Accounting for Uncertainty in Decision Weights for Experimental Elicitation of Risk Preferences

Dylan Turner* and Craig E. Landry†

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Abstract

In the generalized expected utility framework, the multiplicative relationship between preferences and beliefs complicates the identification of risk preferences. In experimental or field settings, the respondent's decision weight (subjective probability) must be known to infer accurate risk preferences. We propose a novel Monte-Carlo based method for expressing uncertainty in the individual's decision weight as uncertainty in their inferred risk aversion coefficient. We implement this procedure on experimentally elicited risk preferences obtained via a mail survey and show that this procedure improves model fit when risk preferences are used as a determinant of behavior in a reduced-form model of insurance demand.

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*Turner: Economist, Economic Research Service, U.S. Department of Agriculture. dylan.turner2@usda.gov.
†Landry: Professor, Department of Agricultural and Applied Economics, University of Georgia. clandry@uga.edu.

1 Introduction

Given the uncertainty over outcomes as diverse as weather, finance, technology, and health, risk is more rule than exception in the microeconomics of decision-making. Yet, decision-making under risk and uncertainty is still considered a sub-field of microeconomics. Integration of individual measures of risk tolerance, however, has started to become standard practice in the empirical analysis of individual decision-making in a variety of domains, including (but not limited to) natural hazard mitigation (Petrolia et al., 2013, 2015), marriage and child-bearing (Schmidt, 2008), migration decisions (Jaeger et al., 2010), and technology adoption (Liu, 2013). Thus, many micro-economic researchers have taken an interest in being able to elicit robust measures of individual proclivity to take risks and to employ those measures in empirical analysis.

Identifying individual preferences over risky outcomes, however, is non-trivial and fraught with challenges, prompting a literature focused on discerning ways to robustly infer individual risk preferences with instruments that are simple and easy for respondents to understand. The existing literature on the measurement of risk preferences can largely be grouped into two distinct categories. The first uses simple queries to very bluntly gauge an individual's degree of risk tolerance (i.e. "How willing are you to take risks, in general?") (Dohmen et al., 2011). From a subject's perspective, this instrument may be easy to respond to and can provide for internal comparisons across risk domains, but the measures have limited construct and external validity; they generally provide only a very vague understanding of an individual's risk-taking behavior, are difficult to interpret, and may not be comparable across subjects.

The second approach entails using economic theory to structurally model an individual's decision over risky outcomes. Observing such choices can permit inference of individual structural risk preference parameters, albeit under the presumptions that the theoretical model sufficiently mimics the individuals' decision-making process and that the domain of inference is relevant for the desired range of empirical analysis. This method is advantageous as it can produce risk preference parameters that map directly to existing economic theory. One way to implement this method is to take advantage of existing observational data in which an individual has made a decision that involves a naturally occurring stochastic outcome (see Barseghyan et al. (2018) for a review). Yet, finding requisite data for this approach can be quite difficult, engendering the popularity of using experimental methods to elicit risk preferences in applied economics research (Holt and Laury, 2002; Eckle and Grossman, 2002; Charness et al., 2013).

Assessing risk preferences in an experimental setting provides researchers with considerable latitude in describing uncertain outcomes and the context in which resolution will occur. It is well recognized, however, that the laboratory environment is not without its drawbacks. One concern with lab-based results is that the environment is often sterile, implying a lack of real work context which can limit generalization to everyday behavior.[1] This critique has motivated the use of field experiments, or "lab in the field" studies, which attempt to maintain the control of the lab while achieving greater domain specificity and generalizability (Levitt and List, 2007a,b, 2008).

Although field experiments do indeed offer some advantages over other methods for obtaining measures of risk preference, they also introduce a unique set of challenges. Most experimental studies that attempt to recover structural risk preference parameters employ the assumption of a generalized expected utility model; this presumes a functional representation that maintains a multiplicative relationship between the probability of outcomes

[1]We note that this is not universally viewed as a limitation and could be an advantage depending on the research question at hand (Falk and Heckman, 2009)

(also known as "beliefs" or "decision weights") and preferences (i.e. utility as a function of consumption and risk preferences). This formulation creates a formidable challenge for the identification of risk preferences, as differences in observed behavior can be explained by multiple combinations of beliefs and preferences - a conundrum that has been well documented and discussed in the existing literature (Luce and Krantz, 1971; Fishburn, 1973; Karni, 2007; Lu, 2019). Identification in cross-sectional data is usually not possible without strong (and arguably unrealistic) sets of assumptions.[2]

Consequently, using experiments to obtain robust metrics of individual risk preferences, either in the lab or through field experiments, is dependent on knowing the precise decision weight that an individual uses when choosing between risky prospects. In a stylized laboratory environment, it is plausible to assume that individuals employ decision weights provided by the researcher.[3] In a field setting, however, where elicitation is usually conducted in a domain-specific context,[4] research participants' perceptions of likelihood are considerably more opaque, invoking subjective assessment of likelihood (which may be based on past experience or expectations of future outcomes in idiosyncratic ways) and assessment of unique domains that could invoke considerable heterogeneity; this implies a potential for variation in subjective decision weights that could be very difficult to control for in microeconomic

[2]Savage (1954)'s original formulation of subjective expected utility achieves identification by specifying a preference relation that is independent of the underlying state of nature along with an infinite state space; these are restrictive assumptions that rule out most interesting cases that are applicable to observed behavior. Following Savage, there have been attempts to incorporate state-dependent preferences into the subjective expected utility framework, yet doing so still requires restrictive assumptions (Karni, 2014).

[3]It is generally accepted, however, that individuals likely engage in some form of probability weighting (or apply a more general probability "distortion") as the concept is a key component of many modern models of decision making under risk and uncertainty (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Quiggin, 1982) and has been shown to be a good way to improve structural model fit in field settings (Barseghyan et al., 2013; Collier et al., 2020). Thus, this assumption may not be as valid as conventional approaches maintain.

[4]Studies invoking domain specificity are generally considered reasonable and appropriate since individual risk preferences are not guaranteed to generalize across domains (Dohmen et al., 2011; Einav et al., 2012).

analysis. For example, if a researcher was eliciting risk preferences in the domain of personal finance, a research subject's past experience with investing may influence their perceived decision weights used in the experiment. If the researcher informs the participant that equities generally return 7% per year after inflation, but the research participant had recently lost substantial money in the stock market, their recent experience may lead them to use decision weights that differ from those provided by the researcher. Thus, failing to account for the research participant's alternative decision weight would lead to incorrect inference concerning their proclivity for taking financial risk.

The multiplicative relationship between beliefs and preferences in the generalized expected utility framework implies the potential for multiple equivalencies among unobserved factors influencing decision weights and attitudes towards risk. Inherently, there is uncertainty in whether a respondent's decision weight matches the objective probability in any experimental setting (with the issue being particularly prominent in domain-specific field experiments). Thus, when respondents are assumed to use objective probabilities for their decision weights (a common assumption in the literature), an additional source of uncertainty is introduced that is not typically acknowledged when making inferences about the individual attitudes towards risk. As such, developing techniques that account for differences in decision weights in experimental elicitation of risk preferences is an important step forward for obtaining robust characterizations of individual decision-making under risk and uncertainty.

