Flood risk perceptions: Accuracy, determinants, and the role of probability weighting.

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Abstract

This study analyzes survey data of US east coast homeowners to characterize accuracy and determinants of homeowner flood risk (mis)perceptions. Using an array of instruments, we assess subjective risk perceptions and compare them to objective risk estimates. Reduced-form regressions suggest flood experience, worry, coastal tenure, education, primary homeownership, income, and wealth influence relative perceptions of risk. Common probability weighting functions do not fit the divergence in risk perceptions, suggesting that the source of the probability distortions is most likely due to misperceiving the true risk rather than a widespread behavioral heuristic.

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1. Introduction

Understanding the motivations behind individual decisions to mitigate against natural hazards is becoming increasingly relevant as the social and economic costs of extreme weather events have been increasing for decades (NOAA, 2020a). Increased development in hazard-prone areas is partly to blame for rising costs (Kunreuther & Michel-Kerjan, 2007), but the 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 are tropical cyclones and associated flooding. For homeowners, flood insurance is a primary tool for limiting fiscal impacts from flooding. Yet, only about 30% of US households in FEMA-designated special flood hazard areas (SFHAs) 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 likelihood of flooding or the associated damages to be low relative to the objective risk, they may forgo investing in flood mitigation strategies based on incorrect beliefs. From a policy perspective, this is particularly noteworthy; if misperceptions are driving flood mitigation behavior, then the accuracy and interpretability of objective risk information available to flood-prone residents could influence personal mitigation and investment decisions (as well as support of public risk management projects).

This study seeks to quantify and assess the relationships among perceived and objective coastal hazard risks. Using a novel survey data set consisting of homeowners from three coastal counties in Georgia, North Carolina, and Maryland, we compare respondents' perceived probability of their home flooding, the damage their home would sustain in the event of a flood, and the likelihood of a major hurricane strike against objective estimates of the same risks. We then analyze the role that observable characteristics have on divergence in risk perceptions to establish potential determinants of misperceiving risk. To help differentiate between idiosyncratic probability misperceptions and systematic probability weighting[1], we estimate a series of structural regression models 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.

[1]Previous analyses that have attempted to estimate structural decision models have struggled with distinguishing between individual probability weighting and probability misperceptions (Barseghyan et al., 2013b; Collier et al., 2021).

Concerning perceptions of general flood risk, we find individuals in the sample do not exhibit any consistent tendencies regarding the probability of a flood; correct, optimistic, and pessimistic perceptions are all well represented in our sample. With respect to expected flood damage, almost all survey respondents overestimate the damages associated with a flood, regardless of the return period. When comparing perceived flood damages against floods of various inundation levels, however, we find the frequency of pessimistic and correct perceptions to be much more balanced. This suggests that individuals' overestimation of damage stems primarily from overestimating the water inundation levels as opposed to misunderstanding the relationship between a fixed level of inundation and home damage.

Our analysis of determinants of risk perceptions reveals that past flood experiences and levels of worry both generally influence risk perceptions. Additionally, we find that objective risk metrics influence perceived flood probabilities but only when the risk metric is highly publicized, which suggests that information campaigns may be an effective way to influence public perceptions of flood risk. Finally, the estimation of probability weighing parameters suggests that the deviations seen between perceived and actual flood probabilities cannot be easily explained by probability weighting, suggesting that the observed deviations are due to idiosyncratic misperceptions of risk.

The results presented here contribute to the existing literature in several ways. First, our results contribute to the literature on the accuracy of risk perceptions from a novel data set obtained from several locations along the US east coast. This is notable since there is a paucity of literature that quantifies the deviations between perceived and objective coastal hazard risks. Additionally, existing studies are not in agreement on the nature of 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, 2022; Royal & Walls, 2019), underestimation of flood water levels (Mol et al., 2020), underestimation of expected damages (Botzen et al., 2015), underestimation of "flood risk exposure" (Royal & Walls, 2019), and some evidence that damage expectations are generally correct (Mol et al., 2020). Variation in findings likely reflects temporal, methodological, spatial, and institutional differences in each study, making it difficult to interpret or generalize the array of results.[2] Thus, our results, representing

[2]For example, the findings of Mol et al. (2020) are based in the Netherlands and thus cannot reliably be generalized to the U.S., given significant differences in institutional setting. Royal & Walls (2019) sample from coastal Maryland, which had not witnessed any major flood events for a number of years before

several locations on the US east coast, help bring the literature closer to a consensus on the nature and determinants of individual perceptions of natural hazard risk.

Second, to our knowledge, we are the first to fit structural probability weighting functions to observational data in the domain of flood risk. This provides important insights for future policy discussions. As noted by Barseghyan et al. (2013b), the distinction between misperceptions and probability weighting does not matter in the sense that both assumptions could lead to models that accurately predict behavior, but policy implications differ under each scenario. For example, if individuals misperceive probabilities of natural hazard risk, information campaigns may be an effective policy intervention, which would have little to no effect if individuals instead have correct perceptions of risk, but distort probabilities when utilizing risk information for actual decisions.

The remainder of this paper is organized as follows. Section 2 provides an overview of the existing relevant literature. Section 3 details the data sources utilized and presents descriptive statistics. Section 4 describes our empirical methodology. Section 5 presents results, while section 6 discusses the results. Section 7 concludes.

2. Literature Review

A number of studies have measured individual perceptions of natural hazard risk using a variety of methods (see Bubeck et al. (2012) and Lechowska (2018) for reviews). Other studies have assessed both lay people and expert measures of flood risk using qualitative scales and interview techniques (Siegrist & Gutscher, 2006; Ruin et al., 2007). However, empirical studies that quantify the difference in homeowners' subjective assessments of flood risk and objective analogs of the same risk are uncommon. Moreover, the few existing studies that explore this topic produce quite different findings 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 using a series of multiple choice questions to elicit each individual's perceived probability of a flood and their expected cost to repair their

the survey; additionally, they only survey SFHA residents, meaning their results may not generalize to homeowners in lower-risk flood zones. Notably, Botzen et al. (2015)'s survey was administered 6 months after hurricane Sandy, implying many survey respondents had vivid memories or recent direct experience with flood damage.

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[3] risk estimates.

Royal & Walls (2019) survey several hundred coastal floodplain residents in Maryland and investigate individuals' 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 in 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 their perceptions of flood risk. Elicitation of the perceived probability of flooding, using an open-ended query, revealed that the majority of homeowners believed the annualized 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. With respect to flood consequences, they find most residents report much lower maximum water levels than objective estimates would suggest. Individuals' expected damages, however, were 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.

Bakkensen & Barrage (2022) 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 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.

To our knowledge, Meyer et al. (2014) is the only study that directly measures individuals'

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

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 on the Gulf Coast and New York City, respectively. They find that individuals in their sample consistently overestimated the probability that their homes would be afflicted by hurricane-force winds.

3. Data

3.1. Survey Data

The empirical analysis we conduct involves three distinct steps. The first compares objective and subjective metrics of flood and hurricane risk and categorizes respondents as being pessimistic, roughly 'correct', or optimistic in their risk assessments. The second step explores possible determinants of the observed heterogeneity in misperceptions by conducting reduced-form regression analyses. Data requirements for our analysis necessitate having 1) subjective risk metrics (i.e., the natural hazard risk individuals think they face), 2) objective risk metrics (i.e., reliable and accurate estimates for the natural hazard risk individuals actually face), and 3) individual characteristics that plausibly influence risk perceptions. Lastly, we test numerous weighting functions to assess their performance in explaining the difference among subjective and objective risk perceptions. The remainder of this section details the sources and collection methods for these data and concludes with descriptive statistics.

3.2. Subjective Risk Metrics

The majority of the data used to conduct our analysis were gathered via mail surveys that took place in five waves between October 2018 and August 2021. Each sample targeted recent home buyers in various coastal locations along the east coast. The first wave was administered in Glynn County, GA in October 2018, followed by a second wave in Dare County, NC in June 2020, the third wave in Worcester County, MD in July 2020, the fourth wave in Dare County, NC in June 2021, and the final 5th wave in Worcester County, MD in July 2021. Figure 1 provides a spatial and temporal overview of our sampling waves.

Most notable for our analysis were questions designed to elicit individuals' beliefs regarding coastal hazard risk. Given that our analysis seeks to compare individuals' subjective assessments of risk to objective analogs, we employ a battery of instruments that include open-ended, multiple choice quantitative measures, frequencies, and Likert scales. This approach permits comparative assessment and triangulation of risk perceptions among multiple domains (i.e., hurricane and general flood risk). With coding and interpretation, most measures can be directly compared with publicly available objective risk perceptions.

Given that flood zones in the U.S. are characterized by explicitly defined flood probabilities[4], we utilize an open-ended query to elicit annualized subjective flood probabilities[5]. Specifically, respondents were prompted to answer the following question:[6]

> "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.)?"

Contrary to flood likelihood, no publicly available measures of flood damage exist (in part due to the measure being unique for each home) to guide development of our instrument for eliciting perceptions of flood damage. 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?"

Unlike floods, likelihoods for hurricane strike are typically measured as historical return period - the number of hurricanes to pass within 50 nautical miles (approximately 58 statue miles) per unit of time (NOAA, 2020b). To create an analogous subjective risk metric, respondents were queried on the following expected frequency response:

[4]For example, FEMA SFHA zones are defined as "the area that will be inundated by the flood event having a 1-percent chance of being equaled or exceeded in any given year".

[5]In addition to being advocated for in recent publications (see Barseghyan et al. (2018), section 7.3 for a review), direct probability queries have the marked advantage of eliciting a direct input for many theoretical models of decision making under risk which make estimation of structural models, like the one described in section 4.3 of this study, possible.

