Article

Risk Perceptions and Flood Insurance: Insights from Homeowners on the Georgia Coast

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Abstract: Scholars highlight a wide array of factors that can influence risk perception and decision making under risk. Utilizing survey data, we explore many potential determinants of coastal storm and flood risk perception and assess how these measures correlate with flood insurance uptake. Our focus is on coastal Georgia, which has lower historical risk, and which many people perceive as relatively safe; this area was recently adversely affected, however, by two major storms. Descriptive statistics suggest that the majority of Glynn county resident's expect coastal storms and hazards to be worse in the future. We find that expected hurricane damage, measures of risk preference, flood zone, and wealth exposure are robust determinants of flood insurance purchase.

Keywords: Flood Risk, Risk Perceptions, Risk Preference, Insurance

1. Introduction

Understanding how to adapt to and limit the impacts from natural catastrophes is an increasingly pertinent issue, as costs associated with U.S. natural catastrophes have been increasing for several decades [1]. This is due to increased global frequency of catastrophic events [2–4], but is also partially a result of increased exposure from urbanization and development in hazard prone areas, particularly in the U.S. [5]. Of naturally occurring catastrophes, tropical cyclones and associated flooding are by far the most costly [1]. Consequently, the U.S. government has been heavily involved in actively mitigating and managing flood impacts. Starting in the early 20th century, the U.S. began trying to limit the impacts from flooding by building flood control infrastructure, which has expanded into a network of over 28,000 miles of levees as well as numerous sea walls, dams, and canals [6]. Measures have been taken to limit fiscal impacts as well. The National Flood Insurance Program (NFIP) was created in 1968 with the stated goal of reducing losses from flooding and limiting public spending for disaster aid.

Despite these well-intentioned efforts to limit the physical and pecuniary impacts from natural catastrophes, the effectiveness of government efforts are often undermined by individuals actions that, in many cases, ultimately define the extent of damages and associated costs. For example, mandatory flood insurance requirements are often circumvented [7]. Individuals have also been shown to forgo insurance when expectations of government ex-post disaster aid are high [8] and to reduce insurance coverage in response to distribution of aid [9–11]. These are some of the contributing factors that explain why only 30% of U.S. homeowners in 100-year flood zones have flood insurance [12]. This statistic is counter-intuitive given that the NFIP offers rates that are not risk-based [13], meaning many policies have positive expected values over the life of a standard 30 year mortgage, and decision predictions of rational choice models suggest households should opt for full coverage [14].

Misinformation and individual mis-perceptions can also be problematic. For example, areas protected by levees are not considered flood zones, despite significant residual risk being present. In such instances, individuals may or may not be aware of such risks, especially if they rely on flood zone classifications as a proxy for risk information. Along this same line, flood zone maps are often imprecisely drawn or outdated, leaving many individuals with a misleading information on the risks they are exposed to. Anecdotally, in the case of Hurricane Harvey, 75 percent of flood losses occurred outside the SFHA, where flood risks were thought to be negligible [15]. More generally, FEMA flood maps indicate that 13 million U.S. households face a one percent annual risk of flooding, while estimates from other researchers put that number at closer to 41 million U.S. households [16].

Government efforts to mitigate impacts from natural hazards are less likely to be effective if the goals of individuals and government are misaligned, or if individuals have inaccurate perceptions and unfounded expectations. Consequently, understanding which individual beliefs and expectations influence individual decisions relevant to natural hazard mitigation is critical for promoting widespread systemic resilience against future natural catastrophes. This is not a trivial task. For instance, the combination of low probabilities and high consequences that natural hazards exhibit create an ideal environment for behavioral biases to manifest; this is but one the many challenges faced in trying to understand individual decisions [17]. Additionally, public perceptions and expectations are dynamic and changing over time, particularly with issues related to climate change [18], meaning existing studies can become outdated quickly.

The aim of this study is to provide insight into the current state of attitudes, expectations, preferences, and perceptions of coastal residents pertaining to low probability, high consequence natural hazards. In particular, we explore how these factors correlate with flood insurance holdings (at both the extensive and intensive margins). Using a novel data set collected via mail survey in the fall of 2018 in Glynn County, Georgia, we highlight some of the most important factors to consider for designing policy that aligns the interests of individuals, with the goal of systemic adaptation to reduce negative impacts from future catastrophes. Several notable findings emerge from our data.

First, elicitation of beliefs about future natural hazard risks suggests that the majority of coastal residents believe that coastal natural hazards will be worse in the future. In addition, a lesser (but still significant) proportion perceives that shoreline armoring and beach replenishment will be effective at mitigating these risks. This suggests that there will likely be increasing pressure to actively manage coastal risks, which has implications for ecological effects and potential induced development.

Second, data analysis reveals that risk perceptions, risk preference, and wealth exposure are highly correlated with flood insurance holdings. Bayesian variable selection methods indicate individual beliefs that retreat from the shoreline will be necessary along some parts of the coast in the near future are strong predictors for flood insurance demand. In addition, a variable indicating that subjects were able to correctly identify their flood zone has a very high inclusion probability in flood insurance uptake and coverage models. These measures likely capture relevant attitudinal and perceptual aspects of household decision making and deserve further scrutiny in future research.

Third, some of the factors we expected to be important determinants of flood insurance demand were poor predictors. We explored numerous measures of worry using standard qualitative measures, but worry over loss of home had low predictive validity in our models. Experience with flood damage also had low predictive power in our models; it's likely that experience shapes risk perceptions and possible that experience measures become redundant in models that include perception measures. As such, experience may serve as an instrument for perceptions in some settings. Similarly, flood insurance premium has low predictive validity in our models. Flood insurance pricing is highly correlated with risk factors [19], and thus may become redundant in reduced-form models. We explore some ways to address this problem in future research.

Lastly, our results are unique in several regards. Many studies focusing on the relationship between individual perceptions of risk and natural hazard mitigation tend to focus on perceptions of present risks [20–23]. For natural hazards that are likely to worsen in the future as a result of climate change (tropical cyclones, sea level rise, coastal flooding), however, beliefs about the future may be a better indicator for natural hazard mitigation decisions. Understanding how individuals update their beliefs about future coastal risks, and whether or not those beliefs about the future are reflected in hazard mitigation decisions appears to be under-explored in the existing literature. In addition, many recent studies investigating individual attitudes, opinions, perceptions, or expectations related to natural hazards mitigation or climate change adaptation have been based on samples collected from outside the U.S. [20,23]. Its not obvious that results from these studies generalize to the institutional setting of the U.S. (due to differences in tropical cyclone risk, development patters, flood insurance markets, and other institutional and cultural factors).

Also, existing studies in the U.S. utilizing survey data tend to draw samples from areas that have extensive historical exposure to natural catastrophes (such as the Gulf Coast [24,25]), areas that have recently experienced a major natural hazard (such as New York City following Hurricane Sandy [21]), or recruit subjects specifically in flood zones [22]. On the contrary, the coastline surrounding Glynn County, GA exhibits a lower hurricane return period than most other areas of the southeast [26,27]; due to shallow offshore bathymetry and concave shape of the coastline, the Georgia coast, in general, is seen as a “safe haven" from tropical storms, but this is based only on recent historical data [28] and does not take storm surge risk into account [29]. Nonetheless, coastal Georgia was recently affected by two significant storms (Matthew in 2016 and Irma in 2017); this situation provides an opportunity to assess how populations with perceived low risk may respond to new information. Climate change is likely to broaden exposure of natural hazards to many individuals that may have not had previous experience; such populations may be particularly vulnerable to behavioral biases and heuristics that may be ineffective at promoting efficient self-protection behaviors. Utilizing Glynn County as a research site provides results for a population that is likely to have lower previous perceptions of risk.

