Decision Making Under Natural Hazard Risk

by

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(Under the Direction of Craig Landry)

Abstract

This dissertation consists of three essays that seek to improve the understanding of how individuals make decisions under the risk and uncertainty associated with natural hazards. The second chapter of the dissertation addresses a long-standing identification problem in the experimental elicitation of domain-specific risk preferences. The work presented in the third chapter of the dissertation classifies the accuracy of homeowners' perceptions of natural hazard risk and identifies determinants that influence the formation of those perceptions. Chapter four presents and estimates a structural expected utility model over the decision to purchase flood insurance and shows that the canonical framework for analyzing decision making under risk and uncertainty appears to be a valid descriptor of observed behavior.

Index words: Natural Hazards, Risk Preferences, Risk Perceptions, Flood Risk Mitigation

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Chapter 1

Introduction

For over three centuries, intellectuals have tried to systematically explain human behavior in situations characterized by risk and uncertainty (Bernoulli, 1738). More recently, economists have taken a particular interest in developing formalized frameworks for analyzing individual decision-making under risk (von Neumann & Morgenstern, 1944). However, a complete and validated theoretical framework that explains observed decisions in a variety of domains and settings has been elusive. Natural hazards represent one such domain where existing theoretical frameworks have yielded relatively little insight into observed human behavior. This dissertation seeks to advance the aggregate understanding of decision-making under risk and uncertainty with an emphasis on decisions related to natural hazard risks. In the fall of 2018 and again in the summer of 2020, survey data was collected from coastal homeowners in three counties along the U.S East Coast. In each of the following chapters, this data set is used to address pervasive problems that have prevented economic researchers from fully explaining and characterizing decision-making in the domain of natural hazard risk.

Chapter two of this dissertation addresses a prevalent identification problem that is present when trying to experimentally elicit risk preferences under the generalized expected utility framework. Expected utility is characterized by a multiplicative relationship between preferences and beliefs which complicates the identification of risk preferences. In experimental or field settings, the respondent's decision weight must be known with certainty to confidently infer accurate attitudes towards risk. Factors such as probability weighting or the influence of past experiences may result in an individual applying a decision weight that differs from the probability used to infer risk preferences. To address this issue, a novel Monte-Carlo based method is proposed for expressing uncertainty in the individual's decision weight as uncertainty in their risk aversion coefficient. This procedure is implemented on experimentally elicited risk preferences and shown to improve model fit when the modified risk aversion coefficient is used as a determinant of behavior in a reduced form model of insurance demand.

Chapter three of this dissertation characterizes the nature and determinants of homeowner misperceptions regarding flood and hurricane risks. Previous literature has examined the tendencies regarding homeowner flood risk misperceptions but has failed to reach a consensus. The results presented in chapter three add another data point to the literature on flood risk misperceptions using a novel data set and extend the literature by including an analysis of misperceptions of tropical cyclone risk. Findings suggest a weak general tendency to overestimate the probability of flooding, but a strong tendency to overestimate the probability of a major hurricane strike. Respondents also overwhelmingly overestimate the damage likely to be caused by a flood or major hurricane. A robustness check suggests that the differences between objective and subjective flood probabilities cannot easily be explained by individuals engaging in probability weighting. Reduced form regressions suggest a variety of individual attributes may influence risk misperceptions including past flood experience, coastal experiences, and levels of worry. Notably, objective risk metrics appear to influence perceptions but only if the source of objective risk is publicly available.

The final chapter of this dissertation is based on the fact that in the economics literature, there is an abundance of critical assessments of expected utility theory that point out the incongruities between the predictions of expected utility and observed behavior. However, most of this literature is based on uncertain situations over small stakes. This final chapter investigates the descriptive validity of expected utility over a large stakes decision by estimating a structural model on the binary decision to purchase flood insurance. Results suggest that the model predicts flood insurance market penetration to within a few percentage points of actual insurance rates in the survey sample and does so with reasonable (low single-digit) estimated coefficients of relative risk aversion, suggesting that expected utility theory may be a viable description of individual decision-making process in this particular domain.

Chapter 2

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

2.1 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 reduced-form analysis of individual decision making in a variety of domains, including (but not limited to) natural hazard mitigation (Petrolia et al., 2015; Petrolia et al., 2013), 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 individuals' proclivity to take risks.

Identifying individuals' proclivity for risk-taking, or "risk preference", however, is non-trivial and fraught with challenges, prompting a literature focused on discerning ways to robustly infer individual risk preferences with simple and easy to implement tools. 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). These methods trade-off simplicity at the expense of granularity, as they generally only give researchers a very vague understanding of the individuals' risk-taking behavior.

The second approach entails using economic theory to structurally model an individual's decision over risky prospects. Observing choices over risky outcomes permits inference of individual structural risk preference parameters (under the presumption that the theoretical model and the domain of inference sufficiently mimic the individuals' decision-making process). 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 popularity of using experimental methods to elicit risk preferences in applied economics research (Charness et al., 2013; Eckle & Grossman, 2002; Holt & Laury, 2002).

Assessing risk preferences in an experimental setting provides researchers with considerable latitude in controlling uncertain outcomes and the context in which resolution will be realized. 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. 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 & List, 2007a, 2007b, 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 (also known as "beliefs" or "decision weights") and preferences (i.e. utility as a function of 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 (Fishburn, 1973; Karni, 2007; Lu, 2019; Luce & Krantz, 1971). Identification in cross-sectional data is usually not possible without strong (and arguably unrealistic) sets of assumptions[1].

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.[2] In a field setting, however, where elicitation is usually conducted in a domain-specific context,[3] 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 non-systematic 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 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

[1] 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).

[2] 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 & Tversky, 1979; Quiggin, 1982; Tversky & Kahneman, 1992b) 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.

[3] 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).

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 with respect to their proclivity to take 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 individuals' 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 control for participant perceptions of probability that differ from those reported in the elicitation instrument. Our particular domain of interest is natural hazard mitigation, and our elicitation instrument utilizes future weather outcomes to introduce uncertainty. Respondents are permitted to choose among four weather-based lotteries, with decreasing likelihood and increasing conditional payout. 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 show that incorporating the Monte Carlo adjusted risk preference coefficients into a reduced form analysis on flood insurance demand improves model fit compared to when uncertainty in decision weights is ignored.

The rest of this chapter is organized as follows. Section 2.2 describes our data collection efforts and provides descriptive statistics. Section 2.3 outlines our empirical approach for both adjustments of implied risk preference intervals and our reduced-form analysis of flood insurance demand. Section 2.4 presents our results. Section 2.5 provides a discussion of the results, while section 2.6 concludes.

2.2 Survey Design and Data Collection

Household-level data for our analysis was gathered via a mail survey in the fall of 2018 in Glynn County, GA. An initial sample of 1914 recent home buyers (sold in 2016 or 2017) was targeted and sent surveys in early October with a response rate of 13.9% (266 returned surveys). Participation was incentivized by offering $5 cash payments for returned surveys. However, respondents did have the option to earn more or less by engaging with the incentive-compatible risk preference instrument. The overarching goal of the survey was to gather a rich profile of homeowners' expectations, beliefs, and perceptions related to coastal living with an explicit focus on climate change induced risks.

Most pertinent to our analysis is our survey questions for elicitation of risk preferences. Our 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 the 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 on the actual randomness of lottery outcomes.

Figure 2.1 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 are 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 2.2 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)"

2.2.1 Descriptive Statistics

Table 2.1 reports descriptive statistics for all variables used in our analysis. Sixty-two percent of survey participants 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 the premium respondents would face. In reality, respondents may not choose full coverage and may choose a different deductible. However, this calculated premium still captures the differences in price individuals face when looking to purchase flood insurance and thus serves its purpose of controlling for price in our reduced form analysis. The mean value of this calculated annual premium was $1426.

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

Figure 2.1: 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 2.2: 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%	○	○	○	○	○

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. 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., 2019). Thirty-five percent of respondents believed they would be eligible for a 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 respondent's home was located in a special flood hazard area (SFHA) 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 5 point Likert scale with 5 being the most worried. Responses were converted to a binary variable by coding responses of 3 or higher 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 2.1 reports results to our debriefing questions in which respondents reported their beliefs regarding the correctness of the objective weather probabilities. Overall, only 22 percent of respondents agreed with all weather probabilities reported. The mean responses regarding lotteries one and two were 2.82 and 2.83 respectively, indicating an aggregate opinion that the probabilities associate with these lotteries were too low. On the other hand, the mean responses for lotteries three and four were 3.21 and 3.24 indicating a general proclivity to believe that these probabilities were too high. Interestingly, these responses are compatible with the predictions of prospect theory which proposes a general tendency to overweight small probabilities and underweight larger probabilities (Kahneman & Tversky, 1979).

2.3 Methods

Our empirical methodology is split into two primary objectives. The primary task being to adjust the elicited risk preference parameters to reflect uncertainty in the individuals' decision weights. The second task being to validate this procedure by incorporating the adjusted risk preference parameters into a reduced form analysis to show they offer an improvement in model fit for a domain-relevant decision. We describe the details of each task in the remainder of this section.

2.3.1 Monte-Carlo Procedure

Our procedure for modifying the CRRA interval that can be inferred from each respondent's choice is done using the following steps.

1. Check if the respondent indicated a disagreement with any of the probabilities reported in the instrument. If the respondent agreed with the accuracy of all objective probabilities, no adjustment is made. If a disagreement exists, the following steps are undertaken.

2. If the respondent thought a particular probability was **slightly** too low (high) the lottery probability is multiplied by $1 + \theta_{slight}$ $(1 - \theta_{slight})$. If the respondent though a probability was **much** too low

(high) the probability is multiplied by $1 + \theta_{much}$ $(1 - \theta_{much})$. The value of θ_{slight} and θ_{much} are drawn from the following uniform distributions [4].

$$\theta_{slight} \sim unif(0, 0.05)$$

$$\theta_{much} \sim unif(0.05, 0.1)$$

3. The perturbed lottery probabilities are then used to calculate the implied CRRA interval that is consistent with the respondent's lottery choice assuming 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 adjustment magnitudes (θ_{slight} and θ_{much})

5. Take the maximum of the N upper bounds and the minimum of the N lower bounds. These values form the new "adjusted" implied CRRA interval.

The procedure described here will produce implied 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 particular lottery was slightly too low, we adjust that lottery probability by up to 5 percent. However, if the respondent interpreted "slightly too low" as 7 percent, our procedure is not guaranteed to produce an interval that contains the true CRRA values.[5]

Panel C of table 2.1 reports summary statistics for original and adjusted CRRA intervals (using various interval sizes for the theta parameters) where each interval has been coded at its midpoint [6]. Overall, the

[4] The appropriate adjustment size for "slightly" and "much" is certainly debatable. Thus, the bounds of the uniform distribution that the θ parameters are drawn from is subject to a sensitivity analysis later on

[5] Although it could still contain the true CRRA depending on the respondent's responses regarding the probabilities of the other lotteries.

[6] The parenthesis next to each CRRA variable indicate the upper bound used for the distribution that the theta parameters are drawn from. For example "CRRA (10,20)" indicates that this CRRA variable was adjusted by drawing θ_{slight} from (0,0.1) and θ_{much} from (0.1,0.2)

mean value of the coefficient tends to be preserved before and after the adjustment regardless of the size of the interval that the theta parameters are drawn from. However, wider theta parameter distributions tend to produce CRRA values with a wider variance. This is also apparent in figure 2.5 which plots histograms of the original and adjusted CRRA values.

2.3.2 Reduced Form Analysis

To validate the usefulness of the previously described adjustment procedure, we conduct a reduced-form analysis of flood insurance demand and assess overall model fit before and after the coefficients have been adjusted using our Monte-Carlo procedure. 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 subject to debate. Thus we conduct a sensitivity analysis with our reduced-form models by estimating a reduced form specification for each of the CRRA variables reported in table 2.1, panel C.

Heterogeneity in Model Improvement

For many of the respondents in our sample, the adjustment procedure had little to no effect on their implied CRRA interval. This occurs due to individuals indicating they agreed with all or some[7] of the objective probabilities or indicating disagreements in objective probabilities in multiple lotteries that mostly cancel each other out. Thus, any source of model improvement is likely to come from individuals 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.

[7] 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

2.4 Results

Table 2.2 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 consistent with what economic theory would suggest. Individuals whose home makes a higher proportion of their net worth, those who expected more home damage from a hurricane, residents in flood zones, and those with college educations were all more likely to have flood insurance policies. The focus of our results however is on the potential improvements that adjusting risk coefficients may have on the ability of the elicit risk preferences to explain domain-relevant behavior.

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. 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[8] model among the competing models under consideration (Burnham & Anderson, 2004). This metric suggests that our base model with un-adjusted risk coefficients has a 9.5% probability of being the best model.

Similarly, we produce a more interpretable analog for the raw BIC values by calculating and reporting Bayes' factor. 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 factor's for each model in table 2.2 range from 1.46 up to 2.56[9] 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 2.2 in favor of using our proposed Monte-Carlo 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. However, if the BIC and

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

[9] 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

Bayes factor are the metrics of choice, 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 2.3 reports the same regressions as in table 2.2 but with the sub-sample of observations that experienced 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. Just like the regressions run on the full sample, all specifications suggest elicited CRRA values (unadjusted and adjusted) are significant determinants of flood insurance status. However, normalized AIC weights 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 has a 64% probability of being the best. Bayes' factors range from 2.3 up 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".

2.5 Discussion

Despite the fact that the identification challenges associated with simultaneous uncertainty in both decision weights and risk preferences have been known for some time (Savage, 1954), uncertainty in decision weights has largely been ignored during experimental elicitation of risk preferences. This is likely due to the fact that most of the previous literature that infers risk preferences from observed choices has been conducted in the laboratory environment where assuming an equivalency between objective probabilities and decision weights is arguably plausible. However, the emerging literature that attempts to characterized risk preferences in non-laboratory settings, 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 to attempt to account for uncertainty in decision weights during experimental elicitation of risk preferences that can also be easily implemented in a field context.

Our results suggest that ignoring uncertainty in individual decision weights (equivalent to assuming that individuals act on objective probabilities) results in a substantially worse model fit for reduced form models utilizing elicited risk preferences. Our adjustment procedure improves the model fit in the full sample, however, it could be argued that these models are not unambiguously better. This is largely due to many individuals having their coefficients of risk aversion altered only slightly due to having beliefs that did not differ substantially from the stated lottery probabilities. However, we show that regressions based on individuals that had substantially different CRRA values after our adjustment procedure see vast improvements in model fit by accounting for uncertainty in decision weights; 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 increase model fit is largely dependent on how much subjective beliefs differ from the objective probabilities which are likely to vary depending on the sample and research context.

Until now, our results have focused on the statistical significance of implementing our risk preference adjustment procedure, but we have yet to discuss the economic significance of this adjustment. The footers of both table 2.2 and 2.3report average marginal effects of the risk preference variable in each reduced form regression. Because a one-unit increase in the CRRA is considered quite large and can completely reclassify an individual's attitude towards risk[10], marginal effects are calculated as semi-elasticises. Thus, table 2.2 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 2.3), this bias is more pronounced. The base

[10]for example a CRRA value of -0.1 is indicative of a risk-loving individual whereas a CRRA value of 0.9 would indicate quite large levels of risk aversion.

model suggests the base model understates the effect of risk preferences by approximately 25%. Overall, our results suggest that flat our ignoring uncertainty in decision weights is not prudent and may very well lead to incorrect inference. That being said, 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 scale. The simplicity is advantageous as it increases the likelihood that any given respondent will answer the question. The downside to this 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. However, open-ended responses are accompanied by their own set of challenges. For example, there is often a tendency for respondents to round open-ended answers (Manski & 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's 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 avenue for future research.

One concern with our analysis is that our small sample size (particularly for the regressions in table 2.3) may mean comparing models based on information criteria derived from the log-likelihood of each model 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). PML, a method proposed by (Firth, 1993), makes use of a likelihood function that has been modified to include an additive penalty term which has been shown to lower bias and variance compared to standard maximum likelihood estimation in logit model coefficients (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. Using a series of Monte-Carlo simulations, Rainey and McCaskey, 2020, show that even with only 30 observations (used to estimate 9 parameters), PML estimated logit coefficients 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 a PML estimated logit model and report the results in tables 2.4 and 2.5. 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 stated objective lottery probabilities. However, we do note that marginal effects 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 intact [11].

2.6 Conclusion

Experimentally eliciting attitudes towards 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. However,in the generalized expected utility framework, 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 risky prospect but instead observes choices

[11] Table 2.4 replicates table 2.2 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 2.5 replicates table 2.3 and suggests the base model exhibits a downward bias of approximately 54%

concerning naturally stochastic events. However, even experimental settings may be prone to this source of bias since it is difficult to verify if the research participant accurately internalized the provided probability.

In this study, we propose a methodological procedure to elicit 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 making payouts conditional on future weather events which have 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 the research participant. 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 the interval of the risk coefficient that can be inferred from the individual's observed choice. Finally, 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 using risk coefficients that ignore potential uncertainty in individual decision weights.

