# Flood Insurance Demand along the Gulf and Florida Coast

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## Problem Statement

Natural disasters cannot be completely controlled by human management. Recently, flood damage in the U.S. has dramatically increased (Flood). The total U.S. population in coastal areas increased by 28 percent between the year 1980 and 2003 (Crossett, et al. 2004). The property value in coastal areas has increased as well. In the U.S, the growth rate of real estate value in coastal areas has been, on average, over 7 percent during last 50 years (Bin and Kruse, 2006).The National Flood Insurance Program (NFIP) was introduced by the National Flood Insurance Act of 1978 to mitigate risk and loss of coastal and fluvial area residents from flood. NFIP offers discounted insurance premium rates and encourages people to protect themselves by constructing elevated houses or by installing storm shutters. Moreover, to prevent more properties from being exposed to flood hazard, NFIP provides fewer incentives for newly constructed buildings in flood zones. Despite the effort of the government to encourage people to buy insurance and reduce the damage level, many people still stay in uninsured (Burdy, 2001).

Each year many people suffer from flood damage. The National Oceanic and Atmospheric Administration (NOAA) estimated that since 1980, losses related in hurricanes—the main reason for flood—exceed $84 billion (Pinelli, et al, 2004). According to a report by Crossett, et al. (2004) addressing coastal area population change, Florida experienced the largest population growth in the U.S.— a 75 percent increase. Because of ocean-views and other natural amenities, people are willing to pay more for housing and other costs. A population increase also causes more businesses move into the area. As a result, the value of properties in coastal areas has dramatically increased (Bin and Kruse, 2006). Once a coastal area or fluvial area is damaged by a powerful flood such as the one caused by Hurricane Katrina or the Great flood in 1993, many people will suffer losses, and society will likely wish to provide financial aid to the area.

In this study, I want to observe residents in coastal areas and find factors that influence flood insurance purchase. For various reasons, people who have properties in flood-hazardous areas tend to avoid insuring their property from risk. By finding appropriate decision-making factors, the government could provide offers more attractive than current insurance.

**Literature review**

According to Kunreuther, people undertake risk mitigation actions because of underestimation of risk probabilities, short-run expectation for benefits, limited budget, influence of neighbors, and expectation for government aids after disasters (2006).

Kunreuther (1996) observed the importance of individual's risk perception for deciding whether to purchase insurance or not. Higher risk perception causes in more consideration for purchasing insurance. McClelland, Schulze, and Coursey (1993) conducted a laboratory experiment about bidding for insurance between high frequency-low damage and low frequency-high potential damages. They found that people tend to bid too much or nothing on high risk-low probability events. In other words, people are severely cared about the high risk-low probability event or ignore completely. After many trials with bad events, choices converged to two results: people who bid zero initially made positive bids and people who made positive initial bids decreased their bid or bid zero. With the same manner, people tend to dismiss probability of losses from floods, because it does not happen frequently, and they have rare experiences. Besides the real probability of risk, personal risk perception affects on insurance purchase.

Many researchers insist that income is an important variable in influencing insurance purchase. Browne and Hoyt (2000) addressed that a property owner with higher income has a greater probability of purchasing insurance and insure a greater amount than a property owner with lower income. At the first analysis, Landry and Jahan-Parvar (2010) could not find the significance of the income parameter, but when they divided income into several categories they found significant difference between higher income category and lower income category. Higher income householders purchase lager amount of coverage than lower income households.

The FHA (Federal Housing Administration) requires the purchase of flood insurance to mortgage loan borrowers if they want to loan FHA-backed mortgage for the house which located in flood zones. In their research, Kriesel and Landry (2004) found mortgaged properties have a 73 percent greater probability of purchasing insurance. Landry and Jahan-Parvar (2010) also found the mortgage is positively related to insurance purchase, though it is not a drastic correlation. However, Browne and Hoyt (2000) observed that mortgage and insurance purchase have a negative relation. They explained their unexpected finding due to avoidable elements of FHA mortgage conditions.

