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# The impact of latent risk preferences on valuing the preservation of threatened lynx populations in Poland*

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A recent innovation in stated preference environmental valuation surveys is to acknowledge uncertainty associated with scientific predictions about ecological outcomes, complexity of management actions and potential difficulties in implementing environmental programs. Still little is known about how individuals assimilate and respond to outcome uncertainty, particularly in terms of how it affects their stated valuations. In this paper, we focus on the impact of individual risk preferences on willingness to pay for conservation of threatened species. Risk preferences are elicited through a standard incentivised multiple price list and preferences for the conservation of the two main lynx populations in Poland through a discrete choice experiment. To account for the uncertainty associated with imprecise scientific knowledge about environmental outcome, attributes in the choice experiment are presented as conservation status in terms of descriptive, non-numerical categories. The results from the multiple price list and the choice experiment are jointly analysed in a latent variable model by assuming that the responses to both are driven by the same preferences. We find that the latent risk preferences are linked to choices of the status quo option, which is the riskiest option in terms of the survival of the endangered lynx populations.

**Key words:** choice experiment, hybrid latent class model, lottery experiment, lynx preservation, risk preference.

## 1. Introduction

It is a common practice in stated preference valuation surveys to assume that the environmental outcomes are certain; however, this contrasts with the situation in the real world. Owing to limited knowledge on natural processes

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and the fact that environmental improvements often involve very long time horizons, the outcomes of conservation policies can entail substantial uncertainty. Uncertainty can be associated with imprecise scientific knowledge about environmental outcomes or with complexity of management actions and the difficulties of achieving policy effectiveness connected with the possible changes to the political, social and economic environment (Glenk and Colombo 2013). Rolfe and Windle (2015) point out that the omission of uncertainty about environmental outcomes may contribute to hypothetical bias in stated preference surveys, because it influences the credibility of the valuation scenario. Given that the outcomes of environmental protection plans can never be known with certainty, researchers need to make judgments about how to include this uncertainty into survey designs (Lew *et al*. 2010).

Recently, several choice experiment (CE) studies published in the field of environmental valuation have aimed at incorporating uncertainty associated with scientific predictions about ecological outcomes or connected with the effectiveness of different delivery mechanisms into their designs. The following approaches can be distinguished: firstly, uncertainty or risk[1] can be provided as a part of the valuation scenarios. This approach is applied, for example, by Wielgus *et al*. (2009) in a CE survey concerning fishing preferences, where respondents were assigned to three split samples and presented with questionnaires in which the probability of occurrence of the valuation scenarios varied. Secondly, risk can be assigned to a single attribute presented in the CE or to alternatives (management options). Rigby *et al*. (2011), for example, specified one of their attributes as the probability of rainfall levels, while Glenk and Colombo (2013) incorporated as an attribute the probability that a soil carbon program might actually fail to deliver climate change mitigation benefits. Rolfe and Windle (2015) in their CE study regarding the Great Barrier Reef protection include a separate attribute for the certainty of outcomes presented in numerical terms. Deliberately, however, alternative outcomes are not described precisely to respondents to assess uncertainty rather than risk.

Another approach of how to incorporate uncertainty is presented by Wielgus *et al*. (2009) in their survey concerned with divers. Instead of providing the probability of event, they incorporate uncertainty by specifying attribute levels as intervals reflecting the varying number of coral fish observed during one dive. In studies investigating the public's preferences for enhancements to the protection of marine species, Lew *et al*. (2010) and Lew and Wallamo (2011) use as attributes the conservation status of marine species accounting for potential outcome uncertainty. This conservation status is based on categories defined in the US Endangered Species Act (ESA). All these approaches mean a step forward in contrast to studies where environmental outcomes were – explicitly or implicitly – presented as certain.

[1] For risky outcome, we assume known outcomes with a known probability in numerical terms, whereas uncertainty entails randomness with unknowable probabilities.

However, how individuals understand and respond to this uncertainty, particularly how it affects their values, remains an open question.

In this paper, we focus on the impact of risk preferences on stated preferences. Risk preferences have been shown to influence behaviour in a number of other domains where uncertainty is a key feature of future outcomes, such as health protection, financial investments, job changes or driving behaviour (Hakes and Viscusi 2007; Anderson and Mellor 2008; Kimball *et al*. 2008). Some studies have tested whether risk preferences measured in an experimental way are linked with real risky behaviour. Anderson and Mellor (2008), for example, show that individuals who are more risk-averse are less likely to smoke and more likely to wear seat belts. Elston *et al*. (2005) report that full-time entrepreneurs are less risk-averse than non-entrepreneurs and that part-time entrepreneurs were more risk-averse than nonentrepreneurs. Lusk and Coble (2005) found that risk preferences are significant determinants of the acceptance of genetically modified food. Meanwhile, Olbrich *et al*. (2011) report that adult farmers in Namibia self-selected themselves onto farms according to their risk preferences (i.e. those with lower risk aversion were found on farms with higher environmental risks).

The main objective of our analysis was to examine the impact, if any, of individual risk preferences on stated willingness to pay (WTP) for lynx conservation in Poland. The first part of the study is a CE designed to value the preservation of the two main lynx populations in Poland: the Lowland population that occupies the north-eastern part of the country and the Carpathian located in the south. Both populations are exposed to a high risk of becoming extinct. Mostly, this is the result of the rapid growth of transport infrastructure and insufficient protection programs.

The outcomes of the conservation programs presented in the CE were specified as uncertain to reflect scientific reality due to imprecise scientific knowledge about environmental processes. Following Lew *et al*. (2010) and Lew and Wallamo (2011) as attributes, we use conservation status of species, in our case based on the International Union for Conservation of Nature (IUCN) Red List of threatened species. Due to limited knowledge of environmental processes some biologists refuse to define the exact size of the population or to assign numerical probabilities about environmental outcomes. Both the IUCN and the ESA present the conservation status of wild species and their links to livelihoods in terms of descriptive, non-numerical categories. If the outcomes of programs are presented just as the number of animals and associated probabilities of survival, it can be misleading, since the chances of survival do not depend solely on the population size. Other factors such as size of habitat or migration possibilities may also influence the species status.

The second part of the study is designed to elicit respondents' risk preferences. In this part, we utilise the standard multiple price list (MPL) approach originally proposed by Binswanger (1980) and later modified and popularised by Holt and Laury (2002). In the MLP experiment conducted by Holt and Laury, individuals made ten choices between two lotteries. For each lottery, the pay-offs are fixed, but the probabilities vary. Rewards are structured such that one lottery is less risky than the other. To estimate risk preferences, the expected gains in two subsequent choices are compared, assuming the relative risk aversion functional form is constant. Robustness of the MPL design has been investigated in a few studies; for example, Anderson *et al*. (2007) found it to be robust to framing effects, whereas Harrison *et al*. (2005) and Holt and Laury (2005) found that scaling up real payments had no impact on hypothetically elicited risk aversion coefficients.

