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Risk Perceptions, Risk Preferences, Risk Ambiguity, and Flood Insurance

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RISK PERCEPTIONS, RISK PREFERENCES, RISK AMBIGUITY, AND FLOOD INSURANCE

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This thesis presents an analysis of subjective risk information and participation in the National Flood Insurance Program (NFIP). Data are taken from a survey of residents in flood-prone coastal regions in the southeastern U.S. Regression models are constructed to better understand factors affecting individuals' perceived risk ambiguity related to flood risk and the role of risk preferences, risk perceptions, and especially risk ambiguity, on the decision to purchase flood insurance. This is the first study not only of the influence of risk ambiguity on NFIP participation, but also of the impact of using different risk perception measures. Results indicate that NFIP participation is significantly affected by mean perceived risk, but the influence of range/variance of perceived risk, which presents one's perceived ambiguity, is mixed.

Key words: subjective risk, National Flood Insurance Program (NFIP), probit with instrumental variable, endogeneity

DEDICATION

I would like to dedicate this research to God and my loving family.

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CHAPTER I

INTRODUCTION

Losses from floods caused by hurricanes have dramatically increased in recent years (National Weather Service, 2011). For example, the monetary losses from Hurricane Katrina were the highest recorded number in history. The southeastern U.S. is highly exposed to flood risk by hurricanes, and a large portion of total flood insurance policies are issued in these areas. For example, the population of Florida consists of only 6% of the total population in the U.S., but 40% of the total flood insurance policies are issued in Florida (Wharton Risk Management and Decision Processes Center, 2011). Related factors, such as increased population in hazard-prone areas, increased property values in these areas, insufficient preparation for floods, and increased frequency of flooding allegedly stemming from climate change, all contribute to this trend. Due to the fact that many people are not sufficiently prepared against floods, most of the burden of supporting victims and recovery is transferred to the government after flooding occurs. In 1968, Congress introduced the National Flood Insurance Program (NFIP) as an alternative to reduce government expenditure to encourage people to participate in mitigation activities. However, NFIP was not as effective as expected, because many people refused to purchase flood insurance.

In response many researchers investigated which factors influence the decision to purchase flood insurance to suggest ideas to invigorate participation in the NFIP. Empirical evidence consistently indicates that a household's income and the price of insurance affect the decision to buy flood insurance and insurance coverage. For example, Brown and Hoyt (2000) found that higher income households are more likely to purchase flood insurance and to have a greater amount of insurance coverage than lower income households. Also, the price of insurance is negatively related to the decision to buy insurance. Kriesel and Landry (2004) also found that the price of insurance has a negative relationship on purchase decisions. In their study, they also showed that people with higher incomes have a greater probability of purchasing insurance than people with lower incomes. Landry and Jahan-Pavar (2010) found that households in a higher income category hold greater flood insurance coverage than households in a lower income category. Their study also confirmed the negative relationship between price and purchasing insurance.

Additionally, it has been found that previous flood damage experience increases the probability of purchasing flood insurance (Browne and Hoyt, 2000; Zahran et al., 2009). The presence of a mortgage also increases the probability of purchasing (Browne and Hoyt, 2000). Damage protection facilities such as seawalls have positive influence on the insurance purchase decision, and the distance from an erosion reference feature such as beach vegetation line is negatively related to flood insurance purchasing (Kriesel and Landry, 2004). A premium deduction with respect to the CRS (Community Rating System) participation also has an influence on the probability of a flood insurance purchase (Zahran et al., 2009). NFIP subsidizes flood insurance premium when CRS participating communities perform floodplain management activities. The floodplain fraction of local community (Zahran et al., 2009) and flood zone affect the decision for a flood insurance purchase (Landry and Jahan-Pavar, 2010). All these variables are related to the risk of a damage causing events, and thus, the decision for purchasing flood insurance is affected by risk factors.

The primary intention of policy holders to purchase insurance is to reduce and potentially avoid unexpected losses. Thus, it seems helpful in understanding the policy holders if we concentrate on risk factors of their decision-makings than other factors. Kunreuther (1996) insisted that perceived risks have a greater impact than the actual risk to which people are exposed. Kunreuther likewise stated that low probability disasters such as floods, hurricanes, and earthquakes challenge people due to the lack of information from accumulated data to estimate precise losses. In other words, the uncertainty about risk exists in such low probability disasters. Burby (2001) indicated that many people willingly hold other insurance for risks which have a lower probability of occurring than flooding. For example, 95% of homeowners hold fire insurance which has a 1% chance of causing damage, but the flood insurance purchase rate is around 20% in spite of a 26% chance of damage in 100-year floodplain (Burby, 2001).

Other empirical results explain why the role of risk ambiguity needs to be better understood regarding the decision to buy insurance. Two similar experiments of Hogarth and Kunreuther in 1985 and 1989 confirmed that people are more willing to purchase insurance at a higher price for a situation with greater ambiguity than for a non-ambiguous situation. Kunreuther et al. (1995) found that an ambiguous probability of a hazardous event leading to a vague estimation of losses results in higher insurance premiums than a non-ambiguous probability situation. In summary, previous research supports the claim that the decision to purchase flood insurance is related to one's attitude toward risk.

Objectives

To help people in danger of flooding and to reduce losses from floods, a better understanding of the determining factors of flood insurance purchasing is necessary to provide an appropriate insurance package and to encourage people to purchase flood insurance. In order to find the determining factors of flood insurance purchasing, we primarily focus on the relationship between risk factors, especially risk ambiguity, and the decision to purchase flood insurance.

Thus, the objectives of this thesis are to:

1 Construct a regression model to better understand factors affecting individuals' perceived risk ambiguity related to flood risk.

2 Construct a regression model to better understand the role of risk preferences, risk perceptions, and especially risk ambiguity, on the decision to purchase flood insurance.

Definitions

This section provides definitions for key terms in this thesis. In *Risk, Uncertainty and Profit* (1921), Frank Knight distinguishes risk--"measurable uncertainty"--from uncertainty--"unmeasurable sense" (p. 20). Since Frank Knight's distinction between risk and uncertainty, alternative definitions that explain risk and uncertainty have care about. Hardaker et al. (1997) state that "risk is imperfect knowledge where the probabilities of the possible outcomes are known" and that "uncertainty exists when these probabilities are not known" (p. 5). Etner et al. (2010) gives a similar distinction: risks are "situations in which information is available, in the form of probability distributions," (p. 3) and uncertainty is the "situation in which the decision maker is not given probabilistic information about the external events that might affect the outcome of a decision" (p. 2). Arrow (1971) indicates that uncertainty arises when there is a certain observed consequence, but an individual cannot explain the subjective probability of the consequence because of the incomplete information.

Similar to uncertainty, ambiguity is also used among scholars who agree with Knight's distinction between risk and uncertainty. Ellsberg (1961) mentions ambiguity as "a quality depending on the amount, type, reliability, and 'unanimity' of information giving rise to one's degree of 'confidence' in an estimate of relative likelihoods," (p. 657) and indicates that ambiguity exists when people do not know enough to be sure about the probability distribution of an event. Cabantous (2006) defines ambiguity as "situations where decision makers do not know the exact likelihoods of each potential event" (p. 219). Etner (2010) mentions that, in most literature, ambiguity and uncertainty are not very distinguishable or are used interchangeable. However, we give some distinctions between ambiguity and uncertainty, and thus ambiguity is a sub-concept of uncertainty in this paper. The following definitions are provided for clear understanding of the terms risk, uncertainty, and ambiguity, as used in this paper.

- Certainty: This indicates the case in which an event it will occur with no risk, i.e., $P[X=x] = 1$.
- Uncertainty: Any case that is not included in the 'certainty' category. Uncertainty is divided into two subcategories: risk and ambiguity.
    - Risk: The case in which an event is known to occur with a fully characterized probability distribution. In the case of a continuous random variable, the distribution can be expressed explicitly; for example, a normal distribution is $X \sim N(0, 1)$. For a discrete random

variable case, one can identify a particular probability, such as P[X=1] = 0.1.

  - Ambiguity: The case in which an event is known to occur with less than fully characterized probability distribution. Unlike risk, under ambiguity one cannot explicitly express the distribution for a continuous random variable completely even though they have some information such as mean, variance or both. The discrete random variable case has a similar problem. One can give only a range of probability instead of a certain point of probability, e.g., 0.1 < P[X=1] < 0.2.

- Risk Perception: The subjective probability held by an individual's for a certain event. In this paper, through questions about the magnitude of damage from major hurricanes and frequency of the hurricane damage occurrences three points of risk perception were measured (the highest, the lowest, and mean values of perceived risk).
- Risk preference: An individual's attitude toward risk expressed as risk loving, risk neutral, or risk averse. According to Nicholson and Snyder (2008), risk aversion means an individual "who always refuses fair bets" and "exhibit[s] a diminishing marginal utility of wealth." A risk loving individual acts the opposite to a risk averse individual, and a risk neutral person does not have a preference for accepting or refusing the fair game, and always has a linear expected utility function with a constant marginal utility.

There are some flood insurance related terms:

- Community Rating System (CRS): Through the voluntary participation in flood protection activities, each community can get incentive from the National Flood Insurance Program (NFIP). CRS consists of ten classes, and depend on the degree of participation in protective activities, each community is provided a reduced insurance premium rate. Class 1 is the most active participation level with the highest premium reduction.
- Flood Insurance Rate Maps (FIRM): This is official map identifying the flood hazard areas by FEMA to provide regional flood risk information. According to probabilities of flooding, areas are classified as different flood zones which indicate the levels of flood risk.
- Special Flood Hazard Area (SFHA): According to the NFIP's map, SFHA is highly flood risk exposed areas.

This thesis is comprised of six chapters. Chapter 1 provides a brief introduction of the research, the objectives, and a few key definitions. Chapter 2 provides background information about flood damage trends and the NFIP. Chapter 3 is a review of literature and theories about risk factors and set the general perceived risk model. Chapter 4 explores the factors that affect the NFIP participation. Based on previous literature, the econometric model to examine these factors is defined. Chapter 5 describes the collected data via online survey. Finally, Chapter 6 discusses the method of estimating influential factors on one's perceived risk and the decision-making for NFIP participation. Also the empirical results are reported. Finally, in Chapter 7, it is discussed significant findings of this study and suggestions for future research.