The purpose of this study is to present a method for eliciting domain-relevant risk preferences that controls for participant perceptions of probability that differ from those reported in the elicitation instrument. Our particular domain of interest is natural hazards, and our elicitation instrument utilizes future weather outcomes to introduce uncertainty. Respondents are permitted to choose among four weather-based lotteries, with increasing mean and variance. After indicating their preferred lottery (including a pass option, which entails forgoing gamble of their incentive payment), they are asked to report their personal assessment of the likelihood of weather outcomes (e.g. more or less likely than indicated by historical data). This information then gets incorporated into a Monte Carlo procedure that adjusts the range of the coefficient of relative risk aversion (CRRA) interval that can be inferred by each respondent's choice. This approach offers a substantial improvement over other risk preference elicitation methods that are typically used, since uncertainty in the individuals' decision weight is no longer ignored but instead conveyed as uncertainty in the implied risk preference metric. We apply this approach to survey data from coastal homeowners, and we show that incorporating the Monte Carlo adjusted risk preference coefficients into a reduced-form analysis of flood insurance purchase improves model fit compared to when uncertainty in decision weights is ignored. We also find larger semi-elasticities for risk preference when we employ the adjustment, suggesting downward bias in empirical analysis when decision weight uncertainty is unaccounted for.

The rest of this paper is organized as follows. Section 2 describes our data collection efforts and provides descriptive statistics. Section 3 provides a theoretical background on the identification problem present in the experimental elicitation of risk preferences. Section 4 outlines our empirical approach for both adjustment of implied risk preference intervals and our reduced-form analysis of flood insurance. Section 5 presents our results. Section 6 provides a discussion of the results, and section 7 concludes.

2 Survey Design and Data Collection

Household-level data for our analysis were gathered via mail survey in the fall of 2018 in Glynn County, GA. The overarching goal of the survey was to gather a rich profile of homeowners' expectations, beliefs, and perceptions related to coastal habitation with an explicit focus on climate change induced risks and adaptation policies. An initial sample of 1,914 recent home buyers (purchased in 2016 or 2017) was targeted in early October. Participation was incentivized by offering \$5 cash payments for returned surveys. Respondents had the option to earn more or less money, however, through the selection of a weather gamble. This instrument is primarily based on Eckle and Grossman (2002), in which participants are asked to select their most preferred choice from a menu of lotteries. Similarly, our respondents were asked to choose between keeping their \$5 incentive payment or gambling their incentive payment by selecting one of four alternative lotteries. Notably, we use weather as a naturally occurring stochastic process to define lottery payoffs. This addresses the issue of domain specificity of risk preferences by framing risk in our domain of interest (natural hazard risk). An additional benefit of this method is that the stochastic process is completely transparent and outcomes are verifiable by the research participant. This alleviates any concerns related to distrust of the researchers or suspicions about the actual randomness of lottery outcomes.

The weather outcomes were specified for occurrence in November of 2018; the survey had a response rate of 13.9% (266 returned surveys during October). Figure 1 displays the risk preference question as it was presented in the survey. Respondents were first informed of the exact time frame and location that weather outcomes would be recorded. The question then reports objective weather probabilities for each weather event based on historical data. Finally, respondents were presented with the lottery choices (along with the option to keep their incentive payment and not engage in a lottery).

After the risk preference instrument, respondents were presented with a series of debriefing questions where they were asked to indicate if they agreed with the objective weather probabilities reported in the instrument. Figure 2 displays the debriefing questions as they were presented in the survey. For each weather probability displayed in the risk preference instrument, respondents could indicate that they thought the probability based on historical data was “About right”, “slightly too (low/high)”, or “much too (low/high)”

2.1 Descriptive Statistics

Table 1 reports descriptive statistics for all variables used in our analysis. Sixty-two percent of survey respondents indicated having a flood insurance policy on their coastal residence. Flood insurance premiums were calculated for each individual by using the national flood insurance program’s (NFIP) flood insurance rate manual along with each respondent’s unique home characteristics. Full coverage and a deductible of $1000 were assumed to calculate each homeowners’ annual NFIP premium. In reality, respondents may not choose full coverage and may choose a different deductible. This calculated premium, however, still captures the variation in price that individuals face when looking to purchase flood insurance, and thus it serves its purpose of controlling for price in our reduced-form analysis. The mean value of this calculated annual premium was $1,426.

Household income was elicited through an ordered categorical scale of eight intervals ranging from “less than $35,000” up to “more than $250,000”. The lowest interval is coded at $30,000 while the top income interval is coded using the method of Hout (2004). This involves handling unbounded intervals through extrapolation by applying frequencies observed in the last and penultimate income intervals to a Pareto distribution. Doing so suggests the top income interval should be coded at $496,000. All other income intervals are coded at their midpoint which suggests a mean household income of $171,000. Respondents were asked to indicate what proportion of their net worth was represented by the equity they have in their Glynn County residence. Responses were elicited in an ordered categorical form ranging from "0%-10 up to "80% - 100%". Coding these intervals at their midpoint suggests the average respondent had 33% of their wealth represented by their coastal home equity.

Subjective expectations of a major hurricane strike were elicited by asking respondents how many major (Category 3 or higher) hurricanes they expected to pass within 30 miles of the county over the next 50 years. These responses were then mapped to an annualized probability, the mean of which was 0.19.[5] Expected personal home damage from a major hurricane strike (passing within 30 miles of the county) as a share of total structure value was elicited in 20 percentage point increments (i.e. 0% - 20% up to 80% - 100%). Coding these ordinal interval responses at their midpoint suggests the average respondent expects damage equivalent to 43% of their home structure value. Individual expectations of disaster aid have been shown to be an important determinant of flood insurance demand and are thus included in our reduced-form analysis (Landry et al., 2021). Thirty-five percent of respondents believed they would be eligible for government issued disaster aid following a natural disaster declaration. Fifteen percent of our sample indicated they had personally sustained flood damage to their home at least once in the past. Twenty-six percent of respondents' homes were located in a special flood hazard area (SFHA)[6] and the average home was located approximately 4.12 km from the coast.

Age was elicited with a series of ordinal responses which suggest a mean age of 55 when responses were coded at their midpoint. Sixty-seven percent of respondents indicated having at least a bachelor's degree or higher. Feelings of worry related to home loss from a natural disaster were elicited on a 4-point Likert scale with 4 being the most worried. Responses

[5] While this probability appears high relative to historical records, Glynn County was recently adversely affected by two hurricanes, which may have heightened risk perceptions (Bin and Landry, 2013; Atreya et al., 2013)

[6] defined as having at least a 1% change of flooding per annum

were converted to a binary variable by coding responses of 3 or 4 as "being worried". This coding suggests 46 percent of responses worried about the loss of their home. Finally, to control for coastal experience, respondents were asked how long they had been living on the coast. Forty-one percent indicated being "relatively new to the coast"

Panel B of table 1 reports results to debriefing questions that gauge subjective perceptions of the accuracy of objective weather probabilities. Overall, only 22 percent of respondents agreed with all historical weather probabilities reported. The mean responses for lotteries one and two were 2.82 and 2.83, respectively, indicating an aggregate opinion that the probabilities associate with these weather outcomes (average rainfall and low temperature in November) were too low. On the other hand, the mean responses for lotteries three and four were 3.21 and 3.24, respectively, indicating an aggregate perspective that these weather outcome probabilities (extreme rainfall and high temperature in November) were too high.[7]

3 Theoretical Background

Expected utility and most of its generalizations maintain a multiplicative structure among beliefs and preferences that guides choice among risky outcomes, often defined as "prospects" over uncertain states of the world (e.g. occurrence of hurricane v. no hurricane). Optimizing EU entails the choice of the prospect that generates the highest level of expected utility. Thus, given two risky prospects, an EU optimizer picks choice A (e.g. purchase of flood insurance) over choice B (e.g. foregoing flood insurance) if the following is true:

[7]Interestingly, these responses accord with the predictions of prospect theory, which proposes a general tendency to overweight small probabilities and under-weight larger probabilities (Kahneman and Tversky, 1979).

$$E[c_A] = \sum_k p_k u(x_k(c_A), \rho) > \sum_k p_k u(x_k(c_B), \rho) = E[c_B] \tag{1}$$

where $k \in K$ represents a singular state of the world (from the set of all possible states of the world, K), p_k represents the probability of state k, and x_k represents the consumptive or monetary payoff associated with state k, which is conditional on the agent's choice, $c \in \{c_A, c_B\}$. The utility function u(.) maps monetary payoffs into individual satisfaction, with the shape of the utility function governed by the parameter ρ, characterizing the agent's risk preferences.

