Understanding Individual Risk Preferences

by

Sulakshan Neupane

(Under the direction of Craig Landry)

Abstract

Many theories of decision making under risk focus on risk perceptions, the most conventional of which are the likelihoods of occurrence and an evaluation of the conditional outcomes. Focusing on hurricane risk, we examine likelihood, expected damage, and expected loss using responses collected from southeastern coastal counties of the USA via mail or online in different periods. Our results indicate that subjective probability of category 3 hurricane, expected damage, and perceived loss is affected by the number of years residents have lived on the coast, previous hurricane exposures, prior experience of flooding damage, education, and gender. Perceived risk is significantly higher in North Carolina and lower in Mississippi relative to Texas. Our results indicate a significant anchoring effect.

Index words: hurricane, risk perceptions, expected damage, loss

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Chapter 1

Introduction

The concept of risk has been used by human beings to describe and analyze various uncertainties in life. A standard construct for describing risk is quantified by the likelihood of occurrence and magnitude of impact (Schwing and Albers 1980)[27]. In the domain of loss, this is defined as the probability of an unfavorable event and the magnitude of damage (Kaplan and Garrick, 1981)[14]. Risk can also be represented as the variance of the probability distribution over the utilities of all possible consequences (Vlek and Stallen, 1980)[39]. Yates and stones (1992)[43] specified loss, the significance of the loss, and uncertainty of loss as the three major components of risk construct. Trimpop (1994)[36] defines risk-taking as any consciously, or unconsciously controlled behavior with a perceived uncertainty about its outcome, and/or about its possible benefits or costs for the physical, economic or psycho-social wellbeing of oneself or others.

Risk is intrinsically a subjective concept, with perception depending upon who is the observer (Kaplan and Garrick, 1981)[14]. It has a different meaning to different people under different circumstances, and distinct circumstances may require different definitions of risk. Large scale societal risks like wars and nuclear meltdowns differ from individual-level risks such as road accidents, injuries, etc. Risk can be conceptualized uniquely by different groups of people, and risk is differently understood in the context of distinct activities (Vlek and Stallen, 1981)[38]. From a behavioral perspective, the risk is a subjective concept, which can have strong or tenuous links to objective reality; much of the literature on decision making under risk, however, is based on the objective assessment of risk. Many plans, policies, and programs are designed based on objective measures of behaviors estimated by experts.

Concern over risk dates back to early mankind's history. The first recorded instance of the risk analysis was the practices carried out by the Asipu in Mesopotamian civilization as early as 3200 B.C., which signifies that people have been dealing with the risk-related problems quantitatively for a long period (Grier, 1981)[9]. The Asipus served as the consultant for risky, uncertain, or difficult decisions by identifying dimensions of the problem, designing alternative actions, and collecting data on likely outcomes, like profit/loss and success/failure. They expressed their results with confidence, certainty, and authority as they were empowered to read god signs, and probability played no part whatsoever (Covello and Mumpower 1985)[6]. Various theories and ideas have been used since the early days of human civilizations to characterize risk and estimate its severity. Even the simplest, most straightforward hazard evaluations depend on theoretical models, whose structure is abstract and presumption laden and whose information sources are reliant upon judgment (Slovic, 2000)[33]. The major categories based on which the natural and technical science judges risk are the extent of harm caused in the context of health, environment, infrastructure, and capital and the probability of occurrence (Renn, 2008)[25]. In general, the risk is the uncertain outcome of any event or action of human beings concerning something we value and risk perceptions refer to various types of attitudes people have or judgments they make about risks and hazards that they are facing or might have to face in the future (Trimpop, 1994)[36]

Risk perception has been the concern of numerous researchers, especially from a psychological or psychometric perspective (Slovic, 2000)[33]. Risk Perception refers to peoples' attitudes, judgment, and analysis of the risk/hazards that they are facing or might have to face in the future. The type of risk and situational context lead to different risk perceptions among individuals. The knowledge about risk, previous experiences, values, emotions, and attitudes all can affect perceptions of risk (Wachinger et al.,2013[40]. There is a vast literature on the relationship between risk perception and behavioral actions of the individual relative to preparedness and management of risk, but many questions remain to be explored. Some of the literature indicates that experience of a negative risky outcome can lead to a greater perception of risk, which then feeds into more efforts toward preparedness and management of risk, but the opposite might occur as well (Wachinger et.al., 2013)[40]. This may be due to experience and motivation, economic and personal conditions, or trust and responsibility issues. Despite perceiving a significant risk, one may not be able to mitigate due to a lack of resources. The person may think this is not their responsibility, but that of someone else, or benefit may not appear to outweigh the associated risk.

Risk-taking is consciously or non-consciously controlled behavior with a perceived uncertainty about its outcome, and/or about its possible benefits or costs for the physical, economic or psycho-social well-being of oneself or others (Trimpop, 1994)[36]. With proper design of survey instruments, one can attempt to quantify measures of risk perception and test psychological, social, institutional, and cultural factors that may influence those perceptions (Slovic, 1992)[32]. Psychometric Paradigm and Cultural Theory have dominated most of the study on the perception of risk. Psychometric Paradigm theory is based on psychological aspects and decision outcomes; a fundamental assumption to this theory is that risk is an intrinsically subjective concept, which can be measured (Slovic, 1992)[32]. This theory has found some success primarily in the qualitative assessment of risk perception. The cultural theory, on the other hand, is a newer approach and is a deviation from psychological assessments of risk. It deals with society, culture, and political structures to assess risk perceptions. Research on risk perception has examined peoples' judgment and evaluation of various hazardous activities and technologies (Slovic, 1987)[31]. By assessing risk-taking on a societal or an individual level, dimensions of subjective/objective risk can be further differentiated (Vlek & Stallen,1980)[39]. Demographic factors such as age and gender can be important in the context of determining individuals' risk perceptions (Kellens et al., 2011 & karanci, 2005)[16, 15]. Besides, personal and risk factors, direct experience of the natural hazards are important in determining the risk perception (Felgentreff 2003, Grothmann and Reusswig, 2006, Terpstra 2010, 2011, Siegrist 2006) [8, 10, 35, 34, 29]. Thus, results of literature review suggest personal, contextual, informational, and risk factors are major determinants of risk perceptions among individuals; risk characteristics, such as familiarity with a type of disaster event and expected or experienced frequency over time, can have significant impacts in shaping risk perception among individuals (Wachinger et al.,2012)[40]. From this perspective, the probability of the undesired events and the potential for harm are important constructs for understanding risk perception (Slovic, 1987 & Renn, 2008)[31, 25]. Some studies (Miceli et al., 2008 &Heitz et al., 2009) [20, 12], however, suggest these characteristics of risk are of little importance in determining individuals' assessment and response to risk.