Table 2.1: 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
Belief: Lottery 1	2.82	0.58	1.00	5.00	242
Belief: Lottery 2	2.83	0.95	1.00	5.00	242
Belief: Lottery 3	3.21	0.86	1.00	5.00	242
Belief: Lottery 4	3.24	0.97	1.00	5.00	240
Panel C: Risk Aversion Coefficients					
CRRA (Origonal)	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 2.2: 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

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: 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

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: 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

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: 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

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

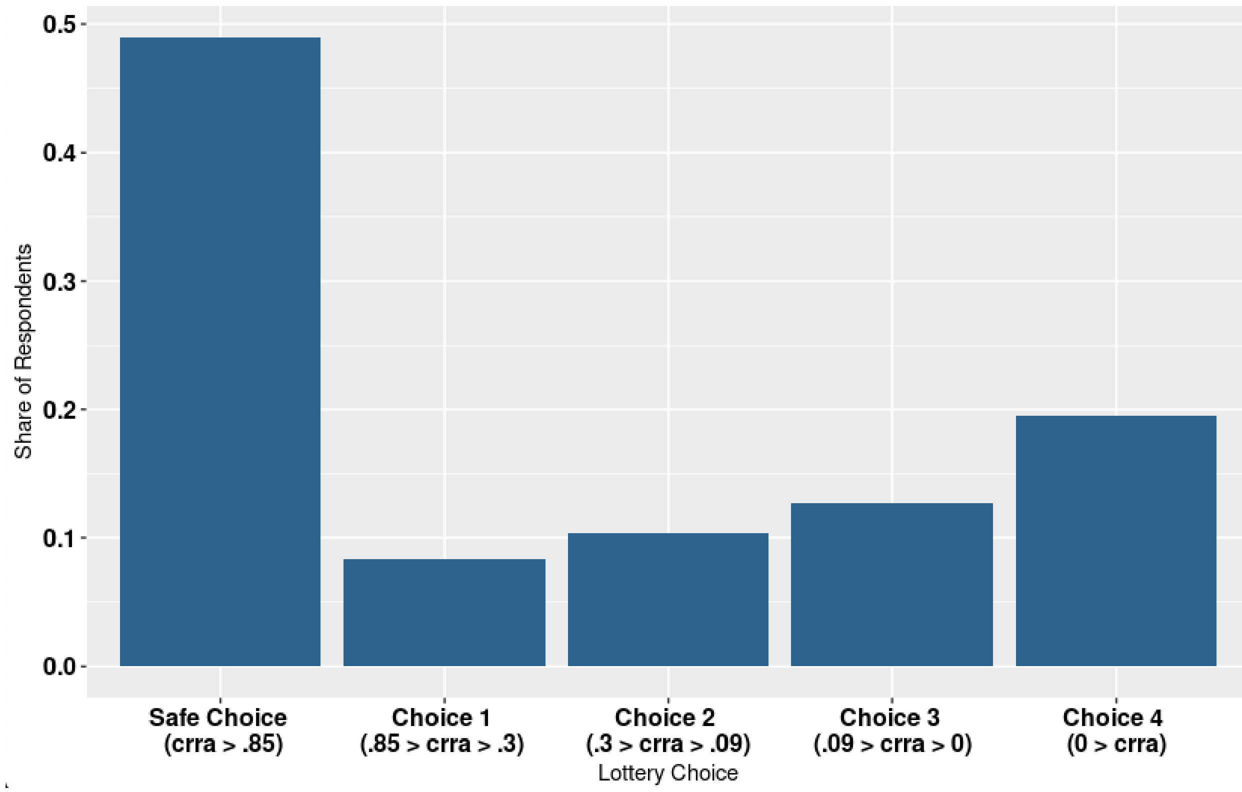


Figure 2.3: Lottery Choices and Corresponding CRRA Intervals

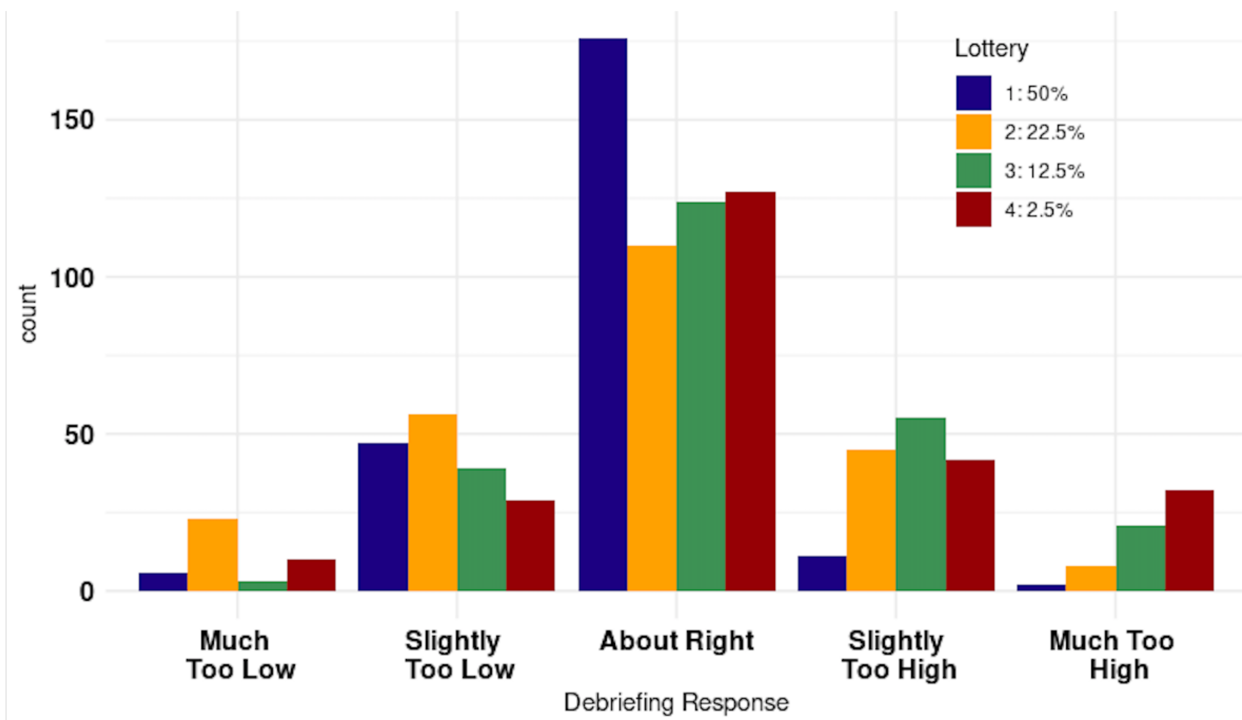


Figure 2.4: Distribution of Debriefing Responses

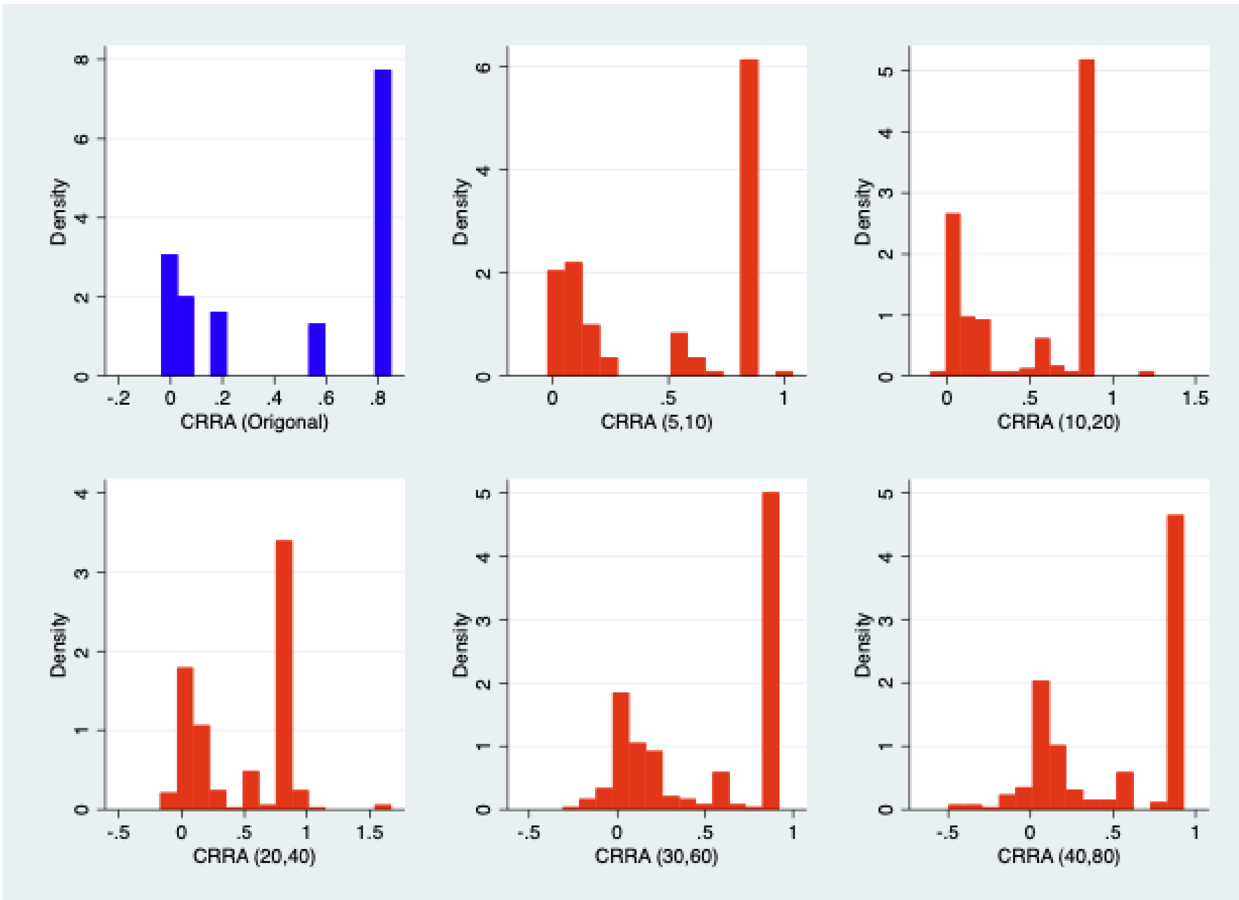


Figure 2.5: Origonal vs Adjusted CRRA Values

Chapter 3

The Nature of Coastal Hazard Risk (Mis)perceptions

3.1 Introduction

As was shown in chapter 2 of this dissertation, erroneously assuming individuals have correct probabilistic perceptions can have a significant effect on the risk aversion parameter implied by observed behavior. A recent trend is the use of real-world observed decisions (sometimes called "field data") to infer risk preferences (see Barseghyan et al., 2018 for a review). Out of necessity, this literature often makes an assumption that subjective and objective risk preferences are perfectly aligned. It's not clear if this assumption is well-founded as perceptions of risk are likely to vary across domains, with consumers generally having correct perceptions in some domains while other domains are more susceptible to widespread misperceptions. Thus, there is a need for studies that directly compare individuals' subjective assessments of risk against objective measures. With respect to flood risk, studies that measure and report the extent of homeowner misperceptions are uncommon. Moreover, the few existing studies doing so do not reach a consensus on the general tendency to overestimate or underestimate risk. Botzen et al., 2015 survey 1000 homeowners in flood-prone regions of New York City and investigate individual awareness of living in a flood zone, perceived flood probability, and perceived flood damages. After eliciting open-ended responses for each individual's perceived probability of a flood and their expected cost to repair their home after a flood, they find that most individuals overestimate the probability of a flood but under-estimate associated damages when compared to objective HAZUS[1] risk estimates. Bakkensen and Barrage, 2017 survey 187 coastal residents in Rhode Island and ask each respondent to indicate their level of worry regarding coastal flood hazards along with their belief about the probability of their home flooding at least once over the next 10 years. They then compare the open-ended subjective flood probabilities against objective probability estimates generated using a variety of sea-level rise projections and flood inundation mapping tools. Overall, they find approximately 70% of residents underestimate the cumulative probability of a flood occurring in the next 10 years.

Royal and Walls, 2019 survey several hundred coastal flood plain residents in Maryland and investigate individual's perceptions of flood risk by first asking individuals to indicate if they thought their home was more or less exposed to flood damages than the median home from their sample. Additionally, they compare each individual's belief about being at lower risk against objective risk assessments generated by HAZUS. In both cases they find residents to generally be overoptimistic in the perceptions of flood risk. Elicitation of the perceived probability of flooding revealed that the majority of homeowners believed the annual probability of a flood to be less than 1% despite all properties in the sample being located in SFHA zones defined by at least a 1% chance of flooding per annum.

Mol et al., 2020 survey roughly 2000 Dutch homeowners to assess flood risk misperceptions and identify determinants of those misperceptions. With regard to perceived flood probability, they find that 89% of their sample have flood risk perceptions that are incorrect even when applying a large 25% margin of error. The majority of their sample (55%) overestimated the probability of a flood, while 34% have flood risk perceptions that are lower than objective estimates. Those who underestimated the probability of a flood were primarily characterized as neglecting the risk altogether by indicating they don't ever expect their personal residence to flood. With respect to flood consequences, they find most residents report much lower maximum water levels than objective estimates would suggest. However, individuals' expected damages were roughly in line with objective estimates about half of the time (when allowing for

[1]Hazards U.S. (HAZUS) is a GIS-based natural hazards analysis tool created and maintained by FEMA

a 25% margin of error). Those who reported expected damages that differed from objective estimates were slightly more likely to underestimate damages than overestimate.

Overall, the existing literature has not fully characterized the nature of flood risk mis-perceptions. The literature has so far found evidence of individuals overestimating the likelihood of flooding (Botzen et al., 2015; Mol et al., 2020), underestimation of the likelihood of flooding (Bakkensen & Barrage, 2017; Royal & Walls, 2019), underestimation of flood water levels (Mol et al., 2020), underestimation of expected damages (Botzen et al., 2015), damage expectations that are generally correct (Mol et al., 2020) and underestimation of "flood risk exposure" (Royal & Walls, 2019).

Complicating matters, temporal, methodological, spatial, and institutional differences in each study make it difficult to isolate the source of the variation in results. For example, Mol et al., 2020 is based in the Netherlands and thus results cannot reliably be generalized to the U.S. given large differences in institutional setting. Royal and Walls, 2019 sample from coastal Maryland which had not had any major flood events for some number of years before the survey. Additionally, they only survey SFHA residents, meaning their results may not generalize to homeowners in lower-risk flood zones. Botzen et al., 2015's survey was notably administered 6 months after Hurricane Sandy, meaning many of their survey respondents had fresh memories or recent direct experience with flood damage.

This study contributes to the emerging but inconclusive literature that compares individual subjective beliefs about flood risks against objective measures of flood risk. Given the contradictory findings of previous empirical studies, the results presented here provide another data point from a novel data set obtained from several unique locations along the US east coast. Analysis of homeowner flood probability perceptions suggests that individuals with over-optimistic, pessimistic, and accurate perceptions are all well represented in the data. However, in general, individuals tend to be most likely to overestimate the probability of a flood, a result that is most consistent with Botzen et al., 2015 and Mol et al., 2020 but differs from the conclusions found by Bakkensen and Barrage, 2017 and Royal and Walls, 2019. With respect to expected flood damage, almost all survey respondents overestimate the damages associated with a flood, a result that is notably different than any of the previous empirical studies that have directly assessed damage misperceptions.

The sample used for this study is drawn from communities on the U.S. east coast, meaning many of the flood events these communities may face are likely to be caused by tropical cyclones. Thus, in addition to flood risk, hurricane risk misperceptions are specifically analyzed which suggests individuals have a general tendency to overestimate the probability of a major hurricane making landfall near their home and generally overestimate the associated damages. To investigate the sources of heterogeneity in misperceptions, a reduced-form analysis is conducted to identify possible determinants of risk perceptions, awareness of one's flood zone, and having accurate risk perceptions. The analysis suggests that a variety of individual attributes correlate significantly with these outcomes including past flood experience, objective risk metrics, coastal experiences, and levels of worry.

Finally, previous literature has struggled with the fact that in structural decision models, it is often impossible to distinguish between probability weighting and probability misperceptions (Barseghyan et al., 2013; Collier et al., 2020). As noted by Barseghyan et al., 2013, this does not matter in the sense that both assumptions could lead to models that accurately predict behavior, but policy implications may be different under each scenario. For example, if individuals are misperceiving probabilities of natural hazard risk, information campaigns may be a potentially effective policy intervention, whereas this would have little to no effect if individuals have correct perceptions of risk, but weight probabilities when utilizing risk information for actual decisions. We conclude the empirical analysis by investigating this issue. We do so by structurally estimating a series of beta regressions that attempt to map each individual's unique objective flood probability to their reported subjective flood probability using six probability weighting functions that are common to the literature. Doing so reveals no improvement in model fit compared to a standard linear regression suggesting that the differences observed between objective and subjective flood probabilities cannot be easily explained by probability weighting.

The remainder of this paper is organized as follows. Section 2 provides an overview of the data sources utilized and presents descriptive statistics. Section 3 describes my empirical methodology. Section 4 presents results, while section 5 discusses my results and compares them to the existing literature. Section 6 concludes.

3.2 Data

Data for this analysis comes from several sources including primary survey data along with data from both government and non-profit agencies. The collection and construction of the data set for this analysis is detailed in this section.