If p_k and x_k are known for all k, the range of risk preference parameters that are consistent with a given functional form for u(.) and an observed choice among prospects can be identified (Eckel and Grossman, 2008; Charness et al., 2013). If p_k (or x_k) is unknown, however, inequality 1 can no longer be solved for ρ given that it contains two unknowns. Similarly, if p_k (for any or all k) is not known with certainty (due, e.g., to subjective probabilities or measurement error), then the corresponding values of ρ that would result in a particular observed behavior cannot be recovered with certainty.

For example, consider the following pair of lotteries that an agent must choose among:

$$\text{Lottery A: 50\% chance of receiving \$10; 50\% chance of receiving \$20} \tag{2}$$

$$\text{Lottery B: 50\% chance of receiving \$5; 50\% chance of receiving \$25} \tag{3}$$

While each lottery has the same expected value, a risk averse EU maximizer would prefer the lottery with the lower variance. Assuming risk aversion is consistent with CRRA utility,[8]

[8]Where CRRA utility over wealth, x, is defined as: $u(x;\rho) = \begin{cases} \frac{x^{(1-\rho)}}{1-\rho} & \rho \neq 1 \\ ln(x) & \rho = 1 \end{cases}$

the choice of lottery A over Lottery B implies:

$$\left(\frac{1}{2}\right)\left(\frac{\$10^{(1-\rho)}}{(1-\rho)}\right)+\left(\frac{1}{2}\right)\left(\frac{\$20^{(1-\rho)}}{(1-\rho)}\right)>\left(\frac{1}{2}\right)\left(\frac{\$5^{(1-\rho)}}{(1-\rho)}\right)+\left(\frac{1}{2}\right)\left(\frac{\$25^{(1-\rho)}}{(1-\rho)}\right) \tag{4}$$

or

$$\left(\frac{1}{2}\right)\left(\frac{\$10^{(1-\rho)}}{(1-\rho)}\right)+\left(\frac{1}{2}\right)\left(\frac{\$20^{(1-\rho)}}{(1-\rho)}\right)-\left(\frac{1}{2}\right)\left(\frac{\$5^{(1-\rho)}}{(1-\rho)}\right)-\left(\frac{1}{2}\right)\left(\frac{\$25^{(1-\rho)}}{(1-\rho)}\right)>0 \tag{5}$$

From an empirical perspective, we can infer from inequality (5) that choosing lottery A implies a risk preference parameter greater than 0 (indicating risk aversion). On the other hand, a choice of lottery B implies a risk parameter less than or equal to 0 (indicating risk-neutral or risk-seeking preferences). Moreover, if we have additional data from a menu of individual lottery choices (e.g. selection of a preferred lottery or a multiple-price list (MPL) (Charness et al., 2013)), we can deduce further bounds on risk preference parameters. This general approach has been used both in the laboratory (Binswanger, 1980, 1981; Holt and Laury, 2002; Eckle and Grossman, 2002) and field (Tanaka et al., 2010; Liu, 2013) to assess individual risk preferences.

Now, suppose that the probabilities in lottery A are subject to some ambiguity, ϵ, such that lottery A is redefined as follows:

$$\text{Lottery A: } (50\% + \epsilon) \text{ chance of receiving } \$10 \text{ ; } (50\% - \epsilon) \text{ chance of receiving } \$20 \tag{6}$$

meaning inequality (5) is now:

$$\left(\frac{1}{2}+\epsilon\right)\left(\frac{\$10^{(1-\rho)}}{(1-\rho)}\right)+\left(\frac{1}{2}-\epsilon\right)\left(\frac{\$20^{(1-\rho)}}{(1-\rho)}\right)-\left(\frac{1}{2}\right)\left(\frac{\$5^{(1-\rho)}}{(1-\rho)}\right)-\left(\frac{1}{2}\right)\left(\frac{\$25^{(1-\rho)}}{(1-\rho)}\right)>0 \tag{7}$$

The level of risk aversion, ρ, that explains the choice of lottery A over lottery B is now dependent on the value of ϵ. Figure 3 plots inequality (7) for various levels of ϵ, demonstrating that the range of ρ values that satisfy inequality (7) (i.e any value of ρ where the function is positive) can be quite different for relatively small values of ϵ. For example, when $\epsilon = -0.05$ (e.g. an agent who believes the probabilities in lottery A to be 45%/55% rather than equal odds.), the minimum value of ρ necessary to reconcile an agent choosing lottery A over lottery B drops from 0 to -0.18 meaning the conclusion that only risk-averse individuals prefer lottery A is no longer correct.

Overall, unless the probabilities associated with an agent's decision are known with certainty (i.e. ϵ can be confirmed to be zero), any derived risk preference measures are prone to errors that are typically not expressed in conventional risk preference elicitation calculations. In the next section, we focus on using the debriefing responses outlined in section 2 (Figure 2) to identify when ϵ differs from zero. We then use that information to widen (or narrow) the risk preference parameter interval that can be implied by the observed choice in the risk preference instrument and in effect produce a final characterization of risk preferences that accounts for uncertainty in the decision weights being used by each individual.

4 Methods

Our empirical methods address two primary research objectives. The first task is to adjust the elicited risk preference parameters to reflect uncertainty in the individuals' decision weights. The second task is to validate this procedure by incorporating the adjusted risk preference parameters into reduced-form regression analysis to assess whether they offer an improvement in model fit for a domain-relevant decision. We describe the details of each task in turn.

4.1 Monte-Carlo Procedure

The example presented in section 3 demonstrates how a single biased probability in a binary lottery among two competing risky prospects can alter the range of risk preference implied by an observed choice. This is the simplest possible scenario; in practice, most risk preference assessment instruments typically involve at least several competing risky prospects all of which may be subject to uncertainty in the decision weights used by the subject. As such, most situations where observing an agent's choice is likely to be useful will be subject to the same identification challenge highlighted in section 3, but with greater complexity. The multitude of possible combinations of decision weights and preference parameters that could underlie risky choices limits application of analytical methods, but opens the door for numerical approaches. Our proposed Monte-Carlo procedure for modifying the inferred CRRA interval utilizes the following steps:

1. Check if the respondent indicated disagreement with any of the probabilities reported in the instrument. If the respondent agreed with the accuracy of all objective probabilities, no adjustments are made. If at least one disagreement exists, proceed to the next step.

2. For any subjective probability that differs from the historical likelihood, randomly perturb the decision weights in accord with the agent's subjective assessment of the likelihood of that particular weather outcome. The size of the perturbation is defined by two parameters θ_s (for "slight") and θ_m (for "much") , which are continuous random variables defined by the following uniform distributions:

$$\theta_s \sim unif(0, \omega_s)$$

$$\theta_m \sim unif(\omega_s, \omega_m)$$

θ_s is the adjustment for respondents that thought the historical probability was "slightly" off (where θ is subtracted from the historical probability if deemed "slightly too high" and added if "slightly too low"), while θ_m is the adjustment for indication of "much" difference among subjective and objective probabilities (as indicated in table 2). The bounds of the uniform distributions are initially set at a $\omega_s = 0.05$ and $\omega_m = 0.1$ (represented by CRRA (5,10) in table 1), but take on different values during sensitivity analysis and model assessment. For "slightly" off, we use $\theta_s = 0.05$, 0.1, 0.2, 0.3, and 0.4, while for "much" difference, we use $\theta_m = 0.1$, 0.2, 0.4, 0.6, and 0.8, respectively. (This procedure reflects the inherent uncertainty in modeling "slightly" and "much" in the context of subjective assessment of likelihood).