Given the current unresolved issues with respect to the direct elicitation and interpretation of environmental risk preferences (Riddel 2012), we chose to elicit financial risk preferences as they have the best theoretical foundation, at least to date. From the experimental literature, there is evidence that risk preferences elicited in the financial domain may be linked with environmental decisions. Grijalva *et al*. (2011) show in their study conducted among students that risk preferences elicited using the Holt and Laury (2002) MPL approach influence decisions to preserve renewable resources. They find that more risk-averse individuals are more likely to support the safe minimum standard preservation choice. Additionally, in the context of CE given the inclusion of a cost variable in choice sets, it does not seem unreasonable to assume that both risk preferences over finance and environment may affect respondents' choices.

The econometric approach we use to jointly analyse our data from the CE and the MPL experiment is based on hybrid choice models, which have been developed over recent years, with key developments by Ben-Akiva *et al*. (1999, 2002) and Bolduc *et al*. (2005). This approach uses latent variables (LVs), which are functions of the socio-demographic variables and an error term, to explain unobserved latent risk preferences. At the same time, in a separate measurement model, these LVs are used to explain answers to follow-up questions, related to psychological constructs included in the model. In our study, the LV represents latent risk preferences.

The key advantage of hybrid choice models is the use of additional data to improve the precision of estimations and to better represent potential heterogeneity, which can be modelled in various ways. The number of applications of hybrid choice models across various fields has increased notably in recent years. Applications in environmental valuation, for example, have been presented by Hess and Beharry-Borg (2012), Hoyos *et al*. (2015) or Mariel *et al*. (2015). Moreover, a recent study that is close to the subject of the present paper uses a LV to incorporate prior outcome beliefs in a stated choice model concerned with investigating how outcome uncertainty affects stated WTP (Lundhede *et al*. 2015). The authors find that respondent's prior beliefs significantly influence the estimated utility of outcome uncertainty and that the LV model gives valuable insight into the patterns underlying concepts of belief in policy outcome and how they influence the stated WTP for conservation measures.

A methodological novelty of the present study arises from the application of a new approach to link the two parts of the hybrid choice model. We estimate a model that resembles a latent class logit model (LCM) by allowing for the interaction of the LV with a utility coefficient in each class. In previous studies such as Daly *et al.* (2012) and Glerum *et al.* (2012), the LV was interacted with attribute coefficients; in Hoyos *et al.* (2015), the LV was explanatory in a class allocation function of an LCM; and in Hess and Stathopoulos (2013), the LV was used to explain scale heterogeneity within the choice model.

The remainder of paper is organised as follows. Section 2 presents the situation facing lynx in Poland, Section 3 describes the case study and its methodology, Section 4 contains the main results, and finally, Section 5 draws conclusions on the application of the hybrid choice model.

## 2. The status of lynx populations in Poland

The Eurasian lynx (*Lynx lynx*) is the third largest predator in Europe after the brown bear and the wolf. Poland is one of the few European countries where lynx have survived in the wild. However, the number of Polish lynx living in the wild has decreased to a third over the past 20 years and is estimated to be about 180–200 individuals in total (Jędrzejewski *et al.* 2002; Von Arx *et al.* 2004). Although lynx have officially been protected in Poland since 1995, little has been done so far to ensure the longer-term survival of the species (Niedziałkowska *et al.* 2006). In general, their current status in Poland is considered to be 'near threatened' according to the IUCN Red List of threatened species.

There are two main lynx populations in Poland: the Lowland population in the northeast and the Carpathian population in the south of the country. Both populations live in border regions and are part of two major populations of this species in Europe. The Polish Carpathian population is larger in number and more widely distributed than the Lowland population, and it is estimated to be about 100 animals. Existing migration corridors allow for the exchange of the Carpathian lynx between countries. Meanwhile, the Lowland lynx population, estimated at about 60 animals, occupies a highly fragmented habitat.[2] This group is more isolated from the lynx populations in other countries. These factors contribute to a higher risk of extinction of the Lowland lynx in comparison with the Carpathian population (Von Arx *et al.* 2004).

[2] In addition to the Lowland and Carpathian lynx populations and a few isolated individuals in the north of Poland, a group of 12–15 lynx lives in central Poland in the Kampinowski National Park. The group is isolated and cannot survive in the wild without human support.

Niedziałkowska *et al*. (2006) identified the fragmentation of forest habitats as a major threat for the survival of the lynx populations in Poland. Other threats to the lynx populations occur as a result of current forest management such as the afforestation of open spaces and failing to leave enough dead wood in forests (Schmidt 2008). Such changes in forests disturb the lynx's hunting and living conditions. Additionally, game hunting and poaching by humans cause food scarcity. If these impacts on habitat conditions continue, it is anticipated that the Polish lynx population may be seriously threatened in the next decades (Niedziałkowska *et al*. 2006).

## 3. Survey design and methodology

### 3.1. Survey structure

The valuation survey consisted of six parts. In part 1 general information concerning forests in Poland was presented and questions about respondents' recreation patterns in forests were asked. Part 2 provided general information on lynx populations in Europe and a detailed description of the two lynx populations in Poland. This information included a physical description of the lynx, its habits, place of occurrence, a current size and status of the Lowland and Carpathian lynx populations and their main threats. Respondents were told that the chances of survival do not depend solely on the population size, but that other factors such as size of habitat or migration possibilities also influence the Lowland and Carpathian lynx status. Then, part 3 depicted potential management actions that could increase the chances of survival of the two main lynx populations in the country. Among those actions, the most important is to create corridors and passes across roads and railway tracks enabling the lynx to migrate between forest complexes. In Part 4, the choice sets were presented prior to eliciting respondents' risk preferences in part 5. Finally, the last part requested socio-demographic information from respondents.