3.2.1 Survey Data

The empirical analysis presented here involves two distinct steps. The first compares objective and subjective metrics of flood and hurricane risk and categorizes respondents as being pessimistic, correct, or over-optimistic in their risk assessments. The second step explores possible determinants of the heterogeneity in misperceptions by conducting a reduced form analysis. Data requirements for this analysis necessitate having 1) subjective risk metrics, 2) objective risk metrics, and 3) individual characteristics that plausibly influence risk perceptions. The remainder of this section details the sources and collection methodology of this data then concludes by reporting descriptive statistics for the data set.

3.2.2 Subjective Risk Metrics

The majority of the data used to conduct our analysis was gathered via a series of mail surveys that took place in several waves between October 2018 and July 2020. Each survey wave targeted recent home buyers in various coastal locations along the east coast. The first wave was administered in Glynn County, GA during October of 2018, followed by a second wave in Dare County, NC during June of 2020, and a final wave in Worcester County, MD during July of 2020. Most notable for this analysis were questions that elicited individual beliefs regarding coastal natural hazard risk. Subjective annualized flood probabilities were elicited by prompting respondents to answer the following open-ended question within the survey:

"In the next 12 months, what do you think the percentage chance is that your home will flood from any weather-related event (rain, storm surge, hurricane, etc.)?".

To obtain an estimate of each respondent's subjective beliefs regarding personal home damage from a weather-related flood, the following open-ended question was posed to survey participants:

"If your home were to flood from any weather-related event (rain, storm surge, hurricane, etc.), approximately how much do you think it would cost to return your home to its prior condition?"

To obtain a subjective probability of a major hurricane strike, survey participants were asked the following question:

"How many major hurricanes (Category 3 or greater, with winds of 111 mph or greater, possibility of tornadoes, and storm surge of at least 10-12 feet) do you expect to pass within 60 miles of your county over the next 50 years?"

Expected hurricane responses were then mapped to a corresponding annualized probability. To elicit expected hurricane damage, the survey first prompted participants with the following question:

"Suppose a Category 3 hurricane (with winds exceeding 110 mph, possibility of tornadoes, and storm surge of at least 10-12 feet) directly struck near your house at high tide. How much damage (expressed as a percentage of total home value) do you think your home would most likely suffer?"

Respondents then indicated a level of damage on an ordered categorical scale ranging from "0%-10%" up to "91% - 100%" in 10 percentage point increments.

3.2.3 Objective Risk Metrics

To assess the accuracy of homeowner's perceptions of risk, we utilize several sources of objective flood risk data. The first, and most simplistic is the FEMA designated flood zone for each property which is obtained by cross-referencing digitized flood hazard layers against geospatial coordinates of each property. As a metric of risk, these flood zone classifications are quite crude with only three primary classifications; "a less than 0.2% percent chance per annum" (Zone X500) , "between a 0.2% and 1% chance per annum" (Zone X), and "greater than 1% chance per annum" (Zones A,V). Additionally, the accuracy of flood maps that assign homes to one of these designations has been called into question. Wing et al., 2018 estimate that 41 million U.S. households face a 1% chance of flooding per annum while FEMA flood maps indicate only 13 million households face that same risk. However, these designations are highly publicized and are the primary risk metric for pricing flood insurance policies, thus they serve as an important control for analyzing determinants of risk perceptions. In addition to FEMA flood zone status, we also obtain detailed flood risk data for each home in the sample from the probabilistic flood model produced by the First Street Foundation (First Street Foundation, 2020). Data from this source includes the annualized probability of a flood along with flood depths for flood events with 5, 10, 20, 50, 100, and 500 year return periods.

To obtain estimates of damage in the event of a flood, we take the First Street flood depths (for each return period) and calculate flood inundation levels based on the first-floor elevation for each home in our sample. These flood inundation levels, along with other home characteristics are used to create flood damage estimates using a variety of flood damage functions[2] which map flood inundation levels into damage as a share of total home structure value.

3.2.4 Objective Hurricane Risk

Objective estimates of a major hurricane making landfall are obtained by using data from the National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center (NHC). The NHC's online "Historical Hurricane Tracks" tool allows hurricanes and tropical storms to be filtered to obtain a list of those that meet the conditions specified out in our survey questions (National Hurricane Center,

[2] We generate damage estimates using multiple damage functions and then average results to obtain a single damage estimate. The damage functions used are FEMA's Flood Impact Analysis Damage Function (FIA), and several produced by the U.S. Army Corps of Engineers (USACE) which include "USACE - IWR", "USACE - Chicago", and "USACE - Galveston"

2020). To obtain an annualized objective probability corresponding to the subjective probabilities elicited in our survey, we simply count the number of hurricanes meeting the conditions specified in the survey question and divide by the total number of years represented in the historical data.

Objective hurricane damage estimates are by far the most complicated and least straightforward to obtain of all the objective risk data needed for our analysis. First, the confluence of wind, rain, and storm surge that work together to generate damage is difficult to model from a physical science point of view. Even if the damage caused by different hurricane conditions can be accurately modeled, the precise future hurricane conditions that will afflict a particular home must be known. Additionally, the precise characteristics of a home must be known to generate accurate estimates using existing damage functions. Some of these characteristics can be obtained via visual inspection (for example, the number of floors in the home or if the home is elevated) whereas other features are difficult to ascertain (such as if hurricane ties were used on the roof trusses).

To address these problems, we use a novel damage estimation procedure that makes use of the National Flood Insurance Program's historical claims database and corresponding historical hurricane data to train a machine learning model to predict damage given a set of hurricane conditions (distance to home, wind speed, cumulative rainfall ... etc) and known home characteristics (stories, base flood elevation, freeboard ... etc) as inputs. Uncertainty in precise future hurricane conditions and home characteristics are addressed using a Monte-Carlo procedure that estimates damage by repeatedly using a random set of hurricane conditions that are drawn from a distribution that is specific to each home. Each home's unique distribution of hurricane conditions is constructed by using k-means clustering to group homes in the NFIP database that are similar in geographic characteristics. For example, inland homes have a different distribution of hurricane conditions than homes near the coast. The output of this procedure is a predicted distribution of hurricane damage that is unique to each home in the survey data. Figure 3.1 depicts a representative example of what this procedure produces for each observation in our survey sample. The distribution depicted suggests that for this particular home, a major hurricane strike is likely to cause between $10,000 and $30,000 of home structure damage.

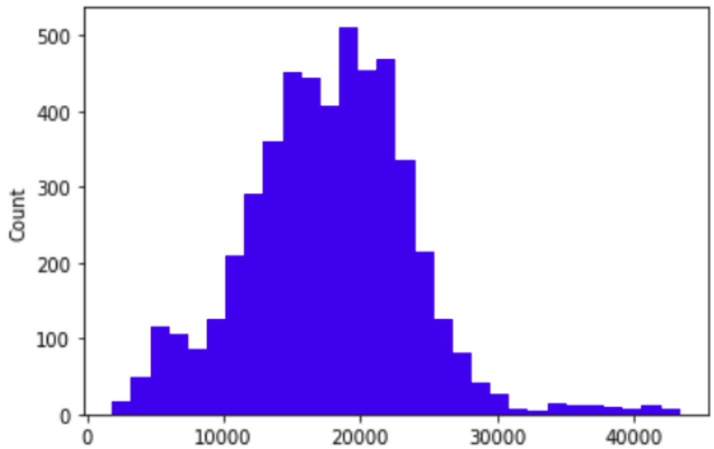


Figure 3.1: Example of Estimated Hurricane Damage Distribution

In general, this procedure appears to provide reasonable predicted damage distributions. When the procedure is used to predict damage distributions for out of sample homes in the NFIP database, the predicted distributions contain the true damage level 90% of the time with the actual damage level falling at the 44th percentile of the predicted distribution on average. Coupling this with the fact that the average modal value of the predicted distributions corresponds to the 42nd percentile of the distribution suggests, that in general, actual damage levels tend to fall in the high probability region of the predicted damage distribution. This is what would be expected for a distribution that is reflective of reality. Full details for the process of generating these predicted damage distributions can be found in appendix A.

3.2.5 Descriptive Statistics

Panel A of table 3.1 reports descriptive statistics for all variables related to subjective risk perceptions. The mean respondent believed there was an approximate 9 percent change of their home flooding from any weather-related event in the next 12 months. The mean annualized hurricane strike probability derived from respondent's expectations on the frequency of future hurricane strikes was 0.25. The average respondent believed if their home was to flood their home would sustain damage equivalent to 11 percent of their home's structure value and that a major hurricane would result in home damage equivalent to 38 percent of their home structure value.

Descriptive statistics for the corresponding objective risk metrics are reported in Panel B of table 3.1. Data from the First Street Foundation suggest the average home in the sample has an 8 percent annual chance of flooding. Data from NOAA indicate there is a 4 percent annual chance of a major hurricane strike, although there is very little variation in this metric since it is observed at the county level. Worcester County has a 2.2 percent historical chance of a major hurricane strike, Glynn county has a 3 percent chance, and Dare has a 6.3 percent chance. Flood damage estimates suggest that in the event of a weather-related flood, the mean home would sustain damage equivalent to 7 percent of the home's structure value. Similarly, objective estimates suggest damage equivalent to 6 percent of structure value in the event of a major hurricane strike.

Descriptive statistics for the remaining variables in our analysis are reported in panel C of table 3.1. Thirteen percent of respondents indicated that they had personally sustained flood damage to their home in the past. The mean level of the most recent flood damage a home had sustained was $2670, although this includes many zero values. Of those who had sustained some positive level of damage, the mean amount was approximately $20,000. Thirty-one percent of respondents resided in an SFHA zone which was obtained by cross-referencing each respondent's address with FEMA's GIS flood hazard layer. In addition to FEMA designated SFHA status we also construct the equivalent of an SFHA zone using data from the First Street Foundation (i.e. an indicator for if data from the First Street Foundation indicates a greater than 1% chance per annum of flooding). This SFHA equivalent is used in our reduced-form regressions to assess the effect of the highly publicized FEMA risk metrics against the metrics produced by the First Street Foundation which are arguable more accurate but were much less publicized at the time of the survey. Overall, the First Street data suggests that 59 percent of households in the sample would be in SFHA zones if FEMA were to use the First Street data for classifying flood zones.

Homes in the survey sample were all fairly close to the ocean with the average home being located just 2.5 km from the coast. Approximately half of the respondents indicated that their coastal home was their primary residence. Coastal experience was elicited from each survey participant. Thirty-nine percent classified themselves as being new to the coast while 36 percent revealed that they had lived on the coast for most or all of their lives. Coefficients of relative risk aversion were elicited using an incentive-compatible risk preference instrument previously described in chapter 2 of this dissertation. The mean coefficient of relative risk aversion was .36 indicating the mean respondent was risk-averse.

Respondents were prompted to report household income by picking one of 8 intervals ranging from "less than $35,000" up to "more than $250,000". Most intervals were coded at their midpoint with the exception of the lowest and highest interval. The lowest interval was assigned a coding of $30,000 while the unbounded top interval was dealt with using the methods suggested by Hout, 2004 which entails extrapolating income on the basis that income follows a Pareto distribution. This results in the top income interval being coded at $496,000 which results in the mean household income of the sample being $170,000. When respondents were asked about their general political leanings, 46 percent considered themselves conservative, 18 percent identified as liberal, while the remainder thought of themselves as moderate. Finally, standard demographics were elicited. Eighty percent of respondents were white, 67 percent completed at least a bachelor's degree, 30 percent were female, and the average age was 56.

Previous literature has noted the role that worry plays in perceptions of risk (Botzen et al., 2015; Mol et al., 2020). To elicit metrics regarding individuals' proclivity to worry respondents were asked to indicate their degree of worry across various domains using a 4 point Likert scale ranging from "Not at all worried" to "Very worried". Domains include worry about being diagnosed with cancer, money, family member's safety, violent crime, pollution, having close friends, one's career, and home loss due to natural disaster. Each Likert response is converted to a binary indicator that indicates worry if individuals answered with a 3 or 4 in a particular domain. Responses from each domain are taken and summed to create a simple worry index, with the exception of worry about home loss from a natural disaster which is excluded from the index. This allows us to isolate the effect of worry over home loss while controlling for general levels of worry as captured by the index. Overall, the worry index had a mean value of 2.10 indicating that on average individuals had feelings of worry in two out of the seven domains. Additionally, 39 percent of respondents indicated worrying about losing their home as a result of a natural disaster.

3.3 Empirical Methodology

Our empirical methodology can be categorized into three distinct parts. The first is a simple descriptive analysis which involves comparing the objective risk metrics elicited in the survey against objective metrics of the same risk type and categorizing respondents based on the accuracy of their risk perceptions. The second part of the analysis entails exploring the possible determinants of the heterogeneity observed in risk perceptions and identifying correlations between individual characteristics and accuracy of perceptions. We do this by regressing subjective risk perceptions onto individual characteristics. Additionally, we run an additional series of regressions using indicators for correct perceptions as the outcome variable to identify any systematic similarities among individuals with accurate perceptions. Finally, we run a robustness check to see if the differences in objective and subjective flood probabilities could plausibly be explained by a systemic proclivity to engage in probability weighting. The remainder of this section details each component of the analysis.

3.3.1 Objective Vs. Subjective Risk Metrics

Following previous research (Botzen et al., 2015; Mol et al., 2020), each subjective risk perception that was elicited using an open-ended response (flood probability, flood damage, and expected hurricane frequency) is categorized as being correct as long as the difference between the subjective and objective metrics are within a certain margin of error. This is necessary since virtually none of the survey respondents have subjective perceptions that exactly match the objective metrics. Any chosen margin of error to use is arbitrary, thus we report results using 1, 2.5, 5, 10, 25, and 50 percentage point margins of error. For subjective risk perceptions that were elicited using categorical responses (hurricane damage), perceptions are classified as being correct as long as the categorical response chosen (which is in the form of a range) contains the objective risk estimate. We use these classification rules to classify each respondent as having correct, pessimistic (overestimation of risk), and optimistic (underestimation of risk) and report the share of respondents in each category.

3.3.2 Regression Analysis

To assess if the accuracy of risk perceptions can be explained by observable characteristics, We run a series of reduced-form regressions that are either directly or indirectly related to perceptions of coastal hazard risk. The first set of regressions focuses on the formation of risk perceptions and uses subjective flood probability, expected flood cost as a percentage of structure value, expected hurricane damage as a percentage of structure value, and expected hurricanes over the next 50 years, as the dependent variables. The first three of these variables are regressed on individual characteristics using a fractional response probit model (to account for the outcomes variable being restricted to the unit interval) while the last uses a negative binomial regression (to account for the outcome being a count variable). All reduced form regressions are estimated using standard maximum likelihood techniques.

In addition to modeling the formation of risk perceptions, we also run a series of probit regressions that use indicators for having correct risk perceptions which are modeled as the dependent variable. The first dependent variable in this series is an indicator for if each respondent was able to correctly indicate their SFHA status. The remaining binary variables indicate if each respondent had correct perceptions of flood probability, flood damage, hurricane probability, and hurricane damage. As previously mentioned, in the comparison of subjective and objective risk metrics, perceptions are counted as being correct if they are within a certain percentage point margin of error (using various margins of error to account for the arbitrary nature of the cutoff). For all regressions, we use a 10 percentage point margin of error for classifying risk perceptions as being correct as this margin of error produces appropriate variation in accuracy of perceptions across all risk metrics considered.

Mis-perceptions or Probability Weighting?

As noted previously, it's possible that individuals have correct risk perceptions but are reporting weighted probabilities. If this is true, then the difference between the individual objective and subjective probabilities should be similar to the distortions proposed by the probability weighting literature. To test this, we estimate a series of structural models where objective probabilities are mapped to subjective probabilities using a handful of commonly referenced probability weighting functions from the literature. Specifically, we consider the five weighting functions proposed by Prelec, 1998,Tversky and Kahneman, 1992a, Gonzalex and Wu, 1999, and Goldstein and Einhorn, 1987. Additionally, a simple power weighting function is considered where each individuals' objective probability is raised to a power, where the power is a parameter to be estimated.

In a standard beta regression, the parameter μ is a linear combination of observable characteristics, **X**, and parameter vector, β, that get passed through a link function $g(.)^{-1}$ (equation 3.1). The link function can be any function that maps the input to the unit interval, such as a logit function. To introduce probability weighting, μ is simply redefined to use a probability weighting function, $\Psi(X;\theta)$ as the link function, and in place of **X**, the objective flood probabilities are used (equation 3.2). The parameter vector θ defines the curvature of the weighting function and contains one or two elements depending on the particular weighting function. Regardless of if probability weighting is used or not, the likelihood function for the beta regression, with the subjective probability P_{sub} as the independent variable, is defined in equation 3.3 where B(.) is the beta function.

$$\mu = g^{-1}(\alpha + \mathbf{X}\beta + \epsilon) \tag{3.1}$$

$$\mu = \Psi(P_{obj};\theta) \tag{3.2}$$

$$f(P_{sub}|\mu,\phi) = \frac{P_{sub}^{(\mu\phi-1)}(1-P_{sub})^{((1-\mu)\phi-1)}}{B(\mu\phi,(1-\mu)\phi)} \tag{3.3}$$

The log-likelihood functions corresponding to structural econometric models often involve highly non-linear functions with local optima meaning applying standard maximum likelihood methods can lead to convergence and stability problems. Accordingly, we estimate the structural beta regressions using standard MCMC methods.