Many papers suggest that women and men differ in their perception of risk without explaining much about the mechanism, why, and how they differ. Gustafsod (2006)[11] argued that gender structures, reflected in gendered ideology and gendered practice, give rise to differences in risk perceptions. Bateman and Edwards (2002)[3] conducted a series of bivariate and multivariate logistic regression of the response collected from the North Carolina households affected by a hurricane and found that men are less likely to evacuate than women because they live at less exposure to risk and they perceive less risk compared to women. Due to gender differences in assigned roles in the society (like caregiving), access to evacuation resources, greater exposure to risk, and high perceived risk, women are more likely to evacuate than men. But the condition could be that men exposed to the higher risky environment are more likely to evacuate than women. Similarly, using multivariate analysis, Kung and Chen (2012)[17] found that gender and previous experience have a significant impact on risk perception. Also using multivariate analysis to study climate change risk, Lujala et al. (2015 [19] found that the differences in attitudes and perceptions are partially explained by gender, educational background, and political preferences. An important factor explaining people's perception of climate change and its possible consequences, however, is their direct personal experience of damage caused by weather-related events such as floods and landslides. This suggests that previous experience is an important determinant of risk perception (Wachinger and Renn, 2010)[41].

The perception of natural hazards is not always consistent across time. Over a period, the level of risk perception for a hurricane can change (Trumbo et.al., 2014)[37]. The effectiveness of information sources can heighten an individual's sense of risk and make them more likely to evacuate (Burnside, 2007)[5]. Hurricane evacuation behavior is a very complex phenomenon influenced by several factors. Many papers in the past have tried to explain the evacuation behavior. Dash and Gladwin (2007)[7] reported that various factors are responsible for evacuation behavior, like age, presence of children/elderly/disable people in the household, gender, ethnicity, income, previous experiences, location of the house, and pet ownership. Various models have been suggested to study evacuation behavior. Whitehead et al. (2000)[42] used the coefficient of the logistic regression model to find how much the subjective and objective explanatory variables impact evacuation behavior and identified intensity of the storm as the major forecaster of evacuation behavior. Also, the perception of flood risk, evacuation orders, and mobile home status lead to a higher likelihood of evacuation. While exploring risk avoidance behavior, this paper does not examine the heterogeneity of risk perception among households. Plapp & Werner (2006)[24] studied factors influencing the natural hazard risk perception in Germany using the Psychometric and cultural theoretic approach and found different influencing factors for general and personal risk. The major factors associated with the general perception of risk are perceived personal risk, fear raised by hazards, knowledge level of the exposed population, likelihood of occurrence of risky events, and its consequences. Whereas personal perception of the risk is affected by the personal experience of the disaster in the past. Perceptions of flood risk immediately after a flood event were investigated by Felgentreff, (2003)[8]; they reported that the perception and awareness of risk is the way more immediate aftermath of the flood event and the level drops back significantly after some period. Some people prepare for precautionary measures, while some do not take such measures in high flood risk areas. The major factor influencing people to take such precautionary measures is personal perception rather than its impacts and previous flood exposures. Homeownership leads to motivation in adopting precautionary measures, as well (Grothmann & Reusswig, 2006)[10]. Ho et al. (2008)[13] studied how risk perception is influenced by disaster type and victim characteristics. They found gender differences in perception of risk, which was measured using the likelihood of a disastrous event, acquaintance with mitigation actions, and perceived financial loss. Type of disaster is a good predictor for both factors of risk perception i.e., impact and level of control. Victims with more experience of the disaster perceived higher occurrence rate of disasters.

In this paper, we try to elicit information on subjective risk perceptions in the context of hurricane hazards. The USA has sustained 265 weather and climate disaster in the period between 1980 and 2020, inflicting loss of more than $1.7 trillion. Tropical cyclones and hurricanes alone resulted in a loss of $945.9 billion, more than all other natural disasters combined (NOAA, 2020). Much focus has been put upon objective measures of risk(national storm surge hazard maps, mapping special flood hazard area) indicating probabilities of hazard events, possible damage, and return period. Perceptions of the risk, however, are arguably more important when it comes to individual decision making, especially given that individual risk perceptions may differ from objective measures of risk (Siegrist & Gutscher

2006)[29]. Existing literature focuses on either probability of events or expected damage in their risk perceptions studies, but usually not both. As risk perceptions are defined as perceived probability times expected damages, then any study ignoring one of these measures suffers from major identification issues, which may limit the generality of results. Previous literature also tells us little about how risk perceptions are formed as they tend to treat risk perceptions as an independent variable. We explore subjective risk perceptions focusing on the perceived probability of category 3 hurricane, expected damage, and perceived losses. In light of this motivation, we try to understand the underlying determinants of the subjective perceptions of the likelihood of disaster and conditional loss. In this research, we look at the effect of previous exposure to risks and experience on individuals' risk perceptions. We also look at the anchoring effects and how they manifest in the measurement of subjective risk perceptions. To address our research objectives, we employed four unique data sets encompassing questionnaire responses collected from different periods and distinct locations. We focus on coastal communities of the southeastern USA in our research.

Chapter 2

Data

For our study, we employed unique data sets, encompassing 1849 questionnaire responses collected from households in different periods and distinct locations, using web-based and mail modes. The survey characteristics are shown in Table 1. The first data set is a pilot study conducted via mail in Dare County, NC in 2006. This modest-sized data set includes 137 responses and contains individual-level information on the expected number of Category Three hurricanes to strike Dare County over the next 50 years and the expected home damage (as a percentage of structure value) that would occur from such a strike. These question formats are repeated in subsequent data sets: a web-based survey of the Gulf Coast in 2010 (N=859)(Landry et. al., 2019[18]; Petrolia et.al., 2015[23]; Petrolia et.al.,2013[22]); a mixed mode (online and mail) survey of Mobile Bay, AL and Pensacola Bay, FL in 2013 (N=582); and a mail survey of Glynn County, GA collected via mail in 2018 (N=261). The Gulf Coast survey comprises 96 counties within Alabama (N=21), Florida (N=256), Louisiana (N=103), Mississippi (N=12), and Texas (N=197). The Mobile_Pensacola data set does not include information on risk preference, but does have data on risk perception and household risk mitigation decisions(Scyphers et. al., 2019)[28]. This data set is split 60% Mobile, AL, 40% Pensacola, FL. Similar to other surveys, the Glynn County instrument included risk perception questions to assess the likelihood of Category Three hurricane and expected conditional damage. All respondents in each survey are aged 18 years or older and residential property owners. Also, we used storm events database from the National Oceanic and Atmospheric Administration, NOAA's national weather service(NWS) to come up with hurricane, flood, and wind exposure details in the previous periods (1988-2015).