### 3.2. CE design

The CE comprises three attributes: the status of both the Lowland and the Carpathian lynx populations in 20 years from now and the annual cost of the particular conservation program per person. Following consultation with forest biologists, instead of employing the commonly used increase in the number of individuals as a measure of the improved protection of endangered species, we decided to describe the status of the lynx populations in terms of its chances of survival. The categories used were based on the IUCN Red List of threatened species. To clarify the categories, the official terminology was simplified slightly (Table 1). Additionally, we informed respondents that the risk of extinction varies from nearly zero, that is having a stable population, to close to 100 per cent, that is the species is critically threatened. The final

**Table 1** Levels of threat

| IUCN Red List | Scale adapted for the choice experiment |
|---|---|
| *Critically Endangered* – Extremely high risk of extinction in the wild | *Critically threatened* – Extremely high risk of extinction in the wild |
| *Endangered* – High risk of extinction in the wild | *Highly threatened* – High risk of extinction in the wild |
| *Vulnerable* – High risk of endangerment in the wild | *Moderately threatened* – Moderate risk of extinction in the wild |
| *Near Threatened* – Likely to become endangered in the near future | *Low threat level* – Low risk of extinction in the wild |
| *Least Concern* – Lowest risk. Does not qualify for a more at risk category | *Stable* – Negligible risk of extinction in the wild |

Note: The International Union for Conservation of Nature (IUCN) Red List includes two additional categories: extinct in the wild and extinct, which were not included in the valuation survey, as they were not seen to be necessary for the purpose of our study.

category descriptions along with the current and the predicted status for both lynx populations were agreed through consultation with experts from the Institute of Nature Conservation and Mammal Research Institute at the Polish Academy of Sciences.

For the purposes of the CE, the future status of the Lowland population could take one of five levels (from critically threatened to stable), while for the Carpathian population, four attribute levels were used (from highly threatened to stable). The payment vehicle was a tax that would go to a special fund established for lynx conservation in Poland. Table 2 shows the full list of attribute levels in the experimental design.

The choice sets were created by using a Bayesian S-efficient design with fixed priors gained from responses by focus group participants. An S-efficient design is aimed at minimising the number of observations necessary to obtain statistically significant parameter estimates (Bliemer and Rose 2011). The final design comprised 24 choice sets that were blocked into four subsets. Each set comprised two policy options and a business-as-usual option. Each option described the effect the conservation measures would have on the lynx populations' chances of survival in the future. Additionally, the sets provided information about the current number of individuals of each population. To illustrate the differences between the hypothetical threat levels, colours following the idea of traffic lights were used to mark attribute levels. Each attribute level was accompanied by a pictogram of a lynx coloured according to the threat level. Each respondent faced seven choice sets in total, including one with a dominant alternative; the latter choice sets were not used in the present analysis. An example of choice set is presented in Figure 1.

### 3.3. Measuring risk preferences with a lottery choice task

Based on the Holt and Laury's (2002) approach, respondents were presented with a series of 10-paired lotteries. For each of the 10 decisions, they were

**Table 2** Attributes and levels in the choice experiment

| Attributes | Levels [Coding] |
|---|---|
| Lowland lynx population (Lowland) | Critically threatened [5] (expected for business-as-usual, i.e. without additional protection measures), highly threatened [4], moderately threatened [3], low threat level [2], stable [1] |
| Carpathian lynx population (Carpa) | Highly threatened [4] (expected for business-as-usual), moderately threatened [3], low threat level [2], stable [1] |
| Cost per person per year (Cost) | 0 zł (business-as-usual), 15 zł, 50 zł, 90 zł, 150 zł |

Note: The nominal exchange rate from February 2011: 1€ = 3.9 zł.

| | **Programme A**<br><br>No additional protection measures<br><br>Expected results in 20 years | **Programme B**<br><br>Additional protection measures<br><br>Expected results in 20 years | **Programme C**<br><br>Additional protection measures<br><br>Expected results in 20 years |
|---|---|---|---|
| **LOWLAND**<br>LYNX POPULATION<br><br>Current number:<br>60 animals | **CRITICALLY THREATENED**<br><br>**Extremely high** risk of extinction<br> | **STABLE POPULATION**<br><br>**Negligible** risk of extinction<br> | **CRITICALLY THREATENED**<br><br>**Extremely high** risk of extinction<br> |
| **CARPATHIAN**<br>LYNX POPULATION<br><br>Current number:<br>100 animals | **HIGHLY THREATENED**<br><br>**High** risk of extinction<br> | **HIGHLY THREATENED**<br><br>**High** risk of extinction<br> | **MODERATELY THREATENED**<br><br>**Moderate** risk of extinction<br> |
| **Cost** per person per year | **0 zł** | **90 zł** | **90 zł** |
| I prefer **the most** | | | |

**Figure 1** Example choice set.

asked to choose either lottery A or lottery B. In each decision, lottery A was the safe choice and lottery B was the risky option. The pay-offs for the safe option were less variable than that for the risky one. For both lotteries, in each successive row, the likelihood of receiving larger rewards increased. For the first four decisions, the expected pay-off for lottery A was higher than that for lottery B, while for the next six decisions, lottery B had the higher expected pay-off. In the last row, no uncertainty was assigned to pay-offs. Following Anderson and Mellor (2008), we presented pay-offs that were three times higher than the Holt and Laury's (2002) baseline amounts. Table 3 shows the full set of decision tasks. To incentivise respondents, one of the 10 decisions was randomly selected as binding by the roll of a 10-sided dice. Then, a dice was thrown again to determine whether the individual received the high or low real monetary pay-off from the chosen lottery.

## 3.4. Econometric approach

To capture more realistically the choice processes, we incorporated the latent characteristics of decision-makers into the model by treating the observed

**Table 3** Lottery choice experiment

| Decision | Lottery A | Lottery B | E(A) − E(B) |
|---|---|---|---|
| 1 | Receive 18 zł if dice throw is 1 | Receive 34.70 zł if dice throw is 1 | 10.6 |
| | Receive 14.50 zł if dice throw is 2–10 | Receive 0.90 zł if dice throw is 2–10 | |
| 2 | Receive 18 zł if dice throw is 1–2 | Receive 34.70 zł if dice throw is 1–2 | 7.5 |
| | Receive 14.50 zł if dice throw is 3–10 | Receive 0.90 zł if dice throw is 3–10 | |
| 3 | Receive 18 zł if dice throw is 1–3 | Receive 34.70 zł if dice throw is 1–3 | 4.5 |
| | Receive 14.50 zł if dice throw is 4–10 | Receive 0.90 zł if dice throw is 4–10 | |
| 4 | Receive 18 zł if dice throw is 1–4 | Receive 34.70 zł if dice throw is 1–4 | 1.5 |
| | Receive 14.50 zł if dice throw is 5–10 | Receive 0.90 zł if dice throw is 5–10 | |
| 5 | Receive 18 zł if dice throw is 1–5 | Receive 34.70 zł if dice throw is 1–5 | −1.6 |
| | Receive 14.50 zł if dice throw is 6–10 | Receive 0.90 zł if dice throw is 6–10 | |
| 6 | Receive 18 zł if dice throw is1–6 | Receive 34.70 zł if dice throw is 1–6 | −4.6 |
| | Receive 14.50 zł if dice throw is 7–10 | Receive 0.90 zł if dice throw is 7–10 | |
| 7 | Receive 18 zł if dice throw is 1–7 | Receive 34.70 zł if dice throw is 1–7 | −7.6 |
| | Receive 14.50 zł if dice throw is 8–10 | Receive 0.90 zł if dice throw is 8–10 | |
| 8 | Receive 18 zł if dice throw is 1–8 | Receive 34.70 zł if dice throw is 1–8 | −10.6 |
| | Receive 14.50 zł if dice throw is 9–10 | Receive 0.90 zł if dice throw is 9–10 | |
| 9 | Receive 18 zł if dice throw is 1–9 | Receive 34.70 zł if dice throw is 1–9 | −13.7 |
| | Receive 14.50 zł if dice throw is 10 | Receive 0.90 zł if dice throw is 10 | |
| 10 | Receive 18 zł if dice throw is 1–10 | Receive 34.70 zł if dice throw is 1–10 | −16.7 |