The rest of the paper is organized as follows. Section 2 reviews our data collection and survey procedures. Section 3 presents and explores descriptive statistics for our data. Section 4 describes our empirical methodology, with section 5 reporting results. Section 6 discusses our findings while section 7 concludes.

2. Data

Our data set consists of household level information that was collected via a mail survey in the fall of 2018. Recent home buyers (transactions in 2016 or 2017) in Glynn County, GA were targeted, and 1,914 surveys were sent out in early October, of which 266 were returned (for a response rate of 13.9%). Incentive payments of $5 were offered for completed and returned surveys. The survey instrument was designed to capture information on homeowner attitudes, expectations, beliefs, and behaviors related to living and investing on the coast, within the context of climate change. Our data set notably includes both flood and wind insurance information, elicited expectations of the likelihood of hurricanes over the next 50 years, expected damages from a hurricane, degree of worry across multiple domains, and elicited risk preferences.

Likelihood of a Category 3 hurricane and expected damage were elicited using subjective assessment instruments. Probability of major hurricane was measured by asking respondents to estimate the number of Category 3 storms, or greater, to strike their community in the next 50 years; we use this data to estimate an annual probability of hurricane strike. To assess expected damages, we ask respondents to indicate the level of damage that they think would result from a Category 3 storm as a percentage of structural home value.

To elicit risk preferences, survey respondents had the option to wager their incentive payment as part of a risk preference instrument based on [30]; the risk preference instruments allows respondents to select from among multiple risky lotteries with varying levels of risk and payoffs (all relative to keeping the incentive payment). The natural uncertainty associated with future weather outcomes was used to generate the randomness in payoffs. Each lottery was based on future weather outcomes at a particular weather station in Glynn County, GA, with payoffs being tied to occurrence of particular weather outcomes. For example, the safest gamble (associated with minor risk aversion), was a 50/50 gamble on rainfall being less or equal to or greater than the historical average, with associated payoffs of $8 or $3, respectively; the riskiest gamble (associated with risk loving) was a 2.5% chance of $300 if a the high temperature reached a particular level ($0 payment if not).

Historical information on rainfall and temperature is relayed to respondents to provide a common basis for objective assessment. As individuals may have subjective assessments of weather that deviate from historical data, we also ask them whether they think particular outcomes are more or less likely than indicated by historical data. This design has the benefit of framing risk in a common and relevant domain (weather outcomes), and it removes any doubt about the randomness of the outcome, since the payoffs are based on data that researchers cannot manipulate and respondents can independently verify.

3. Descriptive Statistics

Tables A1 - A5 lists variable descriptions for each variable in our data, while tables 1 - 2 report descriptive statistics. What follows is a detailed description and discussion of our the elements within our data set.

3.1. Insurance

Current flood insurance policies were held by 62 percent of households in our sample. Policy-holders reported a mean annual flood premium of $1,313. In addition to reported flood premiums, we calculate the flood insurance premium each homeowner would face for full coverage on their home's structure, assuming a $1000 deductible using the NFIP flood insurance rate manual [31]. This calculated premium had a mean value of $1,314, very close to the actual reported mean, but with a lower standard deviation. Actual premiums may vary based on deductible choice and choice of full versus partial coverage, but the calculated premium is tailored to the home's flood zone and characteristics as dictated by the NFIP manual. Thus, calculated premium provides for a consistent (and more plausibly exogenous) metric of price for both policy holders and non-policy holders to be used for analysis of flood insurance demand.

Mean coverage levels for those who had flood policies were approximately $223,000 for structure coverage (just over $139,000 including zeros) and $79,000 for contents coverage (around $37,000 including zeros). The ratio of flood structure coverage to structure value reveals that the average respondent had a coverage level that was approximately 121% of their homes structure value. The mean home structure value in our data set was $269,000 according to 2019 tax assessor data (indicating right skew in the distribution of the ratio). The average property (structure plus land) in our sample sold for $385,000 in either 2016 or 2017 and had a tax assessed value of $405,000 as of 2019.

About half of respondents indicated that their Glynn County home was their primary residence. Flood zone status was elicited from survey respondents, but also verified using flood zone maps. Twenty-six percent of homes in the sample were located in an special flood hazard area (SFHA - zone with a 1 percent flood risk per annum). Seventy percent of respondents correctly identified their flood zone. Substantial heterogeneity in flood risk awareness, however, existed across flood zone. Only 39 percent of residents with homes in SFHA correctly indicated as such, compared to 80 percent of residents with homes in non-SFHA zones. This is possibly indicative of respondents having a tendency to indicate not being in a flood zone if they do not know they are in a flood zone. Additionally, a smaller proportion of homes in SFHA zones were indicated to be primary residences (28 percent) compared to non-SFHA homes (54 percent), which may explain the discrepancy in flood zone awareness as non-permanent residents may be less cognizant of or less concerned with local flood risks. Sixty-three percent of respondents had a wind hazard policy (as a separate contract or as a rider to their homeowner's policy). The average respondent indicated that 33% of their wealth was represented by coastal property ownership.

3.2. Demographics

Thirty percent of respondents were female; eighty-eight percent were white, and 67 percent had completed a bachelors degree or graduate degree. Annual household income was elicited in a series of discrete ranges. For the top income interval, which is censored above $250,000, we apply the methodology of [32], which approximates the upper part of the income distribution by extrapolating based on a Pareto distribution. Doing so suggest coding our top income interval as $496,124. The bottom interval (censored at $35,000) was coded as $30,000, while all remaining intervals were coded at their midpoint. The resulting mean household income in our sample was approximately $171,000. The mean age of a respondent in our sample was 55 (based on eliciting age in discrete intervals and coding the intervals at their midpoint). Twenty-six percent of respondents indicated they were retired, and the mean household has 2.45 members in the household. Finally, self reported political affiliations indicate that approximately half of our sample considered themselves conservative, while 15 percent considered themselves liberal. The remaining respondents identified as politically moderate or "None of the Above".

Forty-one percent of respondents claimed to be new to the coast (not surprising, since our survey focused on recent home buyers), while 35 percent indicated they had lived on or near the coast for most or all of their life. Personal flood history and associated damages were elicited. Most respondents had not personally sustained any home damage due to flooding; 15 percent had sustained flood damage, and 3 percent had sustained flood damage more than once. The average level of damage suffered was $31,800.