Table 1: Survey Characteristics

	Dare County	Gulf Coast	Mobile Bay	Glynn County
Year	2006	2010	2013	2018
Survey Type	Online	Online	Online	Mail
State	NC	AL, FL, LA, MS, TX	AL, FL	GA
No. of Observations	137	859	582	271

2.1 Descriptive Statistics

Table 2 shows the pooled descriptive statistics used in our analysis. The mean age of the respondents was 55 years. About 51.1% were male, 85.6% were white, and 56.1% had obtained at least a bachelor's degree. State-wise, majority of the respondents (44.3%) were from Florida followed by Alabama (16.7%), Georgia (14.7%), Texas (10.7%), North Carolina (7.4%), Louisiana (5.6%) and Mississippi (0.6%). While 14.2% of the respondents had lived in the coast for 3 years or less, 42.1% were coastal veteran, that is, they had lived in the coast for 20 years or more. Similarly, 23.7% of the respondents' reported their home being previously damaged by a flood once, and 22.8% reported their home being damaged by flood multiple times. The mean number of hurricanes that passed within 50 kilometers of the respondents' county of residence one year prior to the survey was 0.4 (SD=0.7); for 5 years prior to the survey, it was 2.5 (SD=1.7); and for 10 years prior to the survey, it was 3.3 (SD=2.2). The mean probability of the expected number of category 3 hurricanes over the next 50 years was 0.17 (SD=0.22). Likewise, the mean expected damage of category

3 hurricanes as a percentage of home values was 38% (SD=25%). Mean expected loss was calculated to be 0.06 (SD=0.11).

Table 2: Descriptive Statistics (Pooled Data)

	mean	sd	min	max
Prob(Cat 3)	0.17	0.22	0	1
Cat 3 Damage	0.38	0.24	0	1
Expected Loss	0.06	0.11	0	1
New to Coast	0.14	0.35	0	1
Coastal Veteran	0.42	0.49	0	1
One Flood	0.24	0.43	0	1
Multiple Floods	0.23	0.42	0	1
Hurricanes ($\leq$ 1yr)	0.37	0.66	0	2
Hurricanes (1 - 5yr)	2.53	1.65	0	7
Hurricanes (5 - 10yr)	3.29	2.22	0	8
Age	55.20	15.02	18	94
FL	0.44	0.50	0	1
MS	0.01	0.08	0	1
AL	0.17	0.37	0	1
LA	0.06	0.23	0	1
GA	0.15	0.35	0	1
NC	0.07	0.26	0	1
time	5.89	3.05	1	12
White	0.86	0.35	0	1
Male	0.51	0.50	0	1
Income Cont	0.51	0.50	0	1
Higher Edu.	0.56	0.50	0	1
Observations	1849			

Means of variables separated by data set are given in Table 3

Glynn dataset

This contains data collected from coastal residents of Glynn County, Georgia. The mean age of the respondents was 55.16 years. The majority of the respondents were males (70%), white (87%), and 44% had obtained at least a bachelor's degree. While 38% were coastal veterans, only 6% were new to the coast. And while 11% reported that their home was previously damaged by a flood once, only 5% reported that their home was previously damaged by flood multiple times. The mean number of hurricanes that passed within 50 kilometers of the respondents' residence was 0 within a year before the survey, and 1 between 1-5 years and between 5-10 years prior to the survey. The mean probability of the expected number of category 3 hurricanes over the next 50 years was 19%. Similarly, the mean expected damage as a percent of home values was 43%, and the mean expected loss was 8%.

Mobile Bay dataset

This contains data collected from coastal residents of two counties in Alabama (Mobile and Baldwin) which lie along the Mobile Bay, and two counties from Florida (Escambia and Santa Rosa) which lie along the Pensacola Bay. The mean age of the respondents was 52.69 years. The majority of the respondents were females (54%), white (88%), and had obtained at least a bachelor's degree (55%). While 25% were new to the coast, only 18% were coastal veterans. And while 34% reported that their home was previously damaged by a flood once, 46% reported that their home was previously damaged by flood multiple times. The mean number of hurricanes that passed within 50 kilometers of the respondents' residence was 0 within a year before the survey, 2.45 between 1-5 years prior to the survey and 2.76 between 5-10 years before the survey. The mean probability of the expected number of category 3 hurricanes over the next 50 years was 16%; the mean expected damage as a percent of home values was 43%; the mean expected loss was 7%.

Gulf dataset

This contains data collected from coastal residents from 92 counties from five states (Louisiana, Mississippi, Alabama, Florida, and Texas) located along the Gulf of Mexico. The mean age of the respondents was 56.21 years. The majority of the respondents were females (56%), white (81%), and had obtained at least a bachelor's degree (58%). While 59% were coastal veterans, only 6% were new to the coast. And while 22% reported that their home was previously damaged by a flood once, only 15% reported their home being previously damaged by flood multiple times. The mean number of hurricanes that passed within 50 kilometers of the respondents' residence was 0.47 within a year before the survey, 2.35 between 1-5 years prior to the survey, and 3.62 between 5-10 years prior to the survey. The mean probability of the expected number of hurricanes was 15%; the mean expected damage as a percent of home values was 34%; the mean expected loss was 5%.

Dare dataset

This contains data collected from coastal residents from Dare County, North Carolina. The mean age of the respondents was 59.04 years. The majority of the respondents were males (76%), white (98%), and had obtained at least a bachelor's degree (73%). While 46% were coastal veterans, 33% were new to the coast. And while 15% reported their home being previously damaged by a flood once, only 7% reported their home being previously damaged by flood multiple times. The mean number of hurricanes that passed within 50 kilometers of the respondents' residence was 2 within a year prior to the survey, 7 between 1-5 years prior to the survey and 8 between 5-10 years prior to the survey. The mean probability of the expected number of hurricanes was 29%; the mean expected damage as a percent of home values was 35%; the mean expected loss was 10%.

Table 4 shows the description of variables used in our analysis.

Table 3: Means: Seperated by Data Set

	Glynn mean	Mobile Bay mean	Gulf mean	Dare mean
Prob(Cat 3)	0.19	0.16	0.15	0.29
Cat 3 Damage	0.43	0.43	0.34	0.35
Expected Loss	0.08	0.07	0.05	0.10
New to Coast	0.06	0.25	0.06	0.33
Coastal Veteran	0.38	0.18	0.59	0.46
One Flood	0.11	0.34	0.22	0.15
Multiple Floods	0.05	0.46	0.15	0.07
Hurricanes ($\leq$ 1yr)	0.00	0.00	0.47	2.00
Hurricanes (1 - 5yr)	1.00	2.45	2.35	7.00
Hurricanes (5 - 10yr)	1.00	2.76	3.62	8.00
Age	55.16	52.69	56.21	59.04
FL	0.00	0.51	0.61	0.00
MS	0.00	0.00	0.01	0.00
AL	0.00	0.49	0.02	0.00
LA	0.00	0.00	0.12	0.00
GA	1.00	0.00	0.00	0.00
NC	0.00	0.00	0.00	1.00
time	12.00	7.00	4.00	1.00
White	0.87	0.88	0.81	0.98
Male	0.70	0.46	0.44	0.76
Higher Edu.	0.44	0.55	0.58	0.73
Observations	271	582	859	137