indicators of the latent characteristics as endogenous (Bolduc and Alvarez-Daziano 2010; Yáñez *et al*. 2010). The hybrid model used in this application was composed of two sets of structural equations and a group of measurement relationships.

The first set of structural equations is represented by the utilities of alternative $i$ for respondent $n$ in the choice occasion $t$ as follows:

$$U_{int} = V_{int} + \varepsilon_{int} = \mathrm{ASC}_i + \beta' x_{int} + \varepsilon_{int}, \tag{1}$$

where $V_{int}$ is a systematic component, and $\varepsilon_{int}$ is a random variable following an extreme value type I distribution with location parameter 0 and scale parameter 1. The term $V_{int}$ depends on observable explanatory variables, which are usually attributes ($x_{int}$) and the vector of estimated attribute parameters ($\beta$). In (1), $\mathrm{ASC_i}$ is an alternative specific constant for alternative $i$ normalised to zero for one of the J alternatives.

The standard LCM specification forms the basis of the developments in this paper. Given membership of class $c_s$, the probability of respondent $n$'s sequence of choices is given by

$$\Pr\left(y_n^t|c_s, x_n\right) = \prod_{t=1}^{T_n} \frac{\exp(\mathrm{ASC}_i^{c_s} + \beta'_{c_s} x_{int})}{\sum_{j=1}^{J} \exp(\mathrm{ASC}_i^{c_s} + \beta'_{c_s} x_{jnt})}, \tag{2}$$

where $y_n^t$ is the sequence of choices over the $T_n$ choice occasions for respondent $n$. Equation (2) is a product of MNL probabilities. If the probability of membership to an LC $c_s$ of respondent $n$ is defined as $\pi_{n,c_s}$, the unconditional probability of a sequence of choices can be derived by taking the expectation over all $C$ classes, that is

$$P_n = \Pr\left(y_n^t|x_n\right) = \sum_{s=1}^{C} \pi_{n,c_s} \prod_{t=1}^{T_n} \frac{\exp(\mathrm{ASC}_i + \beta'_{c_s} x_{int})}{\sum_{j=1}^{J} \exp(\mathrm{ASC}_i + \beta'_{c_s} x_{jnt})}. \tag{3}$$

The class allocation probabilities $\pi_{n,c_s}$ are usually modelled by using a logit structure, where the utility of a class is a function of a constant $\mu_{0,s}$, the socio-demographics of the respondent ($\mathrm{SD}_n$) and corresponding parameters ($\lambda_s$), that is

$$\pi_{n,c_s} = \frac{\exp\left(\mu_{0,s} + \lambda'_s \mathrm{SD}_n\right)}{\sum_{s=1}^{C} \exp\left(\mu_{0,s} + \lambda'_s \mathrm{SD}_n\right)}. \tag{4}$$

The additional constant $\mu_{0,s}$ and parameters $\lambda$ are fixed to zero for one of the classes for normalisation reasons.

As the next step, we used the answers provided by respondents to the lottery choices reported in Table 3. These answers are, together with respondents' choices in the CE, driven by underlying risk preferences; nevertheless, they are not direct measures of them. The latent risk preferences are therefore treated as LVs, and the lottery choices are used as indicators in the model. The structural equation for the LV is given by

$$\mathrm{LV}_n = \gamma_1 Z_{1n} + \gamma_2 Z_{2n} + \cdots + \gamma_m Z_{mn} + \omega_n, \tag{5}$$

where $Z_{1n}$, $Z_{2n}$, …, $Z_{mn}$ are the specific socio-demographic variables, and $\omega_n$ is a random disturbance that is assumed to be normally distributed with a zero mean and standard deviation $\sigma_\omega$.

The measurement equations use the lottery choices as dependent variables and, therefore, as indicators of individuals' risk aversion. The $\ell$th indicator of all $L$ indicators (in our case, $L = 9$ as in the last 10th lottery, lottery B was chosen by all individuals) for respondent $n$ is defined as follows:

$$I_{\ell n} = m(\mathrm{LV}_n, \zeta) + v_n, \tag{6}$$

where the indicator $I_{\ell n}$ is a function of $\mathrm{LV}_n$ and a vector of parameters $\zeta$. The responses to the lottery choice are binary; therefore, the measurement equation for individual $n$ is modelled as a binary logit model for the LV:

$$I_{\ell n} = \begin{cases} 0 & \text{if } -\infty < \mathrm{LV}_n \leq \tau_\ell \\ 1 & \text{if } \tau_\ell < \mathrm{LV}_n \leq \infty \end{cases}, \tag{7}$$

where $\tau_\ell$ are the thresholds that need to be estimated. The likelihood of a specific observed value of $I_{\ell n}$ is then given by

$$L_{I_{\ell n}} = I_{(I_{\ell n}=0)} \left[ \frac{\exp(\tau_\ell - \zeta_\ell \mathrm{LV}_n)}{1 + \exp(\tau_\ell - \zeta_\ell \mathrm{LV}_n)} \right] + I_{(I_{\ell n}=1)} \left[ 1 - \frac{\exp(\tau_\ell - \zeta_\ell \mathrm{LV}_n)}{1 + \exp(\tau_\ell - \zeta_\ell \mathrm{LV}_n)} \right], \tag{8}$$

where $\zeta_\ell$ measures the impact of $\mathrm{LV}_n$ on indicator $I_{\ell n}$ and $\tau_\ell$ is estimated as the threshold parameter. In the present study, we used a novel approach to link the two parts of the model. We estimated an LCM and allowed interaction of the LV defined in (5), with the alternative specific constant of the business-as-usual option ($\mathrm{ASC_{SQ}}$) in each class in order to analyse the effect of the LV on the riskiest alternative in terms of the survival of both lynx populations.