CHAPTER II

GENERAL INFORMATION OF FLOOD AND FLOOD INSURANCE

Flood Damage

Natural disasters are characterized low probability and high magnitude events; in other words, they do not occur frequently, but once they happen, the magnitude of damage is severe and catastrophic. The Insurance Information Institution (2011) defines a catastrophe as an event "when claims are expected to reach a certain dollar threshold, currently set at $2 million, and more than a certain number of policyholders and insurance companies are affected." Flooding is a typical example of a catastrophic natural disaster.

There are two reasons for focusing on floods: huge losses from floods and increased population in coastal areas. According to a trend in the data of losses from floods, flood damage has increased dramatically in recent decades. The National Weather Service (2011) provides the only observable data which cover all states regarding flooding. Figure 1 shows the total amount of flood losses in actual dollar amounts for the years from 1903 to 2007. As Figure 1 shows, the amount of losses from floods is growing in the U.S.; thus, the losses from floods are getting harder to more costly to the government than before.

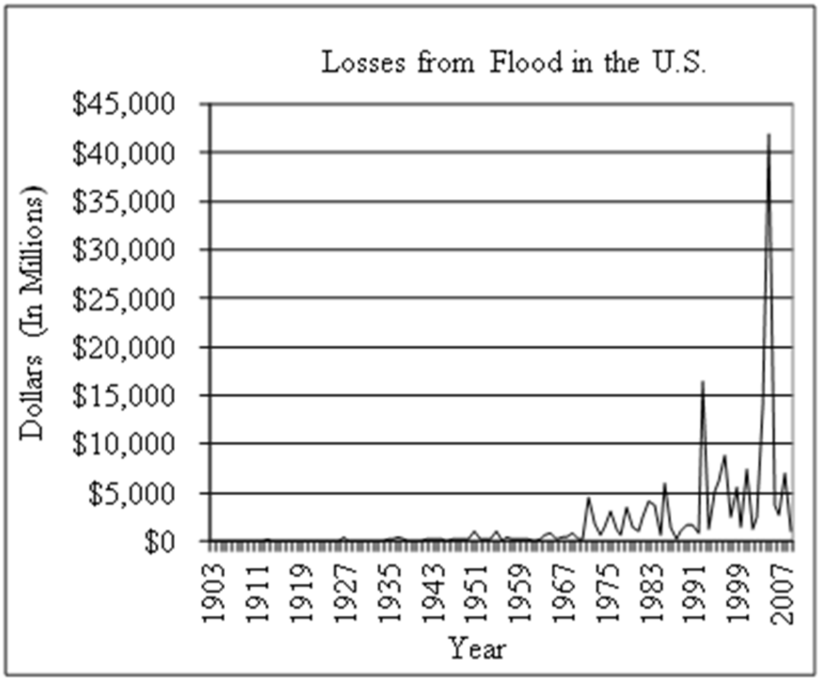

Figure 1 Losses from Flood Damage In the U.S. (National Weather Service, 2011)

One of the main causes of flooding is hurricanes. Swiss Re (2011) reports that the 40 most costly insurance losses in the world, including both natural disasters and man-made disasters, occurred between 1970 and 2009. Table 1 shows the first 10 records of the 40 most costly insured losses. Among the listed events, 9 events occurred in the U.S, and seven events stem from hurricanes. The Insurance Information Institution (2011) reports that the most frequent catastrophic loss events in the U.S. are hurricanes and tropical storms accounting for 45.2% of the total events, and the second most frequent event is tornados, 29%. As a result, coastal areas are exposed to very high potential losses caused by hurricanes.

Table 1 The 10 most Costly Insurance Losses between 1970 and 2009 (Swiss Re, 2011)

Year	Losses(Million USD)	Event	Location
2005	71,163	Hurricane Katrina	US, Gulf of Mexico, Bahamas
1992	24,479	Hurricane Andrew	US, Bahamas
2001	22,767	Terror attack on WTC	US
1994	20,276	Northridge earthquake	US
2008	19,940	Hurricane Ike	US, Gulf of Mexico et al
2004	14,642	Hurricane Ivan	US, Barbados et al
2005	13,807	Hurricane Wilma	US, Mexico, Jamaica, Haiti et al
2005	11,089	Hurricane Rita	US, Gulf of Mexico, Cuba
2004	9,148	Hurricane Charley	US, Cuba, Jamaica et al
1991	8,899	Typhoon Mireille	Japan

Figure 2 shows the population change in percentages between 2000 and 2010 (Census Bureau, 2011). The dark green colored portion indicates a 50% or more increased population, and the dark purple shows decreased population. This figure indicates that many counties located in coastal areas experienced a greater increase of their population than non-coastal counties. The Insurance Information Institution (2011) also analyzes the data of the Census Bureau and indicates that currently, 34.9 million people are exposed to the hazards of Atlantic Hurricanes. This is three times increased number from the 1950's population of 10.2 million.

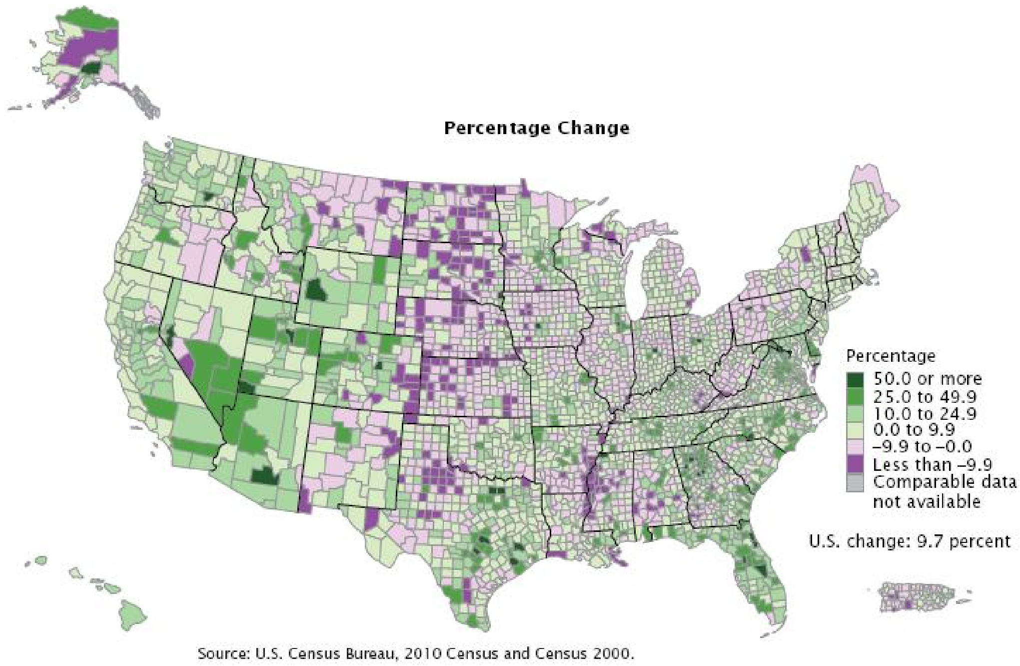

Figure 2 Population Change in County from 2000 to 2010 (U.S. Census Bureau, 2011)

Failure of Private Insurance Companies

Prior to NFIP, private insurance companies provided insurance for flood damage. However, the trials failed to establish enough demand for keeping the operation of these insurance companies. Private insurance companies had abandoned because the high premium rates required by firms were generally higher than what consumers were willing to pay. Skees and Barnett (1999) explained the conditions for an insurable risk by citing Rejda's (1995) expressions: a large number of exposure units, accidental and unintentional loss, determinable and measurable loss, and an economically feasible premium. Floods violate these conditions. Browne and Hoyt (2000) explained reasons of this private insurance market failure using the *Studies of Floods and Flood Damage, 1952-1955.* They listed the reasons of failure as follows: flood results in catastrophic losses, some areas have obvious probability of loss, the amount of the premium exceeds the consumers' willingness to pay, and various levels of loss probabilities for insurers do not exist. Consequently, the failure of private flood insurance stems from the flood risk characteristics that are not insurable. Due to the characteristics of natural disasters, it is obvious that the losses from a flood are more widespread than other risks such as car accidents or house fires, and once a flood happens, the amount of losses is large and consequently leads high premium rates. Moreover, such areas as shorelines and river banks clearly endure a higher risk than other places located far away from the coasts or rivers. All these situations limit the ability of insurance companies to control correlated natural disaster losses. Insurance companies make a profit by taking a premium as compensation for bearing risk instead of the policy holders. Insurance companies use risk aggregation, risk segregation, or both to reduce risk. As already mentioned, unlike automobile insurance, once flooding occurs, flood damage appears in a series and covers broad areas. In other words, insurance companies have to compensate a large number of policy holders at the same time and have to spread their risk to decrease the huge burden of compensation to insurance policy holders. However, the correlation among the insurance policy holders makes risk-spreading difficult. Therefore, the characteristics of natural disasters and systematic risk problems make it hard for small scale private insurance companies to effectively support the recovery from catastrophic disasters within their abilities. Due to the failure of the private insurance market, the National Flood Insurance Program (NFIP) was introduced by the government to mitigate both flood risk and losses of coastal and fluvial area residents.

Introduction of NFIP

The National Flood Insurance Program (NFIP) was introduced by the National Flood Insurance Act of 1968 as an alternative way to control increasing expenses for post-flood disaster aid. The three primary goals of the NFIP are indemnifying losses through the flood insurance program, mitigating future damage through flood plain management of participating states and communities, and reducing expenditures for disaster relief and damage control. This program is the first governmental program that encourages chronic or potential flood victims interact with the government voluntary. The NFIP not only tries to reduce the after-disaster relief expenses through insurance but also tries to prevent flood damage by conducting flood protection activities at the individual and community levels. As an incentive for flood protection performance, the NFIP offers discounted rates on insurance premiums to participating communities with respect to their protective implementation levels (FEMA, 2010). Unfortunately, only 10.5% of the total flood-bearing communities participated in the NFIP by 1973 (Tobin and Calfee, 2005).

