Combining risk attitudes in a lottery game and flood risk protection decisions in a discrete choice experiment

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Abstract

Decision-making about flood protection is surrounded by outcome uncertainty. In this paper we look at the influence of individual risk attitudes on flood protection decisions. To this end, we combine the results of a lottery game with the findings from a discrete choice experiment focusing on flood risk reduction measures. We find that the inclusion of non-linear probability weighting increases the explanatory power of the choice model. The result is however sensitive to behavioral assumptions about decisions under uncertainty, as well as whether the lottery was played in the loss or gain domain. Including risk attitudes in the probability weighted model decreases marginal willingness to pay for measures with a low to intermediate flood risk reduction capacity and increases marginal willingness to pay for measures with a very high flood risk reduction effect. This has important implications for the social acceptability of flood reduction measures under different baseline conditions.

Keywords: Lottery game; Choice experiment; Flood risk; Bayesian Model Averaging;
Risk attitudes

JEL: C11, C57, D81, Q54

1 Introduction

Natural disasters are potentially hazardous events with a high level of uncertainty. Flooding in particular repeatedly caused high economic damages in Switzerland and accounted for more than 70% of the financial damages caused by natural hazards over the last four decades (Hausmann et al. 2012). Vulnerability to flooding is predicted to increase in Switzerland due to growing population density, mobility and the increasing value of economic assets in flood prone areas (Planat 2005). In addition, climate change related variations in peak precipitation is expected to lead to higher flood damages due to surface runoffs (Swiss Academy of Sciences 2016). With an increase in economic damage looming, additional flood protection and mitigation measures become more important. Besides public flood protection, private measures can help to further limit flood damages (Botzen et al. 2009; Grothmann and Reusswig 2006). However, Siegrist and Gutscher (2006) show that precautionary behavior is insufficiently fostered. Although the potential impacts can be very severe, flooding is in most locations a low probability event and individual decisions about flood protection and mitigation are subject to a high level of outcome uncertainty.

Decisions under uncertainty are usually described using von Neumann and Morgenstern's Expected Utility Theory (EUT), where subjective linear probabilities serve to produce weighted outcome values (de Palma et al. 2008). While it has been considered the standard theory for decisions under risk for a long time, EUT is increasingly challenged (Rabin 2002). Main deviations from EUT include sensitivity to the outcome domain and reference dependency. The idea that an economic agent reacts differently depending on whether an outcome is considered a gain or a loss is formulated in Prospect Theory (PT) (Kahneman and Tversky 1979). A second deviation describes the potential bias in the individual evaluation of probabilities as well as outcomes. Non-linear weighting of probabilities is suggested by rank-dependent EUT (Quiggin 1982) and was later implemented into rank-dependent PT (Tversky

and Kahneman 1992). Risk preferences, be it according to EUT or PT, are therefore likely to differ across individuals and baseline conditions. Bruhin et al. (2010) found a large variation in risk behavior related to financial lottery outcomes, with only around 20% of the respondents displaying an almost linear weighting of probabilities, consistent with predictions from EUT. The remaining participants showed moderate (50%) to strong (30%) deviations from linear probability weighting.

Both value and probability can influence a decision under risk, as is the case in the context of flood risk reduction. Petrolia et al. (2013) found a clear influence of risk aversion on the decision to purchase flood insurance in the Gulf of Mexico. The result was domain sensitive as only preferences elicited in the loss domain showed a significant impact. Another study by Botzen and van den Bergh (2012) concludes that Dutch citizens do not behave as predicted by EUT and either ignore flood risks or are willing to overpay for flood insurance. In their flood risk study in the Netherlands, Brouwer and Schaafsma (2013) find evidence of significant preference heterogeneity surrounding the valuation of flood probabilities, with linear preferences for changes in flood probabilities in the gain domain and willingness to pay (WTP), and non-linear preferences for changes in flood probabilities in the loss domain and willingness to accept (WTA) compensation. Koetse and Brouwer (2016) show that the disparity between WTP and WTA is sensitive to flood probabilities change, reference point and direction of change. They furthermore demonstrate that the reference point effect on flood probability valuation is larger for losses than for gains. Brouwer et al. (2013) find non-linearity in the valuation of flood probabilities whilst controlling for preference heterogeneity in a discrete choice experiment (DCE) focusing on flood risk protection carried out in Vietnam. Glenk and Colombo (2013) account for respondents' risk behavior by including weights for risky outcomes into the indirect utility function based on a DCE, but do not find clear evidence in favor of or against the use of probability weighting over EUT.

In summary, there is evidence for non-linear treatment of probabilities. However, studies that specifically include separately elicited non-EUT risk preferences into a choice model are rare. To our knowledge, only Kutluay et al. (2017) applied probability weighting parameters in their discrete choice model focusing on public health risks in a developing country context and individual decision-making to buy malaria pills. However, no study exists that tests the domain sensitivity (i.e. gain or loss) of non-EUT risk attitudes and how the inclusion of externally elicited probability weighting functions in these different domains influences the predictive power of discrete choice models.

This paper hence builds on Kutluay et al. (2017) but aims to test explicitly the impact of including non-EUT risk attitudes from a lottery game played in the gain and in the loss domain into a discrete choice model focusing on public WTP for flood risk reduction measures in a low probability-high impact context. Including risk attitudes is expected to influence public WTP for flood protection measures. The main objective of this study is to test whether interaction effects of the risk attribute in a DCE with individual risk parameters derived from the lottery game decreases the unexplained variance and increases the predictive power of the estimated choice models. Of special interest is the performance of probability weighting reflecting non-EUT risk preferences. Risk parameters are estimated in both the loss and gain domain and their performance is compared in explaining choices in the context of flood risk reduction. Understanding risk attitudes more generally, as elicited in this study through the lottery game, and testing their transferability to flood risk preferences elicited in a DCE can help in the design of future flood protection measures by predicting their social acceptance.

2 Methods

The study builds on two main parts. In a first step, respondents in a large-scale survey are

given a series of lottery choices. From the choices in the lottery game, their risk attitudes are derived. In a second step, a DCE is conducted to measure the respondents' WTP for flood protection measures. A discrete choice model is estimated combining the results from both the lottery game and the DCE.

2.1 Lottery game

A lottery game can be used to obtain individual risk attitudes to uncertain financial outcomes. Its main goal in this study is to test the suitability of EUT to explain choice behavior under uncertainty compared to a combination of probability and value weighting procedures that violate EUT, such as cumulative PT. For the purpose of this paper we apply a variation to the lottery game introduced in Harrison et al. (2010). The game consists of seven lottery tasks with two alternatives, where each alternative features one to three possible outcomes. An example of a lottery card is presented in the Appendix (Figure A1). Respondents were randomly allocated to one of two groups that played different versions of the lottery game, either in the gain or in the loss domain. The lottery game in the gain domain was identical to the lottery used in Harrison et al. (2010), with payouts scaled to a maximum of CHF 11.¹ Since it was not possible to let respondents lose money in the lottery game, in the loss domain version they were given an endowment equal to the maximum payout of CHF 11 and, based on their decisions, they could lose a part of this or the entire amount. The lottery designs for the gain and the loss domain were otherwise identical, aside from turning gains into losses. While losses from an endowment may not be the same as own losses, a study by Etchart-Vincent and L'Haridon (2011) found no statistical differences between the two approaches. As an incentive to state their true preferences, respondents received a payout based on a random selection of one of the 7 lottery tasks and their choice in that particular task. The outcome for the chosen alternative in this lottery task was determined using a random number

¹ Swiss Francs; 1 CHF=1.02 USD (exchange rate as of 30th November 2017).

generator and respondents were paid the amount of money associated with that outcome.

For the evaluation of the lottery choices, we follow the Bayesian modeling approach introduced by Balcombe and Fraser (2015). This allows us to estimate and evaluate different preference functions for risk attitudes. We estimate a total of 36 models using the R package *runjags* (Denwood 2016; R Core Team 2016). Individual risk attitudes are described as a combination of value and probability weighting parameters.

Value weighting describes the utility that respondents obtain from different amounts of money and hence allows us to assess risk attitudes. In this study value weighting is defined over the value range $[0, 1]$, and payouts are normalized by dividing them by the maximum payout over all lottery tasks. Risk averse behavior would, for example, result in the overweighting of small risks, i.e. a decision-maker would choose a small but certain (100%) payout over a payout of twice the size with a 50% probability.