[6]Questions eliciting subjective assessments of general flood risk were added to the survey only after the initial survey wave in Glynn County, GA. Thus, data from Glynn County are only used in our analysis of hurricane risk perceptions.

> "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[7]. Hurricane risk perceptions in the final two waves (Dare and Worcester Counties) were elicited in a slightly modified version of the frequency question that utilized a multiple choice format. This permits an assessment of sensitivity of risk perception measures to modifications in the frequency-based survey instrument. Specifically, respondents were prompted to select either "None", "One", "Two", "Three", "Four", "Five", "Six or more (please specify how many)" with the last option soliciting an open-ended response. We refer to this method as "hurricane risk elicitation method 2", while the former (open-ended frequency) is referred to as "hurricane risk elicitation method 1".

In addition to the subjective probability of a hurricane strike, we also elicit subjective perceptions of hurricane damage, framing damage as a percentage of home structure value (the same way HAZUS damage estimates are conveyed). This is accomplished 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.[8]

3.3. Objective Risk Metrics

To obtain objective estimates of the natural hazard risk individuals in our sample face, we utilize several data sources. The first is the FEMA-designated flood zone for each property,

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

[8] Although we elicit perceptions of hurricane damage and include them here for informational purposes, we do not compare these to objective estimates. This is because, to our knowledge, there is no simple way to credibly estimate hurricane damage without being overly precise in the conditions. For example, hurricane damage is highly dependent on the confluence of wind speed, precipitation, storm surge, tidal conditions, etc. In our opinion, trying to specify these conditions in a survey question would lead to an overly complicated question and risk prompting participant dropout.

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 or equal to 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. Using proprietary catastrophe models designed by re-insurers, Czajkowski et al. (2013) find significant differences in flood risk for identical FEMA flood zones located in coastal and inland parts of Texas, similar loss distributions for properties located in different FEMA flood zones, and considerable storm-surge risk that is not identified by FEMA flood zones.

These FEMA flood zones, however, 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 study property 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, 20, 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,[9] which map flood inundation levels into damage as a share of total structure value. Additionally, we calculate damage estimates for each home under the assumption of 1ft, 5ft, and 10ft water inundation levels. This provides a metric that allows for meaningful comparisons across homes without confounding susceptibility to water inundation with an increased probability of higher floodwaters.[10]

[9] 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".

[10] In other words, this allows us to remove the stochastic element from the flood and measure the damage from essentially pouring water into each home until it reaches the same depth in all homes.

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 return period for a hurricane of given conditions (we use the conditions specified in our subjective risk assessment question)(National Hurricane Center, 2020). The return period is then be mapped into an annualized probability.

3.4. Descriptive Statistics

The remaining data are obtained from the survey, which is 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 8 percent chance of their home flooding from any weather-related event in the next 12 months. The mean annualized hurricane strike probability derived from respondents' expectations on the frequency of future hurricane strikes was 0.18. We note, however, heterogeneity in responses across elicitation methods. Survey respondents who were prompted with only an open-ended frequency had a mean subjective probability of a hurricane strike of 0.25, while those who were prompted with multiple-choice options (in addition to having the option to write in their own value) had a mean subjective probability of 0.09.[11] Concerning perceptions of flood damage, the average respondent believed if their home were to flood, damage would be equivalent to 49 percent of their home's structure value. The average respondent believed a direct strike from a major hurricane would lead to home damage equivalent to 35 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 a 9 percent annual chance of flooding. Data from NOAA indicate 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 "5 Year"[12] flood, the average

[11] Clearly, there are framing effects in our measurement of hurricane risk.

[12] 5-year flood is an event that exhibits a return probability of approximately 20%

flood damage would be equivalent to approximately one-third of one percent of the homes structure value. Similarly, return intervals of 10 years, 100 years, and 500 years are associated with average damages of 1 percent, 3.9 percent, and 6.9 percent of home structure value. Defining a flood based on inundation levels of 1 foot, 5 feet, and 10 feet (which are very low probability events for most homes) suggests average damages of approximately 19 percent, 36 percent, and 51 percent of home structure values.

Descriptive statistics for the remaining variables in our analysis are reported in panel C of table 1. Previous literature has noted the role that affect (fear, worry, dread) 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 multiple domains (e.g., personal health, family health, financial difficulties) using a 4-point Likert scale ranging from "Not at all worried" to "Very worried". 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 worry index, with the exception of worry about home loss from a natural disaster, which is excluded. 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 2.32 indicating that on average individuals had feelings of worry in just over two of the seven domains (excluding home loss). Additionally, 36 percent of respondents indicated worrying about losing their homes as a result of a natural disaster. The variable 'relative worry' is the ratio of worry of home loss to natural disaster to the overall worry index.

The average years of education was 16.5 years, indicating a significant proportion of respondents with some level of post-secondary education. Thirty-two percent of respondent indicated they were female. Seventy-nine percent of the sample indicated that the survey home is their primary residence. The average survey respondent had lived on the coast for approximately 13 years. Thirty-eight percent of respondents resided in an SFHA zone. In addition to FEMA-designated SFHA status, we construct the equivalent of SFHA using data from the First Street Foundation (i.e. an indicator for 1% chance of flooding per annum using First Street's compound flood risk measures). Overall, the First Street data suggest that 54 percent of households in the sample should be classified as SFHA, a roughly 40% increase over officially designated FEMA SFHA properties. Respondents were prompted to report household income by categorical measure, 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 assigned using the methods suggested by Hout (2004), which entails extrapolating income based on a Pareto distribution. This results in top-coded income level of $284,280 and mean household income of $154,000. Household wealth is notoriously difficult to measure, particularly in the context of a survey. In order to create a proxy for wealth, the survey included a categorical response question regarding the impact of total loss of coastal property (without insurance) on net worth (including a brief definition of net worth). The impact measures ranged from 0% (no impact) to 100% (total loss of net worth) in 20% increments. We use the property value and the mid-point of the response category to create a proxy for household wealth, for which the average is $548,000 (median = $340,000). Ten percent of respondents indicated that they had personally sustained flood damage in the past.

4. Empirical Methods

We first offer a simple descriptive analysis, comparing subjective 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. We then explore heterogeneity of deviations in subjective and objective using reduced-form regression models that are tailored to the nature of the dependent variables. Finally, we conclude our analysis by estimating a series of probability weighting functions to assess their ability to control differences among subjective and objective flood probabilities. The remainder of this section details each component of the analysis in turn.

4.1. Objective Vs. Subjective Risk Metrics

Building upon previous research (Botzen et al., 2015; Mol et al., 2020), subjective risk perceptions were elicited using an array of instruments (open-ended for flood probability, percentage of structural value for flood damage, and expected hurricane frequency) and were categorized as being correct as long as the difference between the subjective and objective metrics falls within a margin-of-error. This is deemed necessary since all measures are continuous and virtually none of the survey respondents have subjective perceptions that exactly match the objective metrics. Realizing that any chosen margin-of-error is arbitrary, we conduct sensitivity analysis, reporting results for 1, 2.5, 5, 10, 25, and 50 percentage point margins-of-error. We use these error bounds to classify each respondent as having correct, pessimistic (over-estimation of risk), and optimistic (under-estimation of risk), and we report the share of respondents in each category.

4.2. Regression Analysis

To assess whether the accuracy of risk perceptions can be explained by observable characteristics, we run a series of reduced-form regression models that focus on the variability of differences in subjective and objective measures of flood probability and expected flood damage. For each regression, we take the difference between objective and subjective risk measures and transform this measure by the inverse hyperbolic sine (IHS) transformation (Bellemare & Wichman, 2020).[13] Figure 2 plots the density of IHS-transformed difference in flood probabilities and hurricane probabilities, while Figure 3 plots the densities for IHS-transformed flood damage differences using each available objective reference flood we have available in our data set.

Considering probability differences first, we note that the flood probability based density is irregularly distributed with a clear spike at zero and a large number of observations below zero. In this case, coefficient estimates from standard regression models (Ordinary Least Squares (OLS), for example) will impose restrictive relationships and entail opposite effects depending upon of the sign of the dependent variable.[14] To address this issue, we make use of quantile regression. Our primary specification sets the quantiles such that one contains negative values of the dependent variable and the other contains positive values. Coincidentally, the median of our dependent variable is exactly zero, which means estimating

[13]Inverse Hyperbolic Sine (IHS) transformation for x is given by $ln(x + \sqrt{x^2 + 1})$ but, unlike natural logarithm, is defined for all real x.The shape of IHS is similar to natural log over positive values; it takes a value of 0 at 0, and translates a similar shape to natural log in the negative orthant.

[14]For example, a positive regression coefficient estimate would indicate the IHS-transformed difference in objective and subjective flood probabilities increases with the level of the covariate. For a positive difference (objective > subjective), this implies the differences is getting larger, but for a negative difference (subjective > objective) this implies the difference is getting smaller. In short, estimating the effect of observable characteristics on the IHS-transformed difference in flood probabilities with most regression models would result in a substantial loss of valuable information and make interpretation difficult.

a median regression achieves this goal. We also explore other quantiles to assess sensitivity of elasticities and marginal effects.