The terms $V_{int}$ of (1) corresponding to class $c_s$ are defined as follows:

$$
\begin{aligned}
V_{1nt}^{c_s} &= \left(\mathrm{ASC}_{\mathrm{SQ}}^{c_s} + \delta^{c_s}\mathrm{LV}_n\right) + \beta_{\mathrm{Carpa}}^{c_s}\mathrm{Carpa}_{1nt} + \beta_{\mathrm{Lowland}}^{c_s}\mathrm{Lowland}_{1nt} + \beta_{\mathrm{Cost}}^{c_s}\mathrm{Cost}_{1nt} \\
V_{2nt}^{c_s} &= \mathrm{ASC}_{2}^{c_s} + \beta_{\mathrm{Carpa}}^{c_s}\mathrm{Carpa}_{2nt} + \beta_{\mathrm{Lowland}}^{c_s}\mathrm{Lowland}_{2nt} + \beta_{\mathrm{Cost}}^{c_s}\mathrm{Cost}_{2nt} \\
V_{3nt}^{c_s} &= \beta_{\mathrm{Carpa}}^{c_s}\mathrm{Carpa}_{3nt} + \beta_{\mathrm{Lowland}}^{c_s}\mathrm{Lowland}_{3nt} + \beta_{\mathrm{Cost}}^{c_s}\mathrm{Cost}_{3nt}
\end{aligned}
\tag{9}
$$

where Carpa, Lowland and Cost are the choice attributes described in Table 2, $\delta$ is the parameter corresponding to the LV, which is added to the constant term in the business-as-usual option, and $\beta$ are the class-specific attribute parameters.

The estimation of the model involves maximising the joint likelihood of the observed sequence of choices and observed answers to the lottery choices. The two components are conditional on the given realisation of $\mathrm{LV}_n$. Accordingly, the log-likelihood function of the model is given by integration over $\omega_n$ as follows:

$$
LL(\beta, \mu, \gamma, \mu, \zeta, \tau) = \sum_{n=1}^{N} ln \int_{\omega} (P_n \prod_{\ell=1}^{9} L_{I_{\ell n}}) g(\omega) d\omega, \tag{10}
$$

where $P_n$ is defined in (3), with class allocation probabilities $\pi_{n,c_s}$ defined in (4), and $L_{I_{\ell n}}$ is defined in (8) for $\ell$ = 1, 2, …, 9. The joint likelihood function (10) depends on the parameters of the utility functions $\beta = (\mathrm{ASC}_1^{C_s}, \mathrm{ASC}_2^{C_s}, \beta_{\mathrm{Carpa}}^{C_s}, \beta_{\mathrm{Lowland}}^{C_s}, \beta_{\mathrm{Cost}}^{C_s})$, the parameters $\mu = (\mu_{0,s})$ and $(\lambda_1^s, \lambda_2^s, \ldots, \lambda_K^s)$ contain the parameters used in the allocation probabilities defined in (4), $\gamma = (\gamma_0, \gamma_1, \gamma_2, \ldots, \gamma_m)$ contain the parameters for the socio-demographic interactions in the LV specification defined in (5), and $\zeta = (\zeta_1, \zeta_2, \ldots, \zeta_{10})$ and $\tau = (\tau_1, \tau_2, \ldots, \tau_{10})$ contain the parameters defined in (6) and (7). We follow the Bolduc normalisation by setting $\sigma_\omega = 1$. All model components were estimated simultaneously by using PythonBiogeme (Bierlaire 2003, 2008).

### 3.5. Data

A quota sample of respondents was drawn, representative of the city of Warsaw in terms of gender, age and education. The survey was carried out in February 2011. Interviews were conducted by a professional polling agency by using the computer-assisted personal interviewing system. In total, 300 questionnaires were collected. The main survey was pretested in 50 face-to-face interviews with students from the Faculty of Economics at the University of Warsaw (Table 4).

Individuals were excluded from the analysis if they chose the safe option for decision 10 in the lottery experiment or if they switched constantly

**Table 4** Descriptive statistics of the analysed sample

| | Share (%) | Mean | Median | Min | Max |
|---|---|---|---|---|---|
| Women | 53 | — | — | — | — |
| Age | — | 46 | 47 | 20 | 90 |
| Education | | | | | |
| Primary | 8 | — | — | — | — |
| Secondary | 49 | — | — | — | — |
| High | 43 | — | — | — | — |
| Net monthly household income in zł | — | 4359 | 3500 | 500 | 22,500 |

between lottery A and lottery B for all 10 decisions. The literature shows that generally, a certain share of respondents does not understand the design of the lottery, that is the changes in the probabilities of the outcomes in lottery A and lottery B. These respondents are thus excluded from further analysis. Additionally, respondents who always chose the most expensive alternative in the CE part were omitted. We assumed that these individuals were protesting against some aspect of the survey. This resulted in a final set of responses from 214 individuals corresponding to 1284 observations to be analysed.

## 4. Results

### 4.1. Risk preference elicitation

Of the analysed sample, 69 per cent of respondents started with lottery A, then switched from this option to lottery B just once and played this lottery thereafter. On the contrary, 31 per cent switched back from the risky lottery B to lottery A. Holt and Laury (2002), Lusk and Coble (2005) and Anderson and Mellor (2008) also report this kind of behaviour in their lottery experiments, but the share of multiple switchers in their cases is lower (13, 5 and 21 per cent, respectively). However, the first two surveys were conducted solely among students, while only the Anderson and Mellor's (2008) sample comprised mostly nonstudent adults. In the present survey, respondents were recruited from the general public. This might explain why we observe a larger share of respondents who switch back as could be expected in a sample with students; for example, Table 5 shows the share of 'safe' choices (lottery A) in the sample.

### 4.2 Hybrid latent class model results

Similar to a standard LCM framework, the first task when specifying a hybrid latent class model (HLCM) is to determine the number of classes. Table 6 reports LCM and HLCM's goodness-of-fit indicators together with the number of parameters. As expected, the log-likelihood decreases as the

**Table 5** Responses to the lottery

| Decision | Share of 'safe' choices (Lottery A) (%) |
|---|---|
| Row 1 | 75 |
| Row 2 | 64 |
| Row 3 | 74 |
| Row 4 | 60 |
| Row 5 | 59 |
| Row 6 | 36 |
| Row 7 | 41 |
| Row 8 | 29 |
| Row 9 | 31 |

number of classes increases. For the HLCM, the BIC and CAIC indicate a solution with three classes, while the AIC favours models with four classes. However, the AIC tends to overestimate the number of classes, and moreover, there is consensus in the literature that parsimony is preferable in modelling, especially in this complicated hybrid framework. For the LCM, the three-class model is the preferred option indicated by the three indicators. Therefore, we choose the LCM with three classes for further analysis.

