The Nature of Coastal Hazard Risk Perceptions

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Abstract

Using survey data of homeowners from multiple locations on the U.S. east coast, this study characterizes the accuracy 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 here 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 no general tendency in perceptions of flood probabilities, 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. 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 highly publicized. Finally, estimation of six commonly referred to probability weighting functions reveals that the differences between subjective and objective flood probabilities cannot easily be explained by probability weighting suggesting that the source of the probability distortions is most likely due to mis-percieving the true risk.

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1. Introduction

Understanding the motivations behind individuals' decision to mitigate against natural hazards is becoming increasingly relevant as the costs of such events has been increasing for decades (NOAA, 2020). Increased development in hazard prone areas is partly to blame for rising costs (Kunreuther & Michel-Kerjan, 2007), but increased frequency of global catastrophic events cannot be ignored as a contributing factor (Boustan et al., 2019; Gaiha et al., 2015; Kousky, 2014). By far, the most costly of these hazards is tropical cyclones and the associated flooding. For homeowners, flood insurance is the primary tool for limiting fiscal impacts from flooding, yet only about 30% of individuals in FEMA designated special flood hazard areas (SFHA) have a flood insurance policy (Kousky et al., 2018). One potential explanation for this is widespread individual misperceptions of personal flood risk. If individuals perceive the probability of flooding or the associated damages to be low relative to the objective risk, they may forgo investing in flood mitigation strategies. From a policy perspective this is particularly noteworthy. If misperceptions are the primary cause of low flood insurance market penetration, then simply providing readily available and easy to interpret information about individuals' true flood risk may be the only policy intervention needed to prompt more personal flood mitigation behavior.

Surprisingly, studies that directly compare homeowner's subjective assessments of flood risk against objective measures 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 over-estimate the probability of a flood but under-estimate associated damages when compared to objective HAZUS[1] risk estimates. Bakkensen & Barrage (2017) survey 187 coastal residents in Rhode Island and ask them 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 & 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 over-optimistic in the perceptions of flood risk. Elicitation of 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 asses 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

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

objective estimates. Those who underestimated the probability of a flood were primarily characterized as neglecting the risk altogether. With respect to flood consequences, they find most residents report much lower maximum water levels than objective estimates would suggest. However, individual's expected damages where roughly in line with objective estimates about half of the time (using 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 misperceptions. 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 & 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 non-convergent 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.

Using individual survey data obtained from coastal counties in Georgia, North Carolina, and Maryland, we analyze homeowner perceptions of flood likelihood and find that individuals with overoptimistic, 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 & Barrage (2017) and Royal & 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 geography of our sample means that many of the flood events households in our sample may face are likely to be caused by tropical cyclones. Thus, in addition to flood risk, perceptions of hurricane risk are specifically elicited and compared to objective risk estimates. To our knowledge, Meyer et al. (2014) is the only study that directly measures individuals' subjective perceptions of hurricane risk and compares them to objective estimates. They conduct phone surveys to elicit individual risk perceptions multiple times leading up to Hurricane Issac and Hurricane Sandy making landfall at the Gulf Coast and New York City respectively. They find that individuals in their sample consistently overestimated the probability that their home would be afflicted by hurricane force winds. Notably, their survey sample was focused on a specific eminent hurricane threat that was receiving constant media attention and had prompted evacuation orders for some of their survey participants. Our own survey setting does not focus on a specific hurricane but instead elicits general beliefs in a time with no eminent storm threats.

Our results suggest individuals have a general tendency to overestimate the probability of a major hurricane making landfall near their home and generally overestimate the associated damages that would accompany a major hurricane. To investigate the sources of heterogeneity in misperceptions, we conduct a reduced form analysis to identify possible determinants of risk perceptions. The reduced form 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 misperceive probabilities of natural hazard risk, information campaigns may be a potentially effective policy intervention, which would have little to no effect if individuals instead have correct perceptions of risk, but weight probabilities when utilizing risk information for actual decisions. We investigate this issue 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 reduced form model 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 our empirical methodology. Section 4 presents results, while section 5 discusses the results. Section 6 concludes.

2. Data

2.1. Survey Data

The empirical analysis we conduct involves two distinct steps. The first compares objective and subjective metrics of flood and hurricane risk and categorizes respondents as being pessimistic, correct, or overoptimistic 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 (i.e. the natural hazard risk individuals think they face), 2) objective risk metrics (i.e. the natural hazard risk individuals actually face), 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.