While median regression is appropriate for differences in flood probabilities, modeling the difference in subjective and objective flood damage requires a difference approach. Figure 3 suggests bimodal distributions for each damage measure — an observation that is also supported by statistical evidence[15]. Thus, to analyze the variability in damage risk perceptions, we employ the model of (Vasconcelos et al., 2021) which is based on a modified exponential-Gaussian distribution that the authors refer to as the "odd log-logistic exponential Gaussian" distribution (OLLExGa for short). The primary advantage of the OLLExGa distribution is that it allows for more flexibility in modeling skewness which allows for a regression framework that can accommodate bi-modality (Vasconcelos et al., 2021). This is notable since there are no canonical regression frameworks that explicitly apply to bimodal data. Given that the "100-year flood" is the prototypical reference for flood probability in the U.S.,[16] we construct our dependent variable for flood damage analysis using estimated damage from a 100-year flood as the basis for differences among subjective and objective assessments. Estimation of the OLLExGa regression is carried out by maximizing a log-likelihood function derived from the OLLExGa distribution as described by (Vasconcelos et al., 2021).[17]

4.3. Misperceptions vs Probability Weighting

Our final task entails an assessment of the potential for probability weighting to explain the divergence between objective and subjective risk measures. The literature on probability weighting suggests that this divergence can be summarized by a systematic functional mapping. For example, suggested weighting functions transfer weight from high likelihoods (i.e., greater than 50%) to lower likelihoods (Barseghyan et al., 2018). Given the roughly balanced distributions in figure 2, we do not expect standard weighting functions to fit all

[15] A test proposed by Ameijeiras-Alonso et al. (2019) evaluates the null hypothesis of one mode; we used the multi-mode R package (Ameijeiras-Alonso et al., 2021) to run this test and reject the null with a p-value of 2.2×10^{-16}.

[16] The 100-year flood defines Special Flood Hazard Area (SFHA) zones, which determine when residential flood insurance is required, and governs building codes and special flood mitigation requirements.

[17] A similar analysis is carried out to assess determinants of perceptions of hurricane strike probabilities, but due to lack of variation in objective risk measures (which are defined at the county level) the results are not very informative. We include these results in the appendix for completeness.

of the data, but we explore numerous approaches to assess whether probability weighting is able to provide insight into the divergence of subjective and objective likelihoods.

Given that our outcome variable is a probability, we base our structural model on a beta regression, 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 covariate domain 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[18], 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 whether probability weighting is used, 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, creating convergence and stability problems for standard estimation approaches like maximum likelihood. Accordingly, we estimate the structural beta regressions using standard Monte-Carlo Markov Chain (MCMC) methods. Full details associated with the MCMC estimation procedure can be found in appendix A.

[18]In addition to a simple power weighting function (i.e. raising the objective probability to a power defined by an estimated parameter), estimation is done using the probability weighting functions described by Goldstein & Einhorn (1987), Prelec (1998), Tversky & Kahneman (1992), and Gonzalex & Wu (1999)

5. Results

5.1. 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 respondents that had flood risk perceptions that were consistent with their official flood zone designation. Overall, 38 percent of respondents had flood risk perceptions that were consistent with their flood zone status, with the majority of those being located in the SFHA, the minority located outside the flood zone, and no respondents located in the 500-year flood zone. Almost a third of respondents (31%) had relatively pessimistic risk assessments (though located in the 500-year flood zone or outside the flood zone), while just over a quarter (26.5%) exhibited optimistic flood risk perceptions (the majority of which were located in the 500-year flood zone).[19] While somewhat insightful, FEMA flood zone classifications are too crude as an objective risk metric to be particularly useful in classifying flood risk perceptions.

Figure 4 displays the share of respondents that had subjective probabilities of flooding that were correct (top row) along with the accuracy of damage expectations for floods with various return periods (5-year to 500-year; rows 2 to 5) and water depths (1 foot to 10 feet; rows 6 to 8).[20] The columns of Figure 4 are associated with different margins-of-error, ranging from 1% (first column) to 50% (sixth column). Focusing on the top left, we see that approximately 28 percent of respondents had subjective probabilities of flooding that were within 1 percentage point of their objectively estimated flood probability (indicated by the grey region of the top-left cell in figure 4). The remaining respondents, who had perceptions that differed from the objective estimates by at least 1 percentage point, were mostly pessimistic (41 percent; red region), perceiving that the likelihood of flooding was greater, with the balance being optimistic (30 percent; blue region). As we increase the margin-of-error (moving from first to last column), "accuracy" of flood probability risk perceptions increases, with very few

[19]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 0.2 percent and 1 percent, though we found no evidence of this result.

[20]Table B1 (in the appendix) reports the raw data values used to construct figure 4

inaccurate assessments when allowing for a (rather large) 50% error margin. There is no overwhelming trend in the accuracy of flood risk probability perceptions. At almost every reasonable 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 overwhelmingly 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 an extremely large 50 percentage point margin-of-error still only results in about half of respondents having correct flood damage perceptions.

Employing objective damage estimates from 1-foot, 5-foot, and 10-foot inundation levels, however, suggests greater variation in accuracy of perceptions, with a significant portion of the sample having pessimistic and optimistic perceptions regardless of the permitted margin-of-error. Nonetheless, we note that these levels of water inundation represent exceedingly rare events. For example, First Street data suggest the average inundation level in our sample for a 500-year flood is 1.45 feet (though the standard deviation is large, at 5.13 feet, and the maximum is 13.22 feet). This suggests the pessimism evident from comparison to floods of standardized return periods primarily stems from an overestimation of water inundation levels associated with routine flood events, rather than misunderstanding the damage associated with a given level of water inundation. Figure 5 displays the share of respondents that had correct beliefs (grey) regarding the probability of a major hurricane strike,[21] as well as those that thought the likelihood was greater (pessimistic - red) and less likely (optimistic - blue). 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 their beliefs about the likelihood of a major hurricane strike, regardless of county of residence. Using a one percentage point margin-of-error suggests 71 percent of individuals overestimate the probability of a major hurricane strike. Applying a larger 5 percentage point margin-of-error results in slightly over half of respondents having correct

[21] Table B2 (in the appendix) reports the raw data values used to construct figure 5

perceptions, but with a large share of individuals still overestimating the probability of a strike. Decomposing accuracy of perceptions by county and elicitation method indicate similar patterns, with no major deviations being obvious when compared to the pooled results.

5.2. Determinants of Risk Perceptions

Table 3 reports regression results for the analysis using the IHS transformed difference between subjective and objective flood probability as the dependent variable. Column 1 reports results using a median regression while the remaining columns report quantile regression coefficients at the 25th, 50th, and 75th percentile. Generally, level of worry over loss of home, coastal tenure, education level, flood experience, primary home ownership, and risk designation associated with First Street Foundation are significantly correlated with divergence of subjective and objective risk perception. Given the functional form, we focus on elasticities and average marginal effects evaluated above or below the median (or in the appropriate quantile).

Table 4 reports elasticities (for continuous covariates) and average marginal effects (for binary covariates)[22] based on the coefficient estimates reported in table 3. The average difference in subjective and objective flood measures below (above) the median is -0.165 (0.124). For those below the median (optimistic risk perceptions), we estimate the following elasticities:[23]. relative worry = 1.241; coastal tenure = -0.356; education = 3.087; income = -0.317; wealth = -0.094; and past-flood = 0.11. Thus, for those with optimistic perceptions of flooding, worry over loss of home decreases the difference between subjective and objective risk estimates (i.e. the difference becomes less negative), which indicates their perceptions of risk are more accurate (moving 1.241% towards zero for every 1% increase in the relative worry index); education and previous flood experience have similar effects, with education exhibiting the largest elasticity of 3.087 and a small elasticity of 0.11 for past floods. Alternatively, increases in coastal tenure, income, and wealth have the opposite effect and tend to correlate with more optimistic and less accurate risk perceptions. A one-percent increase

[22]Average marginal effects for our binary variables are equivalent to the raw regression coefficients reported in table 3. We report them again in table 4 to aid in interpreting and comparing results

[23]Since the dependent variable is negative for this group of respondents, we calculate elasticities using absolute value of the dependent variable

in coastal tenure increases the degree of optimism by 0.36%, while a one-percent increase in income (wealth) increases optimism by 0.32% (0.09%).

For those above the median (pessimistic risk perceptions), we estimate the following elasticities: relative worry = 0.633; coastal tenure = -0.124; education = 1.496; income = -0.166; wealth = -0.048; and past-flood = 0.048. The positive elasticities imply moving further away from risk perception parity. Thus, a 1% increase in worry makes the difference in probabilities increase by 0.63% (moving further away from zero). A one-percent increase in education increases the difference among subjective and objective risk measures by 1.5%, while a one-percent increase in past floods increases the difference by 0.05%. Coastal tenure, income, and education have opposite effects. A one-percent increase in coastal tenure reduces the difference in probabilities by 0.12%. A one-percent increase in income (wealth) decreases the difference by 0.17% (0.05%).

Focusing on average marginal effects for binary covariates (Panel B of table 4), we find evidence that primary residence and location in SFHA (as identified by First Street Foundation) tend to have lower values of the outcome variable (marginal effects of -0.035 and -0.082 respectively).[24] This implies those with optimistic perceptions (below median) tend to be more optimistic for their primary home and when they are in a flood zone identified by First Street Foundation. For pessimistic respondents (above the median), primary home ownership and presence in First Street SFHA is associated with more accurate flood risk perceptions (closer to zero).