Table 7 presents the estimations of the plain and the hybrid LCM. As expected, there is little difference in the parameter estimates between these two estimations. The hybrid model uses additional information for the estimation of the choice part model, which allows for a richer interpretation. The Cost coefficient in all three classes and two attribute parameters indicating an improvement in lynx protection is significant at a level of 5 per cent with the expected positive sign in the second and third classes. Respondents in these two classes would be better off if conservation measures leading to better lynx conservation were implemented, but at different costs. However, lynx conservation attributes are not significant in the first class.

The estimation of the allocation model of the plain LCM (Table 8) showed no significant socio-demographics. However, in the HLCM, apart from the constant variable, age was also significant in the allocation function of class 3.

**Table 6** Goodness-of-fit criteria for different numbers of classes

| | Latent class model | | | Hybrid latent class model | | |
|---|---|---|---|---|---|---|
| | 2 Classes | 3 Classes | 4 Classes | 2 Classes | 3 Classes | 4 Classes |
| LogL | −926.4 | −862.7 | −854.6 | −1850.9 | −1796.0 | −1776.5 |
| Number of parameters | 15 | 25 | 35 | 39 | 50 | 61 |
| Sample size | 1284 | 1284 | 1284 | 1284 | 1284 | 1284 |
| AIC | 1882.9 | **1775.3** | 1779.2 | 3779.8 | 3692.0 | **3675.0** |
| BIC | 1960.2 | **1904.3** | 1959.7 | 3981.0 | **3949.9** | 3989.6 |
| CAIC | 1975.2 | **1929.3** | 1994.7 | 4020.0 | **3999.9** | 4050.6 |

**Table 7** Estimation results: choice model component

| | Latent class model | | | | | |
|---|---|---|---|---|---|---|
| | Class 1 | | Class 2 | | Class 3 | |
| Class prob. | 0.06 | | 0.06 | | 0.88 | |
| | Est. | Rob. *t*-rat. | Est. | Rob. *t*-rat. | Est. | Rob. *t*-rat. |
| $ASC_{SQ}$ | 0.577 | 0.60 | −3.12*** | −8.41 | −1.920*** | −4.21 |
| $ASC_{A}$ | −0.873 | −1.18 | 0.47* | 1.85 | 7.720 | 0.86 |
| Carpathian | 0.045 | 0.16 | 0.375** | 2.20 | 0.455*** | 5.03 |
| Lowland | −0.367 | −1.18 | 0.271** | 2.47 | 0.660*** | 7.57 |
| Cost | −0.016* | −1.94 | −0.035*** | −5.69 | −0.003*** | −2.61 |
| | **Hybrid latent class model** | | | | | |
| | Class 1 | | Class 2 | | Class 3 | |
| Class prob. (median) | 0.17 | | 0.17 | | 0.66 | |
| (25th, 75th percentile) | (0.14, 0.23) | | (0.14, 0.23) | | (0.53, 0.72) | |
| | Est. | Rob. *t*-rat. | Est. | Rob. *t*-rat. | Est. | Rob. *t*-rat. |
| $ASC_{SQ}$ | −11.900* | −1.93 | −4.010*** | −3.93 | −1.640*** | −3.25 |
| δ (LV coeff.) | 15.200** | 2.30 | −3.270*** | −3.48 | 0.401 | 0.92 |
| $ASC_{A}$ | 0.546 | 1.40 | −0.057 | −0.14 | 0.066 | 0.59 |
| Carpathian | −0.038 | −0.12 | 0.520* | 1.92 | 0.531*** | 4.36 |
| Lowland | 0.103 | 0.48 | 0.251* | 1.65 | 0.705*** | 6.54 |
| Cost | −0.015** | −2.02 | −0.049*** | −3.11 | −0.004** | −2.39 |

***, **, * denote significance at the 1%, 5%, and 10% level respectively.

The corresponding class probabilities computed according to (4) are presented in Table 7. The highest probability is assigned to class 3 in the two estimated models.

Table 9 presents estimation results of the structural and measurement equations and confirms that the latent risk preferences influence respondents' decision processes as the impact of the LVs on the lottery choices was clearly significant for all nine latent risk preference indicators ($\zeta$). Only household income of the four socio-demographic variables included in the set of structural equations is significant (9), indicating that people with higher household incomes have higher values of the LVs.[3]

According to (7), a higher value of $\mathrm{LV}_n$ implies a lower probability of choosing the safer lottery A (because the term $\tau_\ell - \zeta_\ell \mathrm{LV}_n$ becomes lower) but a higher probability of choosing the riskier lottery B. This result therefore indicates that respondents with higher household incomes are more risk seeking than respondents with lower incomes. On the contrary, for a given value of $LV_n$, the gradual decrease in the parameters $\zeta_\ell$ and $\tau_\ell$ for the sequence of lotteries 1–9 (Table 9) indicates a decrease in the probability

[3] The low number of significant socio-demographics is a typical characteristic of hybrid choice models (Daly *et al.* 2012).

**Table 8** Estimation results: probability allocation functions

| Latent class model | | | | | |
|---|---|---|---|---|---|
| Class 2 | Est. | Rob. *t*-rat. | Class 3 | Est. | Rob. *t*-rat. |
| $\mu_{0,2}$ | 1.610 | 1.32 | $\mu_{0,3}$ | **2.760**** | 2.53 |
| $\lambda_{\text{Age},2}$ | 0.018 | 0.10 | $\lambda_{\text{Age},3}$ | −0.112 | −0.69 |
| $\lambda_{\text{Female},2}$ | −0.432 | −0.77 | $\lambda_{\text{Female},3}$ | −0.250 | −0.47 |
| $\lambda_{\text{Household income},2}$ | 0.271 | 0.20 | $\lambda_{\text{Household income},3}$ | 0.190 | 0.14 |
| $\lambda_{\text{University},2}$ | −0.016 | −0.02 | $\lambda_{\text{University},3}$ | −0.470 | −0.80 |
| Hybrid latent class model | | | | | |
| Class 2 | Est. | Rob. *t*-rat. | Class 3 | Est. | Rob. *t*-rat. |
| $\mu_{0,2}$ | 1.490 | 1.25 | $\mu_{0,3}$ | **2.470**** | 2.43 |
| $\lambda_{\text{Age},2}$ | −0.219 | −1.08 | $\lambda_{\text{Age},3}$ | **−0.277*** | −1.70 |
| $\lambda_{\text{Female},2}$ | −0.078 | −0.11 | $\lambda_{\text{Female},3}$ | 0.078 | 0.14 |
| $\lambda_{\text{Household income},2}$ | −0.649 | −0.74 | $\lambda_{\text{Household income},3}$ | −0.212 | −0.32 |
| $\lambda_{\text{University},2}$ | −0.040 | −0.06 | $\lambda_{\text{University},3}$ | −0.572 | −0.99 |