Congress found that the participation rate was much lower than its original expectations, and more effective methods were requested to encourage the participation of people in peril of flood. As a result, the mandatory purchase of flood insurance was enforced to increase the number of insurance policy holders through the Flood Disaster Protection Act of 1973. This new act required that mortgaged homeowners whose properties are located in a SFHA (Special Flood Hazard Area) purchase flood insurance if their mortgages were borrowed from regulated agencies such as the FRB (Board of Governors of the Federal Reserve System). It was also required that when these homeowners buy flood insurance, their coverage needs to be at least equal to the outstanding mortgage principal or the maximum coverage level. In addition to the mandatory purchase, Congress prohibited regulated lenders from making, increasing, extending, or renewing loans backed by properties located in a SFHA even though the properties were covered by flood insurance. In response to the mandatory requirement of flood insurance, the number of policy holders and participating communities increased significantly. FEMA reported that the number of policy holders increased to 1,200,000 in 1977 compared to 95,000 in 1973, and 71% of the total flood-prone communities participated in the NFIP.

In 1994, Congress again amended the NFIP to complement the Flood Disaster Protection Act. The National Flood Insurance Reform Act of 1994 enhanced the previous regulation by extending the number of institutions requiring flood insurance to mortgage borrowers. Moreover, the mortgage purchases of Fannie Mae and Freddie Mac from the secondary market also became a subject of the mandatory purchase requirement. At this point, the NFIP provided greater coverage levels than before. For example, insurers can be covered up to $250,000 for single-family and multifamily homes compared to $35,000 for a single family residence under the 1973 act. As a result, the number of policies in force has increased almost fourfold, from 1,446,354 in 1978 to 5,646,735 in 2010 (FEMA, 2011). Figure 3 shows the number of policies in force from 1978 to 2010.

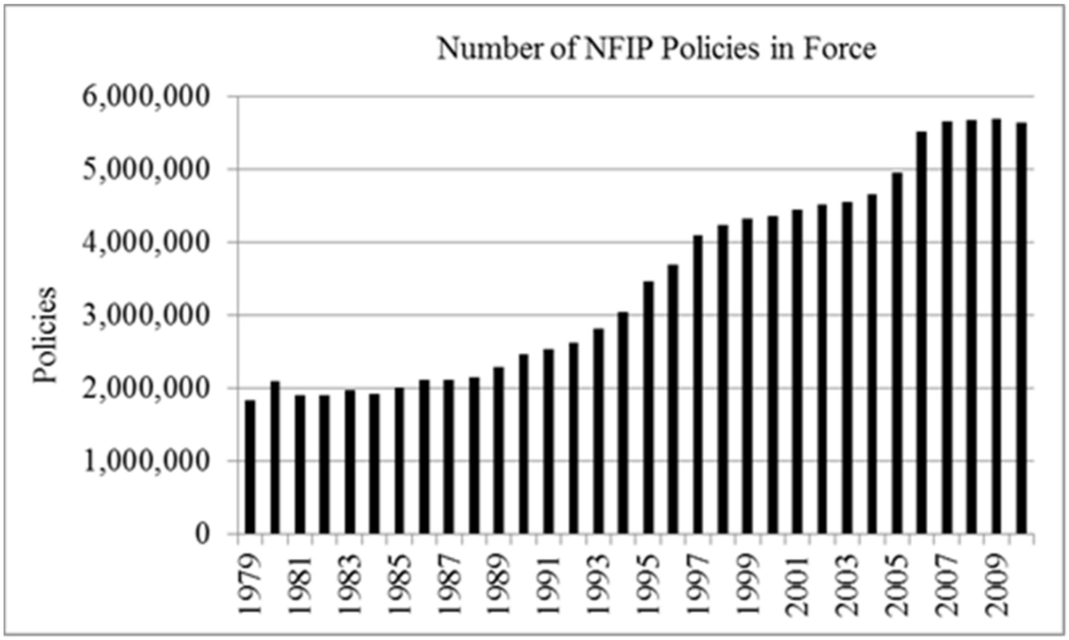

Figure 3 Number of NFIP Policies in Force from 1978 to 2010 (FEMA, 2011)

In spite of continued government intervention, many people at risk of flooding still remain uninsured (Burby, 2001). According to the report of Pricewaterhouse Coopers (1999), the NFIP participation rate of all SFHA structures in 1997 was 28%. The other report in 2006 reported the participation rate of single family house (SFH) in a SFHA is 49% (Dixon et al., 2006). The market penetration had improved, but a half of SFH in a SFHA are still not secured by insurance. Kunreuther (2006) gives five main reasons why people fail to undertake risk mitigation actions such as buying flood insurance. First, they have a tendency to underestimate or to ignore risk probabilities when they face a low probability event; second, people make decisions based on short-run mitigation benefits only; third, the fixed amount of income limits the ability to take mitigating actions; fourth, people tend to imitate their neighbor's behavior; and fifth, people expect government aid after disasters.

CHAPTER III

RISK AND AMBIGUITY

Risk Perception

When people are confronted with risk, two different risks exist: actual risk and perceived risk. Because of difference between these two risks, the expectation for people's behaviors was not match with the actual behaviors. Previous research observed an individual's perceived risk. Kunreuther (1976) found that uninsured people perceive their risk probabilities relatively low than insured people. Moreover, when he compared the expected damage on properties from a severe flood, more uninsured people expect no damage on their properties than insured people.

Miceli, Sotgiu, and Settanmi (2008) explored that an individual's adoption of protective behavior related to hydrogeological risk. They found that protective adoption is significantly related to flood risk perception, participation in Civil Defense activities, age, and closeness to water courses.

Lachlan et al. (2009) focused on the relationship between race and perceived risk. They confirmed that, depending on the race of a person, he would perceive his risk differently, and the perceived risk affect the person's reaction for risk prevention activities. In their research, African-Americans show the lowest level of risk perception and the lowest level of risk preventing actions.

Burrus et al. (2008) observed the influence of several factors on an individual's risk mitigation level. They observed the impact of subjective hurricane risk perception on a home owner's mitigation activities. This study did not focus on insurance, but on mitigation activities. Burrus et al. found that income, deductible, and education level are positively related to risk mitigation. They also noted that low mitigation does not stems from underestimation of probability, but the underestimation of damage level.

Kellens et al. (2011) studied about perceived flood risk and various factors and found that level of risk perception is varied by risk levels of locations. High-risk location residents showed higher risk perception than low-risk location residents. Moreover, they observed that elder people and women have higher risk perception on average.

In sum, one's perceived risk positively related to one's risk resistant reaction such as risk mitigation, protection against risk. Also there are significant findings about the influence of demographic characteristics on one's perceived risk.

Risk Ambiguity

People are confronted with various risks when they make decisions. All else equal, if a person is risk-averse, he has a higher willingness to purchase insurance to avoid a potential risk than a risk-loving person. Similarly, when people expect their risks are severe, they are more willing to purchase insurance to protect themselves from losses. In 1738, Bernoulli spoke that some behaviors under risky situations cannot be fully explained by such existing theories as expected value. Bernoulli, therefore, suggested a new concept, Expected Utility Theory. Later, the von Neumann-Morgenstern axioms clarified how rational behaviors are defined under the Expected Utility Theory. Since the introduction of the von Neumann-Morgenstern axioms, the Expected Utility Theory seemed to accurately explain an individual's decision-making mechanism in risky situations.

However, Ellsberg (1961) found that people violate the von Neumann-Morgenstern axioms when they experience ambiguity of perceived risk. Ellsberg suggested a hypothetical urn experiment which observes an individual's preference between known probability and unknown probability. There were two different urns and each urn had two different colored balls. The number of each ball is known in one urn, and in the other urn, the distribution of the two balls is unknown. According to the von Neumann-Morgenstern axioms, an individual's preference for the same-colored ball is not different regardless of the urns if the pay-off from the same-colored ball is the same. In other words, the distribution of balls does not affect the personal preference as long as a pay-off is the same. However, Ellsberg insisted that the majority of people will chose the urn with a known distribution. Through similar examples, he explained that the real choices under ambiguity are different with the prediction of the Expected Utility Theory. Ellsberg explained that under ambiguous probability people have a hard time to calculate their expected returns or to expect the consequence of a choice, and as a result, people show 'irrational' behaviors violating the von Neumann-Morgenstern axioms. Ellsberg's experiment started the discussion about the impact of risk ambiguity on decision-making.

While Ellsberg explained that ambiguity is a matter of confidence in the estimated probability, Becker and Brownson (1964) suggested that ambiguity is related to the distributions of probability of an event. They assumed a person has ambiguity if the person has a probability distribution rather than a point probability. Therefore, in their experiment ambiguity is the range of distribution and the difference in ambiguity is the absolute difference in ranges. They found that people are willing to pay to avoid an ambiguous selection when the selection has the same expected value with unambiguous selection, and that as ambiguity increases, the willingness to pay to avoid ambiguity increases.

Einhorn and Hogarth (1986) conducted an Ellsberg-like urn experiment to observe the role of ambiguity in decision-making. They found that first, people are averse to ambiguity. Second, people accept a higher insurance premium under ambiguity, and finally, people will more willingness to pay for a low probability of loss than a high probability of loss.