This study tests the specific functions presented in equations (1) to (6). These functional forms relate to common value functions in the literature, a detailed description of which is provided in Stott (2006). In the equations, x describes unweighted and normalized values and α_i describes the value risk parameters. The power value weighting function shows a concave curve for parameter values lower than 1, which is akin to risk aversion. A parameter value higher than 1 leads to a convex weighting curve and represents risk seeking behavior. The Log and Expo functional forms lead to slightly concave utility curves that get steeper with increasing parameter values. The higher curvature of the Expo function leads to a relatively higher weighting of low values. The quadratic functional form features a concave curve reflecting risk aversion.

$$\text{Power:} \quad v(x) = x^{\alpha_1} \quad : \alpha_1 > 0 \quad (1)$$

$$\text{Expo:} \quad v(x) = 1 - e^{-\alpha_2 x} \quad : \alpha_2 > 0 \quad (2)$$

$$\text{Log:} \quad v(x) = \ln(1 + \alpha_3 x) \quad : \alpha_3 > 0 \quad (3)$$

$$\text{Quad:} \quad v(x) = x - \frac{\alpha_4 x^2}{2} \quad : \alpha_4 > 0 \cap \alpha_4 < \frac{2}{x_{max}} \quad (4)$$

$$\text{Power-II:} \quad v(x) = (\alpha_5 + x)^{\alpha_6} \quad : \alpha_5 > 0, \alpha_6 > 0 \quad (5)$$

$$\text{Expo-II:} \quad v(x) = 1 - e^{-\alpha_7 x^{\alpha_8}} \quad : \alpha_7 > 0, \alpha_8 > 0 \quad (6)$$

In addition to the utility that respondents gain from payouts, their perception of outcome probabilities can also influence their evaluation of a monetary prospect. Probability weighting was introduced as value weighting in EUT, which struggled to explain phenomena like the Allais Paradox (Allais 1979). The probability weighting functions are defined over the probability range $w \in [0,1]$. All probability functions are subject to rank dependency. For ordered prospects with $x_1 < x_2 < \dots < x_n$ the weighted probability w_j of a prospect p_j can be calculated as:

$$w_j = w(\sum_{i=1}^j p_i) - w(\sum_{i=1}^{j-1} p_i) : j=1, \dots, n \quad (7)$$

The probability functions shown in equations (8) to (13) are evaluated in this study. The forms suggested by Prelec (1998) and Kahneman and Tversky (1979) (K&T) show an inverse S-curve that weights extreme probabilities close to 0 and 1 stronger than intermediate ones. The Prelec function weights small probabilities stronger in comparison to K&T. The Power function features an overall convex to concave weighting over probabilities, depending on the parameter value. Prelec-II combines the effects of the power and the Prelec function. G&E relates to a Goldstein-Einhorn probability function reflecting preference reversal following a subjective interpolation process (Goldstein and Einhorn 1987). Lastly, linear probability is included to represent the assumption of EUT. For a more detailed description of these functional forms, see Stott (2006).

$$\text{Prelec:} \quad w(p) = e^{-(-\ln(p))^{\beta_1}} \quad : 0 < \beta_1 < 2 \quad (8)$$

$$\text{K\&T:} \quad w(p) = \frac{p^{\beta_2}}{(p^{\beta_2} + (1-p)^{\beta_2})^{\beta_2}} \quad : 0.27 < \beta_2 < 1 \quad (9)$$

$$\text{Power:} \quad w(p) = p^{\beta_3} \quad : 0 < \beta_3 < 2 \quad (10)$$

$$\text{Prelec-II:} \quad w(p) = e^{-\beta_4(-\ln(p))^{\beta_5}} \quad : 0 < \beta_4 < 2, 0 < \beta_5 < 2 \quad (11)$$

$$\text{G\&E:} \quad w(p) = \frac{\beta_6 p^{\beta_7}}{\beta_6 p^{\beta_7} + (1-p)^{\beta_7}} \quad : 0 < \beta_6 < 2, 0 < \beta_7 < 2 \quad (12)$$

$$\text{Linear:} \quad w(p) = p \quad (13)$$

Parameter are estimated based on the lottery results by applying Bayesian inference. Accordingly, parameters are characterized as inherently uncertain apart from some previous knowledge represented through prior information. The prior knowledge is then adjusted based on observed lottery choices according to:

$$P(\beta|X) = \frac{P(X|\beta) * P(\beta)}{P(X)} \quad (14)$$

where $P(\beta|X)$ represents the posterior estimate for preference parameter β given (lottery choice) observations X , $P(X|\beta)$ is the likelihood function, and $P(\beta)$ the prior assumption for the preference parameter β . $P(X)$ is the model evidence or the baseline probability of X . As X is our observed data, we assume it is constant for the purpose of comparison between Bayesian models.

The priors for the parameters α_i and β_i are selected based on the existing literature (Kutluay et al. 2017; Balcombe and Fraser 2015). More specifically, for informative normal priors for the value functions Power, Expo and Log, we follow Kutluay et al. (2017). The priors for all probability weighting functions and the Quad value function are specified as (weakly) informative priors within their theoretical limits (Balcombe and Fraser 2015). We slightly deviate from this in that the variance pre-transformed normal distributed factor is reduced to (13/8) in order to reduce the mass near 0 and 1. For the theoretical limits of the Quad functional form, we follow Kutluay et al. (2017). We estimate the posterior distribution of the risk attitude parameter with the Gibbs sampler runjags (Denwood 2016). In the estimation process, we start with 6'000 repetitions of the prior model estimate, continue with 1'000 adaptation steps and finally use 4'000 repetitions with a thinning factor of 10

2.2 Discrete choice experiment

In the DCE, the same survey respondents who played the lottery game were asked to choose between different flood protection options. The DCE design consisted of two blocks with 6 choice tasks each. Each choice task contained an opt-out option reflecting the status-quo and two hypothetical flood protection alternatives. The alternatives describe the flood risk reduction (25, 50, 75, 100%), the type of flood protection measure (public or private) and the annual costs to each household (4 levels varying between CHF 50 and CHF 500). Respondents were randomly assigned to one of the two blocks that were created in the software Ngene with a D-efficient design (d-error of 0.0007).

The flood risk reduction describes the expected decrease in flood risk compared to the current situation (status quo), measured in a percentage. The measure type describes whether a flood protection measure is private or public. Public measures are communal efforts that were exemplified in the survey to respondents as ranging from better water drainage to extra overflow basins and other protective infrastructure like dikes. These measures are expected to offer protection not only to individual residential homes, but also to public infrastructure (e.g. communal buildings, roads and railways). Private measures are organized by the respondents themselves and offer protection to their homes exclusively. Examples are sandbags, back-flow valves or flood-proofing critical parts of their home, such as electricity boxes. The cost attribute describes the additional yearly expenses for the individual household. The payment vehicle depends on the measure type and is an out-of-pocket cost for private measures and an increase in annual water fees for public measures. These were the preferred payment vehicles based on a pre-test of the survey. Respondents were asked to answer as truthfully as possible and imagine that they would actually pay for their preferred flood protection measures to

enhance the incentive-compatibility of the DCE. The opt-out presented in the DCE is described as no flood risk reduction and hence no additional costs. An example of a choice task is shown in shown in the Appendix (Figure A2). In addition to the DCE, respondents answered questions about their socio-demographic background, their flood experience, flood risk perception, previous investments in flood protection measures and environmental attitudes.

3 Integrated modeling framework

We model public preferences using a random utility model (RUM) consisting of a linear utility function that is defined by a deterministic part V_{itn} and a random i.i.d. type I extreme value distributed error term c_{itn} . Equation (14) shows the random utility of a flood protection alternative i in a choice situation t for respondent n , where X_{it} is an attribute matrix and Z_{it} a covariate matrix. The vector β contains the coefficients for the choice attributes, while γ describes the coefficient vector associated with the respondents' sociodemographic characteristics.

$$U_{itn} = V_{itn} + c_{itn}$$

$$V_{itn} = \beta X_{it} + \gamma Z_n \quad (14)$$

In its most basic form and ignoring for the sake of simplicity the influence of individual covariates, the deterministic part of the utility for a chosen alternative can be described as:

$$V_{itn} = \beta_{risk} * vw(x_{risk}) + \beta_{type} * x_{type} + \beta_{cost} * x_{cost} \quad (15)$$

where β_k describes the parameter for the attribute x_k . A special case within the context of this paper is the treatment of the attribute flood risk reduction x_{risk} , as it is transformed to reflect both the perceived risk of respondents as well as the risk attitudes that were elicited in the lottery game captured by both flood probability w and damage weighting v . The results of the

lottery game thus enter the RUM through the flood risk reduction attribute. The weighting parameters are taken from the results of the Bayesian inference explained in Section 2.1. Probability weighting in the lottery game gives us the parameter w and value weighting the parameter v in equation (15). These parameter values are estimated in a first step through Bayesian Inference at individual respondent level and subsequently added to the indirect utility function estimation in a second step. To account for the panel structure of the data, we apply a mixed logit model (McFadden and Train 2000) where coefficients (β_n) are drawn from a cumulative distribution function $G(d\beta, \theta)$ to allow for preference heterogeneity across respondents. The mixed logit probability of an individual n to choose the alternative i over all other alternatives j in a choice situation t can be expressed as:

$$P_{itn} = \int \frac{\exp(\beta'_n x_{it})}{\sum_j \exp(\beta'_n x_{jt})} * f(\beta) d\beta \quad (16)$$

In the context of flood risk, the choice is subject to inherent outcome uncertainty. For the purpose of this paper we simplify the possible outcomes to two: occurrence or non-occurrence of a flood within the period of one year. We use the status quo flood risk level, as perceived by respondents, and apply the weighting to the perceived risk probabilities. In the terminology of Glenk and Colombo (2013), we account for the indirect influence of risk attitudes on the flood risk reduction attribute. This is non-trivial as the risk reduction as asked in the survey is a relative value depending on an unspecified individual status quo risk level. While it is convenient to not specify the absolute risk level for the purpose of WTP interpretation, it inhibits the application of the presented functional forms for risk attitudes. Both value and probability weighting functions require an absolute value to either normalize the value range (value weighting) or calculate the cumulative probability with a total outcome of one (probability weighting). To account for this, the status quo level of our utility model can be redefined by including choice outcome uncertainty akin to the perceived risk level of the individual respondent. This requires both an estimation of flood frequency and flood damage.