**Table 9** Estimation results: structural and measurement equations

| Structural equation | | |
|---|---|---|
| | Est. | Rob. *t*-rat. |
| $\gamma_{\text{Age}}$ | 0.010 | 0.18 |
| $\gamma_{\text{Female}}$ | −0.198 | −0.86 |
| $\gamma_{\text{Household income}}$ | 0.435** | 3.47 |
| $\gamma_{\text{University}}$ | −0.056 | −0.35 |

| Measurement equations | | | | | |
|---|---|---|---|---|---|
| | Est. | Rob. *t*-rat. | | Est. | Rob. *t*-rat. |
| $\tau_1$ | 3.42** | 2.52 | $\zeta_1$ | 4.36*** | 4.02 |
| $\tau_2$ | 1.55* | 1.79 | $\zeta_2$ | 3.34*** | 3.34 |
| $\tau_3$ | 2.43*** | 2.78 | $\zeta_3$ | 2.90*** | 4.08 |
| $\tau_4$ | 1.33 | 1.42 | $\zeta_4$ | 3.20*** | 2.74 |
| $\tau_5$ | 0.94 | 1.28 | $\zeta_5$ | 2.78*** | 5.12 |
| $\tau_6$ | −0.65 | −0.97 | $\zeta_6$ | 2.48*** | 4.31 |
| $\tau_7$ | −0.38 | −0.84 | $\zeta_7$ | 1.68*** | 3.97 |
| $\tau_8$ | −1.14** | −2.21 | $\zeta_8$ | 1.81*** | 3.92 |
| $\tau_9$ | −0.95*** | −2.63 | $\zeta_9$ | 1.24*** | 3.71 |

of choosing the safer lottery A for the benefit of the riskier choice of lottery B. This finding is in accordance with the expected pay-offs presented in Table 3.

The parameter $\delta$ corresponding to the LV added to the constant term in the SQ alternative (8) is significant at 5 per cent in two of the three classes (Table 7). In the first class, its effect is positive and negative in the second.

Individuals with a high value for these constants are more likely to choose (for the lynx population) the riskier SQ option. In other words, the LV clearly affects respondents' choices and, therefore, their WTP measures. The LV can interact with the choice model in many different ways. For example, it can influence the attribute coefficients in (1) or it can be an explanatory in allocation probabilities (4). The estimation of these alternative specifications led, however, to nonsignificant interaction and that is why only the effect on SQ constant was finally included.

In the next step, WTP measures were computed from the HLCM estimates, giving the implied monetary valuation of different changes in attribute levels. These values are probability-weighted WTP values corresponding to the parameters presented in Table 7; that is for the Carpathian population, the individual WTP values are computed as follows:

$$\mathrm{WTP} = \pi_{n,c_1}\left(-\frac{\beta^{c_1}_{\mathrm{Carpa}}}{\beta^{c_1}_{\mathrm{Cost}}}\right) + \pi_{n,c_2}\left(-\frac{\beta^{c_2}_{\mathrm{Carpa}}}{\beta^{c_2}_{\mathrm{Cost}}}\right) + \pi_{n,c_3}\left(-\frac{\beta^{c_3}_{\mathrm{Carpa}}}{\beta^{c_3}_{\mathrm{Cost}}}\right). \tag{11}$$

Table 10 shows, for the sample population of respondents, the distribution of the WTP values based on the plain LCM and the HLCM for both lynx populations. It also presents the WTP values computed by using the posterior estimate of the LC probabilities defined as follows:

$$\hat{\pi}_{c_s|n} = \frac{\hat{P}_{n|c_s}\hat{\pi}_{n,c_s}}{\sum\limits_{s=1}^{C}\hat{P}_{n|c_s}\hat{\pi}_{n,c_s}}, \tag{12}$$

where $\hat{P}_{n|c_s}$ represents, for the given class assignment, the contribution of individual $n$ to the likelihood through the joint probability of the sequence defined as follows:

$$\hat{P}_{n|c_s} = \prod_{t=1}^{T_n} \frac{\exp(\widehat{\mathrm{ASC}}^{c_s}_i + \hat{\beta}'_{c_s} x_{int})}{\sum\limits_{j=1}^{J}\exp(\widehat{\mathrm{ASC}}^{c_s}_i + \hat{\beta}'_{c_s} x_{jnt})}. \tag{13}$$

According to the definition of the utility function (8), the constant ($\mathrm{ASC}^{\mathrm{c_s}}_{\mathrm{i}}$) for the business-as-usual option is respondent specific and a function of $LV_n$, which at the same time depends on one socio-demographic variable (household income) and a random error term (5), meaning that the constant follows a random distribution. In order to compute the posterior estimate of the LC probabilities, we simulate the constant corresponding to the business-as-usual option according to (5) and (9) by using 10,000 draws for the LV of each respondent, combining the estimated parameter $\gamma_{\mathrm{Household\ income}}$ with the corresponding values of the variable household income and adding generated random errors $\omega$.

**Table 10** Marginal willingness to pay in zł

| | Hybrid latent class model (zł) | | |
|---|---|---|---|
| | 25th percentile | Median | 75th percentile |
| Using prior probabilities | | | |
| Carpathian | 69.1 | 75.2 | 83.1 |
| Lowland | 92.8 | 100.3 | 111.5 |
| Using posterior probabilities | | | |
| Carpathian | 28.5 | 129.9 | 137.8 |
| Lowland | 34.9 | 172.7 | 183.0 |
| | Latent class model (zł) | | |
| | 25th percentile | Median | 75th percentile |
| Using prior probabilities | | | |
| Carpathian | 71.5 | 76.0 | 81.6 |
| Lowland | 98.5 | 105.3 | 113.8 |
| Using posterior probabilities | | | |
| Carpathian | 14.2 | 100.7 | 129.9 |
| Lowland | 13.1 | 144.2 | 188.3 |

As shown in Table 10, the posterior LC probabilities increase the spread of the two distributions and shift them slightly to the right. The WTP for the Lowland population is higher than that for the Carpathian population, suggesting that people prefer to invest more in conservation programs that protect the population at a higher risk of extinction.

Table 11 presents the same WTP values corresponding to the HLCM and based on the posterior LC probabilities. The structure of the HLCM and the two relevant socio-demographic variables in (4) and (5) allow simulation of the WTPs for four subgroups characterised by different age and household income levels. Individuals assigned to the low (high) household income group are those with a household income lower than the 25th (higher than the 75th) percentile. Similarly, assignment to the younger and older age groups is based on the 25th and 75th percentiles of the variable age.