Given that MCMC is a Bayesian procedure, priors must be assigned to each parameter being estimated. For all weighting parameters, gamma priors are assigned with both shape parameters of the gamma function set to 1. This ensures the estimated weighting parameters are positive (a necessary condition for most of the weighting functions to maintain theoretical consistency). This prior distribution places 95% of the probability mass between 0 and 3 which may sound restrictive, but each weighting function can achieve a very diverse set of curvatures using parameter values restricted to the 0 to 3 interval. Estimation is conducted using the Metropolis-Hastings algorithm. In total, 110,000 draws are made to estimate the posterior distribution with the first 10,000 draws being discarded as "burn-in" samples. Further, a thinning interval of 10 is applied to reduce autocorrelation. To check for evidence of non-convergence, visual inspection of trace and auto-correlation plots is conducted. Further, the Geweke diagnostic is employed which tests the null that the first 10% and last 50% of the samples drawn have the same mean (Geweke, 1992). A rejection of the null is evidence that the Markov chain has not converged. The null cannot be rejected for any of the parameter estimates at the 10% significance level indicating no obvious signs of convergence issues.

3.4 Results

In this section, we report the results of our empirical analysis, addressing each component of the empirical analysis in a separate subsection.

3.4.1 Accuracy of Risk Perceptions

As an initial test of flood risk perceptions, we simply check what proportion of respondents reported perceptions that are consistent with their official FEMA designated flood zone. Table 3.2 reports the share of respondents that had flood probability perceptions that were compatible with the flood zone in which they resided. Overall, 39 percent of respondents had flood probability perceptions that were consistent with the SFHA status they were living in. The remaining portion of the sample had incompatible perceptions. Specifically, 36 percent were pessimistic, overestimating the probability of a flood, and 25 percent were optimistic with flood risk perceptions below what their FEMA flood zone would suggest. There is significant heterogeneity by flood zone, although much of this heterogeneity is due to the way FEMA flood zones are structured [3]. Overall, FEMA flood zone classifications are far too crude as an objective risk metric to be particularly useful in classifying flood risk perceptions.

Table 3.3 reports the share of respondents that had subjective probabilities of flooding that were correct along with the accuracy of damage expectations for floods with various return periods. Approximately 29 percent of respondents had subjective probabilities of flooding that were within 1 percentage point of their objectively estimated flood probability. The remaining respondents, who had perceptions that differed from the objective estimates by at least 1 percentage point, were mostly (45 percent) pessimistic and overestimated the likelihood of a flood. The remaining individuals (26 percent) were optimistic and underestimated the probability of their home flooding. Accuracy of flood probability perceptions are reported for other margins of error (panels B - F), but the overarching message is the same; there is no overwhelming trend in the accuracy of flood risk perceptions. At almost every margin of error, a significant proportion of individuals can be classified as having pessimistic, correct, and optimistic perceptions.

Alternatively, perceptions of flood damage tend to be almost uniformly pessimistic. Using a 1 percentage point margin of error suggests that more than 90 percent of the sample overestimated the extent of

[3] Zeros populate the diagonal of this table due to the nature of the flood zone classifications FEMA has created. Those in the SFHA classification cannot be pessimistic since SFHA flood probabilities are unbounded above. Similarly, zone X is bounded below at zero meaning being optimistic is not possible in this zone. Zone X500 residents could have been correct if they reported a flood probability between .2 percent and 1 percent. No one in the sample did this, however.

damage in the event of a flood, regardless of the flood's return period. Even when applying larger margins of error, the general tendency to overestimate damages is evident; only about 20 percent of respondents reported expected flood costs that were within 10 percentage points of objective estimates. Applying a massive 50 percentage point margin of error still only results in about half of respondents having correct flood damage perceptions.

Table 3.4 reports the share of respondents who had correct beliefs regarding the probability of a major hurricane strike. Since hurricane strike probabilities are the same for all residents in the same county we report the accuracy of perceptions for each county individually in addition to an aggregate metric. Overall, individuals in our sample tend to be overly pessimistic in the beliefs about the likelihood of a major hurricane strike, regardless of county of residence. Using a 1 percentage point margin of error suggests 78 percent of individuals overestimate the probability of a major hurricane strike. Applying a much larger 10 percentage point margin of error results in over half of respondents having correct perceptions, but with a large share of individuals still overestimating the probability of a strike.

Table 3.5 reports the share of respondents who had perceptions of hurricane damage that were consistent objective damage estimates. Since hurricane damage was elicited on a fairly crude discrete scale, "correct" responses, in this case, are simply based on if the ordinal response chosen by the respondent contains the level of damage the objective estimates would suggest. For example, if the objective estimates suggest damage that is 25% of the respondent's home value, then the respondent is counted as having correct perceptions if they indicated they expected damages between "20% - 30%" of home structure value. Similar to with perceptions of hurricane likelihood, perceptions of hurricane damage tend to be overly pessimistic. Approximately three-quarters of all respondent's overestimated damage while the remaining individuals were almost all correct in the perceptions (a single individual underestimated damages).

3.4.2 Determinants of Risk Perceptions

Table 3.6 reports regression results that explore the possible sources of risk misperceptions. Results suggest that past experiences play a role in the formation of risk perceptions. Individuals who have directly sustained flood damage to their homes have significantly higher subjective flood probabilities. Similarly, higher amounts of past flood damage correlate with higher subjective perceptions of flood and hurricane damage. However, past flood experience does not appear to have any effect on the expected frequency of major hurricanes.

Objective metrics of risk also appear to significantly influence the formation of risk perceptions. Residing in an SFHA positively influences subjective flood probabilities, but does not appear to have any influence on expected flood cost or expected hurricane damage. This is intuitive and theoretically consistent since the SFHA designation conveys information about the likelihood of a flood and contains no information regarding the likelihood of damage. SFHA status is also correlated with the expected number of hurricanes over the next 50 years, but with a negative coefficient. This implies those in higher-risk flood zones believe hurricanes will be less frequent in the future compared to non-SFHA residents. Our regressions include an additional objective risk metric, "SFHA (First Street)" which, to reiterate, would be each respondent's SFHA status if FEMA were to base its flood zone classifications off of the First Street Foundation's flood probabilities. In direct contrast to the official FEMA SFHA designation, the First Street SFHA designation is not a significant determinant of subjective flood probabilities or expected number of hurricanes but does significantly correlate with both subjective metrics of damage. we revisit this point in the discussion. Residents who are closer to the coast believe the likelihood of flooding and the frequency of future hurricanes to be lower. However, living closer to the coast does appear to significantly increase expectations of the associated damages from these events.

Results also suggest that worry plays a non-trivial role in the formation of beliefs. Individuals who scored higher on our worry index tended to believe flooding and major hurricanes were more likely but did not have significantly different expectations of flood or hurricane damage. Worry, specifically related to home loss from a natural disaster, appears to positively affect subjective flood probabilities and expectations of both flood and hurricane damage. No significant relationship is evident between worry in this domain and the expected frequency of hurricanes, however. Several other notable effects are present in our results but are only significant in one specification. These include a positive relationship between being female and subjective flood probability, a negative relationship between being a "coastal veteran" and expected flood cost, and a negative relationship between higher education and expected hurricane damage.

Table 3.7 reports regression results that use indicators for correct risk perceptions as the dependent variable. Regressing SFHA awareness on individual characteristics suggests past flood experience, residing in an SFHA, being further from the coast, and being new to the coast are all highly significant as determinants of knowing one's SFHA status. Interestingly, those who indicated their coastal residence was their primary home were much less likely to correctly indicate their SFHA status. Those who scored higher on the simple worry index tended to be more likely to know their SFHA status, although the effect is only statistically significant at the 10 percent level.

Focusing on perceptions of flood risk, there is strong evidence that past flood experience lowers the likelihood of having correct flood probability perceptions, whereas there is strong evidence that past flood experience increases the likelihood of having correct perceptions of flood damage. The hypothetical First Street SFHA designation has a highly significant and negative effect on the probability of having correct perceptions of flood probabilities but does not significantly correlate with having correct flood damage perceptions.

With respect to hurricane risk, very few of the individual characteristics considered are significant determinants of having correct risk perceptions. Residing in a First Street equivalent of an SFHA zone appears to be correlated with a higher likelihood of having correct perceptions of a hurricane strike while being female is correlated with a lower likelihood of correct perceptions. With respect to hurricane damage, worry in the domain of home loss, residing in a First Street SFHA equivalent, and being female are all correlated with a lower likelihood of having correct perceptions.

3.4.3 Role of Probability Weighting

Table 3.8 reports results for the analysis that attempts to explain the difference in objective and subjective flood probabilities as being driven by probability weighting. Root mean squared error is reported for each model which can be interpreted as the expected difference between the predicted and actual subjective probability if any one individual in the sample had their subjective probability predicted using only their objective probability as the input. Overall, modeling individuals as agents who engage in probability weighting does not appear to offer any notable advantage in terms of model fit over a standard linear model. Estimation of a standard reduced form beta regression, that uses only the objective probability of a flood as a co-variate, results in a RMSE of 0.147. Some of the structural specifications, that employ probability weighting functions, produce very similar RMSE values, but none of them are better than a standard beta regression. This suggests that the differences in observed objective and subjective flood probabilities are not easily explainable using any of the literature's canonical weighting functions. This is consistent with the narrative that individuals are indeed misperceiving risk rather than just reporting weighted probabilities in surveys.

Figure 3.2 plots subjective flood probabilities against objective flood probabilities along with each estimated weighting function. Visual inspection reveals that any well-behaved function will have a difficult time fitting the data due to it being "L-shaped". A well-fitting function must simultaneously explain a large number of individuals with low objective probabilities but high subjective probabilities and the substantial number of individuals with high objective probabilities but low subjective probabilities. The monotonicity assumption of probability weighting functions is problematic in this regard. For example, a function that fits the vertical portion of the "L", (such as the power weighting function in figure 3.2), cannot decrease to pass near the data points in the lower right corner (those who under-estimate flood risk)[4].

[4]One potentially promising way forward is to classify individuals' probability distortions prior to estimation of the probability weighting function, then estimating unique probability weighting functions for each group. If a set of observables could be identified that reliably segments individuals into the vertical and horizontal portions of the "L" in 3.2 then almost any weighting function could conceivably fit each segment much better than a single weighting function estimated on the full sample. Supervised machine learning techniques could be quite useful in this case (due to the superior regularization routines associated with it) since traditional economic theory does not provide strong guidance on the set of observable to use for this task. Unfortunately, the sample size here is too small to be appropriate for most machine learning techniques, thus this task remains as an avenue for future research.

3.5 Discussion

The results presented here provide another data point from a novel data set which brings the literature regarding the accuracy of flood risk perceptions closer to reaching a consensus. With respect to flood risk, the findings presented here suggest there is no broad generalization that can be made regarding flood probability perceptions. Pessimistic individuals, optimistic individuals, and individuals with correct flood probability perceptions are all well represented in our sample. If any generalization can be made, it is that those with incorrect perceptions of flood probabilities are slightly more likely to overestimate the probability of a flood than underestimate it. This conclusion is most closely aligned with (Mol et al., 2020) who similarly find no overwhelming general tendency, but do find the most common tendency is to overestimate flood probabilities. This is also compatible with those Botzen et al., 2015 who find that most individuals overestimate the probability of a flood (again with the caveat that their survey was administered shortly after Hurricane Sandy). Both Royal and Walls, 2019 and Bakkensen and Barrage, 2017 find that the majority of individuals in their samples underestimate the probability of a flood, a result that is not supported by the analysis presented here.

With respect to expected flood damage, the vast majority of individuals tended to overestimate the damages associated with a flood, regardless of the severity of the flood. This result is notably different than the conclusions of previous literature which have directly looked at misperceptions of flood damage. Botzen et al., 2015 find individuals typically underestimate damage and Mol et al., 2020 find individuals underestimate water levels and generally have correct damage perceptions, but are more likely to underestimate damage than overestimate it. Thus, our results on perceptions of flood damage are starkly different that the findings of the previous literature. One hypothesis for this difference is that the results presented here are based on coastal homeowners in the southeastern United States whereas the previously mentioned studies are based in New York City and the Netherlands respectively. For many of the homeowners in the southeast U.S., tropical cyclones and hurricanes are the primary sources of flood damage. Hurricanes tend to produce examples of spectacular home damage, such as completely leveled homes, which tend to get highlighted by media despite the large number of homes that are mostly unharmed in each storm event. Thus coastal homeowners in the southeast may have more salient examples of complete home destruction to draw on and conjure images of complete home destruction in their local area when thinking of flood damages.

Focusing on hurricane risk, our results suggest individuals overwhelmingly over-estimate the likelihood of a major hurricane strike and over-estimate the extend of the associated damage. Notably, the tendency to overestimate hurricane frequency is much more apparent than the tendency to overestimate flood probabilities. It is possible that this is an artifact of how subjective hurricane likelihoods were elicited. Respondents were asked to report the number of major hurricanes they expected to strike their county of residence over the next 50 years. If individuals believe that climate change will increase the frequency of hurricanes in the future, this belief would get construed as having over-pessimistic perceptions of hurricane likelihoods, which is a limitation of this elicitation methodology.

However, it is not clear what the dominant elicitation methodology for risk perceptions is as each has distinct advantages. Framing hurricane likelihood as a count of the number of hurricanes over the distant future avoids eliciting responses as a percentage which may be more intuitive for respondents who are less numerically literate. Other literature has demonstrated the difficulties respondents have when presented with open-ended probability queries and the proclivity to round answers, particularly near the limits of the unit interval Dominitz and Manski, 1997; Manski and Molinari, 2010. de Bruin et al., 2002 suggests that the tendency for 50% to be over-represented in probabilistic responses is evidence of epistemic uncertainty rather than an expression of a precise belief. Framing probability as a count over a number of years is advantageous in this regard as there is no natural midpoint for respondents to default to. It is possible that differences in elicitation methodology may be partially responsible for the stark differences in recent literature on risk misperceptions. Future research should assess the role that elicitation methodology has on elicited risk perceptions.

Results from the reduced form regressions provide deeper insight into the sources of heterogeneity that are observed in the accuracy of the elicited risk perceptions and echo some of the findings in the previous literature. For example, past research has highlighted the role that past flood experience has on perceptions of flood probability (Botzen et al., 2015; Mol et al., 2020; Royal & Walls, 2019). Similarly, other results presented here also appear to be robust throughout the literature such as the role that worry plays in risk perceptions (Botzen et al., 2015; Mol et al., 2020)

Perhaps the most notable finding presented here is the effect that SFHA status has on flood probability perceptions and the lack of effect that the equivalently defined metric, using data from the First Street Foundation, has. The accuracy of FEMA flood zone maps has been called into question in the past (Wing et al., 2018); assuming that data from the First Street Foundation more accurately describes flood risk, then the results presented here suggest that the highly publicized FEMA flood zones serve as an indicator of flood risk that individuals do indeed internalize. If individuals were unaware of their SFHA status, but simply had an intuition about the likelihood of their home flooding, then the First Street SFHA variable should be correlated with subjective flood probabilities. The fact that no significant correlation exists highlights the role that publicly available flood risk information plays in the formation of subjective beliefs. The results that use an indicator for accurate flood risk perceptions back up this claim where it is evident that residing in an SFHA does not significantly correlate with the likelihood that an individual had accurate flood probability perceptions, whereas individuals who are in First Street SFHA equivalents are much less likely to have correct flood probability perceptions, even after allowing for a 10 percentage point margin of error in perceptions. Again, presumably, this is due to the First Street data being a more accurate, but largely unknown risk metric. From a policy perspective, this result suggests that simply providing individuals with accurate, easily accessible, flood risk information may help align individual subjective beliefs with the objective reality and thus allow households to make optimal flood mitigation decisions.

With respect to the regressions focused on damage (both flood and hurricane), the official FEMA SFHA designation is not significantly correlated with subjective damage beliefs for either floods or hurricanes, whereas the First Street SFHA variable is. These metrics are fundamentally descriptive of flood probabilities and say nothing about associated damages. However, if properties with higher flood probabilities tend to be at lower elevations, damages will be increasing with flood probabilities since water inundation levels will be higher at these properties for any given flood severity[5]. We interpret the difference in significance among the two SFHA variables as evidence that the hypothetical First Street SFHA status is more indicative of actual flood risk in the sense that it more accurately captures the likelihood of flood inundation[6].

Analysis of the determinants of expected future hurricane strikes reveals what is likely an endogenous relationship between the perceived frequency of future hurricanes and objective risk indicators. Individuals, residing in an SFHA, residing in a First Street equivalent of an SFHA, and those closer to the coast all correlate negatively, and significantly, with expected future hurricanes. Most likely, this suggests that beliefs about future natural hazards are to some extent governing home location decisions. This same effect is not evident in the regressions focused on subjective probabilities, which is likely due to the difference in elicitation methodology for the two risk perceptions. Subjective flood probabilities were elicited by asking respondents about the probability of their home flooding over the next year, whereas subjective perceptions of a hurricane strike were elicited based on beliefs over the next 50 years. Thus, perceptions of hurricane strike contain information regarding general beliefs about climate change induced changes in natural hazards which we believe is why there is some evidence of coastal retreat being correlated with hurricane risk perceptions only.

Considering agents as individuals that engage in probability weighting reveals that the observed differences in objective and subjective flood probabilities cannot be easily explained by any of the probability weighting functions common to the literature. This does not indicate that individuals do not engage in probability weighting, just that it is not likely to be the origin of the probability distortions presented here.