The values for individually perceived damages and flood probabilities are derived from answers stated in the survey. For the perceived flood damage, we use respondents' answers to the following 3 statements to account for different types of monetary (material) and non-monetary (immaterial) damage (Brouwer and Schaafsma 2013): "A flood would lead to high financial costs for me", "A flood would lead to high emotional discomfort for me" and "A flood is a physical threat to my life". Response categories are measured on a Likert scale, ranging from 1=strongly disagree to 5=strongly agree. The three answers are added and normalized to a range between 0 (strongly disagree with all three statements) and 1 (strongly agree with all three statements) to establish the status quo damage perception (DP). This method builds on the approach presented in Siegrist and Gutscher (2006), who found that Swiss residents generally consider health threats more important than financial losses. The Likert scale questions focus on the three main aspects related to flood risks and allow us to measure these risks both in absolute and relative terms.

For the perceived flood frequency, we use the response to the question "How likely do you think it is that you will be affected by a flood in your neighborhood in the next 30 years?" Answer categories ranged here from 1="very unlikely" to 4="very likely". To obtain an absolute value, we equate the response categories to the flood return breaking points used in the Swiss hazard maps (FOEN 2016) as follows: "very likely"=1/10 years, "likely"=1/30 years, "unlikely"=1/100 years and "very unlikely"=1/300 years, to re-define the status quo flood probability perception (RP). From this probability weighting can be applied.

As stated by cumulative PT, outcomes within a prospect are weighted cumulatively based on the magnitude of their outcome. As a flood occurring is the most negative outcome considered in the choice model (and the probability of no flood equals 1 minus the probability of a flood), its probability can be used directly as a cumulative probability. The risk attitude towards the remaining flood risk x_{RR} can then be evaluated by subtracting the risk reduction attribute x_{risk}

from 1:

$$x_{RR} = 1 - \frac{x_{risk}}{100} \quad (17)$$

Since the survey does not explicitly distinguish between reduction in probability and reduction in damage impact or magnitude, we assume that both values are reduced proportionally. A reduction of flood risk by for example 50% would therefore affect both the magnitude and the probability of a flood by a factor $\sqrt{0.5}$. The residual risk (RR) can thus be redefined as:

$$f(x_{RR}) = w(\sqrt{x_{RR}} * RP) * v(\sqrt{x_{RR}}) * DP \quad (18)$$

The redefined status quo of the model turns the relative value of risk reduction hence into an absolute value of risk attitude and allows for the application of both value and probability weighting over uncertain outcomes.

The Bayesian inference to model choices in the lottery game is combined here with a frequentist estimation procedure for choices in the discrete choice experiment. The former allows capturing risk attitudes at individual respondent level. The lottery model furthermore profits from Bayesian Inference by being able to include prior knowledge for value weighting from the existing literature and thus avoids extreme estimates. A mixed logit model is employed here because it is the most widespread discrete choice model in the environmental economics literature (e.g. Johnston et al. 2017). Using a Bayesian model to estimate the discrete choice model as well would allow us to include parameter uncertainty from risk attitudes estimates. However, the current approach to use the risk attitudes to predefine utilities is computationally already very intensive.

4 Case study

Although heterogeneous due to topography, flood risks is a natural hazard causing high

damages in Switzerland (Hausmann et al. 2012). The regional Swiss authorities provide detailed hazard maps, but many Swiss residents are not aware of the flood risk in the area where they live and underestimate the risk (Siegrist and Gutscher 2006). As a case study in the city of Zurich shows, this includes owners of buildings in areas with a relative high flood risk (Maidl and Buchecker 2015). This might partly be due to a lack of flood experience. Maidl and Buchecker (2015) find that around 21% of the residents in the city of Zurich were personally affected by a flood in the past. The low risk perception might also be in part due to the high coverage of flood insurance in Switzerland. Out of the 26 Swiss cantons, all except Geneva, Ticino and Valais have mandatory insurance against elementary damages to buildings, most with a public insurance company. The insurance schemes are tightly regulated and based on the principal of solidarity, making the insurance premium mostly independent of the actual risk. While there is no obligation to purchase insurance for damages to home content, the cover rate of these is also very high in Switzerland (Ferber 2013).

Given that the majority of Swiss households is insured against flood-related financial damages, this may decrease the incentive to invest in precautionary or preventive measures. Especially in cantons with public flood insurance this might lead to a moral hazard when protection decisions are taken at the individual household level and the costs are covered from public funding. Studies from the Netherlands show, for example, that government reimbursement decreases mitigation behavior (Botzen et al. 2009). However, even with an insurance in place, households may still be interested to protect their homes. For example, a study by Siegrist and Gutscher (2006) finds that respondents considered the pollution of their house after a flood, the time and effort to clean up the pollution and the possible loss of irreplaceable items worse than suffering financial losses. They also show that emotional discomfort such as feelings of insecurity and uncertainty play a major role in a flood's aftermath for respondents with flood experience. Moreover, while individuals are in most cases covered against financial losses, communities may still suffer damages too. Besides

reducing personal harm, investments in flood protection in large parts of Switzerland also aim to lower public recuperation costs.

5 Results

5.1 Data collection and sample characteristics

To elicit WTP for flood risk reduction, we conducted an online survey in November 2017 among a stratified sample of residents living in the five largest German-speaking Swiss cantons. During three weeks, 1,517 individual households completed the survey. The survey was sent out to a total of 6,717 households, yielding a response rate of 22.6%. A total of 32 (2.2%) individuals were identified as protest respondents and excluded from further analysis, as is common practice in the literature (e.g. Brouwer and Martín-Ortega 2012).

Table 1 provides a summary of the sociodemographic characteristics of the survey respondents. Male respondents are unintentionally slightly overrepresented, while respondents with flood experience were deliberately oversampled, which explains the relatively high share of 50%. The share of respondents who own an apartment or house (48%) is also higher than the Swiss average of 35%, possibly because they might have considered the topic of the survey more relevant than people who rent their house. The gross average household income in the sample is CHF 9,400, which is slightly higher than the last available net average household income of CHF 7,880 (FSO 2016).

The lower part of the table shows the distribution of the perceived flood probability and the three damage categories explained in the previous section. All items were answered on a Likert scale from strongly disagree to strongly agree. The results show that around half of the respondents view floods as causing high monetary damages (agree or strongly agree), a majority agrees that floods can cause great emotional discomfort, and a minority views them

as a potential threat to their life.

[Insert Table 1 here]

The data collection applied a double split sample. Whereas two third of the respondents played the lottery in the loss domain, one third played it in the gain domain. Furthermore, half of all respondents played the lottery before the DCE while the other half answered the DCE first. Both samples are applied orthogonally to exclude their relative influence on each other. There were no statistical significant differences in terms of gender, age, flood experience, home ownership or income between either of the samples, based on a two-sample z-test. Test results are available from the authors on request.

The risk attitude parameters estimated in the Bayes models are presented in the Appendix (Table A8). The estimated parameters for probability weighting w are in the range summarized in Stott (2006). For models with many parameters, especially risk weighting with two parameters, the seven choice tasks might have been insufficient to estimate the parameters precisely. As a result, the numerical solution is very close to 1 for a majority of the respondents. For value weighting, the parameter estimates are in the same order as the values found and applied in the literature, except for the power-II functional form. Here too this may be due to the limited number of observations per person. Estimated value and probability weighting models

To test the influence of the different behavioral assumptions about risk attitudes on choice behavior, we estimated a mixed-logit discrete choice model using 1,000 Halton draws in the R package `gmnl` (Sarrias and Daziano 2017; R Core Team 2016) for each of the 36 weighting combinations and compare these to the EUT base model with linear value and linear probability weighting. Table 2 shows the log-likelihood of all 36 weighted model combinations, with the EUT base model in the upper right corner. The combinations underlined in bold are significant improvements over the base model at the 1% level based on

a likelihood-ratio test with one degree of freedom. Overall, only combinations with a K&T probability function improve the model fit compared to the base model for all but the combination with a Power-II value function. All other probability weighting functions lead to a decrease in model fit across all value weighting functions. Value weighting with linear probability weighting does not improve the model fit either, as shown in the last column of Table 2. The base choice model results in a McFadden R^2 of 0.336, while the best fitting model (K&T x Quad) improves the R^2 slightly to 0.347. These results thus suggest that flood risk probabilities are non-linearly weighted. The K&T probability weighting function follows a S-curve, where extreme events are overweighted compared to intermediate ones. In the context of this study, this means that even very small remaining risks are connected with a sizable level of disutility.