3. The perturbed lottery probabilities are then used to calculate the implied CRRA interval that is consistent with the respondent's lottery choice, assuming that the perturbed lottery probabilities were the decision weights the respondent used when evaluating the lotteries.

4. Repeat steps 2 and 3 N times to generate N individual implied CRRA intervals all of which were derived using randomly drawn perturbation sizes (θ_s and θ_m)

5. Take the maximum of the N upper bounds and the minimum of the N lower bounds for each subject in the analysis. These values form the new "adjusted" implied CRRA interval for each individual.

The procedure described here will produce implicit CRRA intervals that contain the individual's true CRRA value as long as the bounds of the uniform distributions that the theta parameters are drawn from are sufficiently large. For example, if a respondent thought the probability of a particularly lottery was "slightly too low", which to them meant 7 percent too low, but $\theta_s \sim unif(0, .05)$ (i.e. at most the decision weight is perturbed by 5 percent) our procedure is not guaranteed to produce an interval that contains the true CRRA values. By varying the values of ω_s and ω_m and conducting a comparative model fit assessment, we allow the data to indicate the appropriate bounds for adjustment.

Panel C of table 1 reports summary statistics for original and adjusted CRRA intervals based on objective and subjective likelihood assessment, respectively, and using various interval sizes (ω_s and ω_m) for the theta parameters. The numbers in parentheses indicate the proportional probability adjustment for ω_s (first number) and ω_m (second number).[9] Each individual CRRA parameter is estimated as the midpoint of the resulting interval. Overall, the mean value of the CRRA coefficients is consistent before and after the adjustment, regardless of the size of the interval that the theta parameters are drawn from. Wider theta parameter distributions, however, tend to produce CRRA values with wider variance. This is also apparent in figure 4 which plots histograms of the original and adjusted CRRA values.

4.2 Reduced-Form Regression Analysis

To validate the effectiveness of the risk-preference adjustment procedure, we conduct a reduced-form analysis of flood insurance purchase and assess overall model fit before and after the coefficients have been adjusted using the Monte-Carlo procedure described above. Our reduced-form analysis entails the estimation of standard probit models on the binary decision to hold a flood insurance policy. As noted previously, the distribution from which the theta parameters should be drawn from during the Monte-Carlo procedure is *ad hoc*. Thus,

[9]For example "CRRA (10,20)" indicates that this CRRA variable was adjusted by drawing θ_s from (0,0.1) [$\omega_s = 0.1$] and θ_m from (0.1,0.2) [$\omega_m = 0.2$].

we conduct a sensitivity analysis with our reduced-form models by estimating a probit model for each of the CRRA variables reported in table 1, panel C.

4.3 Risk Perception Heterogeneity

For many of the respondents in our sample, the adjustment procedure has no effect on their implied CRRA interval. This occurs due to individuals indicating they agreed with all or some[10] of the objective probabilities or indicating disagreements in objective probabilities in multiple lotteries that tend to cancel each other out.[11] Thus, modeling improvements will be driven by assessments of respondents whose CRRA values were altered the most. We investigate this by estimating an additional series of reduced-form regression that exclude individuals that had minute differences between their original CRRA value (that ignores uncertainty in decision weights) and the adjusted CRRA value that uses the largest theta parameter distributions (CRRA (40,80)). We exclude individuals from this specification that had CRRA values that differed by less than 0.05.

5 Results

Table 3 reports probit regression coefficients for the effect of the adjusted and un-adjusted CRRA values (among other covariates) on flood insurance status. Regression coefficients are

[10] For example, a disagreement in the probability attached to lottery 4 has little to no effect in the implied CRRA interval if the respondent's decision was primarily between choosing lottery 1 or 2

[11] For example, consider an agent who has biased perceptions of the probabilities attached to the events in our risk preference instrument such that they believed lottery 2 to have the probability distribution 0.22/0.78 (as opposed to 0.225/0.775), lottery 3 to have the probability distribution 0.16/0.84 (as opposed to 0.125/0.875), and lottery 4 to have the probability distribution 0.03/0.97 (as opposed to 0.025/0.975). Deriving this agent's implied CRRA range, given their most preferred lottery, would result in the exact same CRRA range regardless of if subjective or objective probabilities were used in the derivation. This is but one example of the many other possible combinations of biased probabilities that would result in exactly the same or arbitrarily similar implied CRRA ranges.

consistent with what economic theory would suggest. Individuals whose home represents a greater proportion of their net worth, those who expected more home damage from a hurricane, residents in flood zones, and those with a college education were all more likely to have a flood insurance policy. The focus of our results, however, is on potential improvements associated with adjusting risk preference coefficients. If our Monte-Carlo procedure is effective in addressing errors in the measurement of risk perception, then we would expect better evidence of internal validity in the reduced-form insurance regression.

Log-likelihood, AIC, and BIC values each suggest that all of the models that make use of adjusted risk coefficients have better model fit compared to the base model (that does not). In addition to raw AIC values, we also report normalized model likelihoods (or "Akaike weights") which can be interpreted as the probability that the given model is the best among the competing models under consideration (Burnham and Anderson, 2004).[12] This metric suggests that our base model with un-adjusted risk coefficients has only a 9.5% probability of being the best model; thus there is a 90.5% chance that the base model is not the best model, suggesting the use of the adjusted risk coefficients generally leads to a model that is a better descriptor of our data. Similarly, we present an adjustment to the raw BIC values by calculating and reporting Bayes' factors. In this instance, Bayes' factor is interpreted as the relative likelihood of two competing models (i.e. our base model against each model with adjusted risk coefficients). Bayes' factors for each model in table 3 range from 1.46 up to 2.56,[13] which suggests the best fitting model is 2.56 times more likely to be the true model given the data when compared to the base model.

Admittedly, the evidence presented in table 3 in favor of using our proposed Monte-Carlo

[12] "best" here refers to the model that minimizes Kullback-Leibler (K-L) information loss

[13] excluding the Bayes' factor for the base model which is not applicable since it is interpreted as the relative likelihood of the base model against itself

procedure is not overwhelmingly strong depending on which model fit metric is being used. The normalized AIC weights suggest the base model with un-adjusted risk coefficients only has a 9.5% probability of being the best model among those presented in the table which is quite encouraging. If the BIC and Bayes factor are the metrics of choice, however, the best Bayes factor of 2.56 is considered evidence for the adjusted model that is "Weak" according to (Raftery, 1995) or "Anecdotal" according to (Jeffreys, 1961). Although, as noted previously, improvements in model fit are likely to be concentrated among individuals that had their CRRA values altered the most by the Monte-Carlo procedure.

Table 4 reports the same regressions as table 3 but with the sub-sample of observations that exhibited substantial differences in their implied risk coefficient after the Monte-Carlo procedure. The improvements in model fit from adjusting the risk coefficients are much more apparent in this specification. In accord with regressions run on the full sample, all specifications suggest elicited CRRA values (unadjusted and adjusted) are significant determinants of flood insurance status. Normalized AIC weights, however, suggest substantial improvements in model fit between the base model and models with adjusted CRRA values. AIC weights indicated a 1.2% chance of the base model being the best model, whereas the model presented in the 5th column of the table (CRRA(30, 60)) has a 64% probability of being the best. Bayes' factors range from 2.3 to 55.8. Raftery (1995) describes a Bayes' factor of 56 as being evidence of the alternative model that is "strong", whereas Jeffreys (1961) describes the evidence as "very strong".