Hogarth and Kunreuther (1989) conducted an empirical experiment with subjects knowledgeable about insurance to test the influence of ambiguity on deciding the level of an insurance premium. They observed differences between consumers' willingness to pay for insurance premiums and the difference between firms' willingness to accept insurance premiums under ambiguous probability and non-ambiguous probability. In the ambiguous probability case, the subjects were provided with conflicting information about the probability, and in the non-ambiguous probability case, the subjects were provide with confirmed, uniform comments about the probability. According to expected utility theory, an insurance premium is not affected by the probabilistic ambiguity of an event, if its expected loss is known. Respondents were asked their maximum (for consumers) or minimum (for firms) insurance premium under a given probability of loss. Both the ambiguous and the non-ambiguous versions of the experiment present the same probability of loss, but for the ambiguity version the probability explained with lack of confidence. For both consumers and firms, mean ratios of ambiguous to non-ambiguous prices were larger in a lower probability of loss, e.g. p=0.1 than a higher probability of loss, e.g. p=0.9. A mean ratio larger than one indicates that the subjects estimated a higher insurance premium for an ambiguous case rather than for a non-ambiguous case.

That is, people are ambiguity-averse. Although ambiguity aversion decreases as the probability of loss increases in both consumer and firm cases, only consumers show an ambiguity preference in the highest probability of loss (p=0.9).

Lauriola and Levin (2001) investigated a subject's attitude toward ambiguity and risk-taking utilizing an Ellsberg-like urn experiment. They agreed that ambiguity plays a significant role in decision-making and wanted to find the relationship between an individual's ambiguity attitude and his real performance. Their empirical results showed that the responses against ambiguity are positively related to the risk-taking attitude of a person. In other words, a person who has a favorable attitude toward ambiguity also shows a positive attitude toward risk-taking. Furthermore, the relationship of an ambiguous attitude and risk-taking attitude is stronger in avoiding losses rather than in achieving gains and is also stronger at a higher probability level than a lower probability level.

Riddel (2009) insisted that the degree of exposure to knowledge involving risk will affect an individual's precise estimation of risk. On the contrary to the general assumption that people estimate risk better with more information than with less information, people who are highly exposed to information tend to experience more ambiguity than people who are less exposed to risk information. She explained that people could be more aware of the inherent ambiguity with more information, and there could be a conflict of information from various sources.

Many researchers proved that there is a significant impact of risk ambiguity on the insurance premium level and on an individual's decision-making process to purchase insurance. However, no significant research exists to observe the influence of risk ambiguity on flood insurance purchasing directly. This chapter focuses on quantifying risk ambiguity and testing various factors that will decide an individual's risk ambiguity in order to eventually observe the influence of risk ambiguity on one's flood insurance purchasing. Since risk ambiguity is derived from perceived risk, our hypotheses and conceptual frame for the perceived risk model includes risk ambiguity model

Conceptual Framework

Riddel (2009) and Nguyen et al. (2010) measured perceived mortality risk and observed what kind of determinants has an impact on subjective risk. They utilized a risk ladder as a method to elicit the subjective risk of respondents. The risk ladder gives visual aid to respondents by showing reference positions of probabilities; for example, there is a rung pointing to exactly 275 deaths caused by falling accidents per 100,000 and a rung of 75 deaths caused by fire accidents per 100,000. People are asked to present their expected probabilities of mortality risk. Respondents can select a certain location on the risk ladder to show their probabilistic perceptions. If a person points to one position, it means the person is sure about the probability of a risk (no ambiguity). Otherwise, the person would have risk ambiguity. Cameron (2005) elicited subjective risks about the climate change issue. When the researcher observed the relationship between subjective risk and external information ambiguity, she measured ambiguity as the range of the highest and lowest guess for the temperature expectation in future. In sum, the range of perceived risk is one of measurements of an individual's risk ambiguity.

Based on previous examples, measuring risk ambiguity by the range of two different points, we also interpret the difference between the highest and the lowest levels of perceived flood risk as an individual's risk ambiguity. When a respondent gives the same values of the highest and the lowest levels of perceived risk, it means the person has no risk ambiguity. However, we do not know if this measurement is the best method for eliciting an individual's flood risk ambiguity, so we decide to use triangular variance additionally. The comparison of difference risk ambiguity measurement methods is conducted in order to examine a better method for measuring flood risk ambiguity.

Since risk ambiguity is derived from risk perception, it is assumed that risk ambiguity and risk perception have the same function. Therefore, the following linear function is general model of risk perception. The determinants for perceived flood risk assumed to consist of one's demographic characteristics, geographic characteristics, and attitude toward risk. Therefore, risk perception is a function of $\mathbf{d}_j$, $\mathbf{g}_j$, $\mathbf{r}_j$, and ε_j, where $\mathbf{d}_j$ is a vector of demographic information variables, $\mathbf{g}_j$ is a vector of geographic characteristic variables, $\mathbf{r}_j$ is a vector of risk attitude variables, and ε_j is an error term. We assume that the risk perception function is a linear function. Therefore, the function can be written

$$Y_j = \boldsymbol{\alpha}'\mathbf{d}_j + \boldsymbol{\beta}'\mathbf{g}_j + \boldsymbol{\gamma}'\mathbf{r}_j + \varepsilon_j \qquad (1)$$

where Y_j is a risk perception variable measured by mean, range, and variance, and $\boldsymbol{\alpha}'$, $\boldsymbol{\beta}'$, and $\boldsymbol{\gamma}'$ are vectors of coefficients.

Hypotheses

In this thesis, risk ambiguity is range and variance of risk perception. Therefore perceived risk model is hypothesized based on relevant knowledge and previous literature related to both risk perception and risk ambiguity. Nguyen et al. (2010) found that age is negatively related to risk ambiguity. Riddel (2009) explained that the information on a potential risk affects an individual's risk ambiguity, but demographic variables do not show a significant influence on risk ambiguity. Kellens et al. (2011) tested various factors affecting perceived flood risk. He hypothesized the impact of a location with different risk levels, demographic factors (gender, age, education, home ownership, presence of children), residence characteristics (having a cellar, residing on the ground floor, visibility of the sea), previous flood experience, and permanent residency. Through three models, he found that a location with different risk levels, age, and gender are consistently significant. For example, a person has a higher risk perception when a person resides in a higher risk location. Older people have higher perceived risk, and females also have a higher risk perception. He expected permanent residents and tourists to show a different risk perception; the risk perception of tourists did not change due to the risk level of the location in which they are residing because they are temporary residents. However, tourists staying in a high risk area did show a higher risk perception.

It is hypothesized that mean, range, and variance of perceived risk is explained by an individual's demographic characteristics (age, gender, income, education, marital status, working status, and ethnicity), geographic characteristics (state, distance from the coast, flood zone, and metro), and the attitude toward a risk (risk aversion, previous damage). Table 2 presents details of variables and their expected signs.

Table 2 Expectation of Explanatory Variables for Perceived Risk Model

Variable	Description	Expected Sign
Risk Aversion	A risk-averse person may have larger perceived risk than a risk-loving person.	+
Previous Damage	A person who had previous flood damage experience may have more perceived risk (Kellens et al. 2011).	+
Distance from the Coast	As the distance from the coast increases, one's perceived risk may decrease because one may feel that they are not as susceptible to flood risk (Kellens et al. 2011).	-
Flood zone	If a person lives in a high flood risk area, he may feel larger risk perception (Kellens et al. (2011).	+
State	A resident in Florida would have more perceived risk because Florida is highly exposed to hurricane strikes.	-
Ethnicity	The risk perception of a person who is classified as Caucasian differs from people of other races, but the amount of different is unknown.	+/-
Working Status	Whether a person works or not would affect risk perception, but the exact influence is not clear.	+/-
Marital Status	A person with a spouse or a cohabitant probably has less risk perception because the other person is also a source of information.	-
Metro	A person who lives in a metropolitan area probably has less perceived risk because it is expected that metropolitan areas are well prepared against flood damage.	-
Age	An elder person has less risk perception (Nguyen et al., 2010l; Kellens et al. 2011).	-
Gender	Being female would probably cause someone to experience more risk perception (Riddel, 2009; Kellens et al. 2011).	+
Income	Income would affect one's risk perception, but the exact influence is not clear.	+/-
Education	With a high educational level, one's risk perception may decrease (Riddel, 2009).	-

CHAPTER IV

DECISION MODEL FOR NFIP PARTICIPATION DECISION

Determinants for Flood Insurance Purchasing

Regarding insurance, Hogarth and Kunreuther (1989) and Kunreuther et al (1995) stated that people have more of a willingness to pay for insurance premiums under ambiguity. Kunreuther (1976) carried out a survey to understand individuals' decision making for insurance against a severe damage-expected event such as flooding or an earthquake. He compared the expected damage on their properties and the subjective probability of an event occurrence of insured people and uninsured people once a catastrophic event occurs. Uninsured people expected no damage or minor damage on their property if there was a severe flood or an earthquake. Moreover, the uninsured group's subjective probability about the occurrence was also lower than the insured group's one.

Browne and Hoyt (2000) estimated a flood insurance purchase model over 50 states using various sources of data such as the NFIP, the U.S Army Crop of Engineers. Data from 1983 to 1993 was analyzed to estimate the model under the same condition of the NFIP structure. They address that a property owner with a higher income has a greater probability of purchasing insurance, and his insurance covers a greater amount than a lower income property owner. The price of flood insurance is also negatively related with a flood insurance purchase. These results suggest that the monetary conditions of a potential policy holder are an important criterion affecting the decision-making in purchasing flood insurance. Preceding flood damage experience has a significantly positive relation with flood insurance purchase. Contrary to expectations, the presence of FHA backed mortgage and insurance purchases are negatively related.

Kriesel and Landry (2004) provided an empirical analysis about an individual's decision for NFIP participation. In their empirical model, predicted insurance prices are utilized instead of actual prices because it is impossible to get the insurance price of uninsured people. The predicted price was induced by regressing seven factors which FEMA uses for rate setting. The researchers found that the predicted price was negatively related to NFIP participation. The results also suggested that the mortgaged properties' owners have a 73% greater probability of participation on NFIP and that the respondents who have a higher income have a greater probability of participation. The distance from the erosion reference features which researchers assumed as a sign of self-insurance had a negative effect on NFIP participation. As the hurricane interval is longer, the probability of participation decreases because this interval represents the risk probability which people are facing. The relationship between NFIP participation and an artificial protection such as seawall, groin, or nourished beach protection was particularly interesting. Kriesel and Landry expected that an artificial protection would be a sign for a protective area or a risk involved area. Their finding seems to suggest that an artificial protection is a sign of risk because more households located near an artificial protection participated in the NFIP.