**Conceptual Framework**

The decision-making process with insurance differs from the decision-making process with commodity goods. People purchase insurances because of the uncertainty of the future, so insurance demand is affected by probabilities of risk. Smith (1968) and Mossin (1968) utilized the expected utility function to estimate the optimal insurance coverage level. Kriesel and Landry (2004) explained the decision to purchase insurance with the random utility maximization function. In this study, we focus on whether people purchase flood insurance or not.  Like Kriesel and Landry, we estimate the insurance demand by the utility maximization function. The utility function is $U_i (p_i, r_i, d_i)$, where $p_i$ is variables related to physical characteristics of the property which is covered by insurance (i.e., distance from coasts, having mortgage, flood zones, whether the house constructed before FIRM(Flood

Insurance Rating Map)), $r_i$ is variables related to individuals risk perception and risk preference, and $d_i$ is demographic characteristics such as income. The utility function without insurance is defined U (p, r, d). The demand is expressed as binary choice; if $U_i > U$ people purchase insurance, then "yes". In contrast, if $U_i < U$ people do not purchase insurance, then "no."

The maximum likelihood method is the most popular method for estimation of probability of insurance demand. Logit regression is utilized to estimate the maximum likelihood of this model.

## Methods and Data

We utilize the survey method to collect data. Usually, the survey method has a low response rate; therefore, to overcome this weakness, the survey is conducted by Knowledge Networks (KN). They are, to our knowledge, the only survey firm that can legitimately say they have a true probability based sample for an online because they employed Knowledge Penal who is recruited by using random-digit dialing (RDD) or by using address-based sampling. In order to include people do not have internet access, KN provides internet access to households. During August to September in 2010, NK recruited 1536 homeowners in 95 coastal counties along the Gulf Coast and Florida's Atlantic Coast which have a relatively high possibility of flood and population density including Al, FL, LA, MS, and TX. Of 95 coastal counties, 2 counties are from AL, 4 counties are from MS, 16 counties are from TX, 28 counties are from LA, and 35 counties are from FL. We have 1070 completed responses. However, there are some missing values; some respondents skip certain questions. The actual response rate is 47% (720 observations) with 67% from FL, 24% from TX, 5% from LA, and 4% collectively from AL and MS.

In order to observe risk-related characteristics, we measured risk perception, risk preference, and the total number of past flood damage experiences. People are asked about their expectation for risky events. They estimate how much damage will be incurred when Category 3 hurricanes hit their house directly. Answers are measured by percentage with a 10 percent interval, ranging from 0% to 100%. Higher percentage means higher expectation for risky events. Risk preference is estimated with a gamble. There are two choices for each question and, every time first choice has lower risk than another. Due to different probability of events we weighed answers. Higher risk choices count 1,2,3,4, or 5 points depending on probability, and lower-risk choice received 0 point. By adding all points, risk aversion is measured with a range from 0 to 15. Zero point means the participant is the most risk-loving and 15 points means the participant is the most risk-averse. Refer to table 1 for understanding survey questions. To find whether the previous flood damage experience affects decision-making for insurance purchase, we asked whether people had flood damage experiences.

Related to property characteristics we asked whether they have a mortgage loan for their house, whether they have flood insurance, and what year their house was constructed. Flood zones are organized into 5 categories from higher risk to low: V, A, B, C, non-flood zone. Only V and A zones have significant flood risk, therefore, we categorized flood zones as either SFHA or non-SFHA. SFHA includes V and A zones (1-percent annual chance flood), while other flood zones and the non-flood zone are included in non-SFHA. Queries for mortgage and insurance are simple binary questions. Additionally, based on property address, we measured the distance from coast to the house in meters. This is not directly related to insurance demand, but it can affect on people's risk perception. CRS (Community Rating System) reports and incentivizes voluntary participation in protective actions of communities where properties are located. A lower number implies more participation in CRS and results in a higher deduction of insurance premiums. In addition, construction year of properties are asked to compare difference before and after FIRM (Flood Insurance Rating Maps).

KN collects demographic information as well. Income is measured with 19 categories, with changing interval sizes. For example, first five categories increase by $2,499, and then difference is $4,999. For last four categories, which income is larger than $100,000, the difference increases by $24,999. House type is one of determinant for insurance premium, therefore, it probably affects on insurance demand. House type are divided to following five categories : Single-family house detached from any other house, single-family house attached to one or more houses, building with 2 or more apartments, mobile home, or boat, RV, etc.