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 individuals 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?"

Responses to the above question were then mapped to a corresponding annualized probability[2]. 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

[2] i.e. We divide the response by 50 and censor values greater than 1

at high tide. How much damage (expressed as a percentage of total home value) do you think your home would most likely suffer?"

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

2.3. Objective Risk Metrics

To obtain objective estimates of the natural hazard risk individuals in our sample actually face, we utilize several sources of 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 geo-spatial coordinates of each property. As a metric of risk, these flood zone classifications are quite crude with only three primary classifications; "a less that 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 designation have been called into question. Wing et al. (2018) estimate that 41 million U.S. households face a 1% change 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) which 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 flood depths (for each return period, which are unique to each property footprint) 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[3] which map flood inundation levels into damage as a share of total home structure value.

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, 2020). To obtain an objective historical annualized 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 straight forward to obtain of 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

[3] 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 Corp of Engineers (USACE) which include "USACE - IWR", "USACE - Chicago", and "USACE - Galveston"

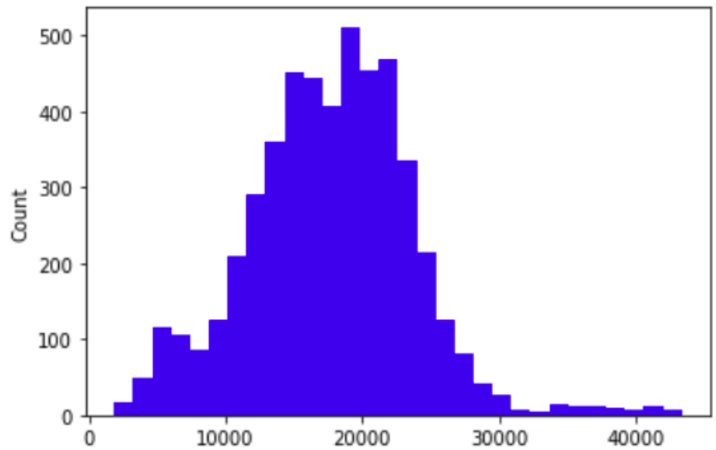
can be obtained via visual inspection (for example, the number of floors in the home or if the home is elevated) where as other features are difficult to ascertain (such as if hurricane ties were used on the roof trusses).

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, free board ... 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 1 depicts a representative example of what this procedure produces for each observation in our survey sample[4].

In general, this procedure appears to provide very 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 contains the true damage level 90% of the time with the actual damage level falling at the 44th percentile of the predicted distribution on average. Meanwhile, the mode of the average distribution is at the 42nd percentile of the

[4]This particular 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 with damage above $30,000 being very improbable.

Figure 1: Example of Estimated Hurricane Damage Distribution



predicted distributions. This suggests, that in general, actual damage levels tend to fall in the high probability region of the predicted damage distribution which 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.

2.5. Descriptive Statistics

The remaining data are obtained from the administered survey which are discussed here alongside descriptive statistics for all data used in the analysis. Panel A of table 1 reports descriptive statistics for all variables related to subjective risk perceptions. The mean respondent believed there was an approximate 9 percent chance 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 were to flood, sustained damage would be equivalent to 67 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 1. Data from the First Street Foundation suggest the average home in the sample has an 9 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 homes structure value. Similarly, objective estimates suggests damage equivalent to 8 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 1. Thirteen percent of respondent's 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 \$2700, 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 a SFHA zone which was obtained by cross referencing 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). Overall, the First Street data suggests that 63 percent of households in the sample would be in SFHA zones if FEMA were to use the First Street data for classifying flood zones. Notable, this is more than double the number of households in our sample that are officially designated by FEMA as being located in an SFHA zone. 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.

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 makes it possible 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.

Approximately half of the respondent's 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 were "Coastal Veterans", i.e. they had lived on the coast for most or all of their lives. Coefficients of relative risk aversion were experimentally elicited using an incentive compatible risk preference instrument similar to that used by Eckle & Grossman (2002). The mean coefficient of relative risk aversion was .36 indicating the mean respondent was risk averse. The elicitation of risk preferences is not the focus of this paper thus full details of the risk preference instrument can found in appendix B.