3.3. Individual Expectations

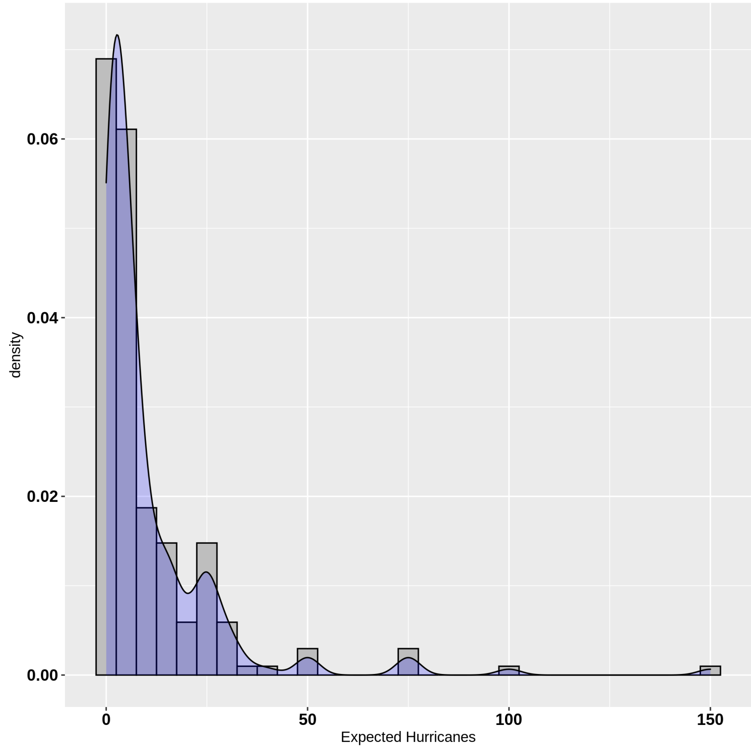
The survey includes measures of individual expectations of natural and economic phenomena, including the likelihood of various types of disaster assistance. Expectations were measured on a 5-point Likert scale and converted to binary indicators using a response of 3 or higher to be considered "In aggreement" with an expectation statement. Approximately 94 percent of respondents agreed that insurance premiums, home prices, and taxes will increase in the future. Seventy-seven percent agreed that erosion will get worse in the future; sixty-one percent agreed that coastal storms will be worse in the future, and 58 percent agreed that parts of the coast will need to embrace some form of managed retreat in the future. Additionally, 54 percent expected coastal armoring to be effective in mitigating future damage of personal property, while 48 percent believed that beach nourishment (adding sand to bolster dunes and beach width) will be an effective way to preserve beaches.

Individuals were asked what type of disaster aid they would expect in the event of a major hurricane strike near their home. Seventy-three percent expected emergency first-response. Additionally, some respondent expected various types of fiscal aid, including public aid to rebuild infrastructure and beaches (58 percent) and personal aid for rebuilding personal property in the form of low interest loans (51 percent) and federal or state issued grants (35 percent).

3.4. Opinions

The survey also focused on opinions of the coastal economy. These data were Likert scale measures converted to binary indicators (as with expectations). Forty-one percent of respondents felt that the coast was currently overdeveloped. Fifty-nine percent believed the cost of coastal housing was too high, and 65 percent considered insurance for coastal property to be too expensive. When asked about social density on the coast, 46 percent agreed that the coast was too congested. Sixty-two percent agreed that the coast needs better infrastructure (water, bridges, ferries, power, etc.). Only 17 percent of respondents thought building regulations were "stifling the coastal economy". Thirty-nine percent felt like the coast was "changing in ways that threaten current development". Finally, only 15 percent agreed that local government policies had helped alleviate risks associated with living on the coast.

Figure 1. Expected Major Hurricanes over 50 years



3.5. Risk Perceptions and Risk Preferences

Regarding flooding and tropical storm hazard, the survey included subjective probability and impact measures associated with Category 3 hurricanes; risk preferences measured with a salient, cash-induced weather experiment; and post-experiment assessments of the perceived accuracy of historical probabilities in characterizing future weather risks. Turning to measures of risk perception, the mean respondent expected just over 10 Category 3 (or greater) hurricanes to strike their community over the next 50 years. The median value was 5, and slightly over half of all respondents expected 5 or fewer. Figure 1 depicts the empirical distribution of storm counts. For reference, NOAA calculates the historical return period for a major hurricane to be about 33 years for Glynn county.

In addition to expectations on the frequency of future hurricanes, respondents were also asked to indicate how much damage they would expect their home to sustain (as a percentage of structure value) if a Category 3 hurricane was to directly strike Glynn county. Damage estimates were elicited on a 5 point scale ranging from 0% - 20% up to 81% - 100%. Figure 2 reports the distribution of responses, where most respondents expected damages of between 21% - 40% of home structure value. Coding each interval at it's midpoint and taking an average suggests the mean respondent expected damages that were equal to 43% of their home structure value.

Table 3 reports the distribution of lottery choices from our risk preference instrument and corresponding implied coefficients of relative risk aversion (CRRA). Roughly half of respondents choose not to wager their incentive payment, which implied a CRRA of at least 0.85 which is considered highly risk averse. About 20 percent choose the riskiest lottery which corresponds to risk loving behavior (CRRA < 0), and the remaining respondents choose lotteries that all correspond to various levels of risk aversion or risk neutrality. The mean risk preference parameter was 0.49, indicating moderate risk aversion.

In addition to using weather outcomes to assess risk preferences, respondents were queried on their beliefs about the current relevance of historical weather probabilities. For the lowest probability

Figure 2. Expected Major Hurricane Damage

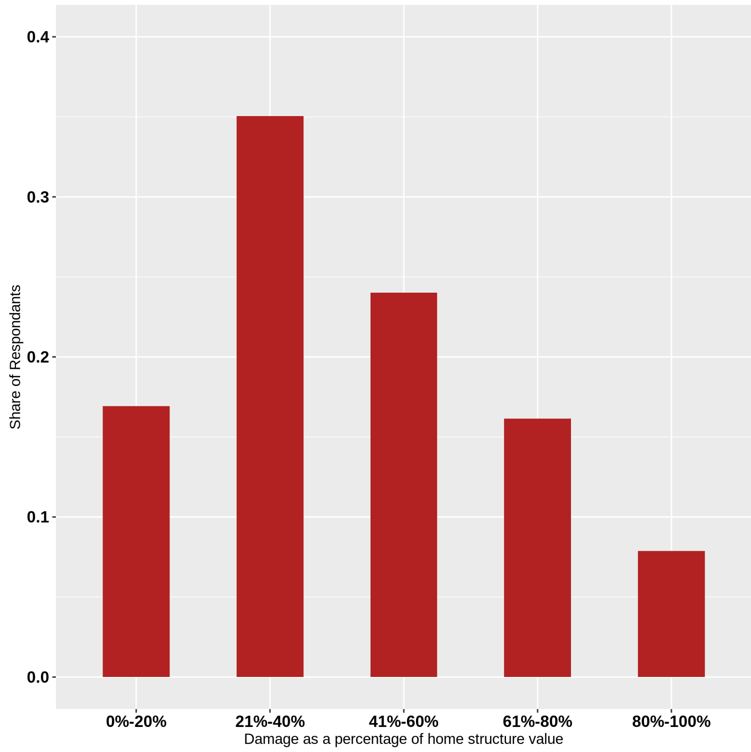
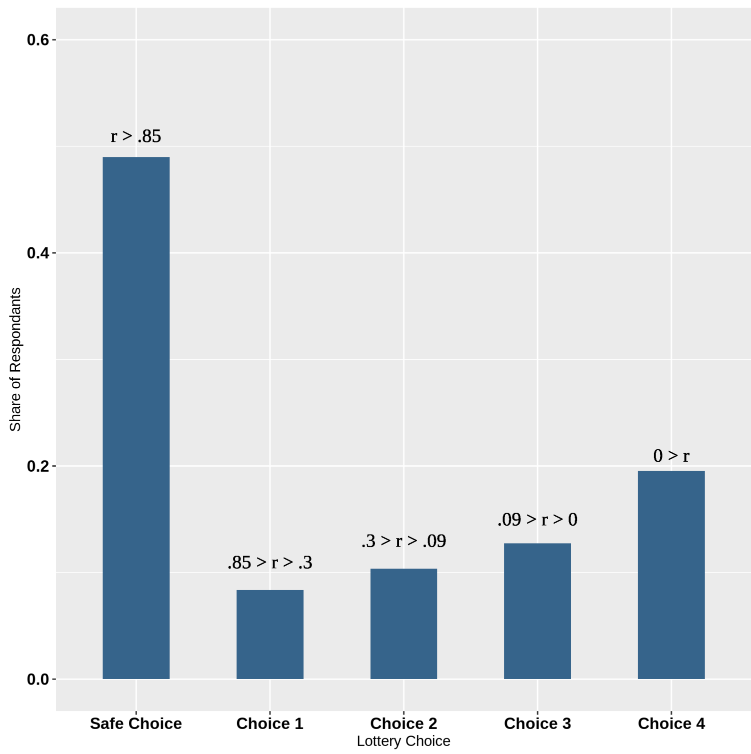