The last 3 columns of table 4 report elasticities and marginal effects based on the quantile regression. The average difference in subjective and objective flood measures at the lower quantile (below 25th percentile) is -0.24. The middle quantile (between 25th and 75th percentile) had a mean difference of 0.01 while the upper quantile (above 75th percentile) had a mean difference of 0.20. Elasticities are qualitatively equivalent to the median regression in the sense that the upper and lower quantiles exhibit the same signs, but the interpretation depends upon whether the level of dependent variable is above or below zero. For example, a one-percent increase in relative worry increases the difference among subjective and objective

[24]Due to the median regression providing a single regression coefficient and marginal effects being calculated based on the change from 0 to 1 for both lower and upper quantiles, the marginal effects are the same for both quantiles of the median regression based results. Because of this, quantile regression results provide a more nuanced view of the effects of the binary covariates across the distribution of flood risk perceptions.

risk probabilities by 0.5% (moving closer to zero) for those in the lower quantile, while the difference increases by 0.38% for those in the upper quantile (moving away from zero). For the middle quantile, a large elasticity of 4.5% is estimated (partly due to the small average difference in this quantile (0.01), which increases the magnitude of the elasticity). Patterns are similar across other covariates.[25]

Turning to determinants of perceptions of damage, table 5 reports coefficient estimates for the OLLExGa regression, which models the differences in subjective and objective perceptions of flood damage associated with 100-year flood (for which all differences are weakly positive, meaning responses were either roughly correct or pessimistic). Regression results indicate that longer coastal tenure is associated with a larger difference in perceived and objective perceptions of flood damage (elasticity of 0.08), suggesting increasing bias in perceptions. Similarly, survey respondents identifying as female had a increased bias in perceptions of flood damage (marginal effect of 0.31). Higher levels of education, on the other hand, were correlated with lower values of the dependent variable indicating lower levels of flood damage perception bias (elasticity of -1.12).

The FEMA-designated SFHA zone and the First Street Foundation's SFHA equivalent had opposite signs, but of similar magnitudes. Residing in a FEMA-designated SFHA zone corresponded to decreased bias in perceptions (marginal effect of -0.45), while residing in the First Street equivalent of a SFHA was correlated with increased bias (marginal effect of 0.40).

5.3. Probability Weighting vs Misperceptions

Figure 6 plots subjective flood probabilities against objective flood probabilities along with each estimated weighting function. Root mean squared error for each estimated weighting function is reported in the legend (in parentheses) and 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 over a reduced-form model. Estimation of

[25]Table C1 reports regression coefficients for differences in subjective and objective hurricane risk probabilities for the full sample and a model with outliers (those with implied annual probabilities of 80% or greater) trimmed, and table C2 reports corresponding elasticities and marginal effects.

a standard reduced-form beta regression, that uses only the objective probability of a flood as a co-variate, results in a RMSE of 0.129. Some of the structural specifications that employ probability weighting functions produce very similar RMSE values, but none of them are notably better than a standard beta regression[26]. This suggests that the differences in observed objective and subjective flood probabilities are not easily explained using any of the literature's canonical weighting functions. This is consistent with the narrative that individuals exhibit idiosyncratic mis-perceptions rather than systematic weighting of objective probabilities.

Visual inspection reveals that any increasing, monotonic function will have a difficult time fitting "L-shaped" empirical observations[27]. 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 6), cannot decrease to pass near the data points in the lower right corner (those who under-estimate flood risk).[28]

6. Discussion

Employing recent advances in assessment and distribution of household-level flood risk measures produced by First Street Foundation, we provide a detailed assessment of objective and subjective measures of flood and hurricane risks. With respect to flood risk, our findings suggest no broad generalization regarding flood probability perceptions. Pessimistic, optimistic, and approximately correct flood probability perceptions are all well represented

[26]The Goldstein-Einhorn weighting function has a RMSE that is 0.001 lower than a fitted linear function.

[27]Interestingly, Botzen et al. (2015) also plot objective and subjective flood probabilities (figure 1) which generates a similar looking figure to our own.

[28]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 6 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 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.

in our sample. This result is most closely aligned with (Mol et al., 2020) who also find most individuals' risk perceptions were incorrect, but optimistic and pessimistic outlooks were both well represented in their sample of Dutch households.

With respect to expected flood consequence, the vast majority of individuals tend to overestimate the damages associated with a flood, regardless of the flood return period. This result is notably different from findings in the previous literature which have looked at perceptions of flood damage. Botzen et al. (2015) find individuals typically underestimate damage and Mol et al. (2020) find individuals underestimate water levels but generally have correct damage perceptions, conditional on water level; when damage perceptions are incorrect, they are more likely to be underestimates than overestimates. When we compare elicited damage perceptions against estimated damage from 1ft, 5ft, and 10ft (which are exceedingly rare events) of water inundation, we find that most perceptions of damage are still incorrect, but that pessimistic and optimistic perceptions are much more balanced. This suggests that individuals are generally overestimating the inundation associated with a routine flood rather than misunderstanding the relationship between damage and a fixed level of water in the home.

An important distinction among the studies that have purported to assess deviations of subjective and objective risk perceptions is the instrument that is applied to measure subjective risk. Barseghyan et al. (2018) advocate for direct probability queries on the basis of the potential of subjective risk measures to improve structural analysis of risky decisions. This approach, however, is not a panacea for analysis of risk preferences and is accompanied by its own set of problems. Direct acquisition of subjective probabilities may provide the most precise elicitation format, yet may be challenging for less numerically literate respondents. Although a number of studies champion direct measurement of probabilities (Manski, 2004; Hurd, 2009; Delavande, 2014), other literature has noted the proclivity to round answers when answering open ended probability questions, particularly near the limits of the unit interval (Dominitz & Manski, 1997; Manski & Molinari, 2010). de Bruin et al. (2002) suggest that the tendency for 0.5 to be over represented in probabilistic responses is evidence of epistemic uncertainty rather than an expression of a precise belief. Presenting probability as a count over a number of years is advantageous in this regard (as we did in our elicitation of hurricane probability perceptions), as there is no natural midpoint for respondent's to default to. Although elicitation of expected frequencies over a set time period did eliminate the tendency to cluster at the midpoint of 50%, it also produced a large number (relative to our direct, open ended, probability queries) of subjective probabilities equal or close to 100%.

Within the context of survey data, authors have used open-ended queries (Botzen et al., 2015; Royal & Walls, 2019), relative risk indicators (Royal & Walls, 2019), and aided direct probability queries (i.e. questions accompanied with visual depictions or predefined intervals) (Mol et al., 2020; Bakkensen & Barrage, 2022) to measure likelihood of flooding. It is unclear the extent to which these different instruments are capable of assessing latent risk perceptions that drive past or future decisions. Also important are aspects of mental accounting that may influence how individuals frame and bracket risk evaluation (Barseghyan et al., 2018). We employ open-ended measures for assessing general flood risk, which may induce error (perhaps only among some respondents), and we utilize an expected hurricane count to infer annual hurricane probability, which may also have limitations. Within the hurricane count instrument, we use both open-ended and multiple choice (during different survey waves).

We find that minor changes in question format significantly affect individual responses across the two random samples. The open-ended format for expected hurricane count results in a mean probability hurricane strike of 0.25, while the multiple choice format (which retained the option to write in any value) results in a mean probability of 0.09.[29] Nonetheless, we found format had little effect on the classification of individuals' beliefs about the probability of a hurricane strike; under both elicitation methods, individuals tended to overestimate the likelihood of a hurricane. Future research that tests and expands on the implications of using different elicitation methodologies in the domain of natural hazard risk could be helpful for informing appropriate methods for future studies.

We find that the inverse-hyperbolic sine transformation and quantile regression provides a useful method to analyze the difference among objective and subjective risk assessments. In addition, to account for bimodal distribution, we use the "odd log-logistic exponential Gaussian" distribution (OLLExGa) to analyze determinants of differences in objective and subjective perceptions of flood damage. 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,

[29] A Kolmogorov-Smirnov test rejects the null (p-value ≈ 0.000) that the distributions of elicited probabilities across the two methods are equal.

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). For each of these measures, we find that they tend to decrease differences in perception of flood risk loss for optimistic individuals (making them more accurate), but increase differences for pessimistic individuals (making them less accurate), and these results hold for quantile regression models (that permit different signs above and below the median).

Other results appear to be new to the literature. Using survey data to estimate income and wealth, we find that these measures increase optimism for those that perceive risks as less than objective estimates; this could reflect increased capacity to manage risk inducing an optimism on level of risk. For respondents that exhibit pessimistic beliefs, however, we find that income and wealth both decrease pessimism, making perceptions more accurate. Moreover, moving from median to quantile regression, we find divergent impacts of income and wealth; in that framework, income has an asymmetric effect on differences among subjective and objective risk (less optimistic and more pessimistic), while wealth has the opposite effect (increasing optimism and decreasing pessimism).

Location in the First-Street-designated SFHA exhibits negative marginal effects in the median regression for flood probability, while the FEMA-designated SFHA exhibits a negative but statistically insignificant effects. The negative effects for FS-SFHA suggests optimistic individuals are more optimistic in the FS-SFHA, while pessimistic individuals are less pessimistic. Since FEMA flood zones are currently the most publicized sources of flood risk information, it is perhaps not surprising that they play little role in mis-perceptions. To the extent that First-Street flood zones provide better estimates of parcel-level flood risk, it is notable that pessimism declines, but optimism increases. These results are robust to quantile regression (which permits divergence of the direction of effect above and below the mean). Overall, the results suggest the FS-flood risk designations are reflected in risk mis-perceptions, but exhibit asymmetries with respect to optimism and pessimism. For perceived flood damage, however, the sources of flood risk information exhibit opposite signs, with FEMA-SFHA associated with lower difference in damage perceptions and First Street exhibiting a larger difference.

Finally, our results focused on trying to explain the observed difference between subjective and objective perceptions of flood likelihood via models of probability weighting complement a broader literature focused on estimating risk preferences with field data (see Barseghyan et al. (2018) for a review). Estimation of structural risk preferences from an agent's observed choices is fairly straightforward in laboratory environments since the probability of outcomes is explicitly stated and precisely controlled. In a field context, for example observing an actual insurance contract purchase, its not clear if agent's internalize and act on the objective probability of each state of the word - i.e they may misperceive the true risk.