Zahran et al. (2009) explored the number of policy holders in the CRS participating counties in Florida to estimate the effect of the CRS on flood insurance purchasing. They used county-level data in Florida because communities in Florida are largely participating in the CRS and also suffering from severe flood damage. They explained that among the CRS participating communities high insurance-purchase rate communities tend to be located in coastal areas, and an enthusiastic CRS participating county, which has a high CRS score, has a high insurance purchase rate. Two demographic variables, median home value, and education level, are positively correlated to insurance purchase rates. Zahran et al. defined a fraction of floodplain in local lands and a previous experience of flood damage as the hazard proximity condition which shows an individual's risk perception. The higher the fraction of floodplain in a local land is, the higher insurance purchase rates become. Moreover, the previous flood experience results in increased insurance purchasing rates.

Landry and Jahan -Pavar (2010) observed the influential variables on a flood insurance coverage choice using community level-data. They focused on the near-shore areas from different states located on east-south coasts. They found that insurance price is negatively related to coverage demand, that subsidized premium holders have a greater insurance coverage level, that a higher insurance coverage level is in the V-zone (high-risk zone) compared to low-risk zones, and that erosion hazard increases the coverage level. Interestingly, flood insurance holdings in areas with coastal management by beach replenishment are greater while flood insurance holdings in areas with coastal armoring are lower. Both actions are a part of coastal defense in a large scope, but reactions against these two are different. The researchers also found that mortgages induce more insurance coverage and that retired people have lower insurance coverage. However, these two factors are not statistically significant. Initially, they could not find the significance of income variables. After transforming income variables into a categorical form, it can easily be revealed that the higher income category has more insurance coverage.

Michel-Kerjan and Kousky (2010) analyzed the characteristics of flood insurance policy holders in Florida based on NFIP data between 2000 and 2005. Policy holders in Florida are mostly single family residents and live in 100-year flood plains areas. About 75% of total policyholders have not buy the maximum coverage of flood insurance, and 80% of total policyholders choose the lowest level of deductible. It seems that most policyholders in Florida want to reduce their premiums and their damage expenses at the same time. However, policyholders in a higher risk area tend to increase their deductible amount relative to people in low-risk areas. It may be because of expensive prices of premiums. Half of policy holders reside in communities with 7 or 8 of CRS classes where their premium discount rates are 15% and 10% respectively. Interestingly, 62% of policies are dropped in 5 years, so the sustaining rate is very low.

Conceptual Framework

Since Smith (1968) and Mossin (1968) utilized the expected utility function to estimate the optimal insurance coverage level, Von Neumann and Morgenstern's Expected Utility Theory has been utilized to explain the decision-making for insurance purchasing, typically. In other words, the decision-making for insurance purchasing could be explained through an individual's expected utility function. However, as Ellsberg's paradox indicated, empirical evidences for human behaviors did not match with the predictions of the expected utility theory, especially, in risk ambiguity cases. For example, people did not purchase insurance even though their expected utility of insurance purchasing exceeds the expected utility of not purchasing insurance.

Kunreuther's (1976) field study reported that the behavior of flood or earthquake-susceptible residents is not consistent with expected utility theory. He surveyed residents in flood or earthquake risk areas including both insured and uninsured people. When he calculated the contingency price ratio, i.e., the ratio of the expected cost of insurance, to observe decision making regarding an individual's risk preference, he found many risk-averse people (39%) are not insured, while many risk-loving people (39%) are insured, which means they did not follow the expected behavior according to the expected utility model. In his analysis of the survey results, Kunreuther explained that the reason why people did not follow the predicted behavior for maximizing utility was because people did not have the ability to process the probabilistic problem using their limited information. Etner (2010) also insisted that the expected utility model is a leading model under risk, but the model is challenged for ambiguous cases. Flooding is a typical example of natural disasters which have a low probability of occurring, but a high magnitude of damage. Although the possibility of flood's occurrence is significantly low, the damage is catastrophic once it happens. The decision-making process for flood insurance purchases is closely related to understanding the probability of the event.

Therefore, in this study, instead of using the Expected Utility model, the demand is estimated based on the Random Utility theory developed by McFadden (1973). Hanemann (1984) developed this Random Utility model for discrete responses using the McFadden's random utility framework. The choice for flood insurance purchasing is a dichotomous choice, and thus there are only two choices: 'yes,' purchasing insurance or 'no,' not purchasing insurance. Therefore, the utility function of a *j*th household under choice *i* is

$$u_{i,j} = u_i(\mathbf{g}_j,\ \mathbf{p}_j,\ \mathbf{r}_j,\ \mathbf{d}_j,\ \varepsilon_{i,j}), \tag{2}$$

where i=0, the utility function expresses the utility for the uninsured household. Otherwise, when i=1, the utility function indicates the insured person's utility. $\mathbf{g}_j$ is a vector of geographic characteristics; $\mathbf{p}_j$ is a vector of flood insurance policy variables; $\mathbf{r}_j$ is a vector of an individual's attitude toward a risk; $\mathbf{d}_j$ is a vector of a household's demographic characteristics; and $\varepsilon_{i,j}$ is an error term which is not explicitly observable. Generally, the price of insurance is called premium, and previous research confirmed that premium is significantly related to one's decision for insurance purchase. However, the price of insurance is not included explicitly in this model. According to Petrolia, Landry, and Coble (2011), the price of flood insurance varies according to observable risk factors of FEMA which are related in determining insurance rates. Therefore, the price of insurance is affected by the amount of exposed risk and additionally one's decision for coverage level. Both exposed risk and coverage level vary by individuals, and thus observable risk factors that can affect the price of insurance such flood zone, CRS, and preFIRM are include in the models instead of insurance premium. If an individual's utility of purchasing insurance exceeds the utility of an uninsured status, the person will willingly purchase flood insurance. An individual is assumed to purchase insurance if:

$$u_{1,j}(\mathbf{g}_j,\ \mathbf{p}_j,\ \mathbf{r}_j,\ \mathbf{d}_j,\ \varepsilon_{1,j};1) > u_{0,j}(\mathbf{g}_j,\ \mathbf{p}_j,\ \mathbf{r}_j,\ \mathbf{d}_j,\ \varepsilon_{0,j};0) \tag{3}$$

The probability of *j*th household's purchasing insurance is thus:

$$\Pr(i=1) = P[u_{1,j}(\mathbf{g}_j,\ \mathbf{p}_j,\ \mathbf{r}_j,\ \mathbf{d}_j,\ \varepsilon_{1,j}) > u_{0,j}(\mathbf{g}_j,\ \mathbf{p}_j,\ \mathbf{r}_j,\ \mathbf{d}_j,\ \varepsilon_{0,j})] \tag{4}$$

Otherwise, a person does not purchase flood insurance.

Using the general probability statement, we need to construct an econometric model for parameter estimation. It is assumed that the utility function of the decision makers is linear in parameters. The linear utility function of *j*th household is written

$$u_{i,j} = \boldsymbol{\beta}_{i,1}\mathbf{g}_j + \boldsymbol{\beta}_{i,2}\mathbf{p}_j + \boldsymbol{\beta}_{i,3}\mathbf{r}_j + \boldsymbol{\beta}_{i,4}\mathbf{d}_j + \varepsilon_{i,j} \tag{5}$$

where $\boldsymbol{\beta}_{i,1}$ through $\boldsymbol{\beta}_{i,4}$ are vectors for parameter estimation for *j*th household's explanatory variable vectors, **g**, **p**, **r**, and **d** respectively. The *j*th household's linear utility function with flood insurance (*i*=1) would be

$$u_{1,j} = \boldsymbol{\beta}_{1,1}\mathbf{g}_j + \boldsymbol{\beta}_{1,2}\mathbf{p}_j + \boldsymbol{\beta}_{1,3}\mathbf{r}_j + \boldsymbol{\beta}_{1,4}\mathbf{d}_j + \varepsilon_{1,j}, \tag{6}$$

and utility function without insurance (*i*=0) would be

$$u_{0,j} = \boldsymbol{\beta}_{0,1}\mathbf{g}_j + \boldsymbol{\beta}_{0,2}\mathbf{p}_j + \boldsymbol{\beta}_{0,3}\mathbf{r}_j + \boldsymbol{\beta}_{0,4}\mathbf{d}_j + \varepsilon_{0,j}. \tag{7}$$

An individual purchases flood insurance when the utility with flood insurance exceeds the utility with no insurance. It can be written as

$$\begin{aligned} u_{1,j} &= \boldsymbol{\beta}_{1,1}\mathbf{g}_j + \boldsymbol{\beta}_{1,2}\mathbf{p}_j + \boldsymbol{\beta}_{1,3}\mathbf{r}_j + \boldsymbol{\beta}_{1,4}\mathbf{d}_j + \varepsilon_{1,j} \\ &> \boldsymbol{\beta}_{0,1}\mathbf{g}_j + \boldsymbol{\beta}_{0,2}\mathbf{p}_j + \boldsymbol{\beta}_{0,3}\mathbf{r}_j + \boldsymbol{\beta}_{0,4}\mathbf{d}_j + \varepsilon_{0,j} = u_{0,j}. \end{aligned} \tag{8}$$

The difference between random components, in here error terms, cannot be identified, so it could be written as a single term, $\varepsilon_j \equiv \varepsilon_{1,j} - \varepsilon_{0,j}$. Moreover, the estimate parameter only estimates the difference between vectors; it does not estimates each vector separately, so we can rewrite this difference as $\boldsymbol{\beta}_t = \boldsymbol{\beta}_{1,t} - \boldsymbol{\beta}_{0,t}$. By rearranging the difference between the utility of insurance purchasing and non-purchasing is

$$\begin{aligned} u_{1,j} - u_{0,j} &= (\boldsymbol{\beta}_{1,1} - \boldsymbol{\beta}_{0,1})\mathbf{g}_j + (\boldsymbol{\beta}_{1,2} - \boldsymbol{\beta}_{0,2})\mathbf{p}_j + (\boldsymbol{\beta}_{1,3} - \boldsymbol{\beta}_{0,3})\mathbf{r}_j + (\boldsymbol{\beta}_{1,4} - \boldsymbol{\beta}_{0,4})\mathbf{d}_j + \varepsilon_j \\ &= \boldsymbol{\beta}_1\mathbf{g}_j + \boldsymbol{\beta}_2\mathbf{p}_j + \boldsymbol{\beta}_3\mathbf{r}_j + \boldsymbol{\beta}_4\mathbf{d}_j + \varepsilon_j, \end{aligned} \qquad 9)$$