Figure 3. Elicited Risk Preferences



weather outcome (approximate 1 percent chance of occurrence involving an unseasonably high temperature in November), 15 percent of respondents indicated the objective probability was too low, while 38 percent indicated the objective probability was too high. The remaining respondents (47%) indicated that they thought the objective probability was roughly correct. For the highest probability event (approximately 50 percent chance of exceeding a particular rainfall total), 20 percent of individuals felt the objective probability was too low, 14 percent though it was too high, with the remaining individuals (66%) considering it to be accurate. Notably, these results are consistent with the theoretical literature on probability weighting, in which individuals tend to overweight low probability events and underweight large probabilities [33–36].

3.6. Worry

Feelings of worry were elicited across various domains using a 4 point scale. An individual was defined as "being worried" if they answered with a 3 or higher. Our primary purpose was to measure worry about risk to property and finances from natural hazards, but to reduce saliency and ameliorate any focusing illusions, we embedded these topics among other potential worries. The worry topics were selected across the domains of health, safety, finance, social, and personal, and were defined over both individual and family effects. Forty-six percent of respondent reported worrying about the loss of their home as a result of a natural disaster. If worry or dread drive insurance demand, this measure of worry may correlate with market penetration.

In addition to reducing focus on worry in our primary domain of interest, elicitation of worry across other domains allows us to control for a baseline level of worry for each respondent. This is done under the presumption that elevated levels of worry in the domain of home loss are less important as a determinant of behavior if the individual tends to worry in general and has elevated levels of worry across multiple domains. To control for baseline level of worry, we create a simple worry index by summing the total number of domains (excluding worry over home loss) for which a respondent was classified as worried. The mean respondent worried about 4.11 out of the 13 domains included in the index. The greatest level of worry (63%) was centered on death of a family member. On average, worry over loss of home (46%) was similar in magnitude to getting cancer (51%), family member being in a car accident (53%), and exposure to pollution in the immediate vicinity (52%). Other risks exhibited lower levels of worry.

Table 1. Descriptive Statistics

	mean	sd	min	max	count
Panel A: Insurance					
Flood Policy	0.62	0.49	0.00	1.00	266
Flood Premium	1313.22	1769.34	0.00	12000.00	147
Flood Premium (Calculated)	1314.94	1294.34	152.57	6036.70	266
Flood Coverage (Structure)	139267.98	115295.32	0.00	250000.00	266
Conditional Flood Cov. (Structure)	223164.36	50132.13	25000.00	250000.00	166
Flood Coverage (Contents)	37155.17	44709.27	0.00	100000.00	261
Conditional Flood Cov. (Contents)	79487.70	30041.19	5000.00	100000.00	122
Flood Cov./Structure Val.	0.75	1.02	0.00	9.16	266
Conditional Flood Cov./Structure Val.	1.21	1.05	0.07	9.16	166
Primary Home	0.48	0.50	0.00	1.00	266
SFHA	0.26	0.44	0.00	1.00	266
Knew Zone	0.70	0.46	0.00	1.00	266
Home Sale Price	385287.59	615132.86	37800.00	6150000.00	266
Home Premium	2340.82	3070.18	350.00	30000.00	223
Wind Policy	0.63	0.48	0.00	1.00	204
Wealth Share	0.33	0.22	0.10	0.90	261
Structure Value	269151.13	289853.95	14600.00	3039000.00	266
Home Value (2019)	405509.77	668938.01	21900.00	7759400.00	266
Km to coast	4.47	2.86	0.33	13.09	266
Panel B: Demographics					
Female	0.30	0.46	0.00	1.00	266
White	0.88	0.33	0.00	1.00	266
Income	171.67	149.36	30.00	496.12	253
Conservative	0.49	0.50	0.00	1.00	266
Moderate	0.27	0.44	0.00	1.00	266
Liberal	0.15	0.36	0.00	1.00	266
Age	55.12	14.49	21.00	80.00	258
Higher Edu.	0.67	0.47	0.00	1.00	266
Retired	0.26	0.44	0.00	1.00	266
Household Size	2.45	1.17	1.00	6.00	257
New to Coast	0.41	0.49	0.00	1.00	266
Life Time Resident	0.10	0.30	0.00	1.00	266
Coastal Vet.	0.35	0.48	0.00	1.00	266
Flood Damage	31800.00	59725.99	300.00	300000.00	37
Flood Settlement	0.32	0.47	0.00	1.00	60
Prior Flood	0.15	0.36	0.00	1.00	261
Observations	266				

Table 2. Descriptive Statistics Continued

	mean	sd	min	max	count
Panel C: Expectations					
Exp. Increase (Insurance Prem.)	0.94	0.24	0.00	1.00	266
Exp. Increase (Home Prices)	0.93	0.26	0.00	1.00	266
Exp. Increase (Taxes)	0.94	0.25	0.00	1.00	266
Worse Erosion	0.77	0.42	0.00	1.00	266
Nourishment	0.48	0.50	0.00	1.00	266
Worse Storms	0.61	0.49	0.00	1.00	266
Armoring	0.54	0.50	0.00	1.00	266
Retreat	0.58	0.49	0.00	1.00	266
Exp. Disaster Aid (Individual)	0.35	0.48	0.00	1.00	266
Exp. Disaster Aid (Public)	0.58	0.50	0.00	1.00	266
Exp. Disaster Aid (Loans)	0.51	0.50	0.00	1.00	266
Exp. Disaster Aid (Emergency Response)	0.73	0.45	0.00	1.00	266
Panel D: Opinions					
Coast Overdeveloped	0.41	0.49	0.00	1.00	266
Housing Too Expensive	0.59	0.49	0.00	1.00	266
Insurance Too Expensive	0.65	0.48	0.00	1.00	266
Coast Too Congested	0.46	0.50	0.00	1.00	266
Need Better Infrastructure	0.62	0.49	0.00	1.00	266
Building Regulations Bad	0.17	0.38	0.00	1.00	266
Development Threatened	0.39	0.49	0.00	1.00	266
Govt. Policy	0.15	0.36	0.00	1.00	266
Panel E: Perceptions					
Expected Hurricanes	10.62	17.34	0.00	150.00	203
prob.cat3	0.19	0.24	0.00	1.00	238
Expected Damage	0.43	0.23	0.10	0.90	254
Underweight Low Prob.	0.15	0.35	0.00	1.00	266
Overweight Low Prob.	0.38	0.49	0.00	1.00	266
Underweight High Prob.	0.20	0.40	0.00	1.00	266
Overweight High Prob.	0.14	0.35	0.00	1.00	266
CRRA	0.49	0.38	0.01	0.85	251
Panel F: Worry					
Worry Index	4.11	2.97	0.00	13.00	266
Worry (Cancer)	0.51	0.50	0.00	1.00	266
Worry (Family Death)	0.63	0.48	0.00	1.00	266
Worry (Family Car Accident)	0.53	0.50	0.00	1.00	266
Worry (Violent Crime)	0.24	0.43	0.00	1.00	266
Worry (Pollution)	0.52	0.50	0.00	1.00	266
Worry (Home Loss)	0.46	0.50	0.00	1.00	266
Worry (Having Friends)	0.19	0.39	0.00	1.00	266
Worry (Attractiveness)	0.09	0.28	0.00	1.00	266
Worry (Relationship)	0.12	0.32	0.00	1.00	266
Worry (Life Meaning)	0.19	0.39	0.00	1.00	266
Worry (Career Path)	0.21	0.41	0.00	1.00	266
Worry (Family Having Money)	0.36	0.48	0.00	1.00	266
Worry (Current Job)	0.17	0.38	0.00	1.00	266
Worry (Financial Difficulty)	0.35	0.48	0.00	1.00	266
Observations	266				