Table 4: Variables Description

Variable	Type	Description
Prob(Cat3)	Continuous	Expected number of category 3 hurricanes over next 50 years, normalized (0,1)
Dam. Cat3	Continuous	Expected damage from cat. 3 hurricane as a percentage of home value, normalized (0,1)
Expected Loss	Continuous	Prob(Cat3)* Dam. Cat3
New to Coast	Binary	=1 if the respondent has lived in the coast for 3 years or less
Coastal Veteran	Binary	=1 if the respondent has lived in the coast for 20 years or more
One Flood	Binary	=1 if the respondent's home has previously been damaged from flooding single time
Multiple Floods	Binary	=1 if the respondent's home has previously been damaged from flooding multiple times
Hurricanes(0-1 year)	Continuous	Number of hurricanes that passed within 50km of respondent's county of residence one year prior to survey
Hurricanes(1-5 years)	Continuous	Number of hurricanes that passed within 50km of respondent's county of residence 1-5 years prior to survey
Hurricanes(5-10 years)	Continuous	Number of hurricanes that passed within 50km of respondent's county of residence 5-10 years prior to survey
Age	Continuous	Age of respondent
White	Binary	=1 if the respondents indicated race as white
Male	Binary	=1 if the respondents indicated they were male
Higher edu.	Binary	=1 if the respondents indicated they had obtained atleast bachelor's degree
GA, FL, MS, LA, TX, NC, AL	Binary	=1 if the respondents home was located in the respective state
Time	Year	Survey Year

Chapter 3

Method

Our dependent variables of interest are the subjective probability of category 3 hurricane and expected damage. To elicit the information on risk perceptions we asked following questions to the respondents:

Based on your experience, how many Category 3 hurricanes (winds 111-129 mph) do you expect to directly strike within 50km of your community over the next 50 years?

Using your best guess, how much damage (expressed as a percentage of home value) do you think your home would most likely suffer if a Category 3 hurricane strikes your community?

Based on existing literature, several independent variables that might influence our dependent variables are chosen. Independent variables are demographic characteristics of the respondents and other variables that may affect an individual's subjective probability of category 3 hurricane occurrence. Subjective probability is derived from the individual's judgment about whether a specific outcome is likely to occur depending only on the subject's experience and opinions. They are different from person to person. Previous exposure to natural hazards such as flood and hurricanes are considered. The number of hurricanes that passed within 50km of resident's county within the past year, 1 to 5 years, and 5-10 years before the survey is considered an important indicator of storm experience. The resident experiencing the flood damage previously, the number of years respondent has lived in the coast are other explanatory variables, we consider for the models.

Besides, standard demographic variables such as age, education level, race, and gender are included. To allow for intragroup correlation within counties, we used Cluster standard errors. We used the anchoring effect, psychological heuristic, to see whether the individual decision making is deviated from rationality depending upon the initial piece of information presented. The anchoring experiment employed a between-subject design; approximately half of the respondents were asked to indicate their expectation about the likelihood of a category 2 hurricane before being asked about the likelihood of category 3 hurricane. The other half of respondents were asked to indicate their likelihood of a category of 3 hurricanes before being asked about the likelihood of category 4 hurricane. Not all the surveys used anchoring experiment. The gulf coast (N= 859) and mobile bay data set(N=582) included anchors. We scaled the expected number of hurricanes to express it as an annual probability of category 3 hurricanes to (0,1). Thus, this dependent variable reflects the odds of a category 3 hurricane or greater striking within 50km of resident's county. Odds are the ratio of the probability that an event will occur to the probability that the event will not occur. Then we generated the log odds of the probability. Conversion to log-odds results in symmetry around 0, which is easier for result analysis.

$$\text{ln odds (Prob cat 3 hurricane)} = \ln\left[\frac{\text{Probability of Category 3 hurricane}}{\text{1 - Probability of Category 3 hurricane}}\right]$$

The log of 1 and 0 are positive and negative infinity respectively. So, to address this issue, we replaced probabilities of 1 and 0 as shown in equations below.

$$\text{ln odds (Prob cat 3 hurricane)} = \ln\left[\frac{0.99}{0.01}\right], \text{if probability of category 3 hurricane =1}$$

$$\text{ln odds (Prob cat 3 hurricane)} = \ln\left[\frac{0.01}{0.99}\right], \text{if probability of category 3 hurricane =0}$$

In our second model, we examine expected damage from category 3 hurricane. Our dependent variable is the log odds transformation of expected damage from category 3 hurricane. Independent variables are same in all three models.

$$\text{ln odds (Cat3 damage)} = \ln\left[\frac{\text{expected damage from cat. 3 hurricane}}{\text{1 -expected damage from cat. 3 hurricane}}\right]$$

We replaced,

$$\text{ln odds (Cat3 damage)} = \ln\left[\frac{0.99}{0.01}\right], \text{if (expected damage from category 3 hurricane =1}$$

$$\text{ln odds ((Cat3 damage)} = \ln\left[\frac{0.01}{0.99}\right], \text{if (expected damage from category 3 hurricane =0}$$

In our third model, we looked at the expected loss from category 3 hurricane. We multiplied expected probability of category 3 hurricane and expected damage to get the expected loss. Like other two models, the variable is transformed to log odds as,

$$\text{ln odds (Expected loss)} = \ln\left[\frac{\text{Expected loss}}{\text{1 - Expected loss}}\right]$$

We replaced,

$$\text{ln odds (Expected loss)} = \ln\left[\frac{0.99}{0.01}\right], \text{if Expected loss =1}$$

$$\text{ln odds (Expected loss)} = \ln\left[\frac{0.01}{0.99}\right], \text{Expected loss} = 0$$

We used standard linear regression focusing on three models for our analysis of risk perception. As our dependent variables of interest are log odds transformations, the parameter estimates are interpreted as the change in log odds as characteristics change, which is very difficult to understand and are not very intuitive. So, we calculated marginal effects of the dependent variables on the probability of expected number of Category Three hurricanes, expected damage, and perceived loss. We compute marginal effects at the observed mean values, which is reported in Table 5. Marginal effects for continuous variables are calculated as follows:

Δp=g($X_i\beta$)*ΔXi * Bj ; g($X_i\beta$) is PDF of probability

Δp= exp($X_i\beta$)/(1+ exp($X_i\beta)^2$ * ΔXi * Bj

Marginal effects for dummy variables are calculated as follows:

Δ Pr = [exp($X_i\beta$)/(1+ exp($X_i\beta$))]after - [exp($X_i\beta$)/(1+ exp($X_i\beta$))] before

Chapter 4

Results

4.1 Probability of Category 3 Hurricanes

The risk perceptions result from our model analysis are presented in Table 5. The table presents coefficients of marginal effects, and their significance at 1%, 5%, or 10% level. Table 6 shows coefficients of estimates without marginal effects.