**Results**

A total of 720 observations is included in the regression model. Whether a person has flood insurance or not is the dependent variable, and other variables which included in utility function are all independent variables. Table 2 compares characteristics of population and sample in terms of age, gender, education, and ethnic. The target population is people aged 18 and over residing in 95 coastal counties in the states of Alabama, Florida, Louisiana, Mississippi, and Texas. From the comparison, our sample is older than the population. The group of people 44 years or younger is smaller, and the group of people 60 years or older is larger than the population. Gender distribution is very similar; both have about 10 percent more female. For ethnicity, our sample has more Whites and fewer Blacks and Hispanics. Our sample is more educated. About 77 percent of our sample has at least high school degree, compare with 60 percent of the population.

The descriptive statistic for variables, including variable type, observation number, mean, standard deviation, minimum and maximum, is presented in Table 3. Only 35 percent of total respondents have flood insurance, and 63 percent of people have mortgage. On average, people are risk averse, but their risk perception is less than half. The mean distance from the coast is 15,784 meters, and the mean value of income ranges $50,000 to $99,999. Some variables are categorized, so the mean value is not as important.

Table 4 gives the detailed compositions of responses related to whether people have insurance. Among 720 observations, 252 (35%) people have insurance. More people who live in SFHA zone purchase flood insurance than those who live in non-SFHA zone: That is, 62% of those live in SFHA zone have insurance whereas 21% of those who live in non-SFHA zone have insurance. Next, the highest five and the lowest five categories of income are compared. Higher income categories have more positive answers for flood insurance purchase. There are two possible reasons; first, they have higher value of properties; second, they have more money. Lastly, we checked the relationship of mortgage loan and insurance purchase. People who have a mortgage loan purchase a slight amount of more flood insurance than people do not have it. With this simple comparison, we found those independent variables have an influence on the decision-making for flood insurance purchase.

For normality test, kurtosis is tested with STATA program. Kurtosis 3 means normal distribution, so less than or more than 3 is reporting skewness of distribution. Because most variables are not normally distributed, logit regression model is utilized to estimate the maximum likelihood. Coefficients in logit model have no meaning by themselves, so, for better understanding, marginal effects for each variable are calculated.

Regression results and marginal effects are reported on table 5. Mortgage positively correlated with flood insurance purchase. If a house owner has a mortgage for the house, the probability of flood insurance purchasing is 9.9 percent more than the probability of a house owner without mortgage. The mandatory requirement of flood insurance for mortgage loan of houses which are located in flood hazardous areas probably affects the decision. Perception of higher risk results in more likelihood of purchasing insurance. Based on the survey responses, if a person increases his or her risk perception by 10 percent—that is they expect 10 percent more damage from the Category 3 hurricane—, the probability of insurance demand increases 1.9 percent. Risk preference is measured with a range from 0 to 15, with higher numbers meaning more risk-aversion. One unit of increased risk preference also increases likelihood of insurance purchase by 3 percent. As expected, risk-averse people have a greater probability of purchasing flood insurance than the risk-loving, however, risk preference is not significant at the 0.1 level. From literature reviews, it is known that income is positively related to insurance purchase. That is also indicated by regression results. Flood zone have a significantly positive coefficient. The marginal effect is 0.301, namely when the house is located in SFHA zone, the house owner has a 30 percent greater probability of purchasing flood insurance than a house owner in non-SFHA zone. Besides well-known influential variables, we observed the distance from coasts in order to estimate the risk perception related to location. The distance is negatively related in insurance purchase. A location farther from the coast reduces the probability of insurance purchase. Related to negative incentive for new constructions in flood hazardous areas, preFIRM properties have positive coefficient, therefore, properties are constructed before FIRM have more probability for flood insurance purchase. CRS also exhibits positive probability for insurance. Properties located in lower-rate participation communities are more likely to purchase flood insurance. Lastly, the influence of the past flood damage experience on insurance purchase is positive. People who have post flood damage have 4.2 percent more likely to purchase insurance, but the probability is not significant at the 0.1 level.