**Table 11** Distribution of the marginal willingness to pay in zł for different subgroups

| | Low household income (zł) | | | High household income (zł) | | |
|---|---|---|---|---|---|---|
| | 25th percentile | Median | 75th percentile | 25th percentile | Median | 75th percentile |
| Younger people | | | | | | |
| Carpathian | 50.1 | 134.1 | 137.8 | 63.0 | 136.6 | 137.9 |
| Lowland | 67.1 | 178.1 | 182.1 | 81.2 | 181.4 | 183.1 |
| Older people | | | | | | |
| Carpathian | 19.4 | 127.7 | 137.7 | 26.0 | 124.1 | 137.8 |
| Lowland | 25.7 | 170.2 | 182.9 | 31.02 | 164.5 | 183.0 |

The results show that older people are less willing to invest in the 20-year protection program than younger people. On the contrary, people with a higher household income are willing to pay more than people with a low household income. An interesting result is that the differences in WTP distributions are much higher between younger and older people than between people with low and high household incomes. This finding means that people are aware of the risk of lynx extinction in Poland and are willing to invest in conservation programs; nevertheless, their WTP increases slowly with household income but decreases rapidly with age.

The two competing models presented in Tables 7 and 8 show very similar parameter estimation and, subsequently, very similar WTP values (Table 10). A comparison of their goodness of fit is, however, not straightforward, and there is still ongoing debate regarding the added value of hybrid models. Seeking an alternative fit comparison, we computed the predicted probabilities for the two models. Afterwards we generated 1000 uniform random numbers between 0 and 1 for each individual and simulated his/her predicted outcome. Table 12 presents the classification table of observed and predicted outcomes for the plain LCM and the HLCM. The Count $R^2$ defined as percentage of correct predictions located on the diagonal cells of the two matrices in Table 11 is 42.5 per cent for the LCM and 41.3 per cent for the HLCM. Thus, similar to the estimation results, the predictions of the two models are very similar.

## 5. Conclusions and discussion

This paper extents our knowledge about the association between individual risk preferences and investments in an environmental good with uncertain results. As far as we are aware of the literature, the study has introduced two new elements: firstly, the use of an incentivised MPL to elicit risk preferences and, secondly, the application of a LV model to link the responses to a lottery and to a CE. Using this approach, we analysed the role that latent risk preferences may play in people's preferences towards lynx protection in Poland.

**Table 12** Classification tables of observed and predicted outcomes for latent class (LC) and hybrid latent class (HLC) models

| HLCM | | | | | LCM | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Predicted | | | | | Predicted | | |
| | | 1 | 2 | 3 | | | 1 | 2 | 3 |
| Observed | 1 | 2.7% | 2.8% | 4.0% | Observed | 1 | 2.3% | 2.1% | 5.1% |
| | 2 | 9.8% | 17.5% | 22.6% | | 2 | 6.5% | 13.6% | 29.8% |
| | 3 | 7.5% | 17.5% | 21.1% | | 3 | 4.8% | 13.6% | 26.6% |
| Count $R^2$ | | 41.3% | | | Count $R^2$ | | 42.5% | | |

The results show that individuals' latent risk preferences are significantly related to the constant of the business-as-usual option, that is the option without additional conservation measures and a zero price, influencing, therefore, the probability that it will be chosen. It is also noteworthy that the incorporated LV is significantly related to the variable household income. This finding is in line with other findings in the literature, suggesting that risk preferences may be correlated with wealth (Rosenzweig and Binswanger 1993; Liu 2013).[4] At the same time, the LV provides a strong explanation of respondents' choices in the series of nine lotteries. The results thus confirm the findings from other studies indicating that respondents' choices are, apart from the attributes of the alternatives, related to their latent risk preferences.

Our findings also indicate that the choice of the business-as-usual option may be linked to fundamental risk preferences, even if exacerbated by psychological influences such as framing or anchoring effects (Tversky and Kahneman 1974). Often, in CEs regarding conservation policies, the business-as-usual option without further measures is the riskiest of the presented alternatives because not carrying out additional measures increases the likelihood that populations become extinct. The other alternatives are usually programs aimed at improving the current environmental situation. Therefore, it may be prudent to elicit individual risk preferences as a possible explanatory variable in order to estimate the impact on estimated WTP.

The methodological novelty of this study arises from developing a new approach to linking the LVs to the choice model part. We estimate the hybrid model, which resembles an LCM but allows for the interaction of the LV with an attribute (in this case, the ASC of the business-as-usual option) in each class. The comparison of the plain LCM and HLCM questions the usefulness of the more complicated approach based on LVs. As already stated in the literature, hybrid models gain in efficiency by the inclusion of additional information, for example attitudinal questions in the choice model. If we compare the performance of our two models, both perform very similarly and no big differences can be found between the estimated parameters and the prediction outcomes. However, the methodologically advanced hybrid model presented in this application shows complex forms of intervariable relations and how they relate to preference heterogeneity. Overall, our findings, that is similar parameter estimates, similar model fit and narrower WTP spread, support the conclusion of Dekker *et al.* (2013) and Kløjgaard and Hess (2014) who point out that advanced hybrid choice models do not result in different key findings compared to standard approaches, despite a greater insight into attitudes as drivers of choices as well as some gains in efficiency. Nevertheless, the outstanding feature of the HLCM in our study is the link of the stated WTP to the socio-demographic variables not found in the plain LCM. That the marginal WTP estimates found in the LV model do not

[4] However, the literature on whether risk preferences vary with wealth level is inconclusive (Cardenas and Carpenter 2008).

significantly differ from those derived from a rather standard modelling approach is also reported by Lundhede *et al.* (2015). They furthermore support our finding that the LV model gives valuable insights into the patterns underlying the stated choices. Regarding the provided insight, it is noteworthy that Lundhede *et al.* (2015) also found a significant influence of age on the LV and subsequently on a lower WTP of older people.

Overall, based on the results, we believe that employing a CE and a lottery in the same survey is a promising combination. Various issues, however, remain and need to be addressed in future studies. Holt and Laury's (2002) MPL, for example, was designed to capture risk preferences in the financial domain. While it has been shown in the literature that risk preferences elicited using this approach are also meaningful in other domains, for example for predicting health behaviours (Andersen and Mellor, 2008), lotteries aiming directly at environmental risks might be more suitable as a determinant of choices among alternatives with uncertain environmental outcomes. Finally, the application of the LV approach is still new to environmental valuation, especially regarding uncertainties of conservation policies. In line with the study by Lundhede *et al.* (2015), the results indicate that these models give richer insights into what determines choice among the offered alternatives. To what extent this finding can be generalised has to be answered by future studies.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article:

**Data S1.** Data and codes.