Households that have lived on the coast for 3 years or less tend to perceive the probability of category 3 hurricane to be significantly higher. The perceived probability of category 3 hurricane increases by 4.7% if the resident is relatively new to the coast, keeping all other variables constant. Similarly, the perceived probability of category 3 hurricane increases by 0.5% if the resident is a coastal veteran. But this was insignificant in our analysis. As expected, households that have experienced single or multiple flooding damage tend to perceive the probability of a category 3 hurricane to be significantly higher.

If the household experiences single and multiple flooding damage, the perceived probability of category 3 hurricane increases by 2.8% and 5.4% respectively. Our results indicate a significant anchoring effect. Respondents who were asked to indicate their beliefs about the likelihood of a category 2 hurricane before being asked about the likelihood of a category

3 hurricane reported lower subjective likelihoods of a category 3 hurricane. In the presence of the anchoring effect, the perceived probability of category 3 hurricane decreases by 34%. The number of hurricanes that passed within the respondent's county prior to 1 year and 1-5 years of the survey is found to be significant. The probability increases by 2% and 1.1% if the household experienced a hurricane one year prior to the survey and between 1-5 years prior to the survey respectively. Considering demographic variables, respondents who are white, are male, and have attended higher education perceive lower expected probability of category 3 hurricane. However, education and race are found to be insignificant. Compared to Texas, the residents of North Carolina perceive higher probability of category 3 hurricane by 22.3% whereas residents of Mississippi perceive lower probability of category 3 hurricane by 7.3%.

Table 5: Risk Perceptions: Marginal Effect

	Probability	Damage	Expected Loss
New to Coast	0.047**	0.143***	0.016***
Coastal Veteran	0.005	0.015	0.002
One Flood	0.028*	0.031	0.007*
Multiple Floods	0.054***	0.040	0.010***
Anchoring Effect	-0.340***	0.076	-0.287***
Hurricanes ($\leq$ 1yr)	0.020*	-0.065***	-0.0013
Hurricanes (1 - 5yr)	0.011*	-0.022*	0.001
Hurricanes (5 - 10yr)	-0.032	0.018**	-0.001
Age	-0.001	-0.002***	-0.001***
FL	-0.031*	0.013	-0.001
MS	-0.073***	-0.097*	-0.017***
AL	-0.009	-0.017	-0.001
LA	0.011	-0.045	0.005
GA	-0.048	-0.074	-0.018*
NC	0.223***	0.630**	0.093***
time	0.022*	0.019*	0.007***
White	-0.009	-0.050**	-0.005
Male	-0.019***	-0.006**	-0.007***
Higher Edu.	-0.02	-0.010**	-0.002**

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

4.2 Expected Damage from Category 3 Hurricanes

We analyzed the expected damage from the category 3 hurricane as a percentage of home values. Households that have lived on the coast for 3 years or less tend to perceive the damage from the category 3 hurricane to be significantly higher. The expected damage from category 3 hurricane increases by 14.3% if the resident is relatively new to the coast. The relationship between perceived damage and coastal veterans is found to be positive but insignificant. The number of hurricanes that passed within 50km of the respondent's county of residence prior to one year of the survey is found to be significantly associated with perceived damage. If the respondent was exposed to hurricanes within one year prior to the survey, the perceived expected damage from category 3 hurricane decreases by 6.5%. Similarly, the perceived expected damage decreases by 2.2% if the resident experiences hurricanes between 1 to 5 years prior to the survey. Respondents who are male, white, and attended higher education are found to be significantly associated with the perceived expected damage. Similarly, with an increase in age by one year, respondents tend to perceive the damage from category 3 hurricane to be significantly lower by 0.2%. Relative to Texas residents, the perceived expected damage is 9.7% lower for Mississippi residents but 63% higher for North Carolina residents. This means the residents of North Carolina and Mississippi significantly differed in their perception of damage from category 3 hurricane compared to Texas. With previous experience of flooding damages, respondents tend to perceive higher expected damage as a result of category 3 hurricane, but the results were insignificant. The anchoring effect seems to have no significant effect on expected damage.

4.3 Expected Loss

We looked at the effect of various independent variables on the expected loss from the category 3 hurricane in the third model. As expected, respondents who are relatively new to

Table 6: Risk Perceptions

	Probability	Damage	Expected Loss
New to Coast	0.34**	0.36***	0.42***
	(0.17)	(0.12)	(0.10)
Coastal Veteran	0.04	0.05	0.05
	(0.09)	(0.09)	(0.07)
One Flood	0.21*	0.09	0.20*
	(0.12)	(0.09)	(0.11)
Multiple Floods	0.39**	0.12	0.27***
	(0.16)	(0.11)	(0.10)
Anchoring Effect	-0.38***	0.10	-0.30***
	(0.12)	(0.15)	(0.03)
Hurricanes ($\leq$ 1yr)	0.18*	-0.29***	-0.04
	(0.10)	(0.10)	(0.07)
Hurricanes (1 - 5yr)	0.10**	-0.10*	0.03
	(0.05)	(0.05)	(0.02)
Hurricanes (5 - 10yr)	-0.03	0.08**	-0.01
	(0.04)	(0.03)	(0.02)
Age	-0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
FL	-0.27*	0.04	-0.03
	(0.15)	(0.17)	(0.08)
MS	-0.86***	-0.31*	-0.68***
	(0.13)	(0.16)	(0.08)
AL	-0.08	-0.05	-0.01
	(0.16)	(0.19)	(0.08)
LA	0.09	-0.13	0.15
	(0.23)	(0.22)	(0.14)
GA	-0.46	-0.24	-0.51*
	(0.45)	(0.34)	(0.27)
NC	1.11***	1.04**	1.40***
	(0.39)	(0.40)	(0.18)
time	0.11*	0.09*	0.14***
	(0.06)	(0.05)	(0.03)
White	-0.10	-0.29**	-0.16
	(0.14)	(0.12)	(0.11)
Male	-0.42***	-0.16**	-0.41***
	(0.09)	(0.07)	(0.07)
Higher Edu.	-0.04	-0.17**	-0.13**
	(0.09)	(0.08)	(0.06)
Constant	-2.37***	-0.31	-3.52***
	(0.42)	(0.32)	(0.30)
Observations	1720	1730	1669

Notes: Cluster-corrected standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the coast tend to perceive the loss to be significantly higher. The perceived expected loss increases by 1.6% if the resident is new to the coast. Households that have experienced previous flooding damage perceived significantly higher loss. The perceived expected loss increases by 0.7% and 0.10% when the household experienced experience previous single and multiple flood damage respectively. Our results show a significant anchoring effect. Respondents who were asked to indicate their expected loss from a category 2 hurricane before being asked about the expected loss from category 3 hurricane reported lower perceived loss. In the presence of the anchoring effect, the expected loss decreases by 28.7%. Being a male and having attended higher education are found to be significantly associated with the loss. With an increase in age, respondents tend to perceive a significantly lower loss. The expected loss is 1.7% lower for Mississippi residents and 1.8% lower for Georgia residents, but 9.3% higher for North Carolina residents compared to Texas residents.