6 Discussion

Identification challenges associated with simultaneous uncertainty in both decision weights and risk preferences have been recognized for some time (Savage, 1954), but uncertainty in decision weights has largely been ignored during experimental elicitation of risk preferences. The bulk of existing literature is focused on laboratory environments, so the presumption of known decision weights could be more defensible in this context. The emerging literature that attempts to characterize risk preferences in non-laboratory settings, however, has been forced to contend with the fact that using objective probabilities as decision weights may not be a justifiable assumption (Barseghyan et al., 2018). To our knowledge, the methodology presented here is the first attempt to account for uncertainty in decision weights during experimental elicitation of risk preferences; the approach should be easily implemented in other field contexts.

Our results suggest that ignoring uncertainty in individual decision weights (equivalent to assuming that individuals act on objective probabilities) leads to relatively poor model fit for reduced-form models utilizing elicited risk preferences. Our Monte-Carlo procedure offers a simple approach to adjust perceived bounds on the likelihood of context-relevant outcomes using simple Likert scale response to assess the qualitative difference among historical, objective likelihood estimates and expressed, subjective estimates (that could reflect knowledge and beliefs about environmental change). While the adjustment procedure offers modest improvements in regression analysis in the full sample, we find substantial impacts when we focus on the sub-sample of respondents for which the correction has a substantial effect on subjective likelihoods relative to the historical data. Bayes' factors for these models suggest they are between 2.3 and 56 times more likely to be the true model relative to the base model. Thus, the degree to which accounting for uncertainty in decision weights can be expected to improve model fit is largely dependent on how much subjective beliefs differ from the objective probabilities, which are likely to vary with sample and context.

We now turn to the economic significance of the Monte Carlo adjustment procedure. The footers of both tables 3 and 4 report average marginal effects (expressed as semi-elasticities) of the risk preference variable in each regression. Table 3 indicates that in the base model (column 1), a 1 percent increase in an individual's CRRA value increases the probability of purchasing flood insurance by 9.6 percent, whereas the best fitting model (column 4) suggests an 11.3 percent increase in probability. In other words, if the best fitting model is presumed to be the true model, then the model that ignores uncertainty in decision weights understates the effect of risk preference on flood insurance purchase decisions by approximately 15%. For our subset of the population most affected by the CRRA adjustment procedure (table 4), this bias is more pronounced. The base model suggests the base model understates the effect of risk preferences by approximately 25%. Overall, our results suggest that ignoring uncertainty in decision weights is not prudent and may very well lead to biased inference. Nonetheless, the procedure proposed here has several limitations.

Our debriefing questions, which allow respondents to indicate disagreement in the objective lottery probabilities attached to each lottery, are based on a simple 5-point Likert scales. The simplicity is advantageous, as it increases the likelihood that a given respondent will understand and answer the questions. The downside is that only a crude approximation of the respondent's true decision weight is revealed by their answer. Ideally, precise decision weights could be elicited through an open-ended response which would reduce uncertainty in the overall implied risk preference coefficient. Open-ended responses,h owever, are accompanied by their own set of challenges. For example, there is often a tendency for respondents to round open-ended answers (Manski and Molinari, 2010); Dominitz and Manski (1997) find that survey respondents tend to report probabilistic expectations in 1 percent increments near the bounds of the unit interval, but tend to round in increments of 5 percent elsewhere. In addition, there is evidence that certain stated probabilities (i.e. "50-50") may be more reflective of an individual's epistemic uncertainty rather than expressions of true beliefs about the probability of the event in question (de Bruin et al., 2002). Thus, it is not obvious that using open-ended responses would yield more accurate implied risk coefficient estimates. Exploring the implications of using alternative subjective probability elicitation methodologies remains an important avenue for future research.

One concern with our analysis is that our small sample size (particularly for the regressions in table 4) may mean comparing models based on information criteria derived from log-likelihoods may be suspect due to the asymptotic distributional assumptions being invalid. To mitigate these concerns we turn to an alternative estimator: penalized maximum likelihood (PML). This method, proposed by (Firth, 1993), makes use of a log-likelihood function that has been modified to include an additive penalty term, defined as the square root of of the determinant of the information matrix.[14] This approach has been shown to lower bias and variance compared to standard maximum likelihood estimation (Copas, 1988; Firth, 1993). One implication of this is that a logit model estimated with PML tends to have much better small sample properties than the same model estimated via standard maximum likelihood. Intuitively, the penalty term $\sqrt{|I(\beta)|}$, which is equivalent to Jeffreys (1946)'s prior, shifts the score function to correct for bias in proportion to the researcher's level of "ignorance".[15] Using a series of Monte-Carlo simulations, Rainey and McCaskey (2021) show that even with only 30 observations (used to estimate 9 parameters), PML estimates only exhibited bias of 6 percent compared to 69 percent bias present in the standard logit coefficients. We re-estimate our reduced form models using PML and report the results in tables

[14] i.e. the function $L^*(\beta|y) = L(\beta|y)\sqrt{|I(\beta)|}$ is optimized where $L(\beta|y)$ is the standard likelihood function and $I(\beta)$ is the Fisher information matrix

[15] i.e. if more data is available, the shift is not as large, since the researcher's level of ignorance is reduced by the information available in additional data. Thus PML and standard ML estimates converge as the sample size grows.

5 and 6. We find that the results are qualitatively equivalent to our primary specifications in the sense that the adjustment procedure results in improved model fit with substantial improvements among the subset of the sample that most disagreed with the objective lottery probabilities. We do note, however, that marginal effects (semi-elasticities) of the CRRA parameter are much larger under PML estimation suggesting that there may be some small sample bias in the magnitude of the regression coefficients in our primary specifications. This does not contradict our primary message, though, since we are primarily concerned with the differences between coefficient estimates between the base model and models making use of adjusted CRRA values. Overall, the conclusion that the base model is likely understating the effect of risk preferences on flood insurance purchasing decision remains robust.[16]

7 Conclusions

Experimentally eliciting attitudes toward risk has become a routine procedure for many empirical studies focused on individual decisions in domains that contain an element of uncertainty. Most of this literature ignores uncertainty in the individual's decision weight or "subjective probability" when deriving the risk coefficient that can be implied by a given choice over risky prospects. In the generalized expected utility framework, however, uncertainty in decision weights is equivalent to uncertainty in preferences towards risk due to the multiplicative relationship between decision weights and the utility function. This means that if the researcher assumes a probability that differs from the individual's actual decision weight, the risk coefficient implied by any model in the expected utility family will be incorrect. This is particularly relevant for field data where the researcher does not control the

[16]Table 5 replicates table 3 using a PML estimated logit model and suggests the base model understates the marginal effect of the CRRA parameter by 17% compared to the best fitting model. Similarly, Table 6 replicates table 4 and suggests the base model exhibits a downward bias of approximately 54%

risky prospect but instead observes choices concerning naturally stochastic events. But, even lab experiments may be prone to this source of bias, since it is difficult to verify whether research participants accurately internalize the provided probabilities.

In this study, we propose a method to measure risk preferences in a domain-specific context that accounts for uncertainty in the individuals' decision weights. Our procedure elicits risk preferences using a menu of lotteries where individuals pick their most preferred out of all presented lotteries (much like Eckle and Grossman (2002)). Each lottery is constructed by specifying payouts conditional on future weather events, which has the benefit of framing risk in our domain of interest (natural hazard risk) and utilizing a stochastic process that is transparent and independently verifiable by research participants. Follow-up questions are then administered where participants can indicate disagreement with the objective probabilities reported in the lotteries. This signals to the researcher that there is uncertainty in the individual's decision weight. We account for this uncertainty by using a novel Monte-Carlo procedure that widens (or narrows) the interval of the risk coefficient that can be inferred from any given individual's observed choice. We show that this procedure produces coefficients of relative risk aversion that improve overall model fit for a reduced form model of domain-relevant behavior (flood insurance purchasing decisions) when compared to models that employ risk coefficients that ignore potential uncertainty in individual decision weights. Finally, we find evidence of downward bias in the estimated effects of risk-aversion on flood insurance decisions when we fail to account for decision weight uncertainty.