## Conclusions

As expected, insurance purchase is positively affected by the individual's risk perception, their risk preference, whether or not they have a mortgage, flood zone residence, their income, CRS, previous flood experience, and the year of construction of house. Coefficients of mortgage and risk perception, income, flood zone are significant at 0.05 the level. Additionally, the coefficient of distance from the coast is only significant at the 0.1 level. In this study, we did not include property value in the model, because collected data quality was poor. To improve data we looked at real market values, but there was not enough information. For later studies, a more accurate measurement of house prices is required to get precise data. In addition, instead of using insurance premium, we utilized indirect measurement such as CRS. Participation in CRS reduces the insurance premium, and by observing CRS, the relationship between insurance premium and demand is indirectly observed. Moreover, we found interesting result from CRS. As more communities participate in CRS, insurers in those communities receive more deductions for insurance premiums. Therefore, because of the deducted price, people have less price constraint in purchasing flood insurance. However, this results in homeowners in lower participating communities being more likely to purchase flood insurance. Lowe-participation communities employ less protective action for flood damage, and as a result, homeowners perceive more risk. This indicates that the decision-making process purchasing insurance not only considers the price but also risk. For better understanding for flood insurance demand, various approaches for risk analysis are recommended.

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Table 1. Survey Questions Sample

Risk perception

Q22. Suppose a Category 3 hurricane (wind speeds of 111-130 mph) did directly strike your community. How much damage **(expressed as a percentage of total structure value)** do you think your home would most likely suffer?

0%----------20%----------40%-----50%-----60%----------80%----------100%
(no damage) (moderate damage) (severe damage) (total loss)

Risk Preference

Q.32 For the following, please indicate which possibility of *gain*, you prefer to face. Keep in mind that one of these will be chosen to determine your actual earnings, so please take each decision seriously!

| | |
|---|---|
| ○ | A 1-out-of-10 chance of gaining $5 and a 9-out-of-10 chance of gaining $4 |
| | OR |
| ○ | A 1-out-of-10 chance of gaining $9.50 and a 9-out-of-10 chance of gaining $0.50 |

Table 2. Comparing Population and Sample Characteristics

| | | Population | | Sample | |
|---|---|---|---|---|---|
| | Category | N | Percentage | N | Percentage |
| Age | 18-44 | 3,099,277 | 28.88 | 149 | 20.69 |
| | 45-59 | 3,311,592 | 30.86 | 250 | 34.72 |
| | 60+ | 4,320,005 | 40.26 | 321 | 44.58 |
| Gender | Male | 5,041,316 | 46.98 | 330 | 45.83 |
| | Female | 5,689,558 | 53.02 | 390 | 54.17 |
| Ethnic | White, non-hispanic | 7,932,073 | 73.92 | 586 | 81.39 |
| | Black, non-hispanic | 927,402 | 8.62 | 37 | 5.14 |
| | Other, 2+Races, non-hispanic | 458,652 | 4.27 | 25 | 3.47 |
| | Hispanic | 1,412,744 | 13.17 | 72 | 10 |
| Education | High School or Below | 4,183,801 | 38.99 | 162 | 22.5 |
| | Some College | 2,881,327 | 26.85 | 229 | 31.81 |
| | Bachelor or Above | 3,665,746 | 34.16 | 329 | 45.69 |