Therefore, the probability statement for a decision maker of insurance purchase (i=1) is

$$\Pr_1 = P(\boldsymbol{\beta}_1\mathbf{g}_j + \boldsymbol{\beta}_2\mathbf{p}_j + \boldsymbol{\beta}_3\mathbf{r}_j + \boldsymbol{\beta}_4\mathbf{d}_j + \varepsilon_j > 0). \tag{10}$$

To estimate the parameters of the utility function, it is required to specify the random components. In most cases, random component ε_j, is assumed independently and identically distributed (IID) with a zero mean. When the error term is IID and has a mean of zero, the normal distribution and logistic distribution are commonly used. This probability of *j*th household responding ‘yes’ can be estimated as

$$
\begin{aligned}
& P(\boldsymbol{\beta}_1\mathbf{g}_j + \boldsymbol{\beta}_2\mathbf{p}_j + \boldsymbol{\beta}_3\mathbf{r}_j + \boldsymbol{\beta}_4\mathbf{d}_j + \varepsilon_j > 0) \\
&= P[-(\boldsymbol{\beta}_1\mathbf{g}_j + \boldsymbol{\beta}_2\mathbf{p}_j + \boldsymbol{\beta}_3\mathbf{r}_j + \boldsymbol{\beta}_4\mathbf{d}_j) < \varepsilon_j] \\
&= 1 - P[-(\boldsymbol{\beta}_1\mathbf{g}_j + \boldsymbol{\beta}_2\mathbf{p}_j + \boldsymbol{\beta}_3\mathbf{r}_j + \boldsymbol{\beta}_4\mathbf{d}_j) > \varepsilon_j]
\end{aligned} \tag{11}
$$

Because the probability distribution is symmetric, it is true that F(x) = 1 - F(-x), and thus, the probability of ‘yes’ for a *j*th household can be rewritten

$$
P(\varepsilon_j < \boldsymbol{\beta}_1\mathbf{g}_j + \boldsymbol{\beta}_2\mathbf{p}_j + \boldsymbol{\beta}_3\mathbf{r}_j + \boldsymbol{\beta}_4\mathbf{d}_j). \tag{12}
$$

Hypotheses

Previous literature provides a background for setting the hypotheses of this research paper. However, some variables we consider in this paper are not found in previous literature. Those variables are hypothesized based on our intuition. The following factors are hypothesized as having an influence on deciding flood insurance purchasing.

Table 3 Expectation for Explanatory Variables for NFIP Participation Model

Variable	Description	Expected Sign
Range/ Variance	When range/Variance of perceived risk increases, the probability of flood insurance purchasing would decreases.	-
Risk Aversion	The probability of purchasing flood insurance increases with a higher degree of a risk aversion attitude (Baumann and Sims, 1978; Kunreuther, 1996).	+
Risk Perception	Risk perception is measured through three scenarios: hurricane frequency, magnitude of damage, expected damage. The probability of purchasing flood insurance increases with the increase of risk perception (Kunreuther, 1996).	+
Mortgage Status	The probability of purchasing flood insurance increases with the presence of a mortgage (Browne and Hoyt, 2000; Kriesel and Landry, 2004; Landry and Jahan-Parvar, 2010).	+

Table 3 (continued)

House Type	It is hypothesized that the homeowner of a single family house detached from other houses has more probability of purchasing insurance because NFIP's insurance premium rate is lower compared to the other house types under the same coverage level.	+
CRS (Community Rating System)	The probability of purchasing flood insurance increases with the decrease of the CRS class or the increase of a CRS participating degree (Zahran et al., 2009).	-
Flood Zone	The probability of purchasing flood insurance increases when the property is located in a high risk area such as a SFHA (Landry and Jahan-Parvar, 2010; Michel-Kerjan and Kousky, 2010).	+
Previous Experience	If a household had a previous flood damage experience, his or her probability to purchase flood insurance increases based on the severity of damage experience (Browne and Hoyt, 2000; Zahran et al., 2009).	+
PreFIRM	If a property is constructed before the publication of FIRM, the probability of the property owner purchasing flood insurance decreases because, after the FIRM publication, the NFIP gives a disincentive for the construction.	-
Distance from the Coast	It is hypothesized that the probability of purchasing flood insurance decreases with the increase of distance from the coast because the greater the distance from the coast lessens the potential risk of damage of flood.	-
Income	The probability of purchasing flood insurance increases with the increase in income (Browne and Hoyt, 2000; Kriesel and Landry, 2004; Landry and Jahan-Parvar, 2010).	+
Age	The probability of purchase flood insurance increases as the age of the property owner increases (Pynn and Ljung, 1999; Nguyen et al., 2010).	+
Gender	Females would have a higher probability for purchasing flood insurance (Riddel, 2009).	-
Education	As education levels increases, so does the probability of flood insurance purchasing (Baumann and Sims, 1978; Zahran et al., 2009).	+
Insurance Confidence	It is hypothesized that the probability to purchase flood insurance increases as a person has a stronger confidence in an insurance company paying for their losses. Due to the fact that people believe that insurance companies have certain abilities and responsibilities to insured people, they willingly purchase flood insurance to reduce their own risks.	+
Expected Government Aid	It is hypothesized that the probability to purchase flood insurance decreases as a person has a stronger confidence in government aid. Because government aid and insurance have a substitutional relationship, it is expected that the confidence for one will decrease the confidence for another.	-

CHAPTER V

DATA

This chapter explains how the data were collected and will provide a general description of the data. The data were collected through online surveys, primarily, focusing on the residents of coastal area.

The survey consisted of 41 questions. Some questions were open ended, and others were discrete or multiple choice questions. Follow up questions were, sometimes, provided to ask for additional comments to get detailed explanations. The survey questions were classified into four categories: geographic information (**g**), flood insurance policy related information (**p**), attitude towards a risk (**r**), and demographic information (**d**). Geographic information includes the property's distance from the coast as well as state and metropolitan area information. Flood insurance questions collected information related to the important determinants of a NFIP insurance premium; such as mortgage presence, CRS level, etc. Attitude towards risk questions included individuals' risk perception, risk ambiguity, and risk preference. Demographic questions included age, gender, education level, income, etc. All questions are not listed in this chapter; for more detail, please refer to the survey sample later in this paper.

The definitions of risk preference and risk perception are declared in the definition section in Chapter 1. The following is a discussion on the measurement method of these two variables, risk preference and risk ambiguity. Risk preference is measured using a lottery method. Holt and Laury (2002) elicited the individual's risk aversion by asking a series of choice pairs. Of the total five choices, one choice is selected as the prize of the lottery, and the respondent will receive real money based on the lottery. It is assumed that real money elicits more accurate human behaviors than other compensation methods, and thus, this lottery method is a prevailing method to elicit human's risk preference. In the survey, we used the same format of Holt and Laury's lottery questions. Two different ways are used to elicit risk preference: a gain scenario and a loss scenario. Both scenarios are represented in each of the five choice pairs with a different probability and an expected return. In the gain scenario, the people will receive money, but in the loss scenario, they will lose their money depending on the respondent's choices and the lottery. Because the real money compensation or deduction relies on the respondent's choice, people should ponder their decision among options to make a bigger gain or a smaller loss. This decision-making process releases an individual's risk preference. The five different pairs of choices which people are given under the gain scenario starts at

> *A. A 1-out-of-10 chance of gaining $5 and a 9-out-of-10 chance of gaining $4* and
>
> *B. A 1-out-of-10 chance of gaining $9.50 and a 9-out-of-10 chance of gaining $0.50.*

Finally, it ends with

> *A. A 9-out-of-10 chance of gaining $5 and a 1-out-of-10 chance of gaining $4* and
>
> *B. A 9-out-of-10 chance of gaining $9.50 and a 1-out-of-10 chance of gaining $0.50.*

In the first choice pair, a bigger compensation has a lower probability to win, but at the end a bigger compensation has a higher probability to win. The difference between choices A and B constitutes a risk-taking attitude because the difference of winning prizes for choice B is a greater than choice A. How the choice represents a risk preference will be discuss later.

We used two questions to elicit an individual's risk perception and to test the impact of different elicitations. An individual's expected risk is measured by using an expected number of major hurricanes in the next 50 years and by using expected damage on properties caused by a major hurricane. As mentioned earlier, a hurricane is a major cause of floods, coastal residents perceive that hurricanes and floods are closely related. Risk perception questions were asked regarding hurricanes instead of floods for improved understanding. In order to help respondents' understand the devastating power of a risky event detailed information given about the hurricane, such as a Category 3 or greater hurricane with winds of 111mph or great. Therefore, using risk for hurricanes as the measurement of one's perceived flood risk is not perfect, but it is a reasonable proxy for coastal flooding risk. The following are examples of hurricane frequency questions to elicit risk perception:

> *"Based on your experience, how many major hurricanes (Category 3 or greater, with winds of 111 mph or greater) do you expect to directly strike your community over the next 50 years?"* (the most likely perceived)
>
> *"Given your previous answer, how many would you say is the <u>most</u> that you could reasonably expect over the next 50 years?"* (the highest perceived)
>
> *"Given your previous answer, how many would you say is the <u>least</u> that you could reasonably expect over the next 50 years?"* (the lowest perceived)

Additionally, the expected magnitude of damage by a major hurricane strike is asked as a different measurement of risk perception. The following are examples of perceived magnitude of damage:

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

"Given your previous answer, what is the most damage to your home that you could reasonably expect from a Category 3 hurricane?" (the highest perceived)

"Given your previous answer, what is the least damage to your home that you could reasonably expect from a Category 3 hurricane?" (the lowest perceived)

The response from the most likely perceived question represents the mean of a person's risk perception. Risk ambiguity is measured by reanalyzing the responses of the risk perception questions. The methods pf how risk perception is converted to risk ambiguity were already discussed in Chapter 3.