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8 Tables

Table 1: Descriptive Statistics

	mean	sd	min	max	count
Panel A: Independent and Dependent Variables					
Flood Policy	0.62	0.49	0.00	1.00	266
Premium (Calculated)	1426.09	1336.43	152.57	6036.70	265
Income	171.67	149.36	30.00	496.12	253
Wealth Share	0.33	0.22	0.10	0.90	261
Prob. Hurr	0.19	0.24	0.00	1.00	238
Exp. Damage	0.43	0.23	0.10	0.90	254
Exp. Aid	0.35	0.48	0.00	1.00	266
Past Flood	0.15	0.36	0.00	1.00	261
SFHA	0.26	0.44	0.00	1.00	266
Km to Coast	4.12	3.37	0.02	13.23	266
Age	55.12	14.49	21.00	80.00	258
Education	0.67	0.47	0.00	1.00	266
Worry	0.46	0.50	0.00	1.00	266
New To Coast	0.41	0.49	0.00	1.00	266
Panel B: Subjective Weather Beliefs					
Correct Beliefs	0.22	0.42	0.00	1.00	266
Weather Probability 1	2.82	0.58	1.00	5.00	242
Weather Probability 2	2.83	0.95	1.00	5.00	242
Weather Probability 3	3.21	0.86	1.00	5.00	242
Weather Probability 4	3.24	0.97	1.00	5.00	240
Panel C: Risk Aversion Coefficients					
CRRA (Original)	0.49	0.38	0.00	0.85	251
CRRA (5,10)	0.50	0.37	0.00	1.04	251
CRRA (10,20)	0.50	0.37	-0.02	1.25	251
CRRA (20,40)	0.51	0.38	-0.12	1.67	251
CRRA (30,60)	0.49	0.37	-0.26	0.92	251
CRRA (40,80)	0.49	0.38	-0.49	0.93	251

Table 2: Decision Weight Adjustments

Debriefing Choice	Original Decision Weight	New Decision Weight
"Much too low"	P_{Obj}	$P_{Sub} = P_{Obj} \times (1 + \theta_m)$
"Slightly too low"	P_{Obj}	$P_{Sub} = P_{Obj} \times (1 + \theta_s)$
"About right"	P_{Obj}	$P_{Sub} = P_{Obj}$
"Slightly too high"	P_{Obj}	$P_{Sub} = P_{Obj} \times (1 - \theta_s)$
"Much too high"	P_{Obj}	$P_{Sub} = P_{Obj} \times (1 - \theta_m)$

Table 3: Probit Regression on Flood Insurance Demand

	CRRA (Unadjusted)	CRRA (5,10)	CRRA (10,20)	CRRA (20,30)	CRRA (30,60)	CRRA (40,80)
CRRA	0.7816	0.8618	0.8875	0.8953	0.8649	0.8536
	(0.2853)	(0.3007)	(0.3010)	(0.2948)	(0.2975)	(0.2896)
Premium (Calculated)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Income	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Wealth Share	2.2279	2.2713	2.3029	2.3526	2.3565	2.4021
	(0.5904)	(0.5951)	(0.5981)	(0.6028)	(0.6067)	(0.6128)
Prob. Hurr	-0.2615	-0.2920	-0.3149	-0.3485	-0.2553	-0.2531
	(0.4476)	(0.4494)	(0.4511)	(0.4542)	(0.4505)	(0.4509)
Exp. Damage	1.1859	1.1777	1.1656	1.1528	1.2189	1.2382
	(0.4937)	(0.4946)	(0.4950)	(0.4951)	(0.4976)	(0.4991)
Exp. Aid	-0.3155	-0.3195	-0.3202	-0.3214	-0.3251	-0.3273
	(0.2183)	(0.2187)	(0.2189)	(0.2191)	(0.2191)	(0.2193)
Past Flood	0.6579	0.6711	0.6810	0.7001	0.6781	0.6874
	(0.4414)	(0.4421)	(0.4422)	(0.4430)	(0.4408)	(0.4409)
SFHA	0.8383	0.8389	0.8465	0.8537	0.8524	0.8422
	(0.3694)	(0.3682)	(0.3677)	(0.3677)	(0.3652)	(0.3652)
Km to Coast	-0.0062	-0.0055	-0.0051	-0.0045	-0.0071	-0.0075
	(0.0329)	(0.0329)	(0.0330)	(0.0330)	(0.0330)	(0.0330)
Age	0.0068	0.0068	0.0066	0.0065	0.0070	0.0072
	(0.0076)	(0.0076)	(0.0076)	(0.0077)	(0.0076)	(0.0076)
Education	0.6284	0.6304	0.6306	0.6317	0.6377	0.6390
	(0.2291)	(0.2296)	(0.2299)	(0.2302)	(0.2303)	(0.2306)
Worry	-0.0661	-0.0620	-0.0592	-0.0609	-0.0493	-0.0513
	(0.2368)	(0.2373)	(0.2376)	(0.2378)	(0.2370)	(0.2374)
New To Coast	-0.1256	-0.1373	-0.1448	-0.1514	-0.1422	-0.1443
	(0.2109)	(0.2116)	(0.2121)	(0.2126)	(0.2119)	(0.2121)
Constant	-2.2486	-2.2995	-2.3048	-2.3107	-2.3366	-2.3589
	(0.7251)	(0.7306)	(0.7316)	(0.7324)	(0.7351)	(0.7374)
Observations	209	209	209	209	209	209
LL	-102.390	-102.013	-101.752	-101.448	-101.862	-101.730
AIC	234.779	234.026	233.505	232.897	233.725	233.461
AIC Weight	0.095	0.138	0.179	0.243	0.161	0.183
BIC	284.914	284.161	283.640	283.032	283.860	283.596
Bayes Factor	1.000	1.457	1.892	2.564	1.694	1.933
CRRA MFX	0.096	0.108	0.111	0.113	0.105	0.102