4. Empirical Methods

To assess the variation in flood insurance uptake and the relevance of our survey measures, we conduct Bayesian variable selection analysis and Maximum Likelihood estimation. As presented in the data section, we have a wide array of potential covariates that could be included in empirical analysis. The array of survey measures stem from different disciplinary approaches to analysis or risk under uncertainty and may suffer from multi-collinearity (in addition to other potential problems). To explore the appropriateness of including any of a surfeit of covariates in the estimating equations for flood insurance demand, we employ several Bayesian econometric models that make use of stochastic search variable selection (SSVS) [37]. This method allows as to assign a marginal posterior inclusion probability to each covariate which provides insight into which regressors are most likely to be in the true (reduced-form) model. We estimate a standard binary probit model that uses flood insurance status as the outcome of interest along with a beta regression model where the outcome of interest is flood insurance coverage (as a percentage of structure value). In addition, we estimate standard reduced-form probit and beta regression models, via Maximum Likelihood, to assess correlation and potential magnitude of covariate effects.

4.1. Stochastic Search Variable Selection

The binary probit model(1=flood insurance; 0=not) takes the standard form as defined in equation 1 where X is a vector of p potential covariates and θ is a parameter vector. To implement SSVS, each element of θ is defined as: $\theta_j = I_j\beta_j$ [38] , where I_j is a Bernoulli distributed indicator variable and β_j is a normally distributed parameter that captures the effect of x_j on the probability that $y = 1$. When $I_j = 0$, x_j is effectively excluded from the model, where as when $I_j = 1$, x_j is included and has estimated effect size β_j. Equation 1 is estimated using Markov-Chain Monte Carlo (MCMC), where the mean parameter value of each I_j can be interpreted as the marginal posterior inclusion probability (i.e. the probability that x_j is in the true reduced-form model).

$$P(y_i = 1|X_i) = \Phi(\alpha + \sum_{j=1}^{p} \theta_j x_{i,j} + \epsilon_i) \tag{1}$$

We take an agnostic view on the degree of sparseness the model should have (i.e. how many covariates the true reduced-from model should have). Additionally, we utilize a random effects approach in estimation of β_j, which allows the prior variance of β_j to be estimated rather than specified. Both of these specification decisions increase model flexibility and reduce the chance that poorly chosen priors influence the results. Thus priors (and hyper prior) distributions for the model are assigned as follows:

$$I_j \sim bernoulli(\rho)$$
$$\rho \sim beta(10, 10)$$
$$\beta_j \sim N(0, \tau)$$
$$\tau \sim gamma(1, .1)$$
$$\alpha \sim N(0, 100)$$

The indicator variables, I, are assigned a Bernoulli prior with probability ρ, which can be interpreted as a parameter on model sparsity. For example, assigning $\rho = .2$ implies an a prior belief that about 20% of the covariates under consideration should be in the true model. Rather than assign a value to ρ we let ρ be a parameter to estimate and assign a beta distribution as the prior with both shape parameters set to 10. This distribution is symmetric around .5 and places over 99% of the probability mass of ρ between .2 and .8, which is reflective of a belief that the true model will not contain less than 20% and not more than 80% of the covariates under consideration. The beta parameters , β_j , are assigned a normally distributed prior with variance τ, where τ is a parameter to be estimated and is assigned a gamma distributed prior with shape parameters set to 1 and .1 respectively. Finally the constant term α is assigned a weakly informative normally distributed prior with mean 0 and variance of 100.

We analyze flood insurance coverage levels by expressing coverage as percentage of structure value. We use a beta regression to model this dependent variable, which is appropriate for a fractional response. To account for the fact that 0 and 1 are included in our outcome of interest we apply the commonly used transformation $\frac{(y(n-1)+.5)}{n}$ (where y is the fractional outcome and n is the sample size) to map our outcome variable to the (0,1) interval. The procedure for estimating the beta regression is analogous to the probit specification. The log-likelihood for the beta regression is defined in equation 2 where B(.) is the beta function, ϕ is a parameter to be estimated, and $\mu = g^{-1}(\alpha + \sum_{j=1}^{p} \theta_j x_{i,j} + \epsilon_i)$ where $g(.)$ is a link function that maps the input to the unit interval. We use the logit function for g(.) in our specification. Prior distributions for the beta regression are the same as those used for the probit specification.

$$f(y_i|\mu,\phi) = \frac{y_i^{(\mu\phi-1)}(1-y_i)^{((1-\mu)\phi-1)}}{B(\mu\phi,(1-\mu)\phi)} \tag{2}$$

All specifications are estimated using MCMC. We run 210,000 iterations of the Metropolis-Hastings algorithm, discarding the first 10,000 iterations as a "burn-in" and applying a thinning interval of 10 to reduce auto-correlation. For each parameter, trace, density, and auto-correlation plots are visually inspected for any sign of non-convergence. Additionally, we apply the Gelman-Rubin diagnostic and use the commonly used potential scale reduction values (PSRF) value of 1.1 as the threshold for convergence [39].

4.2. Reduced-Form Regression Analysis

Aside from exploring what variables the data indicate have the most explanatory power, we also estimate standard reduced-form regression models via Maximum Likelihood. Utilizing the probit for insurance uptake and beta regression for coverage level, we include covariates that theory suggests should be in the models. Following theory of demand for insurance, we include full coverage flood insurance premium, household income, the share of wealth in coastal real estate, risk preference measure (CRRA value), elicited probability of a hurricane, and expected damage. To account for affect, we include a dummy variable for worry over loss of home. To account for flood experience, we include an interaction term that is zero for households that have experienced no past flood losses and is equal to the size of the monetary loss for those that have. Other control variables include location in SFHA, distance from the shoreline, age, and education.

5. Results

Table 3 reports marginal inclusion probabilities from our Bayesian variable selection specifications. Generally, variables that economic theory would suggest should be in the true model tend to have high marginal inclusion probabilities. For the model focused on flood insurance status, higher education has the highest inclusion probability at 92% followed by SFHA status at 91%. Being able to correctly identify the flood zone in which one's home is located was also deemed to be an important predictor with an inclusion probability of 81%. Other covariates deemed important were: coastal home value as a share of total net worth (inclusion probability of 74%); risk preferences (inclusion probability of 64%); and the belief that coastal retreat will be necessary in the future (inclusion probability of 54%). The two variables related to hurricane expectations – expected damage and the probability of a hurricane strike – are also more likely than not in the true model with inclusion probabilities of 57% and 52% respectively. Many of the remaining covariates under consideration have non-trivial inclusion probabilities, but are all more likely to be excluded from the true model than included. Of note, expectations if individual disaster grants is the most likely of the charity hazard variables to be included (probability of 44%), followed by public assistance (35%) and reconstruction loans (31%). Other variables that we expected to be important in the flood insurance decision, like worry of loss of home and income, exhibit low inclusion probabilities.