Respondent's 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 $35,000 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 respondent's 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-seven percent of respondents were white, 67 percent completed at least a bachelors degree, 30 percent were female, with the average of a respondent being 56.

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 conclude our analysis by structurally estimating a series of probability weighting functions to see if the observed differences between subjective and objective flood probabilities could plausibly be explained by probability weighting. The remainder of this section details each component of the analysis in turn.

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 fall 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. However, 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 respondent's in each category.

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 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 characteristic 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 formation of risk perceptions, we also run a series of probit regressions that make use of binary variables that indicate if each respondent had correct risk perceptions which are modeled as the dependent variable. The first 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[5].

3.2.1. Robustness Check: Misperceptions vs Probability Weighting

As noted previously, its 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. In such a case, we should generally be able to describe the differences between objective and reported subjective probabilities with a probability

[5]Using a smaller margin of error generally does not produce appropriate variation in the outcome variable which can lead to estimation bias due to separation or in the extreme case of perfect separation (i.e. a covariate perfectly predicts the outcome of interest) the maximum likelihood estimate does not exist(Albert & Anderson, 1984)

weighting function. Thus being able to accurate describe our observed probability distortions with a probability weighting function would be evidence that the observed distortions are due to probability weighting rather than misperceptions of risk. 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, the 5 weighting functions proposed by Prelec (1998),Tversky & Kahneman (1992), Gonzalex & Wu (1999), and Goldstein & Einhorn (1987). Additionally, a simple power weighting function is considered where each individuals' objective probability is raised to a power, which is a parameter to be estimated.

Given that our outcome variable in this case is a probability, characterized by being defined on the open interval (0,1), we base our structural model on a beta regression model which is specifically constructed for a dependent variable of this type (Ferrari & Cribari-Neto, 2004). In a standard beta regression, the parameter μ is a linear combination of observable characteristics, $\mathbf{X}$, and parameter vector, β, that get passed through a link function $g(.)^{-1}$ (equation 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 $\mathbf{X}$, the objective flood probabilities,P_{obj}, are used (equation 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 where B(.) is the beta function.

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

$$\mu = \Psi(P_{obj}; \theta) \tag{2}$$

$$f(P_{sub}|\mu, \phi) = \frac{P_{sub}^{(\mu\phi-1)}(1-P_{sub})^{((1-\mu)\phi-1)}}{B(\mu\phi, (1-\mu)\phi)} \tag{3}$$

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. Full details associated with the MCMC estimation procedure can be found in the appendix C.

4. Results

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 2 reports the share of respondent's 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. However, there is significant heterogeneity in perceptions across flood zones, although much of this heterogeneity is due to the way FEMA flood zones are structured [6]. 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 reports the share of respondents that had subjective probabilities of flooding that were correct along with 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 (42 percent) pessimistic and over estimated the likelyhood of a flood. The remaining individuals (28 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 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 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

[6] Zeros populate the diagonal of this table due to 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.

point margin of error still only results in about half of respondents having correct flood damage perceptions.

Table 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 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 slightly over half of respondents having correct perceptions, but with a large share of individuals still overestimating the probability of a strike.

Table 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).

4.2. Determinants of Risk Perceptions

Table 6 reports regression results that explore the possible sources of risk misperceptions. Results suggest that past experiences play a role in formation of risk perceptions. Individuals who have directly sustained flood damage to their home 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 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 since the SFHA designation conveys information about the likelihood of a flood and contains no information regarding likelihood of damage in the event a flood does occur. SFHA status is also correlated with expected number of hurricanes over the next 50 years, but with a negative coefficient. This implies those is 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. Resident's who are closer to the coast believe the likelihood of flooding and 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 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 effect subjective flood probabilities and expectations of both flood and hurricane damage. No significant relationship is evident between worry in this domain and 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 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, where as 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 an First Street SFHA equivalent, and being female are all correlated with a lower likelihood of having correct perceptions.

4.3. Robustness Check: Role of Probability Weighting

Table 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 reduced form 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 mis-perceiving risk rather than just reporting weighted probabilities in surveys.

Figure 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 the 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 2), cannot decrease to pass near the data points in the lower right corner (those who under-estimate flood risk)[7].