Table 4: Assessing Heterogeneity in Effect of Adjustment Procedure

	CRRA (Unadjusted)	CRRA (5,10)	CRRA (10,20)	CRRA (20,30)	CRRA (30,60)	CRRA (40,80)
CRRA	3.1917	3.9477	4.1722	3.4647	5.2917	3.9101
	(1.1234)	(1.4044)	(1.4575)	(1.1614)	(1.6692)	(1.1600)
Premium (Calculated)	-0.0004	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Income	0.0020	0.0018	0.0017	0.0016	0.0018	0.0017
	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
Wealth Share	3.5736	3.9163	4.1839	4.4268	5.5902	5.5305
	(1.1356)	(1.1999)	(1.2483)	(1.3022)	(1.5353)	(1.5163)
Prob. Hurr	-0.2714	-0.5104	-0.6962	-0.7601	-0.1889	-0.1408
	(0.7628)	(0.7796)	(0.8009)	(0.8081)	(0.8112)	(0.8123)
Exp. Damage	2.6101	2.6347	2.6308	2.6750	3.8077	3.7270
	(0.9905)	(1.0024)	(1.0105)	(1.0154)	(1.2070)	(1.1859)
Exp. Aid	-0.6486	-0.7338	-0.7838	-0.7885	-0.7954	-0.7889
	(0.3822)	(0.3936)	(0.4018)	(0.4044)	(0.4141)	(0.4105)
Past Flood	0.2090	0.2312	0.2483	0.2927	0.3621	0.3707
	(0.6340)	(0.6431)	(0.6488)	(0.6487)	(0.6628)	(0.6498)
SFHA	2.0515	2.0560	2.0960	2.0757	2.2088	2.0967
	(0.7791)	(0.7779)	(0.7903)	(0.7924)	(0.7963)	(0.7856)
Km to Coast	-0.0854	-0.0843	-0.0854	-0.0861	-0.1047	-0.1013
	(0.0524)	(0.0532)	(0.0540)	(0.0539)	(0.0560)	(0.0547)
Age	-0.0076	-0.0077	-0.0087	-0.0073	-0.0040	-0.0022
	(0.0142)	(0.0143)	(0.0145)	(0.0144)	(0.0148)	(0.0144)
Education	1.5424	1.6382	1.6929	1.7000	1.9334	1.8063
	(0.4895)	(0.5086)	(0.5209)	(0.5246)	(0.5590)	(0.5296)
Worry	-0.4521	-0.4541	-0.4478	-0.4575	-0.5554	-0.5283
	(0.4264)	(0.4289)	(0.4322)	(0.4347)	(0.4507)	(0.4446)
New To Coast	-0.3044	-0.4190	-0.5178	-0.5980	-0.6300	-0.6166
	(0.3736)	(0.3826)	(0.3942)	(0.4011)	(0.4209)	(0.4109)
Constant	-2.2745	-2.5030	-2.4883	-2.5386	-3.8255	-3.6478
	(1.1557)	(1.1782)	(1.1814)	(1.1783)	(1.4066)	(1.3482)
Observations	101	101	101	101	101	101
LL	-39.955	-39.116	-38.535	-38.888	-35.933	-36.935
AIC	109.911	108.233	107.071	107.775	101.866	103.870
AIC Weight	0.012	0.027	0.048	0.034	0.644	0.236
BIC	149.137	147.460	146.298	147.002	141.093	143.097
Bayes Factor	1.000	2.314	4.136	2.909	55.839	20.494
CRRA MFX	0.065	0.093	0.093	0.085	0.086	0.061

Table 5: Firth Logit Regression on Flood Insurance Demand

	CRRA (Unadjusted)	CRRA (5,10)	CRRA (10,20)	CRRA (20,30)	CRRA (30,60)	CRRA (40,80)
CRRA	1.2751	1.4007	1.4413	1.4511	1.4381	1.4189
	(0.4759)	(0.5012)	(0.5019)	(0.4934)	(0.5013)	(0.4876)
Premium (Calculated)	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Income	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Wealth Share	3.5343	3.6057	3.6587	3.7404	3.7760	3.8607
	(0.9874)	(0.9959)	(1.0018)	(1.0112)	(1.0229)	(1.0373)
Prob. Hurr	-0.5044	-0.5579	-0.5979	-0.6540	-0.4986	-0.4938
	(0.7182)	(0.7244)	(0.7302)	(0.7397)	(0.7260)	(0.7266)
Exp. Damage	1.9269	1.9121	1.8908	1.8676	2.0159	2.0551
	(0.8242)	(0.8266)	(0.8281)	(0.8291)	(0.8390)	(0.8434)
Exp. Aid	-0.5051	-0.5125	-0.5143	-0.5165	-0.5241	-0.5282
	(0.3529)	(0.3536)	(0.3539)	(0.3543)	(0.3550)	(0.3553)
Past Flood	0.9836	1.0005	1.0114	1.0359	0.9994	1.0131
	(0.7377)	(0.7378)	(0.7368)	(0.7361)	(0.7346)	(0.7346)
SFHA	1.4720	1.4743	1.4884	1.5019	1.5097	1.4951
	(0.6627)	(0.6603)	(0.6600)	(0.6604)	(0.6558)	(0.6559)
Km to Coast	-0.0140	-0.0132	-0.0127	-0.0121	-0.0166	-0.0174
	(0.0524)	(0.0525)	(0.0526)	(0.0527)	(0.0525)	(0.0526)
Age	0.0118	0.0118	0.0115	0.0114	0.0122	0.0126
	(0.0125)	(0.0125)	(0.0125)	(0.0126)	(0.0125)	(0.0125)
Education	1.0177	1.0218	1.0229	1.0252	1.0409	1.0446
	(0.3754)	(0.3765)	(0.3772)	(0.3780)	(0.3789)	(0.3797)
Worry	-0.0499	-0.0430	-0.0383	-0.0417	-0.0223	-0.0281
	(0.3843)	(0.3856)	(0.3865)	(0.3871)	(0.3858)	(0.3864)
New To Coast	-0.1691	-0.1881	-0.2004	-0.2118	-0.1947	-0.1980
	(0.3441)	(0.3453)	(0.3461)	(0.3469)	(0.3460)	(0.3464)
Constant	-3.5465	-3.6261	-3.6323	-3.6398	-3.7231	-3.7640
	(1.1838)	(1.1944)	(1.1976)	(1.2008)	(1.2057)	(1.2100)
Observations	209	209	209	209	209	209
LL	-71.441	-71.138	-70.889	-70.591	-70.850	-70.683
AIC	172.881	172.275	171.778	171.182	171.700	171.367
AIC Weight	0.096	0.131	0.167	0.226	0.174	0.206
BIC	223.016	222.410	221.913	221.317	221.835	221.502
Bayes Factor	1.000	1.354	1.736	2.338	1.806	2.132
CRRA MFX	0.598	0.669	0.689	0.700	0.665	0.652

Table 6: Firth Logit: Assessing Heterogeneity in Effect of Adjustment Procedure

	CRRA (Unadjusted)	CRRA (5,10)	CRRA (10,20)	CRRA (20,30)	CRRA (30,60)	CRRA (40,80)
CRRA	4.0664	4.8575	5.0578	4.3189	6.5694	4.9360
	(1.6148)	(1.9714)	(2.0286)	(1.6731)	(2.4417)	(1.6929)
Premium (Calculated)	-0.0004	-0.0004	-0.0004	-0.0005	-0.0005	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Income	0.0024	0.0021	0.0020	0.0019	0.0020	0.0020
	(0.0022)	(0.0023)	(0.0023)	(0.0022)	(0.0024)	(0.0023)
Wealth Share	4.6936	5.0527	5.3392	5.6658	7.1064	7.1233
	(1.6888)	(1.7540)	(1.8046)	(1.8843)	(2.2511)	(2.2465)
Prob. Hurr	-0.3446	-0.6573	-0.8823	-0.9750	-0.2184	-0.1492
	(1.1141)	(1.1635)	(1.2191)	(1.2553)	(1.1731)	(1.1774)
Exp. Damage	3.4821	3.4621	3.4369	3.5012	4.9364	4.8855
	(1.4937)	(1.4940)	(1.5036)	(1.5160)	(1.7940)	(1.7752)
Exp. Aid	-0.8628	-0.9706	-1.0228	-1.0213	-1.0352	-1.0234
	(0.5843)	(0.5975)	(0.6057)	(0.6075)	(0.6195)	(0.6153)
Past Flood	0.2494	0.2867	0.3139	0.3766	0.4338	0.4585
	(0.9568)	(0.9566)	(0.9506)	(0.9499)	(0.9706)	(0.9645)
SFHA	2.4782	2.4606	2.4966	2.4820	2.6057	2.4748
	(1.0666)	(1.0595)	(1.0707)	(1.0747)	(1.0720)	(1.0593)
Km to Coast	-0.1176	-0.1142	-0.1148	-0.1157	-0.1416	-0.1367
	(0.0817)	(0.0822)	(0.0832)	(0.0828)	(0.0867)	(0.0843)
Age	-0.0100	-0.0101	-0.0112	-0.0094	-0.0056	-0.0030
	(0.0213)	(0.0215)	(0.0217)	(0.0215)	(0.0222)	(0.0217)
Education	2.0458	2.1404	2.1898	2.2032	2.5077	2.3622
	(0.7272)	(0.7462)	(0.7589)	(0.7662)	(0.8251)	(0.7877)
Worry	-0.6176	-0.6017	-0.5835	-0.5912	-0.7159	-0.6892
	(0.6424)	(0.6399)	(0.6430)	(0.6458)	(0.6633)	(0.6569)
New To Coast	-0.3651	-0.4950	-0.6091	-0.7203	-0.7350	-0.7405
	(0.5706)	(0.5774)	(0.5893)	(0.6001)	(0.6312)	(0.6198)
Constant	-2.9801	-3.2111	-3.1777	-3.2670	-4.8519	-4.7081
	(1.6958)	(1.7183)	(1.7283)	(1.7280)	(2.0198)	(1.9545)
Observations	101	101	101	101	101	101
LL	-17.543	-17.068	-16.653	-16.743	-14.615	-15.135
AIC	65.085	64.137	63.305	63.486	59.231	60.271
AIC Weight	0.027	0.043	0.066	0.060	0.504	0.300
BIC	104.312	103.363	102.532	102.712	98.458	99.498
Bayes Factor	1.000	1.607	2.436	2.225	18.678	11.104
CRRA MFX	0.596	0.821	0.851	0.746	0.917	0.656