The specification focused on flood insurance coverage level suggests far fewer of the considered variables should be included in the true reduced-form model. Being aware of one's own flood zone and residing in the SFHA are the only two variables in this specification that had inclusion probabilities greater than 50%. This suggests that explaining flood insurance status is a more tractable task than explaining the level of coverage. Nonetheless, risk preference and risk perception (expected damage and hurricane probability) are in the top 10 variables for inclusion probability. Also noteworthy, flood insurance premium has a negligible inclusion probability in each model; this is in stark contrast to what economic theory would predict.

Turning to regression analysis, overestimation of the magnitude of effects is likely to occur if the same data is used for both specifying the model (SSVS) and the individual effects of the selected covariates [40]. Thus, we largely ignore the variable selection results in specifying regression models, instead selecting parsimonious specifications populated by variables that theory suggests should influence flood insurance demand[1]. We consider this a first step in exploration of flood insurance with these data. Future research should seek structural specifications that can more directly assess theoretical models.

Table 4 reports coefficient estimates from our reduced-form models estimated via maximum likelihood. Overall, many of the estimated coefficients are significantly correlated with flood insurance decisions and have the anticipated sign. Individuals residing in the SFHA are more likely to hold a flood insurance policy (marginal effect of 23%) and exhibit greater levels of coverage (marginal effect of 14.5%). As home value as a share of total wealth increases, the probability of insuring and coverage level both increase (marginal effects of 58% and 27%, respectively). Experimentally elicited risk preferences are also significantly correlated with flood insurance decision. Increased CRRA coefficients correspond to both higher probability of insuring (marginal effect of 21%) and increased levels of coverage (marginal effect of 12%). With respect to hurricane risk perceptions, expected damage appears to explain some of the variation in flood insurance decisions (marginal effect of 32% for the uptake model and marginal effect of 25% in the coverage model), whereas beliefs about the frequency of future storms do not. Other significant variables include educational attainment and household income which were found to increase the probability of insuring (marginal effects of 17% and .07% respectively) but no significant effect was detectable for coverage level.

6. Discussion

Management of weather risks under changing climate will require a deep understanding of integrated natural and social sciences. Arguably, our knowledge of human dimensions of risk lag significantly behind climate science and engineering. Effective risk management entails exploration of novel and creative adaptation policies, while also finding deeper knowledge of individual decisions that ultimately influence vulnerability. To this end, we seek a broad collection of information on individual attitudes, beliefs, preferences, and expectations that will help us understand decision making under risk. We draw from economics, sociology, and psychology in formulating metrics to measure attitudes and beliefs about coastal development and climate change; expectations of environmental change, market forces, and government policy; subjective perceptions of weather risk; risk preferences; and emotional determinants of risk behavior. Notably, our sample is drawn from a coastal population that has had comparatively less historical exposure to natural hazards and has objective risk measures that are somewhat lower than other coastal areas in the Southeastern United

[1] Our specified models and the variables suggested by SSVS, however, are quite similar due to the SSVS results placing a high inclusion probability on many of the variables dictated by economic theory.

Table 3. Stochastic Search Variable Selection Inclusion Probabilities

Flood Insurance		Flood Coverage	
Variable	Inclusion Probability	Variable	Inclusion Probability
Higher Edu.	0.921	Knew Zone	0.627
SFHA	0.908	SFHA	0.599
Knew Zone	0.813	Expected Damage	0.464
Wealth Share	0.737	CRRA	0.457
CRRA	0.64	Wealth Share	0.452
Expected Damage	0.568	Retreat	0.438
Retreat	0.539	Higher Edu.	0.426
Prob. Hurricane	0.516	Exp. Disaster Aid (Individual)	0.392
Armoring	0.453	Prob. Hurricane	0.383
Exp. Disaster Aid (Individual)	0.44	Life Time Resident	0.382
Employed (Part Time)	0.415	Armoring	0.367
Life Time Resident	0.379	Employed (Part Time)	0.365
White	0.372	White	0.34
Exp. Disaster Aid (Public)	0.355	Liberal	0.328
Km to Coast	0.338	Conservative	0.323
Liberal	0.331	Female	0.321
Moderate	0.31	Worse Storms	0.312
Exp. Disaster Aid (Loans)	0.307	Exp. Disaster Aid (Loans)	0.31
Worse Erosion	0.302	Household Size	0.307
Female	0.302	Retired	0.304
Conservative	0.291	Worse Erosion	0.302
Retired	0.29	Moderate	0.296
Worse Storms	0.286	Worry (Home Loss)	0.288
Worry (Home Loss)	0.283	New To Coast	0.286
New To Coast	0.278	Exp. Disaster Aid (Public)	0.282
Household Size	0.254	Km to Coast	0.181
Income	0.158	Age	0.014
Age	0.015	Income	0.002
Flood Premium (Calculated)	0.000	Flood Premium (Calculated)	0.000
Flood Damage	0.000	Flood Damage	0.000

States. The area was recently affected by two hurricanes, however. This provides a snapshot of the determinants of decision making under risk in the context of (at least perceived) historically low risk, which can provide insight into evolving climate risks.

Our data suggest that the majority of coastal residents in our sample believe that coastal hazards will be worse in the future. The average respondent in our survey expected 10.6 major hurricanes to pass in close proximity to Glynn county over the next 50 years; a number that is much higher than estimated hurricane return periods would suggests [26][2]. This result contrasts with past work on the Gulf coast, which found (using the same metric) a mean response of 6.86 for expected major hurricanes occurring over the next 50 years, though those data were collected almost 10 years prior [24]. We note that coastal Georgia was adversely affected by Hurricanes Matthew (2016) and Irma (2017), which may have caused updating of beliefs or enhanced perceptions of risk. More generally, this is perhaps indicative of patterns that may be found in the general population of coastal households.

The overwhelming majority of respondents expect that housing prices, insurance costs, and taxes will continue to rise in the future. Over three-quarters expect worsening coastal erosion, six-in-ten expect worse coastal storms, and a similar proportion expect that parts of the coastline will need to

[2] NOAA estimates the return period for a major hurricane to be approximately 33 years for Glynn county

Table 4. Estimates for Flood Insurance Demand

	Flood Insurance Status	Flood Coverage Level
	Probit	Beta Regression
SFHA	0.8385**	0.6138**
	(0.3451)	(0.2582)
Higher Edu.	0.6046***	0.3147
	(0.2252)	(0.2102)
Wealth Share	2.0904***	1.1280**
	(0.5830)	(0.4886)
CRRA	0.7545***	0.4915**
	(0.2813)	(0.2450)
Expected Damage	1.1468**	1.0690**
	(0.4893)	(0.4286)
Prob Hurricane	-0.2813	-0.1749
	(0.4393)	(0.4004)
Flood Premium (Calculated)	-0.0000	-0.0001
	(0.0001)	(0.0001)
Income	0.0023***	0.0001
	(0.0009)	(0.0007)
Worry (Home Loss)	-0.0372	-0.0385
	(0.2357)	(0.2065)
Exp. Disaster Aid (Individual)	-0.2990	-0.2538
	(0.2160)	(0.1975)
Flood Damage	0.0000	-0.0000
	(0.0000)	(0.0000)
Km to Coast	-0.0405	-0.0227
	(0.0381)	(0.0351)
Age	0.0066	0.0035
	(0.0075)	(0.0066)
Constant	-1.9931***	-1.2546**
	(0.7028)	(0.6097)
Observations	210	210
LL	-102.821	308.443
AIC	233.641	-586.886
BIC	280.501	-536.680

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

embrace retreat at some point. These represent fairly dire beliefs for coastal sustainability. On the other hand, a majority of respondents (54%) believe coastal armoring will be effective at mitigating property damage, and 48% believe beach replenishment will be effective in maintaining beaches. These mitigation efforts, themselves, have implications for environmental quality, ecological services, and induced development [41–43].