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

[7] 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 figure 2 then almost any weighting function could conceivable fit each segment much better than a single weighting function estimated on the full sample. Supervised machine learning techniques could be quite use in this case (due to the superior regularization routines associated with them) 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.

of flood probabilities are slightly more likely to over estimate 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 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 & Walls (2019) and Bakkensen & Barrage (2017) find that the majority of individuals in their samples underestimate the probability of a flood, a result that is not support 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 own 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 south eastern United States where as the previously mentioned studies are based in New York City and the Netherlands respectively. For many of the homeowners in the south east U.S., tropical cyclones and hurricanes are the primary source 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 south east 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 over-estimate 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. Respondent's 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. Nonetheless, our results are consistent with Meyer et al. (2014) who use a very different methodology and study setting.

Despite the potential limitations of our own methodology, 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 number of hurricanes over the distant future avoids eliciting responses as a percentage which may be more intuitive for respondent's who are less numerically literate. Other literature has demonstrated the difficulties respondent's have when presented with open ended probability queries and the proclivity to round answers, particularly near the limits of the unit interval Dominitz & Manski (1997); Manski & Molinari (2010). de Bruin et al. (2002) suggests that the tendency for .5 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 respondent's 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 in the domain of natural hazard risk.

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; Royal & Walls, 2019; Mol et al., 2020). 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 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, where as 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, easy to access, 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, where as 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[8]. 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[9].

Analysis of the determinants of expected future hurricane strikes reveal what is likely an endogenous relationship between perceived frequency of future hurricanes and objective risk indicators. Individuals, residing in an SFHA, residing in a First Street equivalent of an

[8]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)

[9]Once concern with interpreting the change in significance in the two SFHA variables across regressions (in table 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 6 using the exact same sub-sample for all three regressions. These results are reported in table 9. Two of the three regressions are qualitatively equivalent with the exception being the regression focused on flood damage perceptions which exhibits not statistically significant relationship between wither FEMA or First Street SFHA designations and flood damage perceptions. However, this may be very well be a result of reduced statistical power.

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 respondent's about the probability of their home flooding over the next year, where as subjective perceptions of a hurricane strike were elicited based on beliefs over the next 50 years. Thus, perceptions of hurricane strike contains information regarding general beliefs about climate change induced changes in natural hazards which we believe to be the reason that evidence of coastal retreat is only associated with regressions based on perceptions of hurricane risk.

Running a robustness check reveals that the observed differences in objective and subjective flood probabilities cannot be easily explained by any of 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. The fact that elicited subjective probabilities are not systemically different from objective probabilities in the way that probability weighting functions predict suggest strengthens the claim that informational campaigns that provide individuals with accurate flood risk knowledge may help individuals make more optimal flood mitigation decisions.

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. and find significant heterogeneity in perceptions of flood probability. 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, we 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 a respondents FEMA designated flood zone correlates significantly with their subjective belief about the probability of flooding where as objective flood probabilities obtained from the First Street Foundation, which are generally accepted to be 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 house holds 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.

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7. Tables

Table 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)	0.08	0.06	0.00	0.39	383
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 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: 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	0.423	0.947	0.941	0.929	0.924	0.924	0.894
Correct	0.291	0.047	0.035	0.041	0.041	0.041	0.041
Optimistic	0.286	0.006	0.024	0.029	0.035	0.035	0.065
Panel B: 2.5 Percentage Point Margin of Error							
Pessimistic	0.388	0.900	0.894	0.882	0.876	0.876	0.841
Correct	0.367	0.094	0.088	0.094	0.094	0.088	0.100
Optimistic	0.245	0.006	0.018	0.024	0.029	0.035	0.059
Panel C: 5 Percentage Point Margin of Error							
Pessimistic	0.281	0.865	0.859	0.847	0.847	0.835	0.812
Correct	0.515	0.129	0.124	0.129	0.124	0.129	0.141
Optimistic	0.204	0.006	0.018	0.024	0.029	0.035	0.047
Panel D: 10 Percentage Point Margin of Error							
Pessimistic	0.148	0.800	0.800	0.800	0.782	0.782	0.759
Correct	0.679	0.200	0.194	0.182	0.194	0.194	0.206
Optimistic	0.173	0.000	0.006	0.018	0.024	0.024	0.035
Panel E: 25 Percentage Point Margin of Error							
Pessimistic	0.056	0.653	0.653	0.653	0.647	0.635	0.618
Correct	0.806	0.347	0.347	0.347	0.353	0.365	0.376
Optimistic	0.138	0.000	0.000	0.000	0.000	0.000	0.006
Panel F: 50 Percentage Point Margin of Error							
Pessimistic	0.010	0.488	0.488	0.488	0.488	0.476	0.453
Correct	0.990	0.512	0.512	0.512	0.512	0.524	0.547
Optimistic	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Notes Here