[5] With respect to correlation with elevation, the First Street SFHA variable is more correlated with home elevation (correlation coefficient of -0.201) compared to the FEMA SFHA designation (correlation coefficient of -0.147)

[6] One concern with interpreting the change in significance in the two SFHA variables across regressions (in table 3.6) is that the sample size for the regressions focused on damages is much larger due to the earliest version of the survey not having a question eliciting subjective flood probabilities. As a robustness check, we re-estimate the first three columns of table 3.6 using the exact same sub-sample for all three regressions. These results are reported in table 3.9. Two of the three regressions are qualitatively equivalent with the exception being the regression focused on flood damage perceptions which exhibit no statistically significant relationship between either FEMA or First Street SFHA designations and flood damage perceptions. However, this may very well be a result of reduced statistical power.

The fact that elicited subjective probabilities are not systemically different from objective probabilities in the way that probability weighting functions predict strengthens the claim that informational campaigns that provide individuals with accurate flood risk knowledge may help individuals make more optimal flood mitigation decisions.

3.6 Conclusion

The purpose of this study is to provide another data point from a novel data set to the existing, but contradictory, literature that measures coastal hazard risk misperceptions. Using three distinct study locations along the U.S. east coast, coastal homeowners' subjective risk perceptions regarding their home flooding and a major hurricane striking their county of residence were elicited. We then compare these subjective metrics to corresponding objective metrics. We find that there is significant heterogeneity in perceptions of flood probability as individuals who underestimate the probability of a flood, overestimate the probability of a flood, and those with correct perceptions are all well represented in the survey sample. However, with respect to personal home damage in the event a flood occurs, we find the vast majority of survey respondents overestimate flood damage. Similarly, the vast majority of respondents tended to have expectations of hurricane damage that were much more severe than what objective estimates suggest. Finally, although we find significant heterogeneity in flood risk perceptions, the vast majority of individuals in the sample expected far more major hurricanes to strike the community in the coming decades than what historical return periods would suggest. To gain insight into the possible reasons for differing risk perceptions we regress subjective risk perceptions on a variety of individual and home characteristics. We find that a variety of individual characteristics influence risk perceptions including past natural hazard experience, objective risk information, levels of worry in multiple domains, length of time spent residing on the coast. Most notably, I find that objective risk metrics influence subjective flood probabilities but only if the source of the information is widespread and publicly available. More specifically, we find that respondents FEMA designated flood zone correlates significantly with their subjective belief about the probability of flooding whereas objective flood probabilities obtained from the

First Street Foundation, which are arguably much more accurate, do not correlate with subjective flood probabilities. This result suggests that simply providing households with accurate flood risk information may be a relatively cheap policy intervention that would allow households to make more optimal natural hazard mitigation decisions. However, the precise effect that the introduction of new natural hazard risk information would have on community-wide mitigation behavior, such as flood insurance market penetration levels, is still unknown and remains as an important area for future research.

Table 3.1: Descriptive Statistics

	mean	sd	min	max	count
Panel A: Subjective Risk Perceptions					
Flood. Prob. (Subjective)	0.09	0.15	0.00	1.00	211
Hurr. Prob. (Subjective)	0.25	0.31	0.00	1.00	436
Flood Damage (Subjective)	0.67	0.45	0.00	1.00	507
Hurr. Damage (Subjective)	0.38	0.25	0.05	0.95	488
Panel B: Objective Risk Metrics					
Flood Prob. (Objective)	0.07	0.15	0.00	0.50	483
Hurr. Prob. (Objective)	0.04	0.02	0.02	0.06	501
Flood Damage (Objective)	0.07	0.13	0.00	0.54	380
Hurr. Damage (Objective)	0.06	0.05	0.00	0.33	308
Panel C: Other Household Characteristics					
Past Flood	0.13	0.34	0.00	1.00	495
Flood Damage ($1000)	2.67	18.09	0.00	300.00	507
SFHA	0.31	0.46	0.00	1.00	501
SFHA (First Street)	0.53	0.50	0.00	1.00	507
Dist. To Coast (Km)	2.50	3.03	0.01	13.23	501
Worry Index	2.10	0.52	1.00	3.71	451
Worry (Home Loss)	0.39	0.49	0.00	1.00	501
Dist. To Coast (Km)	2.50	3.03	0.01	13.23	501
Primary Home	0.52	0.50	0.00	1.00	501
New To Coast	0.39	0.49	0.00	1.00	499
Coastal Vet.	0.36	0.48	0.00	1.00	499
CRRA	0.41	0.40	-0.01	0.85	474
Income ($1000)	170.72	126.87	30.00	496.12	473
Conservative	0.46	0.50	0.00	1.00	492
Liberal	0.18	0.38	0.00	1.00	492
White	0.87	0.34	0.00	1.00	498
Higher Edu.	0.67	0.47	0.00	1.00	501
Female	0.30	0.46	0.00	1.00	497
Age	56.15	14.34	21.00	91.00	485

Table 3.2: Share of Respondents with Perceptions Compatible with SFHA status

	Probability			
	All Respondents	SFHA (Zones A,V)	X500	X
Pessimistic	0.355	0	0.404	0.806
Correct	0.393	0.772	0	0.194
Optimistic	0.251	0.228	0.561	0
N	211	92	57	62

Table 3.3: Share of Respondents with Correct Flood Risk Perceptions (N = 211)

		Damage					
	Probability	RP: 5 yr	RP: 10 yr	RP: 20 yr	RP: 50 yr	RP: 100 yr	RP: 500 yr
Panel A: 1 Percentage Point Margin of Error							
Pessimistic	0.454	0.953	0.953	0.942	0.936	0.936	0.930
Correct	0.291	0.041	0.035	0.041	0.041	0.041	0.041
Optimistic	0.255	0.006	0.012	0.018	0.023	0.023	0.029
Panel B: 2.5 Percentage Point Margin of Error							
Pessimistic	0.413	0.906	0.906	0.895	0.889	0.889	0.877
Correct	0.367	0.088	0.082	0.094	0.094	0.088	0.094
Optimistic	0.219	0.006	0.012	0.012	0.018	0.023	0.029
Panel C: 5 Percentage Point Margin of Error							
Pessimistic	0.301	0.865	0.865	0.854	0.854	0.854	0.842
Correct	0.520	0.129	0.123	0.135	0.129	0.123	0.129
Optimistic	0.179	0.006	0.012	0.012	0.018	0.023	0.029
Panel D: 10 Percentage Point Margin of Error							
Pessimistic	0.158	0.801	0.801	0.801	0.795	0.795	0.778
Correct	0.679	0.199	0.193	0.187	0.193	0.193	0.199
Optimistic	0.163	0.000	0.006	0.012	0.012	0.012	0.023
Panel E: 25 Percentage Point Margin of Error							
Pessimistic	0.066	0.655	0.655	0.655	0.649	0.643	0.626
Correct	0.816	0.345	0.345	0.345	0.351	0.357	0.368
Optimistic	0.117	0.000	0.000	0.000	0.000	0.000	0.006
Panel F: 50 Percentage Point Margin of Error							
Pessimistic	0.010	0.497	0.497	0.497	0.497	0.485	0.462
Correct	0.990	0.503	0.503	0.503	0.503	0.515	0.538
Optimistic	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 3.4: Share of Respondents with Correct Perceptions of Major Hurricane Strike

	Probability			
	Dare County	Glynn County	Worcester County	Combined
Panel A: 1 Percentage Point Margin of Error				
Pessimistic	0.769	0.765	0.815	0.775
Correct	0.051	0.168	0.160	0.135
Optimistic	0.179	0.067	0.025	0.089
Panel B: 2.5 Percentage Point Margin of Error				
Pessimistic	0.735	0.639	0.815	0.697
Correct	0.154	0.361	0.185	0.273
Optimistic	0.111	0.000	0.000	0.030
Panel C: 5 Percentage Point Margin of Error				
Pessimistic	0.675	0.534	0.519	0.569
Correct	0.316	0.466	0.481	0.429
Optimistic	0.009	0.000	0.000	0.002
Panel D: 10 Percentage Point Margin of Error				
Pessimistic	0.624	0.382	0.346	0.440
Correct	0.376	0.618	0.654	0.560
Optimistic	0.000	0.000	0.000	0.000
Panel E: 25 Percentage Point Margin of Error				
Pessimistic	0.410	0.239	0.222	0.282
Correct	0.590	0.761	0.778	0.718
Optimistic	0.000	0.000	0.000	0.000
Panel F: 50 Percentage Point Margin of Error				
Pessimistic	0.282	0.076	0.160	0.147
Correct	0.718	0.924	0.840	0.853
Optimistic	0.000	0.000	0.000	0.000
N	117	238[57]	81	436

Table 3.5: Share of Respondents withCorrect Hurricane Damage Perceptions

	All Counties
Pessimistic	0.747
Correct	0.247
Optimistic	0.006
Observations	162

Table 3.6: Determinants of Risk Perceptions

	Fractional Response Probit			Neg. Binomial Reg.
	Subjective Flood Prob.	Expected Flood Cost	Expected Hurr. Dam.	Expected Hurricanes
Past Flood	0.6294***			-0.3509
	(0.0196)			(0.2617)
Flood Damage ($1000)		0.0204*	0.0030**	
		(0.0123)	(0.0013)	
SFHA	0.0791**	0.0501	-0.0642	-0.4009**
	(0.0310)	(0.1629)	(0.0782)	(0.1831)
SFHA (First Street)	0.0941	0.3792**	0.2773***	-0.4615***
	(0.2700)	(0.1535)	(0.0647)	(0.1552)
Worry Index	0.2127***	-0.0277	-0.0320	0.3310**
	(0.0347)	(0.1719)	(0.0702)	(0.1575)
Worry (Home Loss)	0.5409***	0.3902**	0.3783***	0.0976
	(0.0302)	(0.1735)	(0.0713)	(0.1723)
Dist. To Coast (Km)	-0.1118	0.7372***	0.0218**	-0.0837***
	(0.0888)	(0.0764)	(0.0106)	(0.0266)
Primary Home	0.0468	-0.1554	-0.1550**	-0.1920
	(0.2051)	(0.1660)	(0.0745)	(0.1833)
New To Coast	-0.1859*	-0.2519	-0.1118	-0.2178
	(0.1121)	(0.1930)	(0.0783)	(0.1907)
Coastal Vet.	-0.1288	-0.3582*	-0.0404	0.2984
	(0.2912)	(0.1901)	(0.0779)	(0.1944)
CRRA	-0.0151	0.2793	0.1032	0.2526
	(0.0852)	(0.1925)	(0.0807)	(0.2138)
Income ($1000)	0.0000	0.0012*	0.0005	0.0001
	(0.0006)	(0.0006)	(0.0003)	(0.0008)
Conservative	0.0769	-0.0067	-0.0855	0.1215
	(0.1168)	(0.1797)	(0.0756)	(0.1852)
Liberal	0.0484	-0.3063	0.0790	0.1668
	(0.2028)	(0.2132)	(0.0882)	(0.2306)
White	0.3286	0.1273	-0.0585	-0.0910
	(0.3790)	(0.2212)	(0.1077)	(0.2610)
Higher Edu.	0.0231	-0.2652	-0.2179***	0.1131
	(0.1535)	(0.1801)	(0.0760)	(0.1701)
Female	0.1925***	0.1908	0.0385	-0.0175
	(0.0196)	(0.1698)	(0.0676)	(0.1695)
Age	-0.0050	0.0104*	-0.0027	0.0003
	(0.0082)	(0.0057)	(0.0023)	(0.0056)
Constant	-2.1184***	-1.4014**	-0.2187	2.5544***
	(0.2846)	(0.6249)	(0.2781)	(0.6570)
Observations	169	403	397	327
LL	-48.961	-165.727	-251.975	-1236.947
AIC	99.921	367.454	539.950	2511.895
BIC	103.051	439.435	611.661	2583.904

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Determinants of Correct Risk Perceptions

		Flood		Hurricane	
	SHFA Awareness	Probability	Damage	Probability	Damage
Past Flood	0.5272**	-1.0864***	1.2648***	0.0831	0.1040
	(0.2217)	(0.3758)	(0.3879)	(0.2361)	(0.2868)
SFHA	0.6040***	-0.0528	0.5384	0.0236	0.3163
	(0.1579)	(0.2942)	(0.3328)	(0.1689)	(0.2023)
SFHA (First Street)	-0.0794	-1.3308***	-0.3278	0.3087**	-0.2597
	(0.1379)	(0.2672)	(0.3084)	(0.1435)	(0.1816)
Worry Index	0.2544*	-0.2189	-0.5585	-0.0757	-0.0327
	(0.1451)	(0.2838)	(0.3621)	(0.1525)	(0.1983)
Worry (Home Loss)	0.0127	-0.2848	-0.2371	-0.1904	-0.6051***
	(0.1502)	(0.3070)	(0.3680)	(0.1566)	(0.2159)
Dist. To Coast (Km)	0.0917***	0.4014	-0.0796	0.0348	0.0025
	(0.0233)	(0.2441)	(0.3180)	(0.0248)	(0.0310)
Primary Home	-0.5161***	0.0976	-0.3675	-0.0454	0.0735
	(0.1550)	(0.2687)	(0.3342)	(0.1596)	(0.2009)
New To Coast	0.4500***	0.3283	-0.0441	0.1314	0.2421
	(0.1685)	(0.3118)	(0.3907)	(0.1771)	(0.2269)
Coastal Vet.	0.1908	0.0847	0.0479	0.0064	0.0810
	(0.1721)	(0.3188)	(0.3826)	(0.1833)	(0.2378)
CRRA	0.1547	0.0888	0.4337	0.0585	-0.0337
	(0.1714)	(0.3257)	(0.3812)	(0.1812)	(0.2329)
Income ($1000)	-0.0011*	-0.0003	-0.0025	0.0010	-0.0007
	(0.0006)	(0.0015)	(0.0018)	(0.0006)	(0.0009)
Conservative	0.0453	-0.3251	-0.5675	-0.0657	0.1116
	(0.1564)	(0.3099)	(0.3654)	(0.1633)	(0.2042)
Liberal	-0.1089	0.1304	-0.3789	-0.1048	-0.3175
	(0.1974)	(0.3501)	(0.4106)	(0.2088)	(0.2775)
White	-0.1831	0.1461	0.2486	0.1612	0.6179*
	(0.2263)	(0.3673)	(0.4777)	(0.2376)	(0.3607)
Higher Edu.	-0.1276	0.6295**	-0.0532	-0.2096	0.3516*
	(0.1556)	(0.2797)	(0.3422)	(0.1658)	(0.2098)
Female	-0.0510	-0.1981	-0.7314*	-0.3691**	-0.2977
	(0.1481)	(0.2803)	(0.3981)	(0.1572)	(0.2075)
Age	-0.0085*	0.0152	-0.0081	0.0024	-0.0084
	(0.0050)	(0.0099)	(0.0112)	(0.0053)	(0.0065)
Constant	0.0526	0.0591	1.3563	-0.1097	-0.8903
	(0.5694)	(1.0965)	(1.1942)	(0.5936)	(0.7609)
Observations	400	159	140	350	300
LL	-245.336	-73.940	-52.486	-228.232	-136.799
AIC	526.673	183.879	140.972	492.464	309.597
BIC	598.519	239.120	193.922	561.907	376.265

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Structural Probability Weighting Model Fit

	RMSE
Panel A: Probability Weighting Models	
Standard Beta Regression	0.147
Power	0.337
Prelec I	0.211
Prelec II	0.148
Goldstein-Einhorn	0.148
Tversky-Kahneman	0.151
Wu-Gonzalex	0.149

Table 3.9: Determinants of Risk Perceptions

	Fractional Response Probit		
	Flood Prob.	Flood Dam.	Hurr. Dam.
Past Flood	0.6294***		
	(0.0196)		
Flood Damage ($1000)		-0.0226	-0.0225
		(0.0315)	(0.0191)
SFHA	0.0791**	-0.2756	-0.1614
	(0.0310)	(0.2258)	(0.1046)
SFHA (First Street)	0.0941	0.0601	0.3893***
	(0.2700)	(0.1853)	(0.0978)
Worry Index	0.2127***	-0.2867	0.0181
	(0.0347)	(0.2259)	(0.1061)
Worry (Home Loss)	0.5409***	0.5971**	0.2987***
	(0.0302)	(0.2349)	(0.1115)
Dist. To Coast (Km)	-0.1118	0.0531	-0.1620*
	(0.0888)	(0.1958)	(0.0849)
Primary Home	0.0468	0.2845	-0.1059
	(0.2051)	(0.2295)	(0.1040)
New To Coast	-0.1859*	-0.1634	-0.1510
	(0.1121)	(0.2421)	(0.1277)
Coastal Vet.	-0.1288	0.0135	0.0253
	(0.2912)	(0.2551)	(0.1207)
CRRA	-0.0151	-0.0733	0.1936*
	(0.0852)	(0.2392)	(0.1169)
Income ($1000)	0.0000	0.0005	0.0017***
	(0.0006)	(0.0012)	(0.0005)
Conservative	0.0769	-0.0410	0.0968
	(0.1168)	(0.2555)	(0.1189)
Liberal	0.0484	-0.0905	0.2599**
	(0.2028)	(0.2533)	(0.1319)
White	0.3286	-0.2807	0.0621
	(0.3790)	(0.2891)	(0.1299)
Higher Edu.	0.0231	-0.2175	-0.3071***
	(0.1535)	(0.2251)	(0.1161)
Female	0.1925***	0.0299	0.2546**
	(0.0196)	(0.2078)	(0.1093)
Age	-0.0050	0.0175**	-0.0070**
	(0.0082)	(0.0079)	(0.0035)
Constant	-2.1184***	-1.2012	-0.5022
	(0.2846)	(0.7897)	(0.4423)
Observations	169	169	169
LL	-48.961	-77.183	-98.575
AIC	99.921	190.365	233.150
BIC	103.051	246.703	289.488