[Insert Table 2 here]

Table 3 compares the estimated choice attribute parameters in the unweighted base model to those based on the K&T probability weighting function that lead to a model improvement (i.e. all except the power-II value weighting). The estimated discrete choice models in Table 3 are named after the value weighting function that was used in combination with the K&T probability weighting function. The table shows the mean values of the parameter estimates and their standard deviations for the ASC and the three choice attributes (risk, type of measure and costs). The parameters are significant and show the expected signs in all models. The risk attribute and the weighted risk parameters $vw(Risk)$ are as expected negative, because they were redefined to describe the remaining risk in equation (18). The cost attribute is, as expected, also negative. The positive sign for the type of measure indicates that respondents prefer public over private protection measures, possibly because the former also benefit other people's homes and public infrastructure.

The parameter $vw(Risk)$ describes the parameter for the respective value weighting function,

with $vw_{Linear}(\text{Risk})$ describing the linear base model. Not included in the table for the sake of simplicity are the standard deviations of the random choice parameters, although they are all statistically significant at the 1% level, and hence reflect significant preference heterogeneity across individual respondents. The full models including these random parameters are presented in the Appendix (Table A5). Thus, even when controlling for the detected preference heterogeneity across the sample population for each choice attribute, including flood risk reduction, we still find evidence of non-linear risk weighting.

The differences between the presented weighted models are relatively small. The weighted risk attitudes differ between the models, but are not directly comparable due to the differences in the projected range of the weighting functions. In order to compare the effect of the different weighting functions, we therefore calculate the marginal WTP values for the risk reduction attribute in the following section.

[Insert Table 3 here]

We observe in this study that even respondents with a low perceived flood risk are more often than not willing to choose protective measures over the status quo, in line with the overweighting of small probabilities predicted by K&T probability weighting. This contradicts somewhat findings from literature showing respondents ignore low probability events. A reason for the difference might be the perceived relative ease of implementing these measures as described in the survey or the fact that respondents were informed in the survey that flood probabilities are expected to increase in the future.

5.2 *Marginal willingness to pay*

Public WTP for flood risk reductions is calculated by dividing the marginal utility of the risk reduction attribute by the cost coefficient. Marginal utility depends on the parameter estimated in the mixed logit choice model (Table 3) as well as the perceived flood risk. In the

case of the weighted risk models, public WTP furthermore depends on the level of risk reduction, while it is constant over all attribute levels for the unweighted baseline model.

Figure 1 compares marginal WTP for the unweighted EUT base model with the risk weighted models presented in Table 3. Compared to the base model, the weighted models on the left-hand side yield a lower marginal WTP for risk reduction values between 0% and 70%, and a much higher marginal WTP for values higher than 80%. While the base model predicts a constant marginal WTP of around CHF 3.20 per % of risk reduction (the dotted horizontal line on the left-hand side in Figure 1), marginal WTP for risk reductions ranges between CHF 2 for very low and CHF 5 for very high risk reduction in the case of the best performing Quad weighted model.

The graph on the right-hand side in Figure 1 shows the cumulative WTP for each level of risk reduction. Here we observe that a model with an unweighted risk attitude overestimates WTP over the entire value range of risk reduction. These results suggest that public WTP is overall lower than the linear EUT model predicts, but higher for protection measures that are able to effectively reduce flood risks to almost zero %.

[Insert Figure 1 here]

Figure 2 zooms further in on the best fitting functional form, i.e. the combination of a K&T probability and Quad value weighting function, and compares the results for two subgroups based on their perception of the status quo flood probability in their neighborhood (high risk perception = flood is likely or very likely, low risk perception = flood is unlikely or very unlikely). The results show that compared to the Quad model, the unweighted linear model underestimates marginal WTP for respondents with low risk perception for all risk reduction levels, and overestimates marginal WTP for respondents with high risk perception for risk reduction levels below 85%. This is also true for the cumulative WTP presented in the graph on the right-hand side, where the difference between the two subgroups with low RP and high

RP is overestimated across the entire value range of risk reduction levels by the EUT- based linearly weighted choice model compared to the weighted Quad model.

[Insert Figure 2 here]

5.3 Sensitivity and robustness Analysis

The sensitivity of the results is tested by distinguishing between risk attitudes in the loss and gain domain (the lottery was played in two split samples, one playing in the loss and one in the gain domain) and substituting perceived risk levels in the estimated choice model by actual risk levels. Additionally, a split sample played the lottery game after the DCE in order to be able to also control for possible procedural bias. We have also tested how the inclusion of non-monetary items into the risk weighting affects the results. While the model ranking remained the same as for the models that include both monetary and non-monetary items, all models exhibited worse model fit (see Table A3 in the Appendix).

5.3.1 The effect of the lottery domain on the goodness of fit of the estimated choice models

Table 4 shows the log-likelihood values of the same estimated discrete choice models as in Table 1, but this time distinguishing between respondents who played the lottery in the gain and in the loss domain. As flood protection decision-making in the DCE takes place in the loss domain, i.e. we estimate an equivalent surplus welfare measure through public WTP to avoid a welfare loss, this was taken as the main control group in the lottery game, explaining the higher number of respondents who played in the loss domain (N=989) than in the gain domain (N=496). Our prior expectation was that the inclusion of risk attitudes derived from the loss domain lottery would better align with the flood risk reduction choices in the DCE and therefore result in a stronger improvement in model performance than risk attitudes estimated based on the gain domain lottery.

In both cases, the 5 best-fitting non-EUT model combinations, introduced in the previous section for the aggregated models across all lottery choices, remain highly significant at the 1% level. The differences compared to the estimation of the same discrete choice models for all respondents across both lottery domains are relatively small. For the gain domain, the combination with the Prelec-II probability function additionally improves the model fit compared to the unweighted baseline model at the 1% level, while two combinations with Prelec (expo and expo II) fail to do so, but only by a narrow margin. An interesting difference between the two domains is that the combination of the K&T probability with the Quad value function remains the best performing model across lottery choices in the gain domain, as was the case for the aggregated model, while in the loss domain the K&T probability function with the Expo value function performs slightly better. Contrary to expectations, the increase in explanatory power as measured through the models' R^2 is nearly the same for both domains. Whereas the best-fit model in the gain domain improves with 3.4% to a R^2 of 0.336 (from a base level of 0.325), the best-fit model in the loss domain improves with 3.2% to an R^2 of 0.354 (from a base level of 0.343). While a combination of K&T probability weighting and Quad value weighting clearly performs best in the gain domain, we observe that there are three combinations in the loss domain based on K&T probability weighting, namely Expo, Quad and Expo II value weighting, that perform nearly the same and all have the highest R^2 of 0.354. This might suggest that the non-EUT models in the loss domain seem to better explain flood risk protection choice behavior in the DCE.

In order to account for the difference in sample size between the gain and the loss domain, we drew 3 random sub-samples from the loss domain with 496 respondents each and estimated the same models for these 3 sub-samples for the combination that performs best in both domains (K&T and Quad). For all three sub-samples from the loss domain the estimated model performs better in terms of log-likelihood (LL=-2118.1, -2085.4, -2092.8) using the Likelihood Ratio test than for the gain domain sample (LL=-2161.9). This leads us to

conclude that the loss domain risk attitude estimates significantly outperform the gain domain estimates.[Insert Table 4 here]

However, this is not very strong evidence for a systematic better performance of risk attitudes derived from the loss domain. In order to see to what extent preference heterogeneity in the risk attribute plays a role, we estimated exactly the same random parameters choice models again, but this time with a fixed risk parameter. These model results are presented in the Appendix (Table A4). The log-likelihood values underlined in bold again show which combinations of probability and value weighting functions result in a significant improvement over the linear EUT-base model. The results are similar to the models presented in Table 4 based on random parameters for all choice attributes, as most combinations with a K&T probability weighting function lead to an improvement over the base model, except for Power II value weighting. To a lesser degree, models with a Prelec probability weighting function also lead to a significant improvement. Overall, the models' goodness-of-fit is a bit lower than in Table 4 where all parameters were included as random parameters. The R^2 values for the aggregate, gain and loss domain EUT base models are very similar, namely 0.313, 0.312 and 0.314 respectively. The results for the choice models where the parameter estimate for the flood risk attribute is fixed show stronger evidence of non-linear probability weighting: not only do more non-EUT models outperform the EUT base model significantly, the increases in model fit are also larger than the ones presented in Table 4. Moreover, the best performing models including non-linear risk attitudes measured in the loss domain lead to bigger improvements in explanatory power as measured through the R^2 compared to the EUT base model than the best performing models in the gain domain. This finding is in line with our expectation that parameters from the loss domain lotteries are better predictors for flood risk protection choices than parameters from the gain domain lotteries (R^2 values are reported in Table A5 in the Appendix). Thus, allowing the flood risk attribute parameter to vary across individuals might have somewhat obscured this effect by increasing the deviation over the

sample, while fixing it over the sample shows a clear increase in explanatory power due to the inclusion of non-linear risk attitude parameters, especially from the loss domain lottery.