Chapter 5

Discussion

A finding from our analysis indicates that relatively new households who have lived on the coast for three years or less, tended to perceive the probability of hurricane occurrence significantly greater along with the greater expected damage and perceived losses due to hurricanes. New residents may be less informed about hazards like hurricanes and flooding damage, and they exhibit pessimistic assessments of risk. Their inexperience with catastrophic events and related damage may lead them to be fearful due to the underlying uncertainty and potential severity of catastrophes. As they gain more experience, their risk perceptions diminish. It is also possible, however, that their assessment is more accurate than those that have lived at the coast longer. Since natural hazards are rare events, living many years without experiencing losses may lead to a sense of complacency. Luckily, we have data on past losses and historical hurricane occurrences.

Our results suggest that households that have experienced single or multiple flooding damage tended to perceive the probability of hurricane and expected loss significantly higher. When the respondents were asked about the perceived probabilities of category 3 hurricane and expected damage, they could relate this with their own previous flooding damage experiences, hurricane exposures and provide estimates based on that event. This means previous experiences have a significant impact on risk perceptions. This is in line with the finding from the study by Siegrist & Gutscher (2006)[29], where they found respondents' experiences with flooding to be positively related to flood risk perceptions.

Our results suggest that the number of hurricanes that passed the respondent's county of residence within five years prior to the survey has a significant effect on the perceived probability of category 3 hurricane. But if we consider the prior time frame between 5-10 years of the survey, the effect is found insignificant. This can be related to the fading characteristics of the disaster experience. The study conducted by Bin and Landry (2013)[4] on changes in implicit flood risk premium after the major flooding events found significant risk premiums associated with flood prone property but such premiums diminishing over time which suggests that buyers' and sellers' of property tend to forget about flood risk over time and eventually their perceptions fade away. Similarly, Atreya et. al., 2013[2] showed flood risk discounts on properties disappeared between four to nine years after the flood. These findings can be related to our result analysis, and we infer that hurricane risk perceptions can fade away with time.

We find that females perceived a higher probability of hurricane, related damage, and expected losses, as compared to males. This is in line with the studies of Kung and Chen (2012), Bateman, and Edwards (2002)[3], Peacock et. al., (2005)[21], and Savage (1993)[26]. Higher perception of risk by females might be due to differences in gendered assigned roles and responsibilities and their exposure to the riskier environment than their male counterparts. Other reasons could be that females perceive their residence to be at more risk of damage. The sex difference in perceptions of risks and subsequent evacuation can be partly explained by differences in care-giving roles and family obligations (Acker, 1990)[1].

The results suggest that respondents with higher education levels tended to expect lower damage from the category three hurricane and subsequent loss; this could reflect prior flood risk mitigation decisions and investments in self-protection. White people perceived less subjective probability of hurricane and associated damage. These findings are like the results reported by many works of literature and confirm their findings (Savage, 1992; Lujala et. al., 2015, etc.,). The likely explanation for this could be personal exposure to the hazards. Those with lower education levels feel more insecure and have a heightened perception of disasters.

Chapter 6

Conclusion

Hurricanes and their related damages are one of the costliest natural hazards in United States coastal regions. Much focus has been laid upon objective measures of risk; mapping special flood hazard area, national storm surge hazard maps, etc. indicating probabilities of the hazard events, possible damage, and return period. Perceptions of the risk, however, are arguably more important when it comes to individual decision making, especially given that individual risk perceptions may differ from objective measures of risk (Siegrist & Gutscher 2006)[29].

We explore subjective risk perceptions as elicited in four survey data sets that employ the same measurement instruments; these include the expected number of Category 3 hurricanes to strike their community in the next 50 years (which we convert to the subjective probability of category 3 hurricane), expected damage from category 3 hurricane (expressed as a percentage of structure value), and expected loss from category 3 storm (the product of the two measures). We find that residents who are relatively new to the coast tended to perceive the probability of the category 3 hurricane to be significantly higher. They expected more damage and higher loss from the hurricane as compared to the coastal veterans who have lived on the coast for years. This result is in line with our expectations, in that coastal residents who are relatively new may not have experienced such hazards before and don't know what lies ahead of them, which can heighten their risk perceptions. Households that have experienced previous flooding damage perceived higher probability of category 3 hurricane and expected loss.

In this study, we are capable of exploring the relationship between perceptions and previous experience of hurricanes. The number of hurricanes passing resident's county within 50 km prior to one year, 1-5 of the survey has a significant impact on the perception of hurricane risks. But the number of hurricanes prior to 5-10 years of the survey is insignificant. We can infer this as fading characteristics of the disaster experience. Our results indicate a significant anchoring effect. To our expectation, males tended to perceive the lower probability of category 3 hurricanes, lower expected damage, and subsequently lower expected loss as compared to females.

North Carolina Residents are found to perceive the higher subjective probability of category 3 hurricane, expected damage, and expected loss relative to Texas. We find the opposite in the case of Mississippi, where households tended to perceive lower risk perceptions. Interestingly, white respondents perceived significantly lower damage from the category 3 hurricane. With more education, the expected damage and perceived loss is significantly lower which is in line with our expectation.

This research on risk perception of coastal residents can guide us to design and implement better plans and policies concerning coastal communities to some extent. The most obvious policy implication is that it would help design better flood insurance policies. Knowing how people perceive risk will help understand how people will respond to different flood insurance policies or if people will adopt flood mitigation techniques. This research has implications on future risk governance, designing effective communication of natural hazards, and finding an individual's willingness to invest in mitigation activities, and risk preparedness. Many theories have attempted to explain individual decision making and almost all of these theories incorporate risk perceptions in some way or other; that is, they either consider perceived likelihood of an event or perceived consequences not usually both. Our study considers perceived likelihood, expected damage, and expected loss which is very important in the context of hazard preparedness and mitigation activities. The advantage of the expected loss model used in our study is that it captures both concepts at the same time and both concepts probably matter for observed behavior.

Bibliography

[1] Joan Acker. "Hierarchies, jobs, bodies: A theory of gendered organizations". In: *Gender & society* 4.2 (1990), pp. 139–158.

[2] Ajita Atreya, Susana Ferreira, and Warren Kriesel. "Forgetting the flood? An analysis of the flood risk discount over time". In: *Land Economics* 89.4 (2013), pp. 577–596.