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

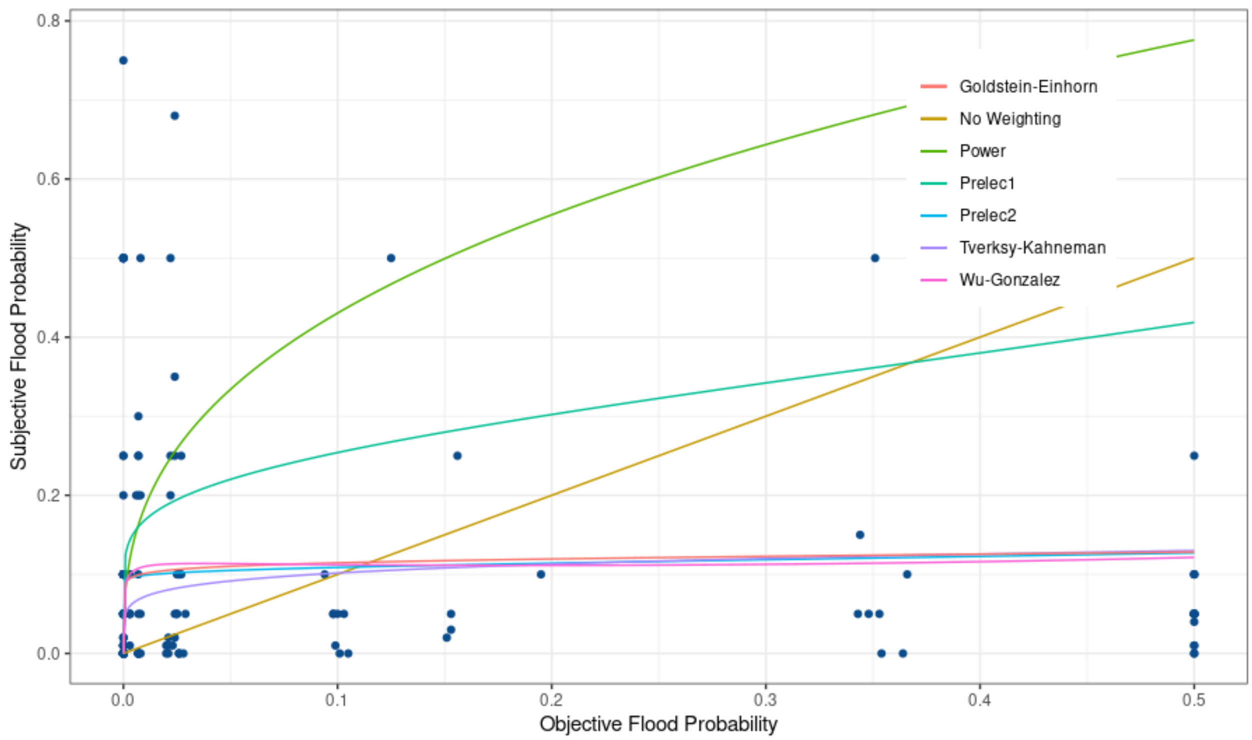


Figure 3.2: Estimated Weighting Functions

Chapter 4

Structural Estimation of Decision Making Under Natural Hazard Risk

4.1 Introduction

The previous two chapters of this dissertation have highlighted how assuming individuals have correct probabilistic perceptions can lead to the wrong classification of an individual's attitudes towards risk. Unfortunately, this is not the only way a researcher could reach incorrect inference regarding an individual's risk preferences. Whether explicitly stated or not, recovering risk preference parameters that map directly back to economic theory is predicated on knowing the functional form that describes the individual's decision-making process. By far, the most prevalent framework for thinking about how individuals navigate a decision characterized by risk is expected utility theory (EUT) and thus serves as the typical default choice for estimating risk preferences from observed behavior. Gabriel Cramer and Daniel Bernoulli began applying the concept of expected utility theory in the early 1700s as a way to reconcile the St. Petersburg paradox (Cramer 1728, Bernouilli 1738). von Neumann and Morgenstern, 1944 later established an axiomatic framework for expected utility, which helped legitimize it as a rational decision criterion. EUT was slow to be adopted, but eventually became the standard theory for models of choice under risk and uncertainty (Moscati 2016).

Consequently, there is a large body of empirical work devoted to analyzing the legitimacy of expected utility as a decision criterion. Among this literature, there is no shortage of critical assessments that point out the paradoxical choices of individuals that routinely deviate from the predictions of EUT. Early laboratory studies primarily pointed to failures of the independence axiom (Starmer, 2000). Later work also highlighted weaknesses of EUT, but rather than pointing out theoretical inconsistencies, these critiques were based on the implausibly high attitudes towards risk implied by observed behavior. As has been pointed out by Rabin, 2000, the classic EUT model motivates risk aversion as being due to declining marginal utility of wealth, meaning individuals should be virtually risk neutral with respect to modest stakes. There is substantial evidence from both laboratory and field studies that demonstrate individuals' do indeed exhibit risk aversion over risky prospects with modest stakes (Eckle & Grossman, 2002; Holt & Laury, 2002; Liu, 2013) . This is problematic for EUT as it implies individuals have an absurdly high-risk premium over prospects with large consequences. Although, this is strictly a theoretical claim. Almost no empirical work has been carried out that measures individuals' attitudes towards risk over large stakes directly, especially in the loss domain. This is primarily due to much of the early empirical work on expected utility being based in the lab, where it is not feasible to replicate high consequence situations. However, in general, situations with high stakes are not common in everyday life meaning even field studies, where risk preferences are inferred from observed choices, are typically based on relatively low stakes risky prospects (Barseghyan et al., 2013; Cohen & Einav, 2007; Sydnor, 2010).

Thus very little direct evidence exists concerning the critique posited by Rabin, 2000. It's possible that expected utility may be a poor decision criterion over small stakes gambles, but is much more appropriate for decisions with consequences of substantial magnitude. To our knowledge only one empirical study attempts to estimate degrees of risk aversion based on observed choices over large stakes in an expected utility framework. Collier et al., 2020 use flood insurance deductible and coverage limit choices to estimate risk aversion parameters. The authors find that household coverage limits are consistent with a mean

CRRA value that is in the low single digits whereas triple-digit CRRA values are necessary to explain deductible choices. Finally, the authors estimate several variations of rank-dependent utility models and find that allowing for probability distortions vastly improves prediction accuracy compared to standard expected utility models. This result is the exact opposite of what Rabin, 2000 predicts since the authors find that reasonable, single-digit, CRRA values explain coverage limits (high stakes) whereas implausibly high, triple digit, CRRA values are necessary to explain deductible choices (low stakes).

Using a novel survey data set consisting of coastal homeowners flood insurance purchasing decisions, we contribute to the sparse but emerging literature that characterizes individual attitudes towards risk using observed choices made in a non-laboratory setting. Additionally, we add to the almost non-existent literature that directly estimates levels of risk aversion over extremely high consequence choices. Our analysis is unique in several regards. First, our study is one of the only ones that estimates individual degrees of risk aversion based on a binary decision to purchase a flood insurance policy, which we believe eliminates concerns regarding several sources of choice set misspecification. Existing studies that estimate risk preferences from field data all do so following traditional discrete choice analysis which is predicated on observing each individual's choice set (Mcfadden 1974). A concern with field data is that the individual may have choices in their consideration set that are not reflected in the data. For most studies based on insurance contract decisions, data is limited to one insurance underwriter. The implicit assumption in these studies is that the options provided by one insurer represent the full choice set. Although necessary for identification, this assumption is suspect since individuals likely consider options of multiple insurers before selecting the insurer that offers their preferred insurance contract. Collier et al., 2020, and our own study, avoid this issue by using flood insurance contract choices. With few exceptions, in the U.S., flood insurance is exclusively offered through the National Flood Insurance Program (NFIP) meaning all consumers of flood insurance face the same known contract choices.

Previous studies also raise concerns about the reliance on behavioral heuristics such as anchoring or "inertia" in insurance contract choices. This is a concern that persists even in the flood insurance context. Notably, it appears that many individuals in insurance settings often chose the default contract options, raising doubt as to if individuals carefully consider all available contract options before finalizing their contract. Barseghyan et al., 2013, who estimate CRRA parameters from auto and home deductible choices, find that 68 percent of their sample choose a $500 deductible (which is typically the default for auto policies) for their auto collision coverage while 43 percent chose the $500 option for the comprehensive coverage. Additionally, 52% chose a $500 option for the home insurance coverage, although its not obvious what the default option was for this coverage. Collier et al., 2020 find that 77% of their sample choose the default deductible for their flood insurance policy and 42% select coverage levels that are exactly equal to the replacement cost of their home. More generally, Dombrowski et al., 2020 analyze 33 million NFIP policy contracts and find that the majority of households chose the minimum (which is the default) deductible and propose that raising the default deductible may increase flood insurance market penetration by diminishing the sticker shock of initial contract quotes.

It's plausible that individuals make the initial binary decision to purchase flood insurance following a decision criterion resembling expected utility while the specifics of the insurance contract (deductible and coverage limits) are governed by more of a heuristic process. [1] More generally, if choosing to insure is a more active decision than choosing specific coverage limits and deductibles, then assuming all available contract options are in each individual's choice set could severely bias estimates of risk aversion. [2]

For this reason, we specify a structural expected utility model over the binary decision to purchase a flood insurance policy based on full coverage and the default deductible and estimate a representative agent CRRA parameter. We believe this specification minimizes the chances that choice set misspecification is influencing the final estimated risk aversion parameter[3]. In contrast to previous literature our model suggests that at an aggregate level, community-level flood insurance uptake can be explained by very

[1]There is some existing support for this claim. Cicchetti and Durbin, 1994 analyze actual purchasing records for the binary decision to purchase telephone wire insurance and find the majority of individuals' decisions to be consistent with a standard expected utility model. However, again their setting involves consequences that are fairly small relative to total wealth and is based on a rather obscure insurance decision that may not generalize to other situations.

[2]To attach a hypothetical anecdotal narrative to this conjecture, consider the following example. New home buyers must decide if they will purchase flood insurance. These home buyers then get an initial quote for a flood insurance policy which is most likely going to be based on a full coverage policy with the default deductible. The home buyers are likely to decide to continue with the purchasing process based on that initial quote and only consider alternative contract options (deductibles and coverage limits) later.

[3]One concern is that individuals never even think about flood insurance, particularly if they are in areas with extremely low flood risk. In this case, assuming they considered flood insurance would lead to a misspecified choice set. We mitigate this

reasonable, low single-digit, CRRA values. Notably, this model appears to perform reasonably well despite the contract choice being based on full coverage and the default deductible, which may not be the homeowners' ultimate choice. We interpret this as evidence that the initial sticker price presented to consumers is often what governs their purchase decision and that the unreasonable CRRA values found by previous literature are likely to do the specifics of the contract being governed primarily by heuristics and behavioral quirks.

Our second notable contribution to the literature comes from the fact that our survey experimentally elicits risk aversion parameters over low-stakes lotteries using an incentive-compatible risk preference instrument. This allows us to directly compare risk aversion parameters elicited in a manner similar to lab studies directly against risk aversion parameters derived from the decision to purchase flood insurance. To our knowledge, we are the first to estimate risk aversion parameters using both field data and an experimental risk preference instrument on the same sample of individuals. Comparing CRRA values elicited through our low stakes experimental instrument suggests about half of respondents made choices in the risk preference instrument that were compatible with representative agent CRRA value estimated using observed flood insurance decisions.

The rest of this paper is organized as follows. Section two outlines the theoretical model that guides the empirical investigation. Data collection and details of our survey are discussed in section three. Section four discusses the econometric model and estimation procedure. Section five presents results. Section six discusses the results and section seven concludes.

4.2 Theoretical Model

Our structural specification is similar to that of Cicchetti and Durbin, 1994 who model a binary decision to purchase telephone wire insurance and Collier et al., 2020 who model deductible and coverage limit choices in the flood insurance setting. Households are assumed to face the following maximization prob-

possibility by using a sample consisting of coastal homes. Its extremely unlikely that these households, which are very close to the coast (the mean home is 2.4km from the shore), have never considered purchasing flood insurance.

lem over the choice to purchase or forgo flood insurance:

$$\max_{c\in\{c_0,c_{full}\}} E[u(w)] = \int_0^d \phi(l)u(w-p(c)-l) + \int_d^c \phi(l)u(w-p(c)-d(c)) + \int_c^h \phi(l)u(w-p(c)-d(c)-l+c)\,dl \tag{4.1}$$

The utility function, $u(w)$, is a standard Von Neumann-Morgenstern (VNM) utility function that is monotonically increasing in wealth, w, and $\phi(l)$ is the probability of a household sustaining a flood loss of magnitude, l. In our setup, we assume individuals make an initial decision to purchase or forgo insurance based on the initial quote provided based on full coverage and the default deductible. Thus, their choice of coverage limit is restricted to either 0, c_0, or full coverage, c_{full}, which is the minimum of the home's replacement value, or $250,000 which is the maximum available coverage through the National Flood Insurance Program. Accordingly, the insurance premium, p, and deductible, d, are conditional on the choice of c. If coverage is forgone, the premium and deductible are both zero. If coverage is adopted, the premium is conditional on the specifics of the home being covered while the deductible is assumed to be the default option of $1,000. If coverage is purchased, the first integrand in equation 4.1 applies for flood losses below the deductible, the second integrand applies for losses between the deductible and full coverage level, and the third integrand applies for losses greater than the full coverage level (which is only applicable for homes with structure values greater than $250,000). Several implicit assumptions follow from our theoretical setup, the first being that households do not sustain more than one flood loss in a given year. The second being that no moral hazard is present, meaning the probability of a loss, l, is the same regardless of the insurance coverage decision made. Finally, our model assumes that households have correct perceptions of the probability of experiencing flood losses of differing severity.

A popular approach with previous literature (see Barseghyan et al., 2013; Cicchetti and Durbin, 1994; Cohen and Einav, 2007) has been to use a second-order Taylor series expansion to approximate the utility function during estimation rather than explicitly defining a functional form. This is advantageous since it does not require prior information on wealth or income and places no restrictions on functional form, thus allowing for flexibility in the structural specification. Given that natural hazards have the potential to generate very large shocks to wealth, however, a Taylor polynomial is not an appropriate choice for representing the utility function; it is meant to be only a local approximation. Therefore we explicitly define our utility function, choosing a CRRA formulation which has been the most prominent specification for empirical analysis across a variety of domains (Wakker 2008) and is likely appropriate in this setting since it captures the purported relationship between increasing wealth and the elevated proclivity to take financial risk. Thus, the utility function is defined as follows:

$$u(x;\rho) = \begin{cases} \frac{x^{(1-\rho)}}{1-\rho} & \rho \neq 1 \\ ln(x) & \rho = 1 \end{cases} \tag{4.2}$$

The theoretical setup presented in this section necessitates the collection of four essential pieces of data to make estimation possible. These include household wealth, flood insurance premiums for insured households and counterfactual premiums for uninsured households, a probability distribution over potential flood losses for each respondent's home, and the precise structure value of each respondent's home. We discuss the collection of these key pieces of data and our survey design more generally in the following section.