Table 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	81	436

Notes: Notes Here

Table 5: Share of Respondents with
Correct Hurricane Damage Perceptions

	All Counties
Pessimistic	0.747
Correct	0.247
Optimistic	0.006
Observations	162

Table 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 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 8: Structural Probability Weighting Model Fit

	RMSE
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

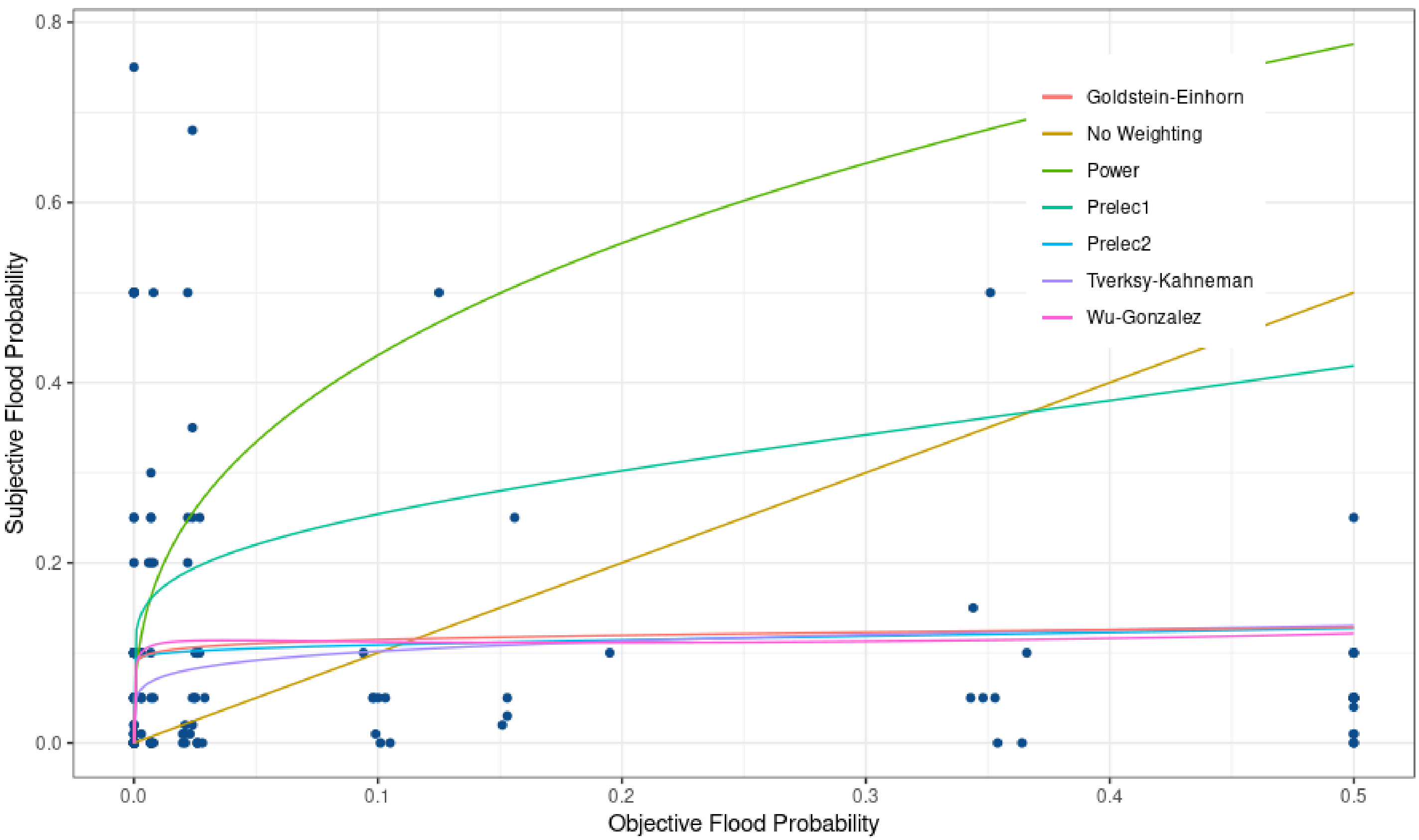
Table 9: Determinants of Risk Perceptions

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

8. Figures

Figure 2: Estimated Weighting Function



9. 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.