5.3.2 The effect of actual flood risk levels on the goodness of fit of the estimated choice models

While the primary purpose in this paper is to evaluate the influence of risk weighting procedures based on respondents' perceived risk, we also tested the influence of the respondents' actual risk based on the Swiss flood hazard maps (FOEN 2016). Using GIS, we were able to quantify the actual flood risk level for the 1,099 respondents who provided their address in the survey. We redefined these respondents' status quo based on their actual flood probabilities and expected damages according to the Swiss flood hazard map. Table 5 shows the performance of all 36 aggregated model combinations for these 1,099 respondents based on both their perceived and actual flood risk levels.

Compared to the discrete choice models that use the perceived risks to define the status quo, using the actual risk instead leads systematically to a worse model fit across all model combinations, as can be seen from the overall lower log-likelihood values in the bottom part of Table 5. As a consequence, the explanatory power of these models is also lower (see Table A6 in the Appendix). Thus, on one hand the actual (objective) risk location is a worse predictor of choices about flood risk protection than respondents' subjective perceived risk. On the other hand, the improvement in model fit when including non-EUT risk attitudes is larger in the case of actual flood risk levels. From the 36 models tested in the lower part of Table 5, 22 lead to a significant improvement at the 1% level, compared to 5 in the case of perceived risk levels in the upper part of Table 5. Furthermore, the improvement in explanatory power (R^2) by including non-linear risk attitudes is also generally larger for a model based on actual risk, possibly because these individual specific risk attitudes manage to

capture a relatively larger share of the unexplained variance in these cases. Another possible explanation is that respondents' perceived risks already (partly) incorporates risk attitudes, where a respondent who overweighs small probabilities might already state a higher perceived risk than a risk neutral respondent.

[Insert Table 5 here]

5.3.3 *The effect of playing the lottery game before the choice experiment*

A final robustness check relates to the possible influence of the lottery game on the choices respondents made in the DCE. In order to test for possible procedural bias, one group of randomly selected respondents played the lottery game after instead of before the DCE in a split sample.

A two-stage Swait and Louviere (1993) test was carried out between the two subsamples on the unweighted mixed logit discrete choice models, and indicates that there is significant procedural bias. Both the null hypothesis of equal preference and scale parameters is convincingly rejected at the 1% significance level (LR test outcome is 36.8 (9 d.o.f. and $p < 0.01$) and 5.0 (1 d.o.f. and $p < 0.025$) for the preference and scale parameters, respectively).

In order to assess how much procedural bias played a role in the outcomes, Table 6 compares the same choice results once again for the sample who played the lottery game before the DCE and the sample that played the game afterwards.

[Insert Table 6 here]

The EUT base model for the two subsamples reaches an R^2 of 0.332 (*before*) and 0.343 (*after*). Besides a slightly higher fit in the base model, the subsample who played the lottery game after the DCE also display a slightly higher degree of non-EUT behavior than the subsample who played the lottery game before the DCE. Not only do all 6 value weighting

procedures under K&T probability weighting now improve the model fit, also the Prelec I and II and G&E probability weighting functions generate significantly better model fits for a limited number of value weighting procedures. The model fit furthermore also improves by a slightly larger amount. The best model fit in the subsample playing the lottery afterwards improves by 4.1% when including non-EUT parameters compared to the EUT base model, whereas the best model fit for the subsample playing the lottery first improves by just over 2%. Hence, the lottery game appears to have significantly influenced choice behavior afterwards in the DCE, but to a lesser extent than perhaps expected, as it somewhat downplayed non-EUT risk attitudes in the subsequent DCE instead of reinforce them. On the other hand, answering the DCE first also seems to have influenced choice behavior in the lottery game to a larger extent, as respondents might have become more focused on the flood risk and carried this attitude into the financial lottery game.

5.3.4 Sensitivity towards risk measurements

The models presented in this paper derive both respondents perceived potential flood damages and perceived flood probabilities from likert scale questions (the exception being the model based on hazard map information). In the case of flood probability respondents also answered a question about direct perceived flood probability in the survey. Different then the likert scale question, the direct probability question appears to be a worse predictor for choice behavior. We tested a model based on this probability and a combination of KT and Quad risk weighting and found that including risk weighting parameter strongly improves the model fit compared to the unweighted model (-6456.7 vs -6658.4), but still ends up with an inferior fit compared to the likert scale probability measure.

Since respondents cannot be assumed to know the levels of the Swiss flood hazard map (Siegrist and Gutscher 2006), we tested the best fit model combination with alternative

probabilities assigned to the Likert scale. We find that assigning probabilities such as 1/25y, 1/50y, 1/75y and 1/100y leads to a similarly strong improvement of the weighted model over the unweighted model. The results presented here thus seem robust and not sensitive to this assumption.

Respondents were also asked about their perceived flood probability in the survey using 5 different quantitative response categories, each describing a different flood repetition period in absolute terms ($>1/5y$, $1/5y$, $1/10y$, $1/30y$, $<1/30y$). We tested the same model based on this survey question and a combination of KT and Quad risk weighting and found that including the risk weighting parameter greatly improves the model fit compared to the unweighted model (LL=-6456.7 compared to LL=-6658.4). However, using the replies to this question from the survey about the specific flood probability quantified by individual respondents' self in a closed question still yields an inferior model fit compared to the converted Likert scale measure of perceived flood probability. The probability question hence appears to be a worse predictor of choice behavior than the Likert scale question.

In order to test the individual influence of the three different items defining the perceived flood damage, we ran two separate models with the perceived damage based only on the (1) material (financial) and (2) immaterial (emotional and health) damage items. These perceived damage variables turn out to be highly significant in both models and have the expected signs. However, the estimated models have a significant worse fit (LL=-6386.0 for the immaterial damage items LL= -6570.1 for the material damage item) than the original model (LL=-6370.8). Based on these model fits immaterial damage perception seems to be a better predictor of choice behavior than material damage perception. Including these two perceived damage categories in separately in the best fitting functional for probability and value weighting (KT and Quad) also yields significant results with the expected (negative) signs, and even a slightly better model fit (LL=-6362.7) compared to the inclusion of the three

damage categories as a single (equally weighted) joint item.

6 Conclusions

The goal of this study is the inclusion of individual risk attitudes into a utility model, by integrating the results from a lottery game into a discrete choice model, and testing the performance of different functional forms of probability and value weighting in reducing unexplained choice variance in the context of individual and public flood risk reduction. Our primary objective is to answer the question whether risk parameters from a financial lottery game can help to improve the fit of models of decision-making under uncertainty in the context of flood risk reduction. Our results show that incorporating individual risk attitude parameters into the choice model through attribute weighting procedures increases the model fit and reduces the unexplained variance. The results furthermore suggest that choice behavior observed in the financial domain can seemingly be meaningfully transferred into the flood risk domain and help explain decisions behavior under uncertainty.

When comparing different behavioral model assumptions underlying the risk attitudes, we find strong evidence that respondents apply non-EUT risk weighting, as non-linear probability weighting leads to a significantly better model fit. We find, however, that the improvement in model fit is sensitive to the assumption about the functional form. The probability weighting form that leads to both the largest as well as the most consistent improvements in model fit over the EUT base model is based on Tversky and Kahneman (1992) prospect theory.

A major prediction from prospect theory is that people weight outcomes differently based on whether they are considered a gain or a loss with regard to some reference point. This differs from EUT predictions that treat gain and loss outcomes equally across the spectrum of possible risk levels. In this study, we explicitly test the impact of risk attitudes on flood risk reduction preferences elicited in the lottery's gain and loss domain. Since flood risk protection

decisions are typically taken in the loss domain, we expected parameters that were estimated in the lottery's loss domain would lead to a better model fit than the same parameters estimated in the gain domain. The results do not provide strong support for this assumption, however, unless the risk attribute parameter is fixed instead of allowed to vary across individual participants, as non-EUT behavior is partly picked up by unobserved preference heterogeneity.

The results have important implications for the estimation of welfare estimates related to flood risk protection. Compared to the predictions of a linear base model (CHF 3.20 per % of risk reduction), the risk weighted models yield an average public WTP that is up to 30% lower for measures with a very low risk reduction potential. The relative difference in public WTP decreases for measures with a higher risk reduction capacity, but is still around 15% lower for measures that reduce flood risks by 80%. Thus for measures that do not lead to a very high flood protection, EUT-based welfare estimates likely overestimate public WTP. The influence of risk weighting on WTP differs between respondents with a low and high perceived flood probability. While a linear EUT model underestimates WTP for the former, it overestimates WTP for the latter. This is relevant information for the planning of flood protection measures, as the difference in welfare estimates for people who benefit from these protection measures and those who do not is likely smaller than the linear EUT model predicts.