[3] Julie M Bateman and Bob Edwards. "Gender and evacuation: A closer look at why women are more likely to evacuate for hurricanes". In: *Natural Hazards Review* 3.3 (2002), pp. 107–117.

[4] Okmyung Bin and Craig E Landry. "Changes in implicit flood risk premiums: Empirical evidence from the housing market". In: *Journal of Environmental Economics and management* 65.3 (2013), pp. 361–376.

[5] Randolph Burnside, DeMond Shondell Miller, and Jason D Rivera. "The impact of information and risk perception on the hurricane evacuation decision-making of greater New Orleans residents". In: *Sociological Spectrum* 27.6 (2007), pp. 727–740.

[6] Vincent T Covello and Jeryl Mumpower. "Risk analysis and risk management: an historical perspective". In: *Risk analysis* 5.2 (1985), pp. 103–120.

[7] Nicole Dash and Hugh Gladwin. "Evacuation decision making and behavioral responses: Individual and household". In: *Natural Hazards Review* 8.3 (2007), pp. 69–77.

[8] Carsten Felgentreff. “Post-Disaster Situations as” Windows of Opportunity”? Post-Flood Perceptions and Changes in the German Odra River Region after the 1997 Flood”. In: *Erde* 134.2 (2003), pp. 163–180.

[9] B Grier. “The early history of the theory and management of risk”. In: *Judgment and Decision Making Group Meeting, Philadelphia, Pa.* 1981.

[10] Torsten Grothmann and Fritz Reusswig. “People at risk of flooding: why some residents take precautionary action while others do not”. In: *Natural hazards* 38.1-2 (2006), pp. 101–120.

[11] Per E Gustafsod. “Gender Differences in risk perception: Theoretical and methodological erspectives”. In: *Risk analysis* 18.6 (1998), pp. 805–811.

[12] Carine Heitz et al. “Local stakeholders’ perception of muddy flood risk and implications for management approaches: A case study in Alsace (France)”. In: *Land Use Policy* 26.2 (2009), pp. 443–451.

[13] Ming-Chou Ho et al. “How do disaster characteristics influence risk perception?” In: *Risk Analysis: An International Journal* 28.3 (2008), pp. 635–643.

[14] Stanley Kaplan and B John Garrick. “On the quantitative definition of risk”. In: *Risk analysis* 1.1 (1981), pp. 11–27.

[15] A Nuray Karanci, Bahattin Aksit, and Gulay Dirik. “Impact of a community disaster awareness training program in Turkey: Does it influence hazard-related cognitions and preparedness behaviors”. In: *Social Behavior and Personality: an international journal* 33.3 (2005), pp. 243–258.

[16] Wim Kellens et al. “An analysis of the public perception of flood risk on the Belgian coast”. In: *Risk Analysis: An International Journal* 31.7 (2011), pp. 1055–1068.

[17] Yi-Wen Kung and Sue-Huei Chen. “Perception of earthquake risk in Taiwan: Effects of gender and past earthquake experience”. In: *Risk Analysis: An International Journal* 32.9 (2012), pp. 1535–1546.

[18] Craig E Landry, Daniel R Petrolia, and Dylan Turner. “Flood Insurance Market Penetration and Expectations of Disaster Assistance”. In: *Available at SSRN 3371980* (2019).

[19] Päivi Lujala, Haakon Lein, and Jan Ketil Rød. “Climate change, natural hazards, and risk perception: the role of proximity and personal experience”. In: *Local Environment* 20.4 (2015), pp. 489–509.

[20] Renato Miceli, Igor Sotgiu, and Michele Settanni. “Disaster preparedness and perception of flood risk: A study in an alpine valley in Italy”. In: *Journal of environmental psychology* 28.2 (2008), pp. 164–173.

[21] Walter Gillis Peacock, Samuel David Brody, and Wes Highfield. “Hurricane risk perceptions among Florida’s single family homeowners”. In: *Landscape and Urban Planning* 73.2-3 (2005), pp. 120–135.

[22] Daniel R Petrolia, Craig E Landry, and Keith H Coble. “Risk preferences, risk perceptions, and flood insurance”. In: *Land Economics* 89.2 (2013), pp. 227–245.

[23] Daniel R Petrolia et al. “Wind insurance and mitigation in the coastal zone”. In: *Land Economics* 91.2 (2015), pp. 272–295.

[24] Tina Plapp and Ute Werner. “Understanding risk perception from natural hazards: examples from Germany”. In: *RISK21-coping with risks due to natural hazards in the 21st century*. CRC Press, 2006, pp. 111–118.

[25] Ortwin Renn. *Risk governance: coping with uncertainty in a complex world*. Earthscan, 2008.

[26] Ian Savage. “Demographic influences on risk perceptions”. In: *Risk analysis* 13.4 (1993), pp. 413–420.

[27] Richard C Schwing and Walter A Albers. *Societal risk assessment: How safe is safe enough?* Springer, 2013.

[28] Steven Scyphers et al. “Designing Effective Incentives to Reverse Coastal Habitat Degradation along Residential Shorelines”. In: *Available at SSRN 3443243* (2019).

[29] Michael Siegrist and Heinz Gutscher. “Flooding risks: A comparison of lay people’s perceptions and expert’s assessments in Switzerland”. In: *Risk analysis* 26.4 (2006), pp. 971–979.

[30] Lennart Sjöberg, Bjørg-Elin Moen, and Torbjørn Rundmo. “Explaining risk perception”. In: *An evaluation of the psychometric paradigm in risk perception research* 10.2 (2004), pp. 665–612.

[31] Paul Slovic. “Perception of risk”. In: *Science* 236.4799 (1987), pp. 280–285.

[32] Paul Slovic. “Perception of risk: Reflections on the psychometric paradigm”. In: 1992.

[33] Paul Slovic. *Risk, society, and policy series. The perception of risk*. 2000.

[34] Teun Terpstra. “Emotions, trust, and perceived risk: Affective and cognitive routes to flood preparedness behavior”. In: *Risk Analysis: An International Journal* 31.10 (2011), pp. 1658–1675.

[35] Teun Terpstra. “Flood preparedness: thoughts, feelings and intentions of the Dutch public”. In: (2010).

[36] Rüdiger M Trimpop. *The psychology of risk taking behavior*. Elsevier, 1994.

[37] Craig Trumbo et al. “An assessment of change in risk perception and optimistic bias for hurricanes among Gulf Coast residents”. In: *Risk analysis* 34.6 (2014), pp. 1013–1024.

[38] Charles Vlek and Pieter-Jan Stallen. “Judging risks and benefits in the small and in the large”. In: *Organizational Behavior and Human Performance* 28.2 (1981), pp. 235–271.

[39] Charles Vlek and Pieter-Jan Stallen. “Rational and personal aspects of risk”. In: *Acta psychologica* 45.1-3 (1980), pp. 273–300.