Data Collection

The data were collected via an online survey contracted through Knowledge Networks (KN). KN is the only online survey firm who offers a probability-based sample. The sample was selected based on a random-digit dialing (RDD) or address-based sampling. Then, KN comprises a "Knowledge Panel" whom is randomly recruited by telephone and by self-administered mail and web surveys. Because KN conducts online surveys, the company provides internet access and equipment to non-internet accessible panelists in order to avoid a biased sample that would stem from a limitation of internet accessibility. The data collection was conducted during August and September 2010. A total of 1536 people were invited; 1070 people completed the survey, and the number of consented responses was 859. The consented rate is 80.3%, but based on the number of the invited panel, the response rate is 55.92%. Compared to existing survey response rates, this percentage indicates a very high response rate. The respondents were 18 years of age or older, homeowners, and residents in one of the 93 coastal or near-coastal flood-prone counties in Alabama, Florida, Louisiana, Mississippi, and Texas. Because the primary purpose of conducting a survey is to observe the behaviors of the coastal and flood-prone area residents, we asked NK to include some specific counties' residents in the sample.

Unfortunately, some survey questions may have raised confusion to the respondents, and thus they provided some nonsensical responses. For instance, some people gave a higher mean-expectation than the highest-expectation, and rarely some gave a higher lowest-expectation than the mean or the highest-expectation. We concluded that the respondents who provide these irrational answers do not fully understand the intention of the question; so, we dropped the data set of these respondents. After dropping all ineligible data, we finally have 446 observations that can be usable for estimation. All the following estimations have the same observation number, 446.

Survey Results

On Table 4, the demographic information of both the sample and the population is presented. The demographic data of population is provided by NK. Compared with the population, our sample is comprised of older people, more female, more white, and more educated people. In the sample, 79.4% of people were 45 years of age or older, while these respondents only comprise 71.12% of the actual population. The sample also has a slightly bigger proportion of female (55.65%) than the actual population (50.02%). The ethnic composition is similar; white takes the largest portion, and hispanic/other and black follow, respectively. Education levels show a significant difference between the population and the sample. As education level increases, the portion also increases in the sample. Thus, bachelor or above level takes the largest portion in the sample. On the other hand, in population, high school or below takes the largest portion, and bachelor or above takes the second largest. When combined, more than three fourths (77.53%) of the sample has at least some college level education, while 61.01% of the population are located in that education level. Therefore, the sample consists of people with a higher education level. The regional distributions and the comparisons about living in a metropolitan area between the sample and the population are similar. Another significant difference between the sample and the population can be seen in the ability to access the internet. Only 5% of the sample does not have internet access while more than 25% of the population does not have internet access. It may be because KN is an online based survey company despite the fact that the company also recruits people without internet access.

Table 4 Comparison of Demographic Information of Sample and Population

		Sample (N=859)	Population
Age	18-44	0.206	0.289
	45-59	0.360	0.309
	60+	0.434	0.402
Gender	Male	0.444	0.500
Ethnicity	White	0.814	0.739
	Black	0.056	0.086
	Hispanic, Other	0.130	0.175
Education	High school or below	0.225	0.390
	Some college	0.317	0.268
	Bachelor or above	0.458	0.342
State	AL or MS	0.038	0.043
	FL	0.612	0.641
	LA	0.121	0.136
	TX	0.229	0.180
Metropolitan Area	Non-Metro	0.050	0.062
	Metro	0.950	0.938
Internet	No	0.056	0.277
	Yes	0.944	0.723

Table 5 describes the summary statistics of the demographic information of the survey responses. The average age of respondents is 56 years, and the average number of people per household is 2.47 persons. More female respondents (54%) participated than male respondents (46%). Some college is the average level of education, and bachelor or above takes more than half. Respondents are white (84.9%), hispanic (8.1%), black (3.4%), and other races (1.6%). The average income falls between \$50,000 and \$59,999 range. 56.9% of total are currently employed. The largest portion is taken by the working-paid group (46.4%), and the second largest share is non-working- retired group (28.9%). Most respondents are living with a spouse (68.8%). In order to increase the explanatory power of these two variables, working status and marital status, these responses were transformed into a binary form. For example, any forms of employed statuses are included in a working group, and all others are included in a non-working group. Married and living with a partner were combined together because cohabitating is assumed to affect one's decision-making. Therefore, marital status consists of married/cohabitating or having no one.

Table 5 Summary Description of Demographic Characteristics (N=446)

Variable	Type	Description	Mean	Std. Dev.	Min.	Max.
Age	Continuous	Respondent's age	56.00	13.45	19	85
Household Size	Continuous	The number of people in respondent's household	2.47	1.27	1	8
Gender	Binary	Gender of respondent (0=Female / 1=Male)	0.46	0.50	0	1
Education	Category	Education level	3.31	0.81	1	4
		1= Less than High School	(2.2%)			
		2= High School	(15.5%)			
		3= Some College	(31.2%)			
		4= Bachelor's Degree or above	(51.1%)			
Ethnicity	Category	Races of respondents	1.39	1.00	1	5
		1= White, Non-Hispanic	(84.9%)			
		2= Black, Non-Hispanic	(3.4%)			
		3= Other, Non-Hispanic	(1.6%)			
		4= Hispanic	(8.1%)			
		5= 2+ Races, Non-Hispanic	(2.0%)			
Marital Status	Category	Current status of marriage	1.93	1.60	1	6
		1= Married	(68.8%)			
		2= Widowed	(4.9%)			
		3= Divorced	(11.4%)			
		4= Separated	(0.5%)			
		5= Never Married	(8.1%)			
		6= Living with a partner	(6.3%)			
Working Status	Category	Current working condition	2.92	2.10	1	7
		1= Working-paid employee	(46.4%)			
		2= Working-self-employed	(10.5%)			
		3= Not working-temp. layoff	(0.7%)			

(Table 5 Continued)

		4= Not working-looking for work	(4.1%)			
		5= Not working-retired	(28.9%)			
		6= Not working-disabled	(3.8%)			
		7= Not working-other	(5.6%)			
Household Income	Category	Total household members' income	12.74	3.86	1	19
		1= less than $5,000	(0.9%)			
		2= $5,000 to $7,499	(0.5%)			
		3= $7,500 to $9,999	(1.1%)			
		4= $10,000 to $12,499	(0.7%)			
		5= $12,500 to $14,999	(1.4%)			
		6= $15,000 to $19,999	(1.6%)			
		7= $20,000 to $24,999	(4.3%)			
		8= $25,000 to $29,999	(4.9%)			
		9= $30,000 to $34,999	(2.9%)			
		10= $35,000 to $39,999	(6.7%)			
		11= $40,000 to $49,999	(8.9%)			
		12= $50,000 to $59,999	(8.0%)			
		13= $60,000 to $74,999	(13.9%)			
		14= $75,000 to $84,999	(7.4%)			
		15= $85,000 to $99,999	(11.0%)			
		16= $100,000 to $124,999	(9.2%)			
		17= $125,000 to $149,999	(5.8%)			
		18= $150,000 to $174,999	(4.5%)			
		19= $175,000 or more	(5.8%)			

In order to observe the relationship between insurance policy holing and demographic characteristics, Table 6 to 12 will describe the share of insurance policy holders and non-policy holders by each variable. According to Table 6, in small household sizes, the share of non-insurance almost twice as large, but in medium size, the share of insured people increases. Table 7 shows that the shares of insured and uninsured groups are similar in different genders.

Table 6 Distribution of Insurance Policy Holder by Household Size

Household Size	Has Insurance	No Insurance	Total
1	28 (35.90%)	50 (64.10%)	78
2	74 (34.10%)	143 (65.90%)	217
3	21 (29.17%)	51 (70.83%)	72
4	19 (45.24%)	23 (57.76%)	42
5	11 (47.83%)	12 (52.17%)	23
6	7 (70.00%)	3 (30.00%)	10
7	0 (0%)	1 (100%)	1
8	1 (33.33%)	2 (66.67%)	3
Total	161	285	446

Table 7 Distribution of Insurance Policy Holder by Gender

Gender	Has Insurance	No Insurance	Total
Male	80 (33.20%)	161 (66.80%)	241
Female	81 (39.51%)	124 (60.49%)	205
Total	161	285	446

Table 8 and 9 describe the shares according to education level and ethnicity, respectively. In low education levels, the share of the uninsured group is significantly bigger than insured group, but the difference decreases in higher education levels. In Table 9, white, black and other, non-Hispanic races have a significantly larger share of the uninsured group, and Hispanic and 2+races, non-Hispanic races have similar share. However, the similarity of last two races stems from the small number of observations.

Table 8 Distribution of Insurance Policy Holder by Education Categories

Education Level	Has Insurance	No Insurance	Total
Less than High School	3 (30.00%)	7 (70.00%)	10
High School	14 (20.29%)	55 (79.71%)	69
Some College	52 (37.41%)	87 (62.59%)	139
Bachelor or Above	92 (40.35%)	136 (59.65%)	228
Total	161	285	446

Table 9 Distribution of Insurance Policy Holder by Ethnicity

Ethnicity	Has Insurance	No Insurance	Total
White	133 (35.09%)	246 (64.91%)	379
Black	5 (33.33%)	10 (66.67%)	15
Other, non-Hispanic	2 (28.57%)	5 (71.43%)	7
Hispanic	17 (47.22%)	19 (52.78%)	36
2+ race, non-Hispanic	4 (44.44%)	5 (55.56%)	9
Total	161	285	446

Table 10 shows the respondents' income distribution. In lower income levels between \$7,500 and \$19,999, the insured group has a larger share than the other levels, and in higher income levels between \$85,000 and \$149,999, the insured group also shows a larger share than the other levels. In Table 11, two employed statuses have similar share of insured and uninsured groups. Interestingly, the uninsured group's share of disabled people is significantly higher than the share of insured group. Also, almost all people that responded as 'looking for a job' are not insured. In Table 12, the majority of respondents are married, with other marital statuses being similar except 'divorced' and 'separated' statuses.