9 Figures

Figure 1: Risk Preference Instruments

26. You will earn $5 for participating in this research. You now have the ability to earn more (or less) depending upon weather outcomes in Brunswick, GA in November of 2018 and the choices you make.

Note, weather outcomes will be measures by reported statistics at Brunswick Malcom Mckinnon Airport weather station (ID = GHCND:USW00013878) between 12:01am November 1st and 11:59pm November 30th.

Historical data on November weather in Brunswick, GA (from the airport weather station, going back to the 1970s) indicate the following:

- 50% chance of getting rainfall below 1.5 inches
- 22.5% chance of November low temperature below 33°F
- 12.5% chance of getting rainfall greater than or equal to 5 inches
- Approx. 2.5 % chance of November high temperature equal to 89°F

Using this information, we offer you four alternative choices that lead to better or worse outcomes relative to your current $5 payment, depending on the weather. You may also keep the $5 that you will earn, forgoing any risk presented by the alternative choices. Please evaluate each choice before you decide and indicate below.

○ Keep $5 and do not choose the alternative opportunities (still have to wait until December to receive payment) → **Skip to question #27 on page 6**

○ Forego the $5 and choose one of the alternative opportunities (payments in December)

Select only one of the following choices. Your most preferred choice will be used to determine your earnings.

○ Choice 1: receive $8 if November rainfall in Brunswick is ≤ 1.5 inches (50% historical chance)
receive $3 if November rainfall in Brunswick is > 1.5 inches (50% historical chance)

○ Choice 2: receive $22 if Brunswick November low temp is ≤ to 33°F (22.5% historical chance)
receive $2 if Brunswick November low temp is > 33°F (77.5% historical chance)

○ Choice 3: receive $60 if November rainfall in Brunswick is ≥ 5 inches (12.5% historical chance)
receive $0 if November rainfall in Brunswick is < 5 inches (87.5% historical chance)

○ Choice 4: receive $300 if Brunswick November high temp is = 89°F (2.5% historical chance)
receive $0 if Brunswick November high temp is ≠ 89°F (97.5% historical chance)

Thank you for your response. We will mail you the outcomes of each of these weather events, along with your payment on or around December 14th, 2018.

Figure 2: Weather Probability Debriefing Questions

27. The weather probabilities given in the prior question are based on historical information for Brunswick, GA. Please indicate how well you think historical information predicts weather outcomes for this November 2018:

	This weather prediction is...				
	Much too low	Slightly too low	About right	Slightly too high	Much too high
The likelihood of 1.5 inches of rainfall is 50%	○	○	○	○	○
The likelihood of low temp less than or equal to 33°F is 22.5%	○	○	○	○	○
The likelihood of rainfall greater than 5 inches is 12.5%	○	○	○	○	○
The likelihood of high temp equal to 89°F is 2.5%	○	○	○	○	○

Figure 3: Inequality 7 for various ϵ

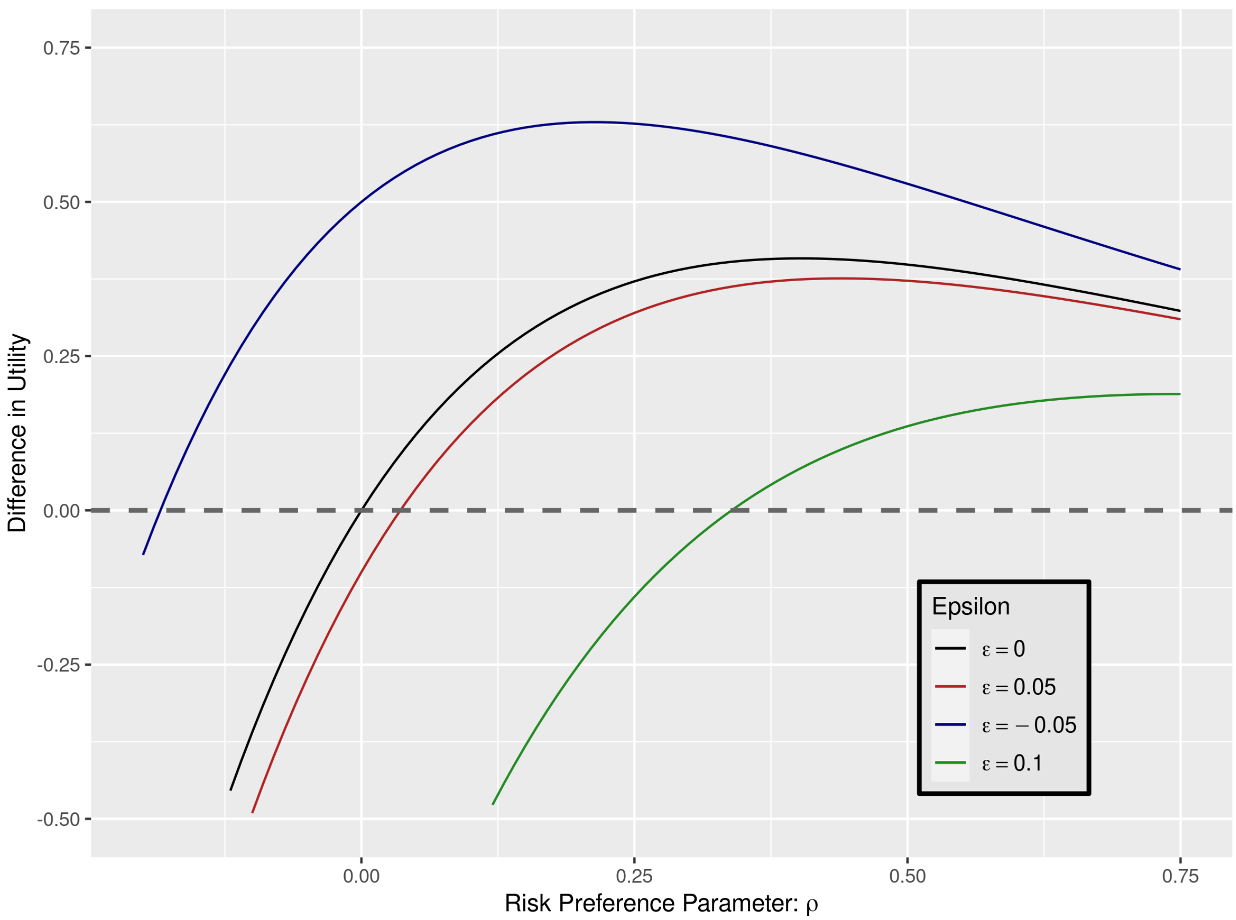

Figure 4: Original vs Adjusted CRRA Values