For studies that find incorporating probability distortions to be an important component to achieving good model fit when estimating risk preferences from field data (Barseghyan et al., 2013b; Collier et al., 2021), a dilemma persists on whether the distortions should be attributed to non-linear weighting of probabilities or idiosyncratic misperceptions of true probability. In some specific cases, it is possible to distinguish between probability weighting and misperceptions (Barseghyan et al., 2013a), but the conditions necessary to do so are not universally present. Our results suggest that distortions observed between objective and subjective probabilities, at least in the context of flood risk, cannot generally be explained by probability weighting - a finding that is notable for future studies making use of field data to estimate behavioral model parameters.

7. Conclusion

Using a novel survey data set representing homeowners from three distinct locations on the U.S. East coast, this study elicits individual perceptions of natural hazard risk and compares them to equivalently defined objective risk metrics to gauge the accuracy of perceptions. Individuals who underestimate the probability of a flood, overestimate the probability of a flood, and those with correct perceptions are well represented in the survey sample. With respect to perceptions of personal home damage in the event a flood occurs, however, we find the vast majority of survey respondents overestimate the cost of flood damage. We find evidence that this overestimation of flood damage is primarily a result of overestimating the level of water inundation, rather than the destructiveness of a given level of water. Similarly, we assess the accuracy of perceptions regarding a major hurricane strike and find that the vast majority of individuals overestimate the likelihood of a major hurricane making landfall in their county of residence; moreover, subjective perceived hurricane risk exhibits framing effects arising from question format (open-ended frequency count v. multiple-choice).

In addition to assessing the accuracy of risk perceptions, we examine the determinants of divergence of risk perceptions via estimation of several reduced-form regressions. For probability of flood loss, we utilize median and quantile regressions to evaluate how differences in objective and subjective vary with individual and household variables, and we utilize bimodal regression to evaluate similar effects for differences in flood damage. Worry over home loss, coastal tenure, education, flood experience, flood risk, primary home ownership, income, and wealth tend to vary systematically with differences in subjective and objective risk measures. Of note, quantile regression results suggests that household income has an asymmetric effect on differences among subjective and objective risk, rendering those with optimistic assessment of flood risk less optimistic, but those that are pessimistic in their assessment of flood risk and more pessimistic. Household wealth, on the other hand, has the opposite effect, increasing optimism among the optimistic and decreasing pessimism among the pessimistic. These results suggest that relative risk perception exhibits divergent underlying effects in relation to covariates that could be indicative of fundamental differences in formation or evolution of risk perceptions. Also of note, we find significantly different impacts associated with FEMA and First Street flood risk designation that could be indicative of local understanding of flood risk factors that are not captured by the FEMA maps.

Finally, we evaluate deviations among objective and subjective flood probabilities with six probability weighting functions common to the behavioral economics literature. We find that the estimated weighting parameters do not explain the probability deviations any better than a linear regression, suggesting that what we observe is related to idosyncratic misperceptions rather than some type of widespread behavioral heuristic. It is also possible that there are heterogeneous framing effects in measuring subjective risk perception that manifest in different ways depending upon underlying individual characteristics. Validity of subjective assessment measures is an important topic for future research; lab and field experiments could be particularly useful in this regard.

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8. Tables

Table 1: Descriptive Statistics

	mean	sd	min	max	count
Panel A: Subjective Risk Perceptions					
Flood Prob. (Subjective)	0.08	0.13	0.00	1.00	566
Hurricane Prob. (Subjective)	0.18	0.25	0.00	1.00	749
Hurricane Prob. (Subjective, Method1)	0.25	0.31	0.00	1.00	391
Hurricane Prob. (Subjective, Method2)	0.09	0.11	0.00	1.00	358
Flood Damage (Subjective)	0.49	0.39	0.00	1.00	473
Hurricane Damage (Subjective)	0.35	0.25	0.05	0.95	876
Panel B: Objective Risk Metrics					
Flood Prob. (Objective)	0.09	0.15	0.00	0.50	858
Hurricane Prob. (Objective)	0.04	0.02	0.02	0.06	894
5yr Flood Damage (Objective)	0.00	0.02	0.00	0.29	661
10yr Flood Damage (Objective)	0.01	0.05	0.00	0.41	661
100yr Flood Damage (Objective)	0.04	0.10	0.00	0.54	661
500yr Flood Damage (Objective)	0.07	0.15	0.00	0.60	661
1ft Flood Damage (Objective)	0.19	0.04	0.12	0.22	663
5ft Flood Damage (Objective)	0.36	0.06	0.29	0.41	663
10ft Flood Damage (Objective)	0.51	0.05	0.44	0.55	663
Panel C: Other Household Characteristics					
Relative Worry	0.15	0.05	0.05	0.43	575
Primary Home	0.79	0.41	0.00	1.00	807
Coastal Tenure	13.31	13.81	1.00	80.00	861
SFHA	0.38	0.49	0.00	1.00	894
SFHA (First Street)	0.54	0.50	0.00	1.00	858
Education	16.45	3.07	10.00	20.00	894
Female	0.32	0.47	0.00	1.00	869
Income	153868.50	81885.28	35000.00	284280.28	841
Wealth	547678.03	724306.02	16222.22	6416000.00	825
Past Flood	0.10	0.31	0.00	2.00	883

Table 2: Share of Respondents with Perceptions Compatible with SFHA status

	Probability			
	All Respondents	SFHA (Zones A,V)	X500	X
Pessimistic	0.309	0	0.413	0.707
Correct	0.383	0.71	0	0.293
Optimistic	0.265	0.29	0.527	0
N	566	245	150	147

Table 3: Determinants of Difference in Subjective and Objective Flood Probability

	Median Regression	Quantile Regression		
	50th Pct	25th Pct	50th Pct	75th Pct
Relative Worry	0.1487^{**}	0.0344	0.1487	0.3228^{*}
	(0.0743)	(0.0930)	(0.1315)	(0.1656)
Coastal Tenure	$-.00047^{*}$	-.00015	-.00047	-.00109
	(.00025)	(.0003)	(.00037)	(.00069)
Education	$.00321^{**}$	.00143	.00321	.00044
	(.00146)	(.00231)	(.00234)	(.00262)
Income	-3.8e-08	7.8e-09	-3.8e-08	6.0e-08
	(5.8e-08)	(7.0e-08)	(6.3e-08)	(1.2e-07)
Wealth	-3.5e-09	-9.4e-09	-3.5e-09	$-1.3\text{e-}08^{**}$
	(2.7e-09)	(7.7e-09)	(4.5e-09)	(6.3e-09)
Past Flood	$.03664^{***}$	.02528	.03664	.08569
	(.01111)	(.02942)	(.02477)	(.05913)
Primary Home	$-.03638^{***}$	-.02236	$-.03638^{**}$	-.01986
	(.00754)	(.02176)	(.01585)	(.01685)
SFHA	-.00356	-.0114	-.00356	.00534
	(.00761)	(.02009)	(.01104)	(.01418)
SFHA (First Street)	$-.08347^{***}$	$-.29326^{***}$	$-.08347^{***}$	$-.06785^{***}$
	(.01201)	(.03805)	(.01581)	(.01587)
Female	.01446	.01116	.01446	$.04328^{**}$
	(.01213)	(.01377)	(.01397)	(.02105)
Constant	-.01342	-.0015	-.01342	.02883
	(.02617)	(.04161)	(.04411)	(.0584)
Observations	381	381		

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

Table 4: Elasticities and Average Marginal Effects for Flood Probability Regressions

	Median Regression		Quantile Regression		
	Lower Quantile	Upper Quantile	Lower Quantile	Middle Quantile	Upper Quantile
Panel A: Elasticities					
Relative Worry	1.241	0.633	0.463	4.486	0.378
	(0.001 , 2.457)	(0.001 , 1.254)	(0.207 , 0.742)	(0.795 , 7.948)	(-0.017 , 0.759)
Coastal Tenture	-0.356	-0.124	-0.104	-1.219	-0.07
	(-0.732 , 0.021)	(-0.255 , 0.007)	(-0.161 , -0.05)	(-2.07 , -0.354)	(-0.153 , 0.013)
Education	3.087	1.496	0.075	0.675	0.056
	(0.261 , 5.709)	(0.126 , 2.766)	(-0.643 , 0.807)	(-6.456 , 7.873)	(-0.595 , 0.705)
Income	-0.317	-0.166	0.09	0.799	0.069
	(-1.279 , 0.597)	(-0.669 , 0.313)	(-0.121 , 0.301)	(-0.802 , 2.448)	(-0.191 , 0.35)
Wealth	-0.094	-0.048	-0.062	-0.563	-0.045
	(-0.234 , 0.047)	(-0.118 , 0.024)	(-0.131 , 0.01)	(-0.934 , -0.19)	(-0.088 , -0.001)
Past Flood	0.11	0.048	0.039	0.357	0.085
	(0.038 , 0.174)	(0.017 , 0.076)	(0.012 , 0.065)	(0.154 , 0.554)	(-0.029 , 0.201)
Panel B: Average Marginal Effects					
Primary Home	-0.035	-0.036	-0.021	-0.037	-0.019
	(-0.05 , -0.021)	(-0.051 , -0.021)	(-0.062 , 0.018)	(-0.07 , -0.005)	(-0.052 , 0.013)
SFHA	-0.003	-0.003	-0.011	-0.004	0.006
	(-0.017 , 0.01)	(-0.017 , 0.011)	(-0.047 , 0.025)	(-0.026 , 0.017)	(-0.023 , 0.031)
SFHA (First Street)	-0.082	-0.083	-0.282	-0.083	-0.066
	(-0.104 , -0.059)	(-0.105 , -0.059)	(-0.352 , -0.211)	(-0.115 , -0.053)	(-0.096 , -0.034)
Female	0.015	0.015	0.011	0.014	0.042
	(-0.008 , 0.037)	(-0.008 , 0.038)	(-0.015 , 0.038)	(-0.013 , 0.042)	(0.003 , 0.082)

Notes: 95% confidence intervals in parenthesis.