Many private sector actions, such as the location of neighborhoods, the density and quality of buildings, installation of mitigation measures, and uptake of flood insurance, have significant implications for coastal vulnerability. As such, the public sector often imposes regulations and restriction on these actions. While we are not able to examine all of these factors, our data do include information on household flood insurance. Thus, we take two non-structural approaches to exploring determinants of flood insurance demand. We use Bayesian variable selection methods to let the data tell use which of a bevy of factors are correlated with uptake and coverage levels, and we estimate regression models to assess reduced-form correlations.

In both Bayesian variable selection and regression analysis, we find that expected hurricane damages significantly correlate with flood insurance status and level of coverage, whereas expected frequency of futures hurricanes exhibits much less correlation. Existing literature on the role that individual risk perceptions has in flood mitigation behavior has reached mixed conclusions with many empirical studies finding no evidence of a relationship between the two (see [44] for a review). Notably, many previous studies that model mitigation or insurance behavior do not decompose risk perception into probability and consequences and instead focus on one or the other [44]. Our results, however, suggest that the distinction between probability and consequences is an important one for future work on the role that risk perceptions play in mitigating against natural hazards.

One plausible explanation for the insignificant effect of expected hurricane frequency on flood insurance decisions is potential heterogeneity in how individuals process experiences with natural hazards. As has been noted by [45], the *gamblers fallacy* and the *availability heuristic* predict diverging behaviors in response to a recently experienced natural disaster. The former suggests individuals believe the future likelihood of a low probability event is less likely following the occurrence of the event,a bias rooted in a misunderstanding of probabilistic independence, while the later suggests perceived likelihood increases following the occurrence of the event due to increased salience. Complicating matters, both biases have been shown to be present with varying degrees of prominence depending on the subset of the population [45] meaning even similar past experiences may very well be prompting competing effects to manifest.

It is also possible that our data suffer from measurement issues associated with open-ended assessment of the expected number of hurricanes over a given interval of time. Studies have shown that people have a difficult time responding to probability queries [46–48]. Building on previous research [24], we utilized the storm count over 50 years, but it's also possible that this approach induces difficulties. Future research should explore whether discrete (i.e. Yes/No) responses to stated numbers of storms produce more valid estimates of the distribution of hurricane expectations. There is ample evidence that this approach is more effective (in terms of reducing bias and increasing item response) in assessing willingness to pay for non-market commodities [49,50].

All models suggest that risk preferences play a significant role in insurance demand. We utilized an economics experiment with salient monetary incentives defined over future weather outcomes to classify respondents on a risk-tolerance spectrum. Bayesian model selection indicates that these measures predict flood insurance uptake (and to a lesser extent coverage), and our regression results suggest that more risk-averse household are more likely to hold flood insurance and exhibit greater levels of coverage. This evidence of internal validity suggests that monetary risk experiments defined over the domain of weather outcomes may be effective in producing estimates of risk aversion for flood (and possibly other kinds of disaster) insurance. Future research should assess external validity of these estimates.

One would expect that the exposure of wealth to risk would increase demand for insurance and mitigation. Our survey included a measure of the proportion of household wealth that was in coastal property exposed to storm risk. We find that this variable exhibits a high inclusion probability in Bayesian analysis and has positive correlation with flood insurance uptake and coverage levels. This variable exhibits higher inclusion probabilities than household income in the Bayesian selection models and greater correlation than income in regression models.

Calculated flood insurance premium for full structure coverage exhibited low inclusion probabilities in Bayesian analysis and low statistical significance in regression analysis. Previous literature has noted the difficulties in identifying flood insurance price effects [19,51,52]. This problem appears particularly severe in our new homebuyer dataset and complicates standard economic analysis. Price analysis can suffer from endogeneity, since the premium reflects the level of coverage and deductible chosen. Our premium measure, however, was specified for total coverage and the most common premium level [53]. As such, our measurement issues likely stem from correlation of pricing with risk. Addressing this limitation in future research could entail assembling demand data across time (in which there are changes in the federal rate structure) or pooling data across space. Spatial differences in flood risk and administrative differences in community NFIP enrollment dates could be sufficient to introduce exogenous variation in rates structures that would permit identification of price effects.

Amongst attitude and belief measures, expectations that coastal retreat would be necessary in some cases exhibits the highest inclusion probabilities in Bayesian analysis. This was not included as a covariate in regression analysis, but should be explore in future analysis. Belief that armoring would be effective in mitigating property losses also had relatively high inclusion probabilities. A covariate that we did not include in the regression models, but that exhibited high inclusion probabilities in both models was an indicator that the respondent knew their flood zone. This does not quite fit into the theory of decision making under risk, but could be indicative of whether an individual is cognizant of flood risk.

We find no evidence that worry over loss of home to natural disaster correlates with flood insurance choices. Likewise, experience with floods has low inclusion probabilities and insignificant regression effects. The lack of importance of affect may relate to our measurement protocol. Flood experience likely influences risk perceptions, so correlation of these measure may render flood experience unimportant in our reduced-form models. Expectations of disaster aid (in the form of individual grants for rebuilding) were included to assess the potential for charity hazard. This variable had only modest inclusion probabilities and exhibited a negative (as expected), but insignificant, effect in regression analysis.

7. Conclusions

The purpose of this study is to provide an up-to-date profile of coastal resident's risk posture by characterizing their attitudes, perceptions, beliefs, and expectations related to coastal hazards and exploring how these correlate with flood insurance uptake. We do so by administering survey's to recent homebuyers in Glynn County, GA and eliciting a variety of responses to construct a rich profile of each respondent's characterization of coastal living and perceptions of risk. Although this paper is not the first to utilize individual survey data in a natural hazards context, it is notable in that it targets US coastal residents in an area with relatively low historical natural hazard exposure. Analysis of our data suggests that many respondents expect exacerbation of coastal hazards in the future, including greater destructive power of storms, increased rates of erosion, and greater frequency of major hurricanes (significantly greater than what historical data would suggest). Modeling flood insurance decisions as a function of elicited responses suggests that future expectations and beliefs play a role in hazard mitigation decisions. Notably we find that greater expected damages from a major hurricane significantly impact flood insurance decisions; contrarily, we find no significant relationship between expected hurricane frequency flood insurance decisions. Measures of risk aversion are robust predictors for flood insurance decisions, as are presence in the SFHA and the share of wealth in coastal property exposed to storm risk.

The results presented here contribute to understanding of individual expectations, beliefs, and perceptions related to natural hazards and how those individual characteristics effect hazard mitigation decisions. As climate change and associated sea level rise alter objective risks for coastal communities, understanding the nuanced differences in how different populations respond to changes in those objective risks will be a important consideration for future policy discussions. Additionally, since individual perceptions and expectations of natural hazard risk are important determinants of mitigation adoption, gaining insight into how quickly expectations change in response to changes in objective risk metrics will be particularly important moving forward. Longitudinal studies would be especially helpful in this regard and remains as an opportunity for future research.