Robustness tests of the results identified a number of recommendations and areas for further future research. First of all, procedural bias was detected, meaning that the order or sequence in which the lottery and the DCE were played influenced public preferences for flood risk reduction. More research is needed to better understand how the two interact and influence each other, in the same and in other environmental risk areas. This will at the same time help to further assess to what extent public attitudes towards financial risks are transferable to

environmental risks. Our results suggest that playing the lottery after the DCE led to significantly better results and is hence preferred, not least because this also avoids any procedural bias.

Secondly, asking the survey participants directly for their current flood risk perception, i.e. their quantified (numerical) expectation of the frequency and impact of flooding in their neighborhood and the risk to their home under status quo conditions appeared too difficult for a large share of the respondents, despite extensive pretesting of these questions before the survey was implemented online. The level of perceived flood risk applied in this study was therefore simplified and elicited using other questions in which we used a Likert scale to elicit views on the probability of a flood in the neighborhood. This was subsequently matched with the flood probability levels found in the Swiss flood hazard map. Comparing this approach with the actual flood probability levels in the Swiss flood hazard map resulted, as expected, overall in a better model fit, possibly because participants' replies to the flood risk questions in the survey already included some degree of subjective risk perception or risk attitude for which we were unable to control. Although we relied on an increasingly growing social science literature in this field when developing our survey, more research is needed to improve the elicitation of public perception of flood risks, using alternative risk perception elicitation procedures (e.g. risk ladders or grids), and further test the robustness and general applicability of the results presented here.

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Figure 1: Marginal and cumulative WTP for flood risk reduction using different risk weighting functions

Figure 2: Marginal and cumulative WTP values for flood risk reductions across low and high risk perception samples derived from the linear EUT base model and the best fitting risk weighted model (K&T and Quad)

Table 1: Sample characteristics

<i>General</i>	<i>Mean</i>	<i>Std.dev.</i>	<i>min</i>	<i>max</i>	
Age (years)	47.37	16.05	18	88	
Male respondents (% of sample)	53.9				
Flood experience (% of sample)	49.6				
Home owner (% of sample)	47.7				
Monthly household income (CHF)	9361.50	4724.55	<1500	>21000	
<i>How likely do you think it is that a flood occurs in the next 30 years in your neighborhood?</i>	<i>Very unlikely</i>	<i>Unlikely</i>	<i>Likely</i>	<i>Very likely</i>	
Perceived flood probability (% of sample)	22.2	38.1	31.7	8.1	
<i>To what extent do you agree that a flood would have the following consequences for you?</i>	<i>Strongly disagree</i>	<i>Disagree</i>	<i>Neither agree nor disagree</i>	<i>Agree</i>	<i>Strongly agree</i>
High financial damage (% of sample)	11.8	27.5	18.7	32.4	9.7
Great emotional discomfort (% of sample)	8.1	15.1	13.7	38.6	24.6
Threat for life (% of sample)	27.6	26.9	21.0	18.0	6.5

Table 2: Estimated log-likelihood values for all probability and value weighted choice models aggregated across all lottery choices in both lottery domains

All lottery choices							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-6477.3
	Power	-6512.5	-6384.1	-6508.8	-6495.7	-6485.5	-6482.8
	Expo	-6476.9	-6377.3	-6510.4	-6481.5	-6480.9	-6497.4
	Log	-6504.5	-6386.5	-6556.4	-6499.0	-6482.5	-6502.3
	Quad	-6521.4	-6370.8	-6502.9	-6484.4	-6484.4	-6480.1
	Power II	-6725.3	-6534.8	-6523.5	-6587.3	-6584.0	-6657.0
	Expo II	-6477.6	-6380.7	-6512.9	-6487.5	-6480.8	-6498.7

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level.

Table 3: Results of the estimated mixed logit discrete choice models using different risk weighting procedures aggregated across all lottery choices

	Base model	Power	Expo	Log	Quad	Expo II
	Coefficient (Std. error)	Coefficient (Std. error)	Coefficient (Std. error)	Coefficient (Std. error)	Coefficient (Std. error)	Coefficient (Std. error)
<i>ASC</i>	2.704 *** (0.105)	3.051 *** (0.116)	3.027 *** (0.115)	3.007 *** (0.115)	2.928 *** (0.113)	3.048 *** (0.116)
<i>vwLinear (Risk)</i>	-296.850 *** (10.707)					
<i>vwPower (Risk)</i>		-78.949 *** (2.970)				
<i>vwExpo (Risk)</i>			-123.490 *** (4.601)			
<i>vwLog (Risk)</i>				-95.735 *** (3.566)		
<i>vwQuad (Risk)</i>					-98.829 *** (3.624)	
<i>vwExpoII (Risk)</i>						-113.010 *** (4.232)
<i>Type of measure</i>	0.296 *** (0.022)	0.273 *** (0.022)	0.290 *** (0.023)	0.287 *** (0.022)	0.300 *** (0.023)	0.286 *** (0.022)
<i>Cost</i>	-0.011 *** (0.000)	-0.011 *** (0.000)	-0.011 *** (0.000)	-0.011 *** (0.000)	-0.011 *** (0.000)	-0.011 *** (0.000)
<i>LogLik</i>	-6477.3	-6384.1	-6377.3	-6386.5	-6370.8	-6380.7
<i>Pseudo R²</i>	0.336	0.345	0.346	0.345	0.347	0.346
<i>Observations</i>	8910	8910	8910	8910	8910	8910

Note: Parameter significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimated log-likelihood values for all combinations of probability and value weighted models in the lottery games' loss and gain domains

Gain domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-2195.8
	Power	-2202.4	<u>-2169.9</u>	-2210.7	-2196.7	-2197.6	-2200.5
	Expo	-2193.0	<u>-2169.1</u>	-2210.9	-2195.0	-2196.4	-2206.1
	Log	-2198.9	<u>-2168.0</u>	-2232.0	-2197.7	-2195.3	-2209.4
	Quad	-2203.5	<u>-2161.9</u>	-2207.9	<u>-2192.3</u>	-2195.7	-2197.2
	Power II	-2282.2	-2227.4	-2210.8	-2231.7	-2233.1	-2268.7
	Expo II	-2193.0	<u>-2170.6</u>	-2214.4	-2197.0	-2197.3	-2206.5
Loss domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-4266.8
	Power	-4300.0	<u>-4204.5</u>	-4285.0	-4289.3	-4277.0	-4267.1
	Expo	-4272.6	<u>-4198.7</u>	-4287.2	-4275.2	-4271.4	-4276.0
	Log	-4294.3	<u>-4207.5</u>	-4315.1	-4292.7	-4275.3	-4287.1
	Quad	-4307.4	<u>-4199.1</u>	-4281.0	-4281.1	-4275.9	-4268.0
	Power II	-4423.0	-4282.9	-4299.1	-4345.3	-4347.2	-4363.6
	Expo II	-4273.9	<u>-4201.0</u>	-4285.7	-4280.0	-4270.6	-4276.4

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level

Table 5: Estimated log-likelihood values for all probability and value weighted choice models based on respondents' perceived and actual risk levels aggregated across all lottery choices

All lottery choices – Perceived risk							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-4756.5
	Power	-4798.4	<u>-4694.6</u>	-4773.4	-4773.2	-4764.9	-4760.9
	Expo	-4760.4	<u>-4684.8</u>	-4774.8	-4757.2	-4756.3	-4769.0
	Log	-4786.9	<u>-4694.9</u>	-4805.0	-4770.8	-4757.5	-4771.4
	Quad	-4804.4	<u>-4684.3</u>	-4771.6	-4765.6	-4765.6	-4758.9
	Power II	-4960.9	-4799.1	-4792.6	-4855.1	-4857.5	-4916.6
	Expo II	-4762.1	<u>-4687.4</u>	-4775.7	-4760.1	-4756.1	-4769.8
All lottery choices – Actual risk							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-5121.7
	Power	<u>-5051.4</u>	<u>-4889.9</u>	-5119.5	<u>-5071.5</u>	<u>-5106.0</u>	-5121.0
	Expo	<u>-5077.9</u>	<u>-4892.6</u>	-5120.7	<u>-5089.3</u>	<u>-5118.1</u>	-5122.4
	Log	<u>-5057.9</u>	<u>-4902.8</u>	-5121.2	<u>-5070.6</u>	<u>-5109.7</u>	-5120.1
	Quad	<u>-5074.5</u>	<u>-4891.4</u>	-5118.4	<u>-5094.2</u>	-5119.8	-5121.8
	Power II	-5119.3	<u>-4979.5</u>	<u>-5112.8</u>	<u>-5102.9</u>	<u>-5109.4</u>	-5138.2
	Expo II	<u>-5076.5</u>	<u>-4889.1</u>	-5120.5	<u>-5085.6</u>	-5118.4	-5122.5

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level. Models are estimated based on the 1,099 respondents who stated their full address in the survey, which permitted quantification of their actual flood risk levels based on the Swiss Federal Office for the Environment's flood hazard map.