Table 5: OLLExGa Regression on Difference in Subjective and Objective Flood Damage

	Coefficient Estimate	Elasticity	Marginal Effect
Relative Worry	-0.743	-1.291	
	(0.481)	(-3.09 , 0.281)	
Coastal Tenure	0.05**	0.083	
	(0.023)	(0.004 , 0.153)	
Education	-0.642***	-1.123	
	(0.108)	(-1.879 , -0.567)	
Income	0.054	0.086	
	(0.039)	(-0.047 , 0.191)	
Wealth	-0.083	-0.137	
	(0.058)	(-0.349 , 0.05)	
Past Flood	0.099		0.156
	(0.1)		(-0.195 , 0.419)
Primary Home	-0.091		-0.16
	(0.064)		(-0.378 , 0.062)
SFHA	-0.257***		-0.445
	(0.079)		(-0.769 , -0.175)
SFHA (First Street)	0.239***		0.402
	(0.076)		(0.174 , 0.612)
Female	0.199***		0.311
	(0.062)		(0.123 , 0.494)
Cons	0.027		
	(0.348)		
Observations	234		

Parenthesis contain standard errors for the column containing coefficient estimates. All other columns report 95% confidence intervals in parenthesis.

9. Figures

Figure 1: Spatial and Temporal Distribution of Survey Waves

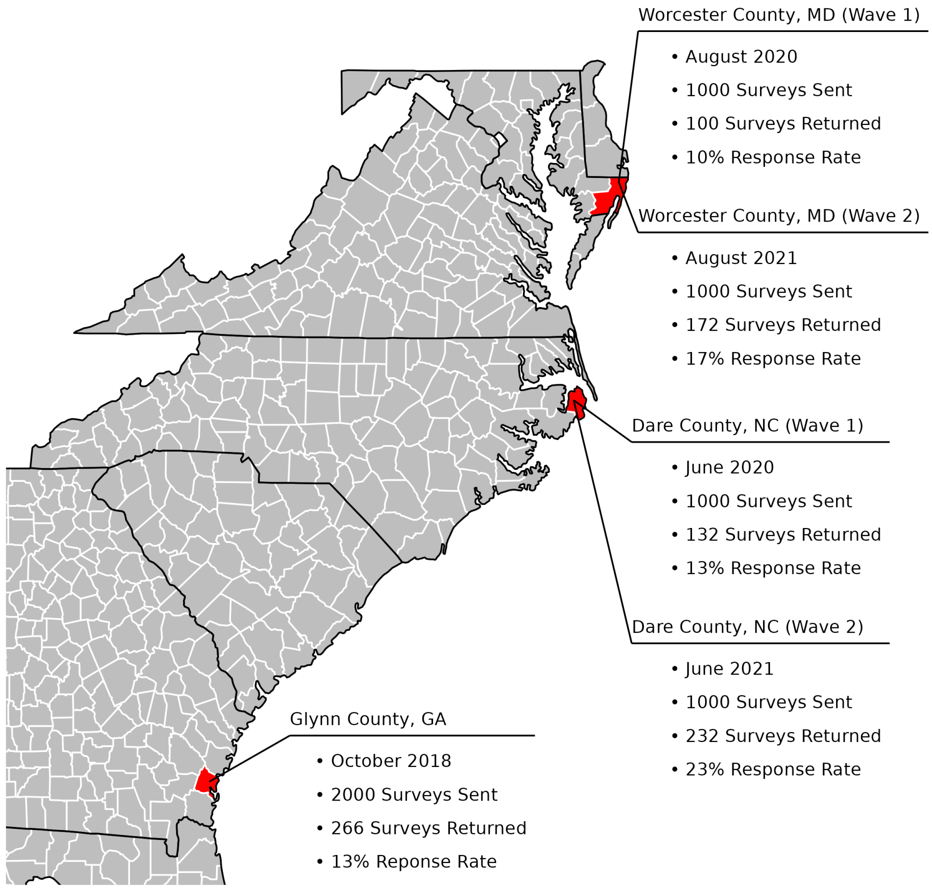


Figure 2: IHS Transformed Difference Between Subjective and Objective Flood Probabilities

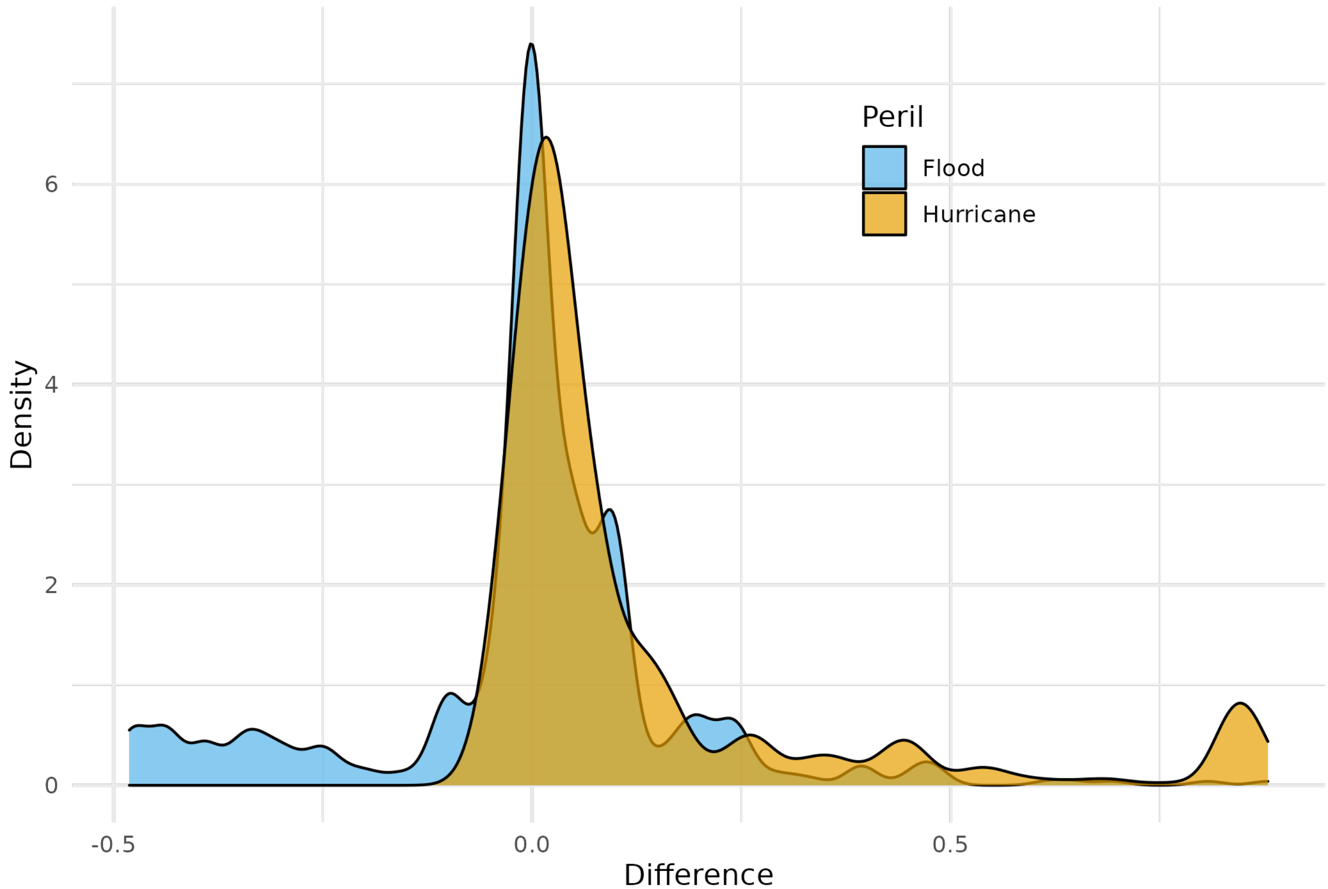


Figure 3: IHS Transformed Difference Between Subjective and Objective Flood Damage