[40] Gisela Wachinger et al. “The risk perception paradox—implications for governance and communication of natural hazards”. In: *Risk analysis* 33.6 (2013), pp. 1049–1065.

[41] Gisella Wachinger et al. “Risk perception and natural hazards”. In: *WP3-Report of the CapHaz-Net Projekt. URL: http://www. caphaz-net. org. Synergien zwischen Naturschutz und Klimaschutz–Wasser/Gewässer (-Management)* (2010).

[42] John C Whitehead et al. “Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behavior”. In: *Global Environmental Change Part B: Environmental Hazards* 2.4 (2000), pp. 133–142.

[43] J Frank Yates and Eric R Stone. “The risk construct.” In: (1992).

Appendix A

Additional Figures

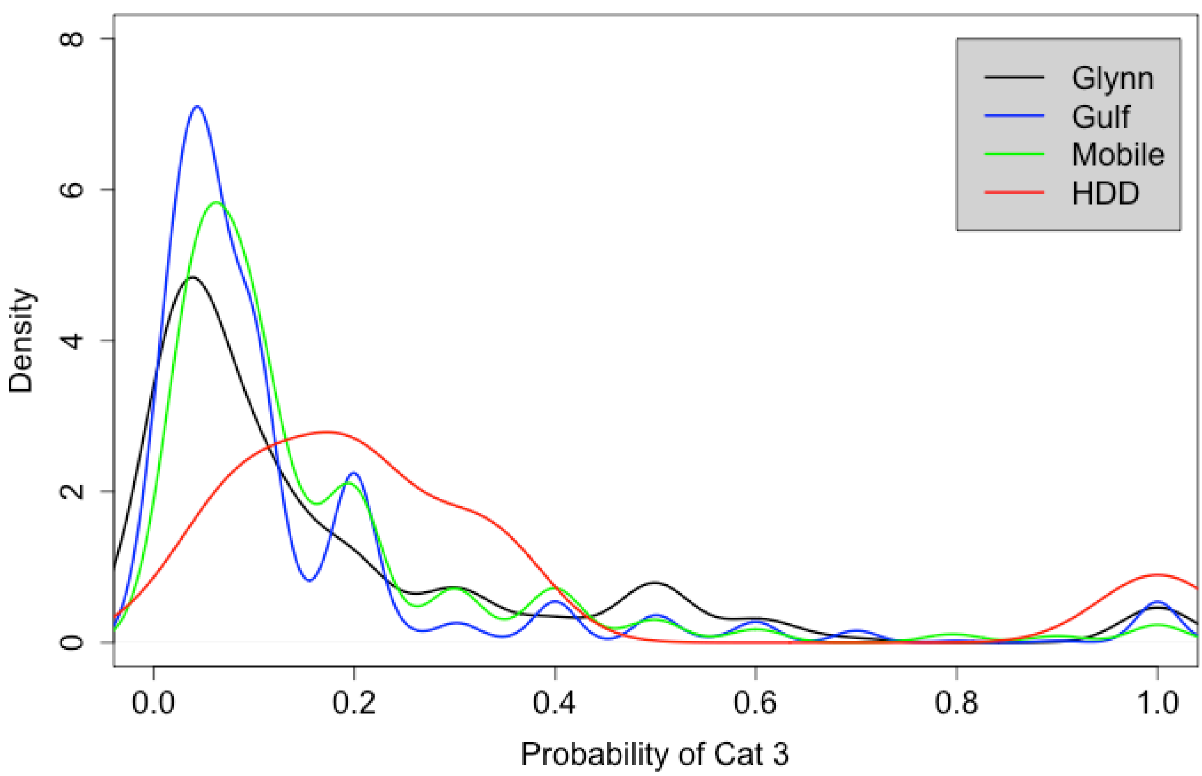

Figure 1: Probability Density of Category 3 Hurricane

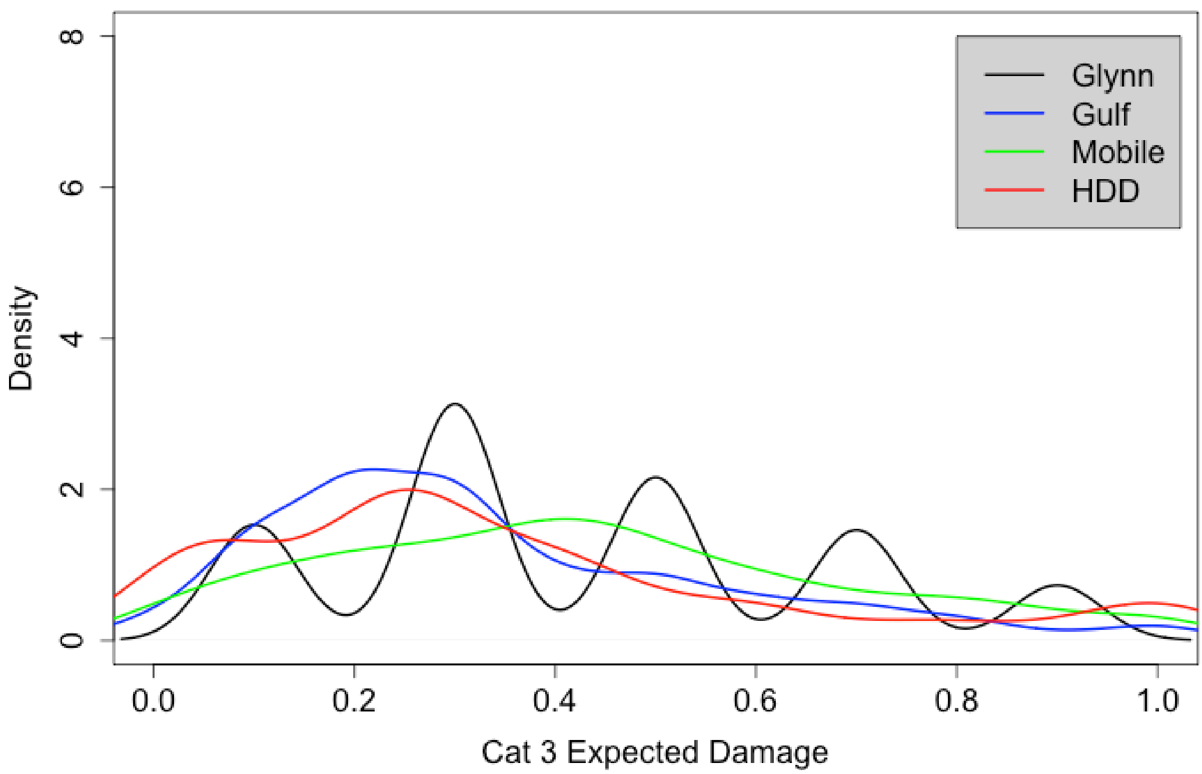

Figure 2: Probability Density of Expected Damage