Table 6: Estimated log-likelihood for all probability and value weighted choice models aggregated across respondents who played the lottery game before and after the DCE

All lottery choices for respondents who played the lottery <i>before</i> the DCE							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-3213.1
	Power	-3244.9	<u>-3187.7</u>	-3219.5	-3231.8	-3225.5	-3217.2
	Expo	-3221.7	<u>-3179.0</u>	-3218.2	-3221.3	-3216.7	-3214.5
	Log	-3239.6	<u>-3191.6</u>	-3232.2	-3229.8	-3221.9	-3215.8
	Quad	-3248.7	<u>-3180.7</u>	-3214.0	-3225.9	-3223.7	-3215.1
	Power II	-3341.3	-3261.7	-3234.3	-3282.6	-3288.8	-3293.9
	Expo II	-3222.1	<u>-3180.0</u>	-3219.6	-3222.7	-3217.1	-3214.8
All lottery choices for respondents who played the lottery <i>after</i> the DCE							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-3245.8
	Power	-3248.0	<u>-3179.8</u>	-3272.6	-3247.1	<u>-3242.4</u>	-3248.7
	Expo	<u>-3237.8</u>	<u>-3183.8</u>	-3276.6	<u>-3241.1</u>	-3245.8	-3265.1
	Log	-3244.8	<u>-3178.1</u>	-3312.6	-3251.0	<u>-3242.2</u>	-3271.2
	Quad	-3253.5	<u>-3173.7</u>	-3271.6	<u>-3241.4</u>	-3242.9	-3247.2
	Power II	-3363.7	<u>-3239.4</u>	-3272.5	-3286.3	-3282.2	-3379.4
	Expo II	<u>-3238.6</u>	<u>-3186.4</u>	-3278.2	-3245.7	-3247.1	-3266.1

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level

Appendix

Figure A1: Example lottery task

Figure A2: Example choice task

Table A1: Lottery tasks for respondents in the gain domain

Lottery task	Lottery A						Lottery B					
	<i>p1</i>	<i>v1</i>	<i>p2</i>	<i>v2</i>	<i>p3</i>	<i>v3</i>	<i>p1</i>	<i>v1</i>	<i>p2</i>	<i>v2</i>	<i>p3</i>	<i>v3</i>
1	1/4	5.-	1/2	2.-	1/4	0.-	1	2.-				
2	1/4	5.-	3/4	2.-			1/2	2.-	1/2	0.-		
3	3/4	5.-	1/4	0.-			1/2	5.-	1/2	2.-		
4	1/2	11.-	1/2	0.-			3/4	5.-	1/4	0.-		
5	3/4	5.-	1/4	0.-			1/2	5.-	1/4	4.-	1/4	0.-
6	1/2	11.-	1/2	0.-			1/2	5.-	1/4	4.-	1/4	0.-
7	1/4	10.-	3/4	0.-			3/4	3.-	1/4	0.-		
Source: Adapted from Harrison et al. (2016)												

Table A2: Lottery tasks for respondents in the loss domain

Lottery task	Lottery A						Lottery B					
	<i>p1</i>	<i>v1</i>	<i>p2</i>	<i>v2</i>	<i>p3</i>	<i>v3</i>	<i>p1</i>	<i>v1</i>	<i>p2</i>	<i>v2</i>	<i>p3</i>	<i>v3</i>
1	1/4	-5.-	1/2	-2.-	1/4	0.-	1	-2.-				
2	1/4	-5.-	3/4	-2.-			1/2	-2.-	1/2	0.-		
3	3/4	-5.-	1/4	0.-			1/2	-5.-	1/2	-2.-		
4	1/2	-11.-	1/2	0.-			3/4	-5.-	1/4	0.-		
5	3/4	-5.-	1/4	0.-			1/2	-5.-	1/4	-4.-	1/4	0.-
6	1/2	-11.-	1/2	0.-			1/2	-5.-	1/4	-4.-	1/4	0.-
7	1/4	-10.-	3/4	0.-			3/4	-3.-	1/4	0.-		
Source: Adapted from Harrison et al. (2016)												

Table A3: Log-likelihood for all probability and value weighted choice models based on respondents' perceived flood probability (same as in the main evaluation) and the perceived flood damage based on monetary damages exclusively (compared to a sum of monetary and non-monetary items) according to lottery domains (aggregated, gain and loss)

All lottery choices							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-6519.1
	Power	-6557	-6433.5	-6545.6	-6539.3	-6528.5	-6522.5
	Expo	-6519.1	-6427.6	-6547.6	-6523.3	-6521.4	-6534
	Log	-6548.1	-6439.4	-6593.2	-6542	-6523.6	-6540.1
	Quad	-6565.6	-6424.1	-6541.9	-6530	-6527.8	-6520.6
	Power II	-6749.3	-6565.2	-6560.7	-6631.4	-6623.2	-6681.6
	Expo II	-6518.7	-6430.7	-6550.2	-6527.9	-6520.6	-6534.5
Gain domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-2216.8
	Power	-2225.5	-2195.8	-2228	-2221.1	-2220.5	-2221.8
	Expo	-2215.3	-2194.4	-2228.4	-2216.7	-2216.2	-2224.2
	Log	-2223.2	-2195.3	-2247.3	-2221.1	-2217	-2226.8
	Quad	-2225.7	-2189	-2225.4	-2215.3	-2217.8	-2218.2
	Power II	-2297	-2247.8	-2231.5	-2254.3	-2253.4	-2278.8
	Expo II	-2215	-2196.1	-2231.5	-2219.1	-2217.4	-2225.1
Loss domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-4291.1
	Power	-4323.7	-4230.5	-4305.5	-4310.7	-4299.3	-4288.4
	Expo	-4294.7	-4225.4	-4309.3	-4298	-4291.4	-4298.2
	Log	-4316.5	-4235.4	-4340	-4313.3	-4297.1	-4302.9
	Quad	-4330.7	-4228.1	-4305.5	-4304.5	-4299.1	-4292.5
	Power II	-4440.7	-4321.5	-4318.4	-4371.6	-4365.9	-4378.3
	Expo II	-4294.7	-4226.8	-4307.8	-4301	-4293.3	-4297.8

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level

Table A4: Log-likelihood for all probability and value weighted choice models based on respondents' perceived flood risk with a fixed risk parameter according to lottery domains (aggregated, gain and loss)

All lottery choices							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-6698.3
	Power	-6694.0	-6547.5	-6728.5	-6702.2	-6706.8	-6703.1
	Expo	-6683.3	-6542.6	-6731.6	-6701.4	-6701.9	-6716.0
	Log	-6685.6	-6551.0	-6795.8	-6720.8	-6709.6	-6740.0
	Quad	-6706.6	-6539.6	-6717.7	-6699.2	-6705.8	-6699.6
	Power II	-6932.0	-6856.3	-6807.7	-6799.4	-6828.3	-6993.4
	Expo II	-6681.0	-6545.8	-6731.7	-6700.9	-6701.1	-6716.8
Gain domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-2237.0
	Power	-2237.5	-2203.9	-2258.3	-2244.5	-2242.8	-2243.1
	Expo	-2233.7	-2204.5	-2260.1	-2242.4	-2241.1	-2252.2
	Log	-2236.6	-2200.7	-2293.2	-2255.2	-2245.2	-2264.2
	Quad	-2237.9	-2195.4	-2250.9	-2234.8	-2237.1	-2237.7
	Power II	-2349.9	-2328.8	-2271.7	-2298.3	-2311.9	-2357.3
	Expo II	-2233.4	-2206.9	-2261.7	-2245.0	-2241.7	-2253.4
Loss domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	-4455.0
	Power	-4449.9	-4339.3	-4464.9	-4451.1	-4456.9	-4454.0
	Expo	-4443.6	-4333.8	-4468.1	-4453.2	-4455.1	-4459.9
	Log	-4443.8	-4346.2	-4501.3	-4462.6	-4460.1	-4474.0
	Quad	-4461.7	-4339.6	-4462.3	-4457.2	-4461.2	-4455.2
	Power II	-4577.6	-4518.2	-4523.3	-4497.8	-4511.0	-4630.3
	Expo II	-4441.6	-4334.5	-4466.3	-4450.2	-4453.4	-4459.4

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level

Table A5: R2 for all probability and value weighted choice models based on respondents' perceived flood risk with a fixed risk parameter according to lottery domains (aggregated, gain and loss)