Table 3. Description of Summary Statistics of Variable

| Variable | Description | Type | N | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|---|
| Insurance | Whether people have flood insurance (0 = no, 1 = yes) | Binary | 720 | 0.350 | 0.4773 | 0 | 1 |
| Mortgage | Whether people have mortgage loan for houses (0 = no, 1 = yes) | Binary | 720 | 0.629 | 0.4834 | 0 | 1 |
| Risk aversion | Risk preference (large number is risk aversion) | Category | 720 | 10.276 | 4.1812 | 0 | 15 |
| Risk perception | Personal risk perception (percentage) | Category | 720 | 4.400 | 2.2626 | 1 | 11 |
| preFIRM | Whether the house was constructed before FIRM (0 = no, 1 = yes) | Binary | 720 | 0.436 | 0.4962 | 0 | 1 |
| Distance | Distance from the coast (meters) | Continuous | 720 | 15784 | 17375 | 0 | 78198.3 |
| Flood zone | SFHA zone or non-SFHA zone (0 = no, 1 = yes) | Binary | 720 | 0.225 | 0.4179 | 0 | 1 |
| House type | House type | Category | 720 | 1.324 | 0.8029 | 1 | 5 |
| Experience | Previous flood damage experience (0 = no, 1 = yes) | Continuous | 720 | 0.345 | 0.4759 | 0 | 1 |
| CRS | Community Rating System Classification | Category | 720 | 6.913 | 1.4533 | 5 | 10 |
| Income | Household income<br>( 1=less than $5,000<br>2=$5,000 to $7,499<br>3=$7,500 to $9,999<br>4=$10,000 to $12,499<br>5=$12,500 to $14,999<br>6=$15,000 to $19,999<br>7=$20,000 to $24,999<br>8=$25,000 to $29,999<br>9=$30,000 to $34,999<br>10=$35,000 to $39,999<br>11=$40,000 to $49,999<br>12=$50,000 to $59,999<br>13=$60,000 to $74,999<br>14=$75,000 to $84,999<br>15=$85,000 to $99,999 | Category | 720 | 12.050 | 3.9602 | 1 | 19 |

16=$100,000 to $124,999
17=$125,000 to $149,999
18=$150,000 to $174,999
19=$175,000 or more )

Table 4. Detail for Responses for Insurance Purchase by Variables

| | | N | Percentage |
|---|---|---|---|
| Insurance | No | 468 | 65.00% |
| | Yes | 252 | 35.00% |
| | Total | 720 | 100.00% |
| | | | |
| SFHAzone | No | 62 | 38.27% |
| | Yes | 100 | 61.73% |
| | Total | 162 | 100.00% |
| | | | |
| non-SFHAzone | No | 400 | 72.76% |
| | Yes | 152 | 27.24% |
| | Total | 558 | 100.00% |
| | | | |
| Income | | | |
| Highest 5 categories | No | 112 | 53.33% |
| | Yes | 98 | 46.67% |
| | Total | 210 | 100.00% |
| | | | |
| Lowest 5 categories | No | 39 | 81.25% |
| | Yes | 9 | 18.75% |
| | Total | 48 | 100.00% |
| | | | |
| Mortgage -yes | No | 275 | 60.71% |
| | Yes | 178 | 39.29% |
| | Total | 458 | 100.00% |
| | | | |
| Mortgage -no | No | 193 | 72.28% |
| | Yes | 74 | 27.72% |
| | Total | 267 | 100.00% |

Table 5. Regression Results of Logit Model and Marginal Effect for Flood Insurance Demand

N= 720 Likelihood=-409.75109

| Variable | Coefficient | Standard Error | z | p>\|z\| | | Marginal Effect+ |
|---|---|---|---|---|---|---|
| Mortgage | 0.513282 | 0.187473 | 2.74 | 0.006 | ** | 0.097755 |
| Risk perception | 0.102679 | 0.039577 | 2.58 | 0.010 | ** | 0.019725 |
| Risk aversion | 0.017196 | 0.021040 | 0.82 | 0.414 | | 0.003315 |
| Income | 0.102678 | 0.024047 | 4.10 | 0.000 | ** | 0.019797 |
| Flood zone | 1.561998 | 0.202346 | 7.72 | 0.000 | ** | 0.340596 |
| Distance | -0.000009 | 0.000005 | -1.83 | 0.067 | * | -0.000002 |
| preFIRM | 0.120750 | 0.179649 | 0.67 | 0.501 | | 0.003860 |
| CRS | 0.005214 | 0.059133 | 0.09 | 0.930 | | 0.001005 |
| Experience | 0.218290 | 0.181834 | 1.20 | 0.230 | | 0.042517 |
| House type | -0.213140 | 0.127123 | -1.68 | 0.094 | | -0.041095 |
| Constant | -2.975240 | 0.685020 | -4.34 | 0.000 | | |

Note : * significant at 0.1 level
** significant at 0.05 level
+ For binary questions, marginal effect for factor levels is the discrete change from the base level.