4.3 Data and Survey Design

Household-level data was collected using a series of mail surveys that were administered over the course of several waves that took place between October of 2018 and July of 2020. The surveys targeted recent homebuyers in three counties on the U.S. east coast with the goal of obtaining a profile of attitudes, beliefs, and expectations on topics pertinent to coastal living with an emphasis on coastal climate change issues. Figure 4.1 displays the counties sampled along with sample sizes and response rates. Initial sample frames were constructed by web scraping property transaction details from county tax assessors' websites. Homes

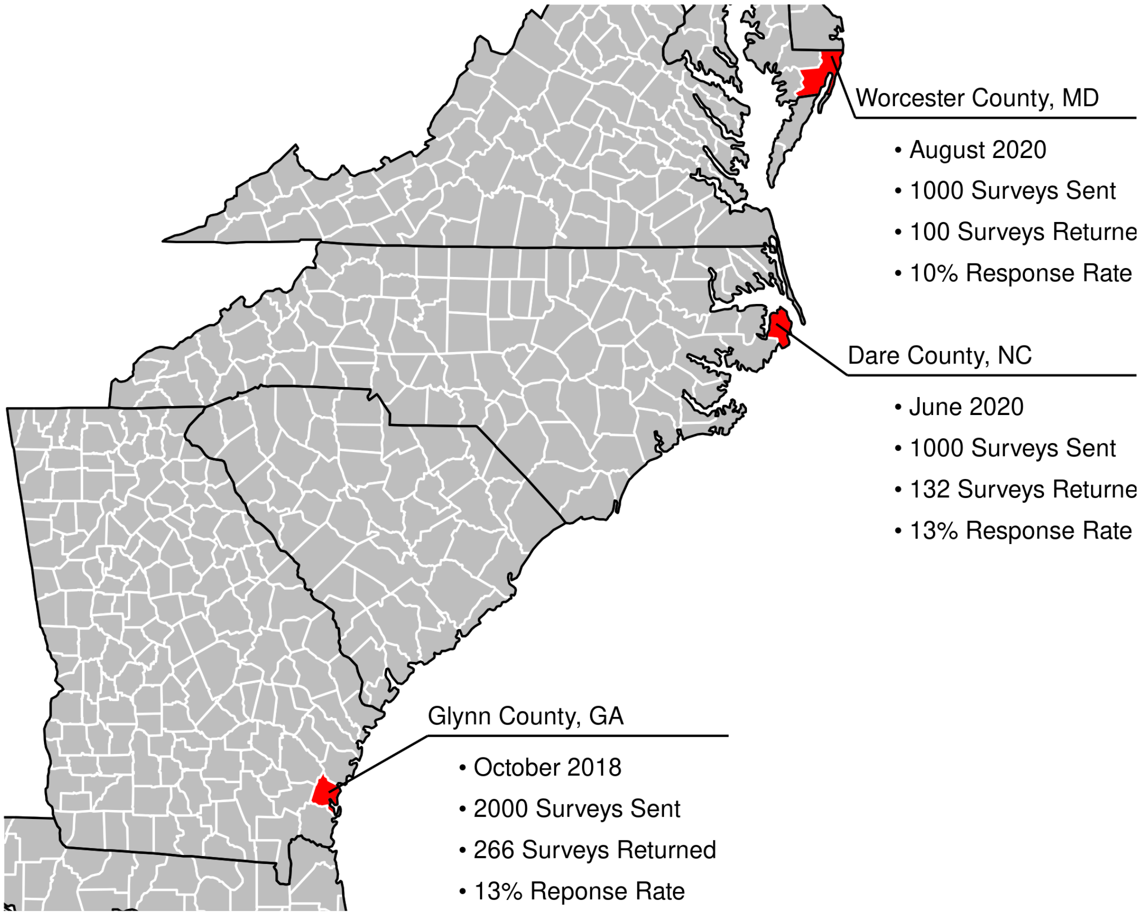


Figure 4.1: Sampled Counties

that had not been sold in the three years prior to the survey being sent out were dropped from the sampling frame. Further, to maintain a focus on coastal homeowners, homes that were further than 10 miles from the coast were dropped from the sampling frame. The remaining homes were randomly sampled. Glynn County, GA was used as a pretest site with 2000 surveys being sent out in October of 2018, 266 of which were completed and returned. Residents of Dare County, NC (The Outerbanks) received 1000 surveys in June 2020, 132 of which were ultimately completed and returned. Finally, an additional 1000 surveys were sent to the residents of Worcester County, MD and resulted in 100 completed and returned surveys.

To encourage participation in the survey, cash incentive payments of $5 were awarded for completed and returned surveys. However, these payments also played an integral role in an incentive-compatible risk preference instrument that was included in the survey and designed to capture respondent's proclivity towards risk-taking in a domain relevant to coastal natural hazards. Our risk preference instrument is very closely modeled after Eckle and Grossman, 2002 in the sense that participants are presented with a menu of lotteries and asked to choose their single most preferred lottery. Respondents had the option to keep their $5 incentive payment or forgo the payment and based their incentive payment on the results of the lotteries associated with the risk preference instruments. This design allows for framing of risk in the loss domain while ensuring that respondents end the survey with no less money than they started with. To frame risk in a domain that is tangentially related to natural hazard risk, future weather outcomes were used as a naturally occurring stochastic process on which the lottery payoffs in the instrument were based[4].

Figure 2.1 displays the risk preference instrument as it was presented to respondents in Glynn County, GA. Before making any decisions, respondents were first informed of the exact time frame and location that weather outcomes would be recorded and were presented with the historical objective probabilities that defined each weather event in the lotteries. Finally, respondents were tasked with choosing to keep their $5 incentive payment or chose one of the presented risky prospects. Table 4.3 reports the distribution of respondent's choices in the risk preference instrument along with corresponding implied coefficients of relative risk aversion. . Overall, about 40% of respondents chose to keep their $5 incentive payment with

Table 4.1: Elicited CRRA Parameters

Choice	Implied CRRA	Responses	Percentage
Safe $5	$\rho > 0.85$	132	39.64%
Lottery 1	$0.85 > \rho > 0.3$	25	7.51%
Lottery 2	$0.3 > \rho > 0.09$	26	7.81%
Lottery 3	$0.09 > \rho > 0$	55	16.52%
Lottery 4	$0 > \rho$	95	28.53%
Total		333	100%

[4] In addition to measuring risk tolerance in a domain-specific context, this method alleviates any concerns respondents may have about the true randomness of the lottery outcomes since they are independently verifiable by respondents.

certainty which corresponds to a CRRA value of at least 0.85. On the other extreme, 28.5% of respondents chose lottery 4, the riskiest lottery, corresponding to a CRRA value below zero which would characterize them as "risk-loving". The remaining respondents were distributed among the remaining lottery choices all of which imply varying degrees of risk aversion.

In addition to risk preferences, the survey elicited a plethora of other information on respondents including attitudes and opinions about the coast, flood and wind insurance information, subjective probabilities of flooding and hurricane strikes, conditional expectations of hurricane and flood damage, expectations of disaster assistance payments, levels of worry in various domains, and basic demographics. Most of the information collected is superfluous to the particular analysis presented here, thus we don't expound on it. For the remainder of this section, we present details on the collection of the data that allows for populating and estimating the theoretical model presented in section 2.

The theoretical model is constructed under the pretense that individuals seeking a flood insurance policy make their initial decision to insure based upon the default contract options. Thus, flood insurance premiums are needed for each household that corresponds to a full coverage, lowest deductible policy. These premiums are obtained by using the National Flood Insurance Program's rate manual which defines premiums based on the specific characteristics of a given home. Household wealth is necessary since it is an input for the CRRA utility function. Obtaining accurate measures of household net worth is particularly difficult due to individuals' reluctance to share intimate financial details. Individuals may also fail to report accurate net worth values, for example, it may not be clear to some households that home equity or retirement account balances should be included in the net worth calculation. A common approach is to use a proxy for wealth, such as the value of the respondent's home (Collier et al., 2020). Using home value as a proxy for wealth has the downside of ignoring differences in home equity and thus is rather crude in its approximation of wealth. Accordingly, we use household income as a proxy for wealth which is straightforward and unambiguous for survey respondents which should provide a better approximation for the variation in wealth among households.

Household income was elicited by having respondents select one of eight intervals ranging from "less than $35,000" up to "more than $250,000". With the exception of the top and bottom income intervals, each income interval was coded at its midpoint. The bottom interval was coded at $30,000 while the top interval, which is unbounded above, was coded according to the methodology suggested by Hout, 2004. This involves extrapolating income under the premise that income tends to follow a Pareto distribution. Applying this procedure results in a suggested top income coding of $496,124. The penultimate component of the theoretical model, home structure values, serves as the upper bound on the financial loss that households could experience due to a natural disaster. Tax assessed home structure values were obtained directly from each county's tax assessor website.

4.3.1 Estimation of Loss Distributions

The final component necessary to populate the theoretical model is a probability distribution that attaches a probability to all possible financial losses that could occur from a flood. Given that our survey sample consists only of homes that are very close to the coast, most flood events that survey respondents may experience in the future (or at least the ones most concerning from a public policy perspective) are likely to be the result of coastal tropical storms. Accordingly, to obtain a probability distribution over potential flood losses associated with a tropical storm, data from the National Flood Insurance Program's redacted claims database is used to train a machine-learning algorithm that can be used to predict damage when given the specific characteristics of a home along with weather conditions as inputs. This procedure was previously described in section 3.2.4 and full details of the procedure can be found in the appendix A.

4.3.2 Descriptive statistics

Table 4.2 reports descriptive statistics for the data that is required for estimation of the theoretical model. Self-reported flood insurance status suggests that 57 percent of the sample had a flood insurance policy at the time of the survey. The constructed annual flood insurance premiums (again based on the default full coverage, lowest deductible options) had a mean value of $1204. Mean household income was $159,000 after adjusting the unbounded upper-income interval. The average home structure value of a respondent in the survey was $197,000. Finally, taking the mode of each home's predicted flood damage probability distribution, normalizing it to the value of the home's structure value, and then averaging across all households suggests a mean value of 0.07. This value indicates that on average, damage equivalent to 7% of the home's structure value is the most probable amount of damage in the event of a major hurricane strike. .

Table 4.2: Descriptive Statistics

	mean	sd	min	max
Panel A: Dependent Variable				
Flood Policy	0.566	0.496	0.00	1.00
Panel B: Independent Variables				
Premium	1203.90	1223.19	152.60	10814.10
HH Income (Wealth Proxy)	158563.70	116065.70	30000	496124.3
Home Structure Value	197304.6	119823.5	18000	968200
Predicted Flood Damage	0.07	0.13	0.00	0.54
Observations	380			

4.4 Econometric Model and Estimation

For tractability and computational feasibility, we discretize the probability distribution of possible loss magnitudes and consider losses in 5 percent increments ranging from 0% to 100% of a home's structure value. Thus given a households coverage decision, c, their expected utility can be expressed according to the following equation

$$EU_i[w; c] = \sum_{l} \phi_i(l)u_i(l) = \sum_{l=0}^{h_i} \phi_i(l)u_i(w - p - min(d, l) + min(o, c - l)) \tag{4.3}$$

where $l \in \{0h_i, 0.05h_i, ..., 1h_i\}$ representing potential flood loss magnitudes as a percentage of household i's home structure value, h_i, in five percentage point increments. To account for seemingly contradictory decisions among households that are observably identical, we derive choice probabilities in accordance with McFadden (1981)'s random utility framework, which assumes utility is separable into deterministic and random components. Thus, the households value function becomes:

$$v_i(x;\epsilon) = u_i(x) + \epsilon_i \tag{4.4}$$

where ϵ_i is a Type 1 extreme value random variate associated with unobserved factors affecting the utility. Since the difference in Type 1 extreme value variates is distributed logistic, the probability that an individual purchases insurance is defined by:

$$Pr(c = c_{full}) \equiv \frac{1}{1 + exp\left(-(E[v(x;\epsilon, c_{full})] + E[v(x;\epsilon, c_0)])\right)} \tag{4.5}$$

Thus, an individual's probability of purchasing insurance increases as the difference between their expected utility with insurance and their expected utility without insurance increases.

Ultimately, our empirical strategy culminates by optimizing the following log-likelihood function by letting the CRRA value be a structural parameter, ρ, to estimate.

$$argmax_{\rho} \sum_{i=1}^{N} y_i ln\left(Pr(c_{full})\right) + (1 - y_i) ln\left(1 - Pr(c_{full})\right) \tag{4.6}$$

Structural models often lead to likelihood functions that are intractable (highly non-linear functions with local maxima). In such situations, maximum likelihood methods often exhibit convergence and stability problems. Accordingly, we estimate our model using MCMC. We specify a relatively vague normal prior distribution for ρ with a zero mean and variance of 100. We then perform 110,000 parameter draws with the Metropolis-Hastings algorithm, discarding the first 10,000 draws as a burn-in period which reduces the influence of starting values on the final estimates. Additionally, a thinning interval of 10 is applied to reduce auto-correlation, leaving us with 10,000 draws that define the posterior distribution of the structural parameter of interest, ρ. Trace plots and auto-correlation plots were visually inspected to check for evidence of non-convergence. Additionally, as a more formal test, the Geweke diagnostic was used which tests the null hypothesis that the first and last portions of the drawn samples have the same mean (Geweke, 1992). Rejecting this null is interpreted as evidence of a Markov chain that has failed to converge. No evidence of non-convergence was found using any of the previously mentioned diagnostics.

4.5 Results

Table 4.3 reports estimates for the coefficient of relative risk aversion for our sample. The estimated posterior distribution had a mean value of 5.98 and a median value of 5.9. 2.5% and 97.5% quantiles of the posterior distribution indicate a 95% credible interval that ranges from 1.5 to 11.5.

Table 4.4 reports the actual flood insurance market penetration rate of our sample along with the level of market penetration predicted by the estimated model. The model predicts that 58.3 percent of the sample should purchase insurance if expected utility theory is guiding their decisions. In reality, 56.6 percent of our sample held a flood insurance policy which is quite close to the model's prediction.

Table 4.3: Structural Parameter Estimates

			Quantiles				
Parameter	Mean	SD	2.5%	5%	50%	95%	97.5%
ρ	5.984	2.805	1.522	1.758	5.903	10.770	11.462

Table 4.4: Structural Model Fit

Market Penetration (Predicted)	Market Penetration (Actual)
0.583	0.566

4.6 Discussion

The critique of expected utility theory laid out by Rabin, 2000 is founded on the notion that if individuals exhibit moderate degrees of risk aversion over small stakes then expected utility implies they will exhibit absurd levels of risk aversion over much larger stakes. However, to date, almost no empirical evidence exists that measures levels of risk aversion over large stakes. This is due primarily to the impracticability of conducting incentive-compatible experiments using large stakes which leaves estimation of risk preferences using observed real-world decisions as the next best alternative. Similar to (Collier et al., 2020), we find that only modest coefficients of relative risk aversion are necessary to motivate observed choices over large stakes. Collier et al., 2020 find that flood insurance coverage limit decisions imply a representative agent coefficient of relative risk aversion of only 2.72 while our own results suggest a value of 5.9 for alternatively framed binary decision to purchase insurance.

Further, our unique data set allows us to directly compare CRRA values that were elicited over low stakes using an experimental instrument against the representative agent CRRA value estimated from the structural model. The majority of our sample (71 percent) exhibited some degree of risk aversion over the low stakes lotteries presented in our survey instrument which would again imply levels of risk aversion over large stakes that can't possibly be descriptive of observed behavior. However, as we have shown, our own estimates are at odds with this prediction.

As previously noted, status quo bias appears to be quite pervasive in the selection of insurance contract options. In our own data set 93.4 percent of respondents who had a flood insurance policy reported have a full coverage policy and 56.7 percent reported having the default deductible. Despite approximately 43 percent of our sample ultimately selecting a different deductible option, the model specification based on the default $1000 deductible predicts actual levels of market penetration quite accurately. We interpret this as evidence of the "two-step" procedure (proposed in the introduction) that individuals employ where the initial insurance quote (based on the default options) determines if individuals ultimately insure. Only later do some households consider and select alternative contract options. In light of this, we echo the sentiments of Dombrowski et al., 2020 and believe that changing the default flood insurance contract options so that the initial premiums households see are lower would have a positive impact on flood insurance market penetration. Identifying the effect of alternative default flood insurance contract options remains an important area for future research.

Overall, the use of theoretical structural models from decision theory in applied economics research is scarce despite being a potentially powerful method for gaining insight into how individuals make decisions in everyday situations characterized by risk and uncertainty. The limited use of these models is largely a product of the identification challenges that arise from structurally modeling behavior observed outside of the laboratory setting (sometimes referred to as “field data"). When estimation is possible, its typically accompanied by strong assumptions that may or may not hold in reality. For example, in the generalized expected utility framework, assuming individuals have perfect knowledge of the probabilities associated with each possible state of the world (as we do in our analysis) is a common way to avoid the identification challenges associated with simultaneous estimation of beliefs and preferences. However, as was highlighted in both chapters 2 and 3, this assumption likely does not hold for at least a subset of individuals.

One way to approach these identification problems is through direct elicitation of key model parameters using surveys (as was done in chapter 2 with risk preferences), but this is not a panacea for all identification problems. For example, this chapter makes use of an objective probability distribution over flood losses; eliciting a subjective analog would be extremely difficult using traditional survey methods. Another possibility is using survey responses to transform objective data in a way that more accurately reflects subjective beliefs. For example, simple Likert scales (something akin to the debriefing responses in chapter 2 (figure 2.2) could conceivably be used to provide guidance on how to transform objective probability distributions to better reflect the subjective beliefs of the individual. How to do this in a non-arbitrary manner is not clear though and remains as a potential avenue for future research.

Recent work has started to make use of models that incorporate estimated probability distortions as a way to deal with some of the aforementioned problems. For example, (Collier et al., 2020) simultaneously estimate probability distortions and risk preferences in a rank-dependent expected utility model for flood insurance deductible choices and coverage limits. However, again estimation is predicated on arguably suspect assumptions. Specifically, simultaneous estimation of beliefs and preferences in the insurance deductible context is contingent on the existence of variation in premiums and claims probabilities that are exogenous to household risk preferences. In the flood insurance setting, this may not hold. For example, homes designated as “Zone A" by FEMA have flood premiums set based on first flood height above base flood elevation (or “freeboard"). It’s easy to imagine that risk-averse individuals tend to select coastal homes with higher freeboard. If true, the utility function curvature would be correlated with flood premiums (and most likely claim probabilities) which would violate the previously mentioned identifying assumption. More generally, there are a host of alternative behavior models within the generalized expected utility framework, such as disappointment aversion (Bell, 1985a; Loomes & Sugden, 1986) and regret aversion models (Bell, 1985b; Loomes & Sugden, 1982; Quiggins, 1994; Sugden, 1993) and prospect theory based models (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992b) which can either be explicitly specified or nested within a general framework as a special case. However, as just discussed, the particulars of the study context can have implications for which identification assumptions are valid and must be closely examined. In short, structural decision models offer many advantages in applied research (such as direct mappings to theory and the ability to construct policy counterfactuals) but the difficulty associated with achieving robust identification of model parameters means extra care must be taken in the data collection and estimation phase, particularly if the results are to be used to influence policy discussions.