A.1. Clean and Construct Data

Two data sources are used for training the model that ultimately is used to predict the hurricane damage distributions. Data on flood insurance claims from the National Flood Insurance Program (NFIP) are obtained directly from FEMA's redacted claims dataset[10] (Federal Emergency Management Agency, 2020) which contains flood insurance claims amounts and basic home characteristics of each home (flood zone, home type, if the home is elevated, if the home contains a basement, and number of floors.). Historical hurricane conditions are also obtained using the Hurricane Exposure package in R (Anderson, Yan, et al., 2020; Anderson, Schumacher, et al., 2020) which allows for easy recovery and manipulation of historical data. This data source contains data on historical hurricane 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

[10]FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

event date associated with the claim was within 5 days[11] of the hurricanes closest approach. Once this procedure is done, the resulting data base contains approximately 800,000 flood insurance claims and the precise hurricane conditions that resulted in those claims. All claim values are then inflation adjusted to 2020 dollars. 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.

A.2. Train Machine Learning Model

Next, a machine learning model is trained to predict the damage to a home's structure using hurricane conditions[12], home characteristics[13], and geographic characteristics[14]. 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.

[11] We use a very conservative time frame here to limit the probability of erroneously attributing claims to the event of interest. For example, a claim made within 1 month of an event of interest may not obviously be associated with that event.

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

[13] 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

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

A.3. 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 conditions. This is addressed by first clustering the data on geographic features using K-means[15]. 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 hurricane conditions that other observations within the same cluster are also likely to experience. For example, all homes in coastal counties in the south-east may end up in a single cluster. Intuitively, clustering avoids a situation where hurricane conditions are used to predict home damage for a home that is very unlikely to experience those hurricane conditions. For example, using coastal hurricane conditions to predict damage on an home far inland would not be appropriate since the inland home is very unlikely to experience coastal hurricane conditions.

A.4. Run Monte-Carlo Simulation

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

1. The cluster that the selected observation belongs to is identified and all historical hurricane 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

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

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 times (N is chosen to be 1000 in this case) 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.

A.5. 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, the observed level of damage in the NFIP data base 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 where the average modal value of all distributions is at the 43rd percentile. This indicates that 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.

B. Details on Survey Methodology

Risk preferences were elicited using an incentive compatible instrument that is primarily based on Eckle & Grossman (2002). Respondents were initially informed that they would receive a $5 incentive payment for returning a completed survey. Later on in the survey, they were prompted to choose between keeping their $5 incentive payment or entertaining a series of risky prospects. If a respondent chose to forgo their $5 incentive payment, they were asked to select one of four alternative lotteries. These alternative lotteries take advantage of the naturally stochastic nature of weather events to incorporate randomness into the lotteries. For example, the first lottery paid out $8 if the cumulative November rainfall was less than 1.5 inches (50% historical probability) and paid out $3 otherwise. This has the advantage of domain specificity, which has been shown to be an important consideration in analysis of risk preferences (Dohmen et al., 2011; Einav et al., 2012). Additionally, weather events are independently verifiable by the survey respondent which alleviates any potential concern a respondent may have about the genuine randomness of the outcome.

Figure B1 displays the risk preference question as it was presented in the survey. Respondents were informed of the exact dates and weather station that would be used to record weather outcomes. The question then provides the historical probability of each weather event occurring. Finally, respondents were presented with the lottery choices (along with the option to keep their incentive payment and not engage in a lottery).

Figure B1: Risk Preference Instrument

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.

C. Details on MCMC estimation

As previously noted, for computational feasibility, MCMC methods are employed to estimate the likelihood function for the structural beta regressions that incorporate probability weighting functions. Given that this 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 a random walk Metropolis-Hastings sampler meaning each proposal distribution (which is defined as normal) is centered on the previous iteration. 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 auto correlation. To check for evidence of non-convergence, visual inspection of trance 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.