \] The conditional posterior on \( \rho^*_i \) is evaluated for every individual \( i \) specifically.

The final parameter in the structural model, \( \sigma^2_\rho \), has \[ \prod_{i=1}^n \rho^*_i \] as its associated likelihood. Again this is a product of normal densities. Koop (2003) shows that by assigning an inverse gamma prior with scale parameter \( \kappa \) and shape parameter \( \eta \), the posterior for \( \sigma^2_\rho \) also follows an inverse gamma density with scale parameter \( \bar{\kappa} = \kappa + \frac{n}{2} \) and shape parameter \( \bar{\eta} = \eta + \sum_{i=1}^n (\rho^*_i)^2 \).

### A.4.3 The measurement model

Conditional on \( C_{it} \) the measurement model reduces to an ordered probit model for which the threshold parameters \( \psi \) need to be estimated. The complexity of the likelihood function of the ordered probit model implies a Metropolis-Hastings algorithm needs to be used to update the elements of \( \psi \). The posterior for \( \psi_g \) is described in Equation 8, where \( (I_{it} = g) \) denotes a binary indicator taking the value 1 if certainty level \( g \) is indicated and zero otherwise.

\[
p(\psi_g | \psi_{\neq g}, I, C) \propto \prod_{i=1}^n \prod_{t=1}^T (I_{it} = g)(\Phi(\psi_g - C_{it}) - \Phi(\psi_{g-1} - C_{it}))

+ (I_{it} = g + 1)(\Phi(\psi_{g+1} - C_{it}) - \Phi(\psi_g - C_{it})) \exp\left(\frac{\psi_g - \mu_{\psi}}{2\sigma^2_{\psi}}\right)
\] (8)

In mapping the values \( I_{it} \) on a continuous scale \( I^+_{it} \), we know from the prior that \( I^+_{it} \) has a normal density. After observing \( I_{it} = g \), we know \( I^+_{it} \) lies between \( \psi_{g-1} \) and \( \psi_g \). Hence, \( I^+_{it} \) can be updated by taking a draw from its prior, but truncated from below at \( \psi_{g-1} \) and from above at \( \psi_g \). In between it can take any value.

The final parameter in the ICLV model, \( C_{it} \) affects the choice model and the measurement model. Therefore its likelihood is represented by the product of these two at a specific observation, i.e. \( p(Y_{it}|C_{it}) \cdot p(I^+_{it}|C_{it}) \). Now the structural model \( p(C_{it}|\delta, \omega, \rho^*_i) \) acts as the prior. It is not hard to imagine that the conditional posterior on \( C_{it} \) is complex and requires a Metropolis Hastings algorithm to generate draws from in the Gibbs Sampler. The posterior is evaluated for every individual and choice task specifically and described in Equation 9.

\[
p(C_{it}|Y_{it}, I^+_{it}, \beta_f, \beta^*_i, \tau_1, \tau_2, \delta, \omega \rho^*_i) \propto \prod_{i=1}^n \prod_{t=1}^T p(Y_{it} = j|\beta_f, \beta^*_i, \tau_1, \tau_2, C_{it}) p(I^+_{it}|C_{it}) p(C_{it}|\delta, \omega, \rho^*_i)
\] (9)

The Gibbs Sampler is coded in Matlab and the code is available upon request from the corresponding author.