Another limitation of the results presented here is the use of a representative agent specification in which a single value of the risk aversion parameter, ρ, is estimated for the sample. In reality, individuals are known to exhibit (sometimes extreme) heterogeneity in individual attitudes towards risk. Although our model presented here appears to make a reasonable prediction regarding aggregate level flood insurance uptake, it is limited in its ability to analyze individual-level behavior since the sole estimated value of ρ will not be indicative of actual levels of risk aversion for most individuals. We explore a possible extension of the model by specifying a variant of the model that accounts for observed heterogeneity in levels of risk aversion. We discuss this further in the appendix B.

4.7 Conclusion

The purpose of this study is to assess the validity of expected utility theory in its ability to describe observed behavior in situations characterized by risk over high stakes that stems from real-world situations (i.e. outside the lab). In particular, using a novel survey data set consisting of coastal homeowners, we estimate a structural expected utility model over the decision to purchase flood insurance. We posit that individuals are particularly prone to status quo bias when selecting specific options regarding an insurance policy (i.e. many individuals do not stray from the default deductible and coverage limits) which may be a source of bias in previous literature. We avoid this potential source of bias by specifying our structural model based on the binary decision to insure which alleviates any concern of choice set misspecification. Estimation of the model results in a reasonable mean coefficient of relative risk aversion of 5.9. Further, the estimated model predicts that 58.3% of our sample should purchase insurance compared to the 56.6% of the sample that actually did. This suggests that despite the large literature that has pointed out the ways in which expected utility theory fails to describe observed behavior, the theory may still have descriptive validity over decision making when the stakes are particularly large.

Appendix A

Procedure for Estimating Objective Hurricane Damage

Estimating distributions of potential hurricane damage for each home in the survey sample is carried out in several steps, each of which is detailed below.

Clean and Construct Data

Two data sources are used for training the model that ultimately is used to predict potential loss distributions. Data on flood insurance claims is obtained directly from FEMA which contains flood insurance claims amounts (which corresponding to professional assessments of incurred flood damage) and basic home characteristics of each home (flood zone, home type, if the home is elevated, if the home contains a basement, and the number of floors.). To maintain a focus on flood damage associated with tropical storms, the NFIP claims data must be filtered to only contain flood damages that were the result of a tropical storm. Doing so requires cross-referencing historical tropical storm data to identify NFIP claims that are likely the result of a tropical storm. Historical tropical storm conditions are obtained using the "Hurricane Exposure" package in R (B. Anderson, Schumacher, et al., 2020; B. Anderson, Yan, et al., 2020) which allows for easy recovery and manipulation of historical data. This data source contains data on historical tropical storm tracks, along with precipitation and wind speed data for 171 named tropical cyclones that passed within 250km of at least one U.S. county between 1988 and 2018. These two data sources are combined using dates and latitude/longitude pairs to match up NFIP claims that can be attributed to one of the hurricanes in the historical hurricane data. More specifically, an NFIP observation is attributed to a hurricane if the hurricane passed within 200km of the home that filed a claim and the event date associated with the claim was within 5 days of the hurricane's closest approach. Once this procedure is done, the resulting database contains approximately 800,000 flood insurance claims and the precise storm conditions that resulted in those claims. All claim values are then inflation-adjusted to 2020 dollars using inflation data from the Federal Reserve Economic Data (FRED). Mean county home values are assigned to each claim observation using data from Zillow's home value index (Zillow, 2020) to control for regional variation in home prices.

Train Machine Learning Model

Next, a machine learning model is trained to predict the damage to a home's structure using storm conditions[1], home characteristics[2], and geographic characteristics[3]. The XGboost algorithm is used for this application which is advantageous here since the data is structured and contains some missing values (both of which XGboost can handle better than most other machine learning algorithms)(Chen & Guestrin, 2016). Training is done using standard machine learning practices. Eighty percent of the data is used as the training set, with the remaining 20 percent reserved as a test set. Hyper-parameters are tuned using a random search and 3 fold cross-validation.

Cluster Observations

The trained XGboost algorithm has the ability to generate point predictions of hurricane damage, but distributions of damage are required that account for uncertainty in the precise future hurricane condi-

[1]storm conditions include the closest distance the storm was from the home, total precipitation, maximum sustained wind speed, maximum wind gust speed

[2]Home characteristics include the homes free-board, base flood elevation, indicators for basement, crawlspace, and if the home was elevated, the home's FEMA designated flood zone, number of floors, and if it was built after FEMA flood maps took effect

[3]Geographic characteristics include if the home was in a coastal state or coastal county, indicators for the region, such as "south-east" (as determined by FEMA), latitude, and longitude.

tions. This is addressed by first clustering the data on geographic features using K-means[4]. This is done to create geographic clusters of observations that are likely to experience similar hurricane conditions. These clusters of observations then form a database of historical storm conditions that other observations within the same cluster are also likely to experience. Intuitively, clustering avoids a situation where coastal hurricane conditions are assumed to be present for an inland home.

Run Monte-Carlo Simulation

To create a probability distribution of potential home structure damage caused by a tropical storm the following steps are carried out for each observation:

1. The cluster that the selected observation belongs to is identified and all historical storm conditions that are associated with the other observations in that cluster become the pool of hurricane conditions that the selected observation could plausibly experience.

2. A random set of hurricane conditions from the pool of plausible hurricane conditions is taken and plugged into the pre-trained XGboost algorithm along with the home characteristics of the selected observation. The resulting point estimate generated by the XGboost algorithm is recorded.

3. Step 2 is repeated N[5] times to generate N point estimates, all of which have been generated with different hurricane conditions that are plausible for the selected observation. Together, these N point estimates form the probability distribution by recording how often each level of damage is predicted given the N different sets of hurricane conditions.

Validation

The previously described procedure is validated by generating damage distributions for each observation in the test set and seeing how the predicted distributions compare to the known levels of damage. Overall,

[4] Clustering is carried out using all geographic variables including indicators for coastal state and county along with latitude and longitude

[5] N is chosen to be 5000 in this case

the observed level of damage in the NFIP database is within the minimum and maximum values of the predicted distribution 90% of the time. Further, on average, the actual level of damage is at the 45th percentile of the predicted damage distribution indicating observed levels of damage tend to be associated with the high probability region of the predicted distribution which is what would be expected if the predicted distributions generally reflect reality. Once this procedure was deemed sufficiently accurate, it was applied to the survey data to generate predicted hurricane damage distributions for each observation in the survey sample.

Appendix B

Modeling Observed Heterogeneity in Estimated Risk Preferences

Specification of our model to allow for observed heterogeneity entails redefining of ρ in equation 4.2 as follows,

$$\rho = \alpha + X\beta + \epsilon$$

where α is a constant to be estimated, X is a matrix of observable characteristics, β is a parameter vector to be estimated, and ϵ is an error term. For this specification, rather than estimating ρ directly, α and β are instead estimated which then define each individual's value of ρ which is conditional on their observed characteristics. This allows us to estimate different values of ρ for different subsets of the population by specifying X so that it includes covariates that are likely to segment the sample into subsets with similar levels of risk aversion. What exactly should be included in X to optimize model fit is not entirely obvious, thus we make use of the Bayesian variable selection technique outlined in Kuo and Mallick, 1998. This allows us to include a surfeit of plausibly appropriate covariates in X. The model space then is randomly searched to provide insight into which of the 2^k (where k is the number of covariates included in X) possible models is most likely to be the true model.

We include 9 covariates in X which we believe, based on economic theory, have the potential to segment the sample by risk attitudes. These include indicators for education [1], coastal experience[2], flood risk[3], gender, and past flood experience[4] Additional covariates include the respondent's lottery choice from the risk preference instrument in the survey and an ordinal variable that captures how impactful the uninsured loss of the respondent's home would be to their total net worth[5]

After obtaining marginal inclusion probabilities for each co-variate we then identify the top five most probable models which are displayed in table B.1. Overall, specifying X to include an intercept (α), education status, lottery choice, home wealth share, SFHA status, gender, and an indicator for being new to the coast has the highest probability of being the true model (15.9%). We then use this specification and estimate the model in the same way that the representative agent model was estimated. Figure B.1 summarizes the coefficient estimates (β vector) which are the effects of each covariate in X on the estimated value of ρ that best explains the individual's flood insurance status within the expected utility framework. For example, individuals residing in an SFHA exhibit flood insurance purchasing decisions that are consistent with a lower level of risk aversion. The coefficient estimates displayed in figure B.1 can then be used to construct each individual's estimated level of risk aversion. Figure B.2 displays the distribution of all individuals' estimated risk aversion parameters once observed heterogeneity has been incorporated. Overall, the estimated values are very reasonable ranging from just above 0 up to just under 2. With respect to individual prediction accuracy, this specification accurately predicts an individual's flood insurance status approximately 65% of the time. However, the model tends to disproportionately

[1]"Higher Education" =1 if the respondent has at least a bachelor's degree

[2]"Coastal Vet." = 1 if the respondent indicated living most or all of their life on the coast. "New to Coast" = 1 if the respondent indicated being "new to the coast".

[3]"SFHA" = 1 if respondent's home is in a special flood hazard area.

[4]"Past Flood" = 1, if the respondent reported that their home has previously flooded.

[5]"Home Wealth Share" = 1 if home equity is 0%-20% of the respondent's net worth up to = 5 if home equity is 81% - 100% of their net worth.

Table B.1: Most Probable Models

Variable	Model Frequency 0.159	0.123	0.123	0.065	0.058
Intercept	■	■	■	■	■
Higher Education	■		■	■	
Lottery Choice	■	■	■	■	■
Coastal Vet.				■	■
Home Wealth Share	■	■	■	■	■
Age				■	
SFHA	■	■	■	■	■
Female	■	■	■	■	■
New To Coast	■			■	■
Past Flood				■	■

predict flood insurance uptake (about 97% of the time), which raises questions about how well this model would work for a sample characterized by much lower rates of flood insurance uptake.

One major caveat with this approach is that once ρ is modeled as a linear function of observable, MCMC convergence becomes extremely difficult to achieve using a traditional random walk Metropolis-Hastings algorithm. Even after 5 million draws with a thinning interval of 500, substantial auto-correlation in the Markov chain remains present. Thus we do not condone interpretation of the results presented in this appendix, but rather suggest that it be used as a framework to guide further research. Again, the primary concern with these results is the lack of convergence in the MCMC estimator. Alternative estimation techniques, either in the Bayesian realm, or perhaps more modern techniques (such as differential evolution (Mullen et al., 2011; Price & Storm, 2006)) may alleviate this issue.

Figure B.1: Effect of Covariates on Estimated Risk Preferences

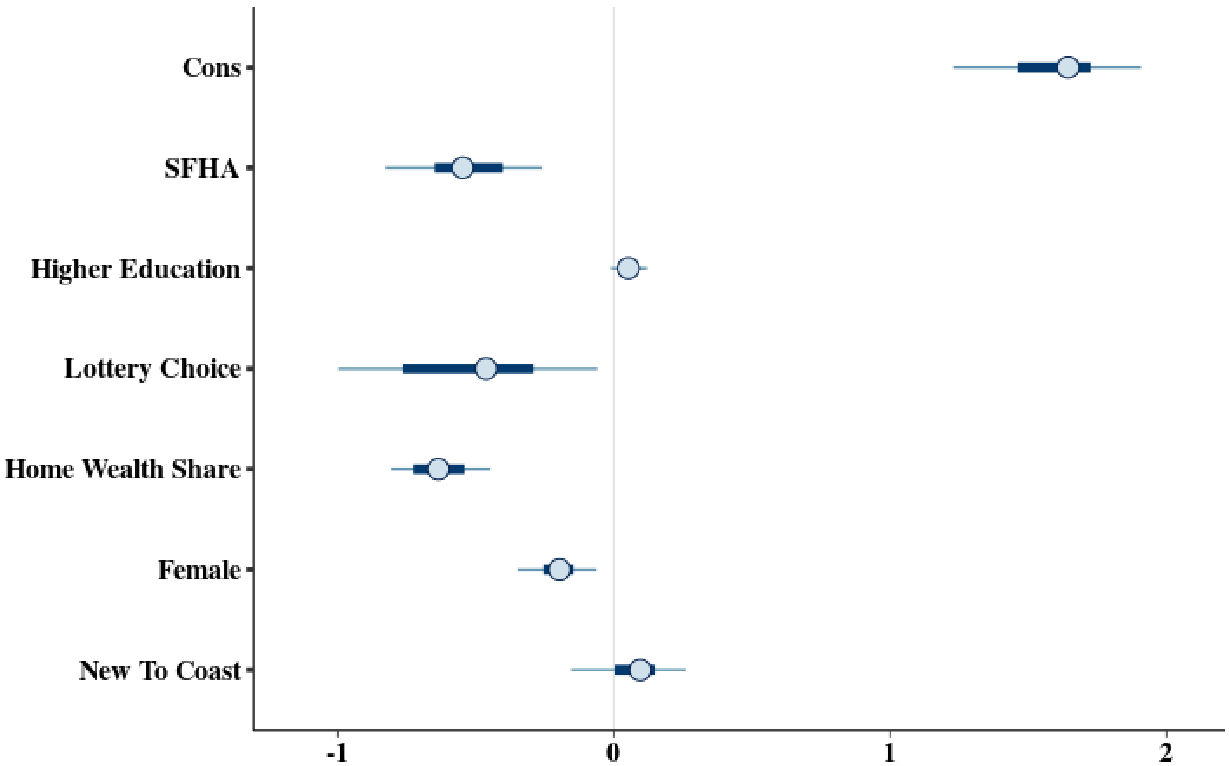
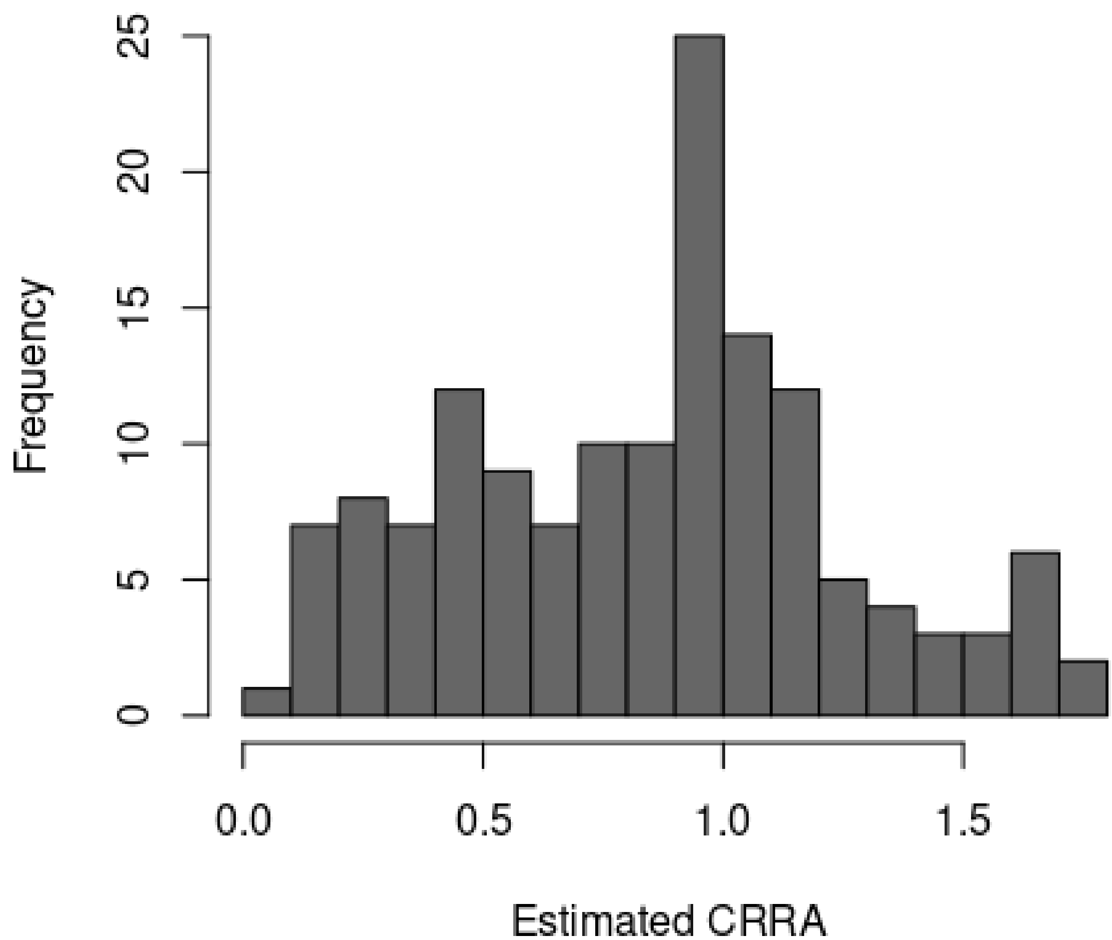


Figure B.2: Distribution of Heterogeneously Estimated Risk Preferences



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