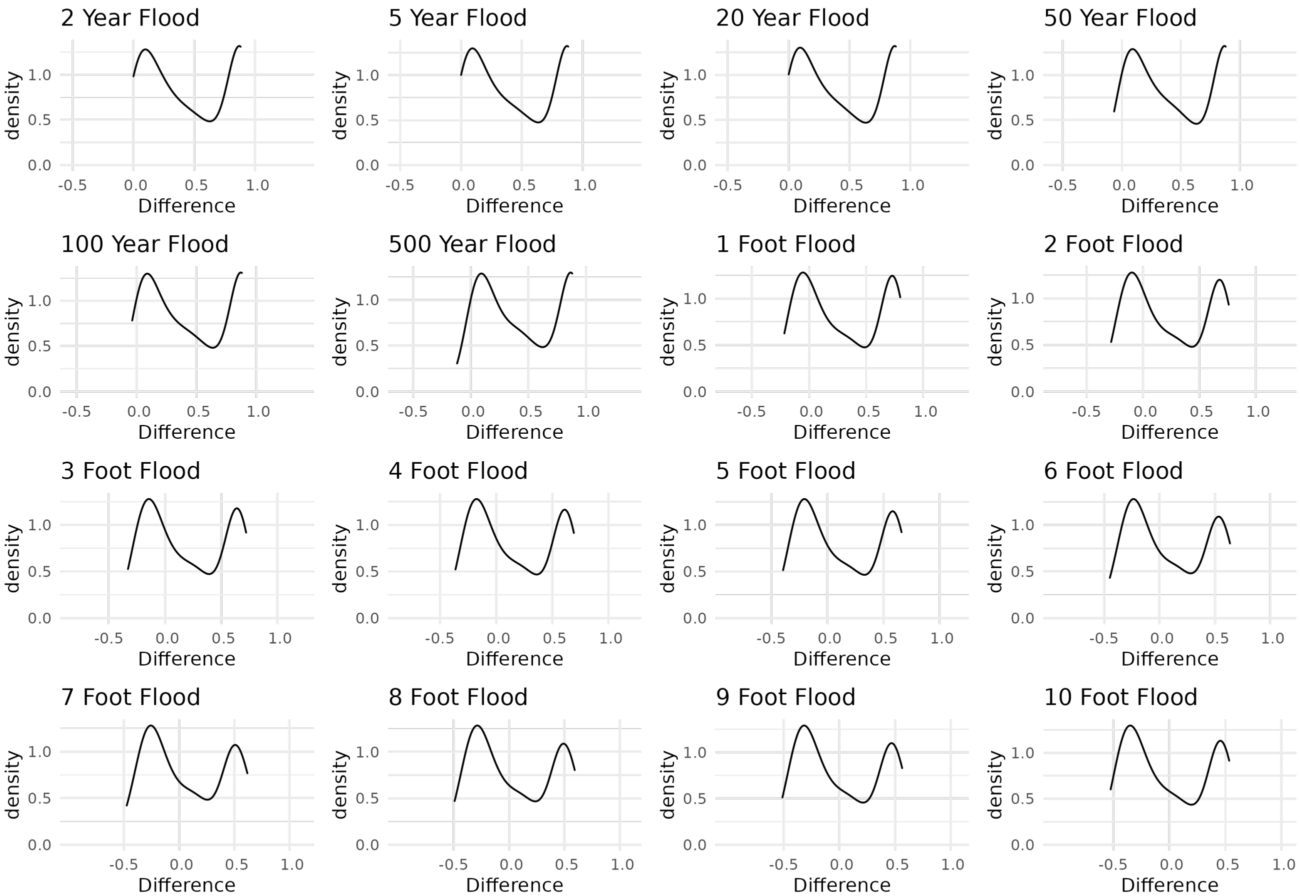
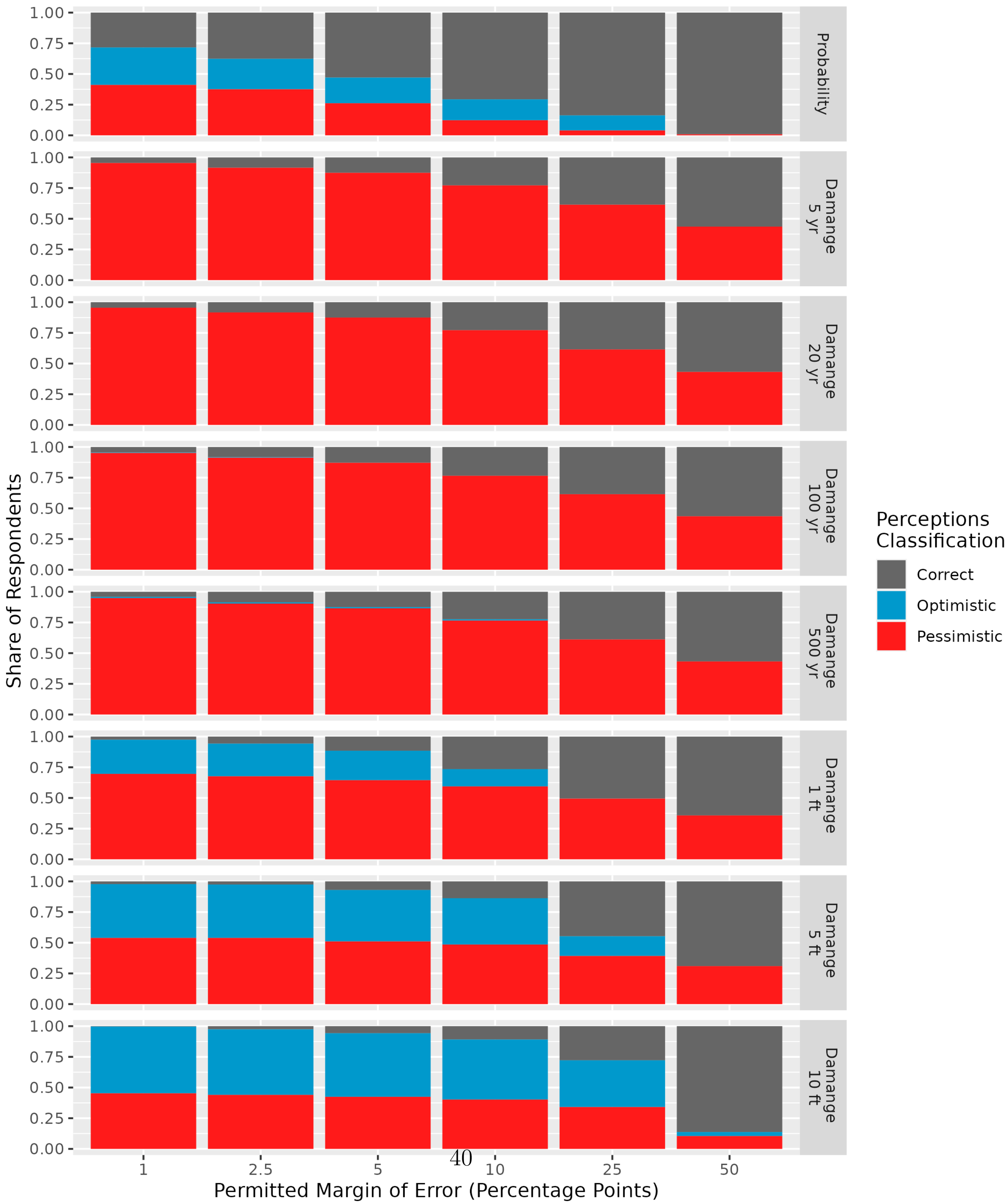
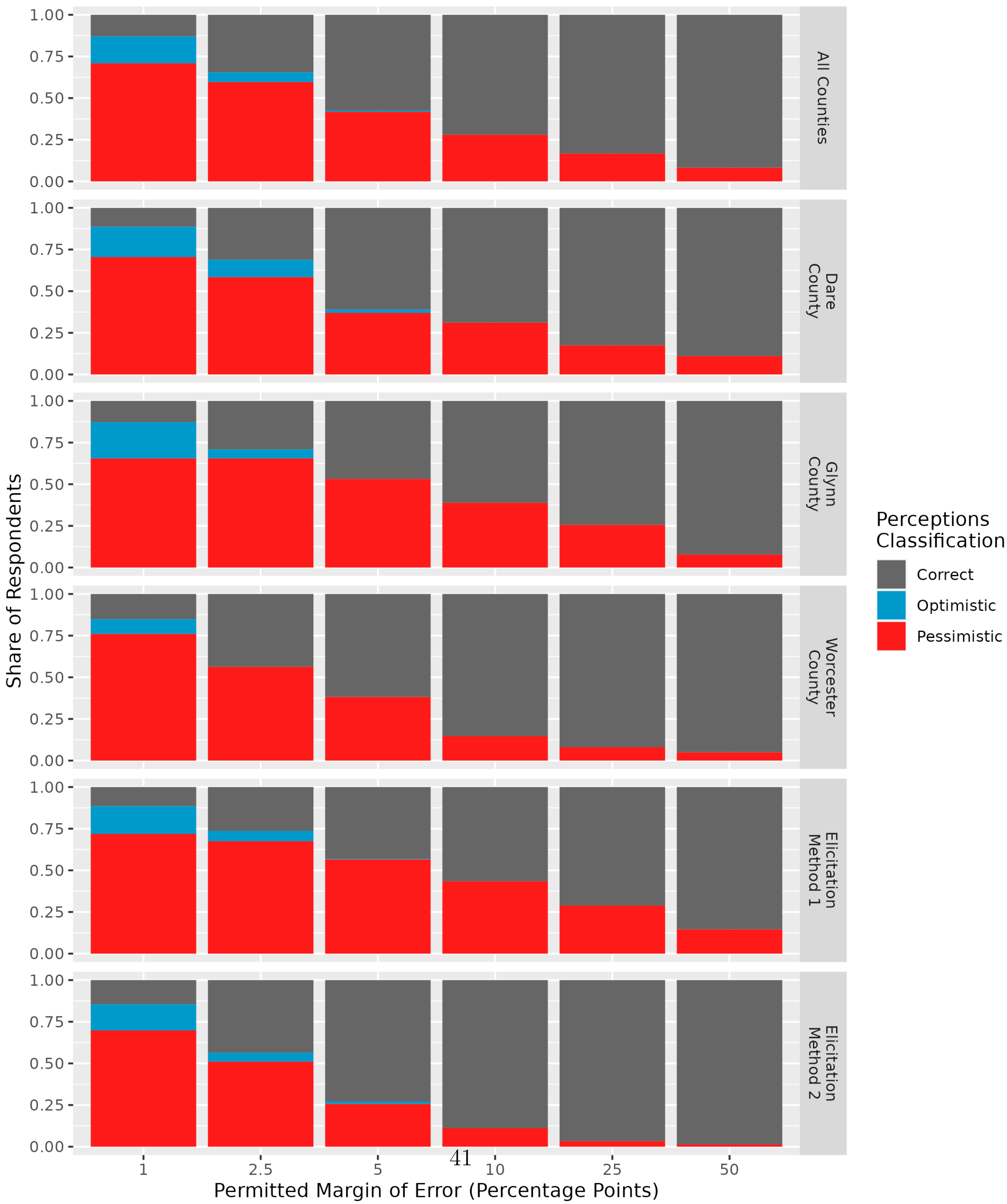