All lottery choices							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	0.313
	Power	<u>0.314</u>	<u>0.329</u>	0.310	0.313	0.312	0.313
	Expo	<u>0.315</u>	<u>0.329</u>	0.310	0.313	0.313	0.311
	Log	<u>0.314</u>	<u>0.328</u>	0.303	0.311	0.312	0.309
	Quad	0.312	<u>0.329</u>	0.311	0.313	0.312	0.313
	Power II	0.289	0.297	0.302	0.303	0.300	0.283
	Expo II	<u>0.315</u>	<u>0.329</u>	0.310	0.313	0.313	0.311
Gain domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	0.312
	Power	0.312	<u>0.323</u>	0.306	0.310	0.311	0.311
	Expo	0.314	<u>0.322</u>	0.305	0.311	0.311	0.308
	Log	0.313	<u>0.324</u>	0.295	0.307	0.310	0.304
	Quad	0.312	<u>0.325</u>	0.308	0.313	0.312	0.312
	Power II	0.278	0.284	0.302	0.294	0.289	0.276
	Expo II	<u>0.314</u>	<u>0.322</u>	0.305	0.310	0.311	0.307
Loss domain only							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	0.314
	Power	<u>0.315</u>	<u>0.332</u>	0.313	<u>0.315</u>	0.314	0.315
	Expo	<u>0.316</u>	<u>0.333</u>	0.312	0.315	0.314	0.314
	Log	<u>0.316</u>	<u>0.331</u>	0.307	0.313	0.314	0.311
	Quad	0.313	<u>0.332</u>	0.313	0.314	0.313	0.314
	Power II	0.296	0.305	0.304	0.308	0.306	0.287
	Expo II	<u>0.316</u>	<u>0.333</u>	0.313	<u>0.315</u>	0.315	0.314

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level

Table A6: Estimated R2 values for all probability and value weighted choice models based on respondents' perceived and actual risk levels aggregated across all lottery choices

<i>All lottery choices – Perceived risk</i>							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	0.340
	Power	0.334	<u>0.349</u>	0.338	0.338	0.339	0.340
	Expo	0.340	<u>0.350</u>	0.338	0.340	0.340	0.339
	Log	0.336	<u>0.349</u>	0.334	0.338	0.340	0.338
	Quad	0.334	<u>0.350</u>	0.338	0.339	0.339	0.340
	Power II	0.312	0.334	0.335	0.327	0.326	0.318
	Expo II	0.339	<u>0.350</u>	0.338	0.340	0.340	0.338
<i>All lottery choices – Actual risk</i>							
		Probability weighting					
		Prelec	K&T	Power	Prelec II	G&E	Linear
Value weighting	Linear	-	-	-	-	-	0.290
	Power	<u>0.299</u>	<u>0.322</u>	0.290	<u>0.297</u>	<u>0.292</u>	0.290
	Expo	<u>0.296</u>	<u>0.321</u>	0.290	<u>0.294</u>	<u>0.290</u>	0.289
	Log	<u>0.298</u>	<u>0.320</u>	0.290	<u>0.297</u>	<u>0.291</u>	0.290
	Quad	<u>0.296</u>	<u>0.322</u>	0.290	<u>0.293</u>	0.290	0.290
	Power II	0.290	<u>0.309</u>	<u>0.291</u>	<u>0.292</u>	<u>0.291</u>	0.287
	Expo II	<u>0.296</u>	<u>0.322</u>	0.290	<u>0.295</u>	0.290	0.289

Note: Entries underlined in bold represent significant improvements in choice model fit at the 1% level. Models are estimated based on the 1,099 respondents who stated their full address in the survey, which permitted quantification of their actual flood risk levels based on the Swiss Federal Office for the Environment's flood hazard map.

Table A7: Complete mixed logit model, including sample deviations

	Base model	Power	Expo	Log	Quad	Expo II
<i>ASC</i>	2.704 *** 0.105	3.051 *** 0.116	3.027 *** 0.115	3.007 *** 0.115	2.928 *** 0.113	3.048 *** 0.116
<i>vwLinear (Risk)</i>	-296.850 *** 10.707					
<i>vwPower (Risk)</i>		-78.949 *** 2.970				
<i>vwExpo (Risk)</i>			-123.490 *** 4.601			
<i>vwLog (Risk)</i>				-95.735 *** 3.566		
<i>vwQuad (Risk)</i>					-98.829 *** 3.624	
<i>vwExpoII (Risk)</i>						-113.010 *** 4.232
<i>Type of measure</i>	0.296 *** 0.022	0.273 *** 0.022	0.290 *** 0.023	0.287 *** 0.022	0.300 *** 0.023	0.286 *** 0.022
<i>Cost</i>	-0.011 *** 0.000	-0.011 *** 0.000	-0.011 *** 0.000	-0.011 *** 0.000	-0.011 *** 0.000	-0.011 *** 0.000
<i>Sd ASC</i>	4.548 *** 0.162	4.873 *** 0.174	4.835 *** 0.173	4.866 *** 0.173	4.822 *** 0.172	4.844 *** 0.173
<i>Sd vwLinear (Risk)</i>	269.910 *** 10.739					
<i>Sd vwPower (Risk)</i>		68.981 *** 3.328				
<i>Sd vwExpo (Risk)</i>			106.980 *** 5.124			
<i>Sd vwLog (Risk)</i>				80.541 *** 3.791		
<i>Sd vwQuad (Risk)</i>					84.436 *** 3.896	
<i>Sd vwExpoII (Risk)</i>						98.522 *** 4.760
<i>Sd Type of measure</i>	0.674 *** 0.073	0.687 *** 0.074	0.690 *** 0.074	0.681 *** 0.074	0.690 *** 0.074	0.689 *** 0.074
<i>Sd Cost</i>	0.009 *** 0.000	0.009 *** 0.000	0.009 *** 0.000	0.009 *** 0.000	0.009 *** 0.000	0.009 *** 0.000
<i>Observations</i>	8910	8910	8910	8910	8910	8910
<i>LogLik</i>	-6477.3	-6384.1	-6377.3	-6386.5	-6370.8	-6380.7
<i>Pseudo R²</i>	0.336	0.345	0.346	0.345	0.347	0.346

Note: Parameter significance: *** p<0.01, ** p<0.05, * p<0.1

Table A8: Estimated risk attitude parameter with mean and (standard deviation)

v-form	w-form	Alpha 1	Alpha 2	Beta 1	Beta 2
Power	Prelec	0.55 (0.23)	-	0.97 (0.13)	-
Power	K&T	0.52 (0.21)	-	0.63 (0.042)	-
Power	Power	0.55 (0.23)	-	1.01 (0.091)	-
Power	Prelec_II	0.54 (0.22)	-	0.98 (0.12)	1.01 (0.091)
Power	G&E	0.54 (0.23)	-	0.99 (0.11)	0.98 (0.098)
Expo	Prelec	1.13 (0.54)	-	0.98 (0.091)	-
Expo	K&T	1.09 (0.33)	-	0.63 (0.028)	-
Expo	Power	1.13 (0.53)	-	1.00 (0.055)	-
Expo	Prelec_II	1.13 (0.51)	-	0.99 (0.084)	1.00 (0.055)
Expo	G&E	1.13 (0.51)	-	0.99 (0.077)	0.99 (0.059)
Log	Prelec	1.52 (0.96)	-	0.98 (0.15)	-
Log	K&T	1.31 (0.29)	-	0.63 (0.052)	-
Log	Power	1.50 (0.97)	-	1.00 (0.094)	-
Log	Prelec_II	1.52 (0.91)	-	0.98 (0.14)	1.00 (0.099)
Log	G&E	1.48 (0.75)	-	0.99 (0.12)	0.99 (0.11)
Quad	Prelec	0.32 (0.041)	-	0.99 (0.12)	-
Quad	K&T	0.33 (0.055)	-	0.64 (0.038)	-
Quad	Power	0.32 (0.038)	-	1.00 (0.086)	-
Quad	Prelec_II	0.32 (0.038)	-	0.99 (0.11)	1.00 (0.087)
Quad	G&E	0.32 (0.044)	-	1.00 (0.084)	0.99 (0.097)
Power-II	Prelec	1.20 (0.58)	1.11 (0.29)	1.00 (0.17)	-
Power-II	K&T	1.18 (0.70)	1.07 (0.32)	0.65 (0.037)	-
Power-II	Power	1.31 (0.92)	1.13 (0.33)	0.99 (0.15)	-
Power-II	Prelec_II	1.22 (0.49)	1.11 (0.26)	1.01 (0.17)	0.99 (0.15)
Power-II	G&E	1.20 (0.54)	1.11 (0.29)	1.01 (0.14)	1.00 (0.15)
Expo-II	Prelec	1.36 (0.78)	1.00 (0.011)	0.98 (0.095)	-
Expo-II	K&T	1.33 (0.54)	1.00 (0.011)	0.63 (0.029)	-
Expo-II	Power	1.36 (0.76)	1.00 (0.011)	1.00 (0.057)	-
Expo-II	Prelec_II	1.36 (0.74)	1.00 (0.01)	0.98 (0.087)	1.00 (0.059)
Expo-II	G&E	1.36 (0.74)	1.00 (0.011)	0.99 (0.081)	0.99 (0.06)
Power		0.56 (0.25)	-		-
Expo		1.13 (0.57)	-		-
Log		1.52 (1.06)	-		-
Quad		0.32 (0.04)	-		-
Power-II		1.35 (1.20)	1.13 (0.38)		-
Expo-II		1.36 (0.81)	1.00 (0.011)		-