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524 ## Appendix A Variable Descriptions

Table A1. Variable Descriptions

Variable	Type	Description
Panel A: Insurance		
Flood Policy	Binary	= 1 if homeowner has flood insurance (self reported)
Flood Premium	Continuous	Self reported annual flood insurance premium
Flood Premium (Calculated)	Continuous	Calculated hypothetical annual flood insurance premium
Flood Coverage (Structure)	Continuous	Self reported flood insurance coverage on home structure
Conditional Flood Cov. (Structure)	Continuous	Self reported flood insurance coverage on home structure only for non-zero coverage levels
Flood Coverage (Contents)	Continuous	Self reported flood insurance coverage on home contents
Conditional Flood Cov. (Contents)	Continuous	Self reported flood insurance coverage on home contents only for non-zero coverage levels
Flood Cov./Structure Val.	Continuous	Flood Coverage (Structure) divided by tax assessed structure value
Conditional Flood Cov./Structure Val.	Continuous	Conditional Flood Cov. (Structure) divided by tax assessed structure value
Primary Home	Binary	= 1 if respondent indicated Glynn County home was their primary residence
SFHA	Binary	= 1 if home is located in SFHA (based on GIS and lat/lon)
Knew Zone	Binary	= 1 if self reported SFHA status matches actual SFHA status
Home Sale Price	Continuous	Purchase price of home
Home Premium	Continuous	Self reported annual homeowners insurance premium
Wind Policy	Binary	= 1 if respondent has a separate wind policy or homeowners policy covers wind damage
Wealth Share	OrderedCategorical	Self reported home value's share of net worth ranging from "less that 20%" up to "81% - 100%"
Structure Value	Continuous	Tax assessed structure value of home
Home Value (2019)	Continuous	2019 tax assessed value of home
Km to coast	Continuous	Kilometers from respondent's home to coast

Table A2. Variable Descriptions

Variable	Type	Description
Panel B: Demographics		
Female	Binary	=1 if respondent indicated being female
White	Binary	=1 if respondent indicated their race as being white
Income	OrderedCategorical	Household income: ranging“less than $35,000" up to “more than $250,000"
Conservative	Binary	= 1 if respondent indicated they were politically conservative
Moderate	Binary	= 1 if respondent indicated they were politically moderate
Liberal	Binary	= 1 if respondent indicated they were politically liberal
Age	OrderedCategorical	Respondent’s age: ranging from “18-24" up to “75+"
Higher Edu.	Binary	=1 if respondent indicated they has a bachelors degree of higher
Retired	Binary	= 1 if respondent indicated they were retired
Household Size	Discrete	Number of members in household
New to Coast	Binary	= 1 if respondent indicated they were new to the coast
Life Time Resident	Binary	= 1 if respondent indicated they have lived on the coast most or all of their life
Coastal Vet.	Binary	= 1 if respondent indicated they had lived on the coast for all or most of their life
Flood Damage	Continuous	The amount of the most recent flood damage (in dollars) the respondent had incurred
Flood Settlement	Binary	= 1 if respondent had received an insurance settlement for any reported flood damage
Prior Flood	Discrete	=1 if respondents home has been damaged from flooding

Table A3. Variable Descriptions

Variable	Type	Description
Panel C: Expectations		
Exp. Increase (Insurance Prem.)	Binary	= 1 if respondent expected insurance premiums will increase.
Exp. Increase (Home Prices)	Binary	= 1 if respondent expected home prices will increase.
Exp. Increase (Taxes)	Binary	= 1 if respondent expected taxes will increase.
Worse Erosion	Binary	= 1 if respondent expected erosion will get worse.
Nourishment	Binary	= 1 if respondent expected beach nourishment will preserve beaches.
Worse Storms	Binary	= 1 if respondent expected coastal storms will get worse.
Armoring	Binary	= 1 if respondent expected coastal armoring will protect personal property.
Retreat	Binary	= 1 if respondent expected parts of the coast will need to embrace coastal retreat.
Exp. Disaster Aid (Individual)	Binary	= 1 if respondent expected government grants to be available for for rebuilding personal property after a hurricane
Exp. Disaster Aid (Public)	Binary	= 1 if respondent expected government assistance to help rebuild infrastructure and beaches after a hurricane
Exp. Disaster Aid (Loans)	Binary	= 1 if respondent expected access to low interest loans for rebuilding personal property after a hurricane
Exp. Disaster Aid (Emergency Response)	Binary	= 1 if respondent expected emergency first response after a hurricane

Notes: Respondents were defined as “expecting" or “agreeing with" a statement if they indicated a 3 or higher on a 5 point scale for that statement.

Table A4. Variable Descriptions

Variable	Type	Description
Panel D: Opinions		
Coast Overdeveloped	Binary	= 1 if respondent agreed that coast is overdeveloped
Housing Too Expensive	Binary	= 1 if respondent agreed that coastal housing is too expensive
Insurance Too Expensive	Binary	= 1 if respondent agreed that insurance is too expensive
Coast Too Congested	Binary	= 1 if respondent agreed that the coast is too congested
Need Better Infrastructure	Binary	= 1 if respondent agreed that the coast needs better infrastructure
Regulations Stifle	Binary	= 1 if respondent agreed that building regulations stifle the coastal economy
Development Threatened	Binary	= 1 if respondent agreed that the coast is changing in ways that threaten current development
Govt. Policy	Binary	= 1 if respondent agreed that local government policies have helped alleviate risk on the coast
Panel E: Perceptions		
Expected Hurricanes	Continuous	Expected number of cat. 3 hurricanes expected to pass within 25 miles over next 50 years.
Expected Damage	OrderedCategorical	Expected damage as a share of home value from cat 3. hurricane (1 indicates 0% - 20% up to 5 indicating 81% - 100%)
Underweight Low Prob.	Binary	= 1 if respondent thought lowest probability weather event in the risk instrument was too high.
Overweight Low Prob	Binary	= 1 if respondent thought lowest probability weather event in the risk instruments was too low.
Underweight High Prob.	Binary	= 1 if respondent thought highest probability weather event in the risk instrument was too high.
Overweight High Prob	Binary	= 1 if respondent thought highest probability weather event in the risk instruments was too low.
CRRA	OrderedCategorical	Elicited CRRA value from risk preference instrument

Notes: A respondent is said to "expect" an outcome if they indicated a 3 or higher on a 5 point scale indicating the likelihood of the outcome occurring.

Table A5. Variable Descriptions

Variable	Type	Description
Panel F: Worry		
Worry Index	Discrete	Total number of domains respondent indicated worrying about, excluding home loss due to natural disaster.
Worry (Cancer)	Binary	= 1 if respondent worried about getting cancer
Worry (Family Death)	Binary	= 1 if respondent worried about a family member dying
Worry (Family Car Accident)	Binary	= 1 if respondent worried about someone in their family being in a traffic accident
Worry (Violent Crime)	Binary	= 1 if respondent worried about being a victim of a violent crime
Worry (Pollution)	Binary	= 1 if respondent worried about pollution in their environment
Worry (Home Loss)	Binary	= 1 if respondent worried about the loss of their home to natural disaster
Worry (Having Friends)	Binary	= 1 if respondent worried about not having enough close friends
Worry (Attractiveness)	Binary	= 1 if respondent worried about being attractive
Worry (Relationship)	Binary	= 1 if respondent worried about their closest relationship breaking up
Worry (Life Meaning)	Binary	= 1 if respondent worried about their life not being meaningful
Worry (Career Path)	Binary	= 1 if respondent worried about things not working out in their studies or job
Worry (Family Having Money)	Binary	= 1 if respondent worried about a family member not having enough money
Worry (Current Job)	Binary	= 1 if respondent worried about not being able to get or keep a good job
Worry (Financial Difficulty)	Binary	= 1 if respondent worried about financial difficulty in the future

Notes: A respondent is said to “worry" about an issue if they indicated a 3 or higher on a 4 point scale indicating their level of worry over the outcome occurring.

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