Figure 4: Share of Respondents with Correct Flood Risk Perceptions



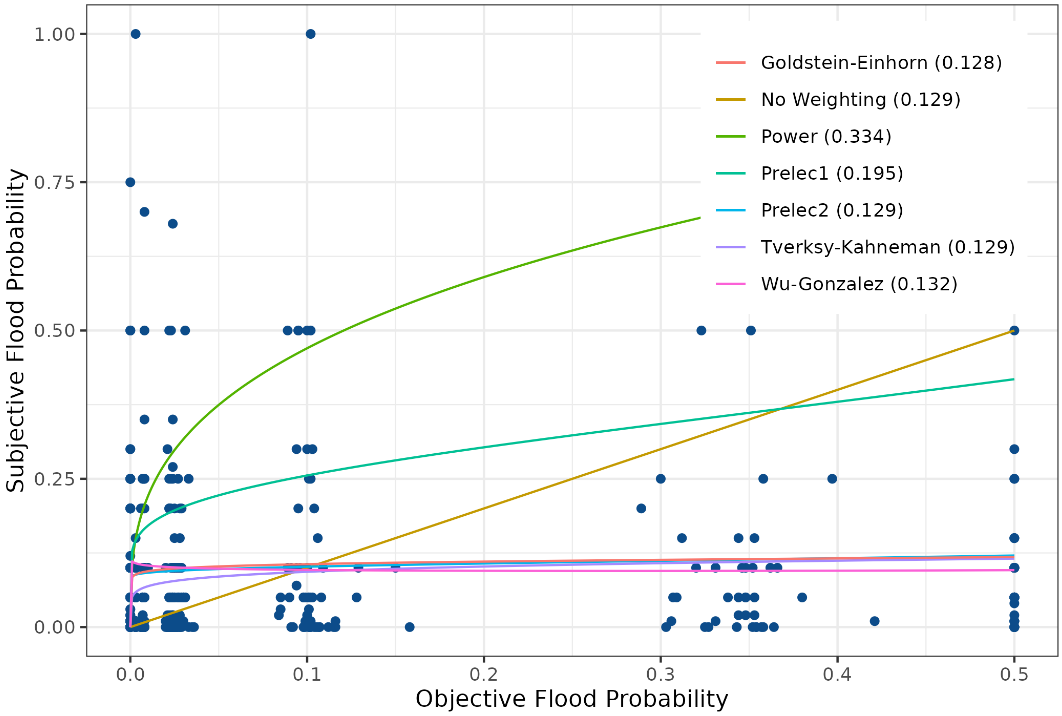
Note: N = 542 for probability comparisons. N = 312 for year based damage comparisons, and N = 313 for depth based damage comparisons.

Figure 5: Share of Respondents with Correct Perceptions of a Hurricane Strike



Note: N = 749 for 'All Counties', N = 308 for 'Dare County', N = 203 for 'Glynn County', N = 238 for 'Worcester County', N = 391 for 'Elicitation Method 1', and N = 358 for 'Elicitation Method 2'.

Figure 6: Estimated Weighting Function



Appendices

A. 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 autocorrelation. To check for evidence of non-convergence, a 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.

B. Tables for Natural Hazard Risk Perceptions Accuracy

Table B1: Share of Respondents with Correct Flood Risk Perceptions)

		Damage						
	Probability	5 yr	20 yr	100 yr	500 yr	1 ft	5 ft	10 ft
Panel A: 1 Percentage Point Margin of Error								
Pessimistic	0.41	0.96	0.96	0.95	0.95	0.70	0.54	0.45
Correct	0.28	0.04	0.04	0.04	0.04	0.03	0.02	0.00
Optimistic	0.30	0.00	0.00	0.00	0.01	0.28	0.44	0.54
Panel B: 2.5 Percentage Point Margin of Error								
Pessimistic	0.38	0.92	0.92	0.91	0.90	0.68	0.54	0.44
Correct	0.38	0.08	0.08	0.08	0.09	0.06	0.03	0.03
Optimistic	0.25	0.00	0.00	0.00	0.01	0.27	0.43	0.53
Panel C: 5 Percentage Point Margin of Error								
Pessimistic	0.26	0.88	0.88	0.87	0.87	0.65	0.51	0.42
Correct	0.53	0.12	0.12	0.13	0.12	0.12	0.07	0.06
Optimistic	0.21	0.00	0.00	0.00	0.01	0.24	0.42	0.52
Panel D: 10 Percentage Point Margin of Error								
Pessimistic	0.12	0.77	0.77	0.77	0.77	0.59	0.49	0.40
Correct	0.71	0.23	0.23	0.23	0.22	0.27	0.14	0.11
Optimistic	0.17	0.00	0.00	0.00	0.01	0.14	0.38	0.49
Panel E: 25 Percentage Point Margin of Error								
Pessimistic	0.04	0.62	0.62	0.62	0.61	0.50	0.39	0.34
Correct	0.84	0.38	0.38	0.38	0.39	0.50	0.45	0.28
Optimistic	0.12	0.00	0.00	0.00	0.00	0.00	0.16	0.38
Panel F: 50 Percentage Point Margin of Error								
Pessimistic	0.01	0.44	0.43	0.44	0.43	0.36	0.31	0.11
Correct	0.99	0.56	0.57	0.56	0.57	0.64	0.69	0.86
Optimistic	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
N	542.00	312.00	312.00	312.00	312.00	313.00	313.00	313.00

Table B2: Share of Respondents with Correct Perceptions of Major Hurricane Strike

	Probability					
	Dare County	Glynn County	Worcester County	All Counties	Elicitation Method 1	Elicitation Method 2
Panel A: 1 Percentage Point Margin of Error						
Pessimistic	0.705	0.655	0.761	0.709	0.719	0.698
Correct	0.114	0.128	0.151	0.130	0.115	0.145
Optimistic	0.182	0.217	0.088	0.162	0.166	0.156
Panel B: 2.5 Percentage Point Margin of Error						
Pessimistic	0.584	0.655	0.563	0.597	0.675	0.511
Correct	0.312	0.291	0.437	0.346	0.263	0.436
Optimistic	0.104	0.054	0.000	0.057	0.061	0.053
Panel C: 5 Percentage Point Margin of Error						
Pessimistic	0.370	0.532	0.382	0.418	0.565	0.257
Correct	0.610	0.468	0.618	0.574	0.432	0.729
Optimistic	0.019	0.000	0.000	0.008	0.003	0.014
Panel D: 10 Percentage Point Margin of Error						
Pessimistic	0.312	0.389	0.147	0.280	0.435	0.112
Correct	0.688	0.611	0.853	0.720	0.565	0.888
Optimistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: 25 Percentage Point Margin of Error						
Pessimistic	0.175	0.256	0.080	0.167	0.289	0.034
Correct	0.825	0.744	0.920	0.833	0.711	0.966
Optimistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel F: 50 Percentage Point Margin of Error						
Pessimistic	0.110	0.079	0.050	0.083	0.146	0.014
Correct	0.890	0.921	0.950	0.917	0.854	0.986
Optimistic	0.000	0.000	0.000	0.000	0.000	0.000
N	308	203	238	749	391	358

C. Tables for Hurricane Probability Regressions

Table C1: Determinants of Subjective Hurricane Probability

	Full Sample	Outliers Dropped
Relative Worry	0.1081	0.3299**
	(0.2637)	(0.1447)
Coastal Tenure	.00364***	.00103*
	(.00107)	(.0006)
Education	.00731	.00376
	(.00479)	(.00265)
Income	-1.3e-07	8.7e-09
	(1.7e-07)	(9.7e-08)
Wealth	-1.7e-08	-2.2e-08**
	(1.8e-08)	(9.7e-09)
Past Flood	.00115	.02519
	(.04538)	(.025)
Primary Home	-.01795	.00191
	(.03103)	(.01718)
SFHA	-.03614	-.04427***
	(.02802)	(.01544)
SFHA (First Street)	-.01784	-.01161
	(.02775)	(.01526)
Female	-.00969	-.00215
	(.02809)	(.01547)
Constant	.02082	-.01912
	(.10004)	(.05526)
Observations	362	336

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

Table C2: Elasticities and Average Marginal Effects for Hurricane Probability Regressions

	Full Sample	Outliers Dropped
Panel A: Elasticities		
Relative Worry	1.056	3.361
	(-4.044 , 6.107)	(0.372 , 6.195)
Coastal Tenture	2.723	0.789
	(1.22 , 4.295)	(-0.077 , 1.604)
Education	7.451	3.854
	(-2.059 , 16.896)	(-1.44 , 9.189)
Income	-1.33	0.112
	(-4.861 , 2.226)	(-1.822 , 2.035)
Wealth	-0.66	-0.785
	(-1.91 , 0.593)	(-1.552 , -0.088)
Past Flood	0.004	0.153
	(-0.545 , 0.565)	(-0.147 , 0.466)
Panel B: Average Marginal Effects		
Primary Home	-0.019	0.002
	(-0.079 , 0.043)	(-0.031 , 0.036)
SFHA	-0.035	-0.043
	(-0.091 , 0.019)	(-0.074 , -0.012)
SFHA (First Street)	-0.017	-0.011
	(-0.072 , 0.034)	(-0.041 , 0.017)
Female	-0.009	-0.002
	(-0.064 , 0.047)	(-0.03 , 0.027)

Notes: 95% confidence intervals in parenthesis.