Table 10 Distribution of Insurance Policy Holder by Income

Income	Has Insurance	No Insurance	Total
less than $5,000	0	4 (100%)	4
$5,000 to $7,499	0	2 (100%)	2
$7,500 to $9,999	2 (40.00%)	3 (60.00%)	5
$10,000 to $12,499	2 (60.67%)	1 (33.33%)	3
$12,500 to $14,999	3 (50.00%)	3 (50.00%)	6
$15,000 to $19,999	3 (42.86%)	4 (57.14%)	7
$20,000 to $24,999	7 (36.84%)	12 (63.16%)	19
$25,000 to $29,999	6 (27.27%)	16 (72.73%)	22
$30,000 to $34,999	5 (38.46%)	8 (61.54%)	13
$35,000 to $39,999	3 (10.00%)	27 (90.00%)	30
$40,000 to $49,999	13 (32.50%)	27 (67.50%)	40
$50,000 to $59,999	11 (28.95%)	27 (71.05%)	38
$60,000 to $74,999	18 (29.03%)	44 (70.97%)	62
$75,000 to $84,999	11 (33.33%)	22 (66.67%)	33
$85,000 to $99,999	24 (48.98%)	25 (51.02%)	49
$100,000 to $124,999	16 (39.02%)	25 (60.98%)	41
$125,000 to $149,999	12 (45.15%)	14 (53.85%)	26
$150,000 to $174,999	7 (35.00%)	13 (65.00%)	20
$175,000 or more	18 (69.23%)	8 (30.77%)	26
Total	161	285	446

Table 11 Distribution of Insurance Policy Holder by Working Status

Working Status	Has Insurance	No Insurance	Total
Working-Paid employ	78 (37.68%)	129 (62.32%)	207
Working-Self employ	17 (36.17%)	30 (63.83%)	47
Not working-Temp. Lay-off	2 (66.67%)	1 (33.33%)	3
Not working-Looking for a job	1 (5.50%)	17 (94.50%)	18
Not working-Retired	49 (37.98%)	80 (62.02%)	129
Not working-Disabled	5 (29.41%)	12 (70.59%)	17
Not working-Others	9 (36.00%)	16 (64.00%)	25
Total	161	285	446

Table 12 Distribution of Insurance Policy Holder by Marital Status

Marital Status	Has Insurance	No Insurance	Total
Married	108 (35.18%)	199 (64.82%)	307
Widowed	9 (40.91%)	13 (59.09%)	22
Divorced	15 (29.41%)	36 (70.59%)	51
Separated	0	2 (100%)	2
Never married	16 (44.44%)	20 (55.56%)	36
Living with a partner	13 (46.43%)	15 (53.57%)	28
Total	161	285	446

Table 13 depicts the summary description of flood insurance policy variables. Since the insurance question is binary (whether a person has flood insurance or not, no=0 and yes=1), the mean value falls between 0 and 1. Therefore, the mean value of the insurance variable (0.36) can be interpreted that 36% of the respondents have a flood insurance policy. In the same way, 63% of respondents have a mortgage loan on their property. The finding that 212 out of 308 people (68.8%) who currently have flood insurance have kept flood insurance for their entire tenure is particularly interesting. Some researchers have reported that many people drop their insurance policies in a few years, but our finding differs from their reports.

Originally, 52% of respondents answered that their properties are not located in a flood zone, and 24% of respondents were not sure about their flood zone or did not know their properties are located in a flood zone. Due to the lack of unawareness of property owners, many data for flood zones were missed. In order to improve the quality and quantity of flood zone data, additional information were collected by looking for the flood zone of each property manually. After additional data collection, the flood zones of all the properties were founded except for 22 properties, and then flood zone data were divided into only two groups: properties located in a Special Flood Hazard Area (SFHA) or properties located in a non-SFHA. As a result, it is found that 37% of total properties are located in a SFHA. In addition to survey data, the class of Community Rating System (CRS) of the community where a property is located and the property construction year were collected. Although originally CRS class is divided into 10 classes, all responses fall between a class 5 and a class 10. The average level is a class 7 which means a community in a SFHA receives a15 % flood insurance premium reduction while a community in a non-SFHA receives 5 % reduction. Through the construction year, properties were identified as whether they were constructed before the publication of the FIRM (Flood Insurance Rating Map) or not. 37% of total properties were constructed before the publication of FIRM. House type is also a determining factor of NFIP's insurance premium; so, we assumed that housing type will affect the decision-making for flood insurance purchasing. People were given 5 choices: 1) a one-family house detached from other houses, 2) a one-family house attached to one or more houses, 3) a building with 2 or more apartment, 4) a mobile home, 5) boat, RV, van, etc. From responses, 85.2% of the total respondents lived in a single family house detached from other houses. Since other house types have small number of responses, house type variable is turned into a binary form to observe the difference between a single family house detached from other houses and other house types.

Table 13 Summary Description of Characteristics Involving Flood Insurance Policy (N=446)

Variable	Type	Description	Mean	Std. Dev.	Min	Max
Insurance	Binary	Whether a person has flood insurance or not (1=Yes,0=No)	0.36	0.36	0	1
Mortgage	Binary	Whether a person has mortgage loan or not (1=Yes, 0=No)	0.66	0.48	0	1
SFHA	Binary	Whether a property is located in SFHA(Special Flood Hazard Area) or not (1=Yes, 0=No)	0.17	0.37	0	1
CRS (Community Rating System)	Category	Premium reduction based on participating NFIP	6.97	1.48	5	10
		5=25%(SFHA)/10%(non-SFHA)	(18%)			
		6=20%(SFHA)/10%(non-SFHA)	(22%)			
		7=15%(SFHA)/5%(non-SFHA)	(30%)			
		8=10%(SFHA)/5%(non-SFHA)	(14%)			
		9=5%(SFHA)/5%(non-SFHA)	(4%)			
		10= no reduction for both	(11%)			
PreFIRM	Binary	Whether a property is constructed before the publication of FIRM(Flood Insurance Rating Map) (1=Yes, 0=No)	0.37	0.48	0	1
House Type	Category	Housing type	1.30	0.78	1	4
		1= A house detached from others	(85%)			
		2= A house attached to others	(5%)			
		3= Apartments complex	(5%)			
		4= A mobile home	(5%)			
		5= Boat, RV, Van, etc.	(0%)			

* There vce variable shoreline.dataocated in 2 km from the shoreline,

From Table 14 to 18, detailed comparisons about flood insurance policy variables between insured and uninsured groups are described. In Table 14, the share of insured and uninsured groups is similar in having a mortgage and no mortgage statuses.

Table 14 Distribution of Insurance Policy Holder by Mortgage Status

Mortgage Status	Has Insurance	No Insurance	Total
Has Mortgage	50 (32.68%)	103 (67.32%)	153
No Mortgage	111 (37.88%)	182 (62.12%)	293
Total	161	285	446

Table 15 shows that people live in a SFHA have a twice large share of insured respondents, and most respondents who live in a non-SFHA are not insured. It seems reasonable that people in high risk more likely to purchase insurance than people in low risk.

Table 15 Distribution of Insurance Policy Holder by SFHA

SFHA	Has Insurance	No Insurance	Total
SFHA	56 (75.68%)	18 (24.32%)	74
Non-SFHA	105 (28.23%)	267 (71.77%)	372
Total	161	285	446

Table 16 describes the policy holder distribution by CRS classes. The responses for class 9 are significantly low in both insured and uninsured groups, but the reason is not clear. For class 9 and 5, the insured group has a larger share, but other classes have a larger share of uninsured people. The comparison of the preFIRM variable between insured and uninsured groups is not different in Table 17; about one third of respondents are insured in both before FIRM and after FIRM.

Table 16 Distribution of Insurance Policy Holder by CRS Class

CRS	Has Insurance	No Insurance	Total
Class 5	41 (51.90%)	38 (48.10%)	79
Class 6	24 (24.00%)	76 (76.00%)	100
Class 7	42 (30.66%)	95 (69.54%)	137
Class 8	25 (38.46%)	40 (61.54%)	65
Class 9	9 (52.94%)	8 (47.06%)	17
Class 10	20 (41.67%)	28 (58.33%)	48
Total	161	285	446

Table 17 Distribution of Insurance Policy by preFIRM

FIRM	Has Insurance	No Insurance	Total
Before FIRM	101 (36.20%)	178 (63.80%)	279
After FIRM	60 (35.93%)	107 (64.07%)	167
Total	161	285	446

Table 18 shows the comparison of the house type variable. Most people live in a single family house detached from other houses, and there is no response for the RV, Van, and etc. house type in the data used in the models. The uninsured group has significant larger share in mobile homes. This can be interpreted in two ways: a lack of interest to buy insurance or a lack of financial source to buy insurance.

Table 18 Distribution of Insurance Policy Holder by House Type

House Type	Has Insurance	No Insurance	Total
Detached House	141 (37.11%)	239 (62.89%)	380
Attached House	7 (30.43%)	16 (69.57%)	23
Apartments	9 (45.00%)	11 (55.00%)	20
Mobile Home	4 (17.39%)	19 (82.61%)	23
RV, Van, and Etc	0	0	0
Total	161	285	446

Table 19 explains the geographic characteristics of properties. The state variable shows in what state the property is located. Most of the properties are located in Florida; the second largest concentration is in Texas; and others are less than 10%. The mean of metro variable, 0.95, shows that 95% of properties are located in a metropolitan area so it seems hard to observe the different impact between the metro and non-metro areas. In addition to the survey data, the distance from the nearest shoreline of each property is observed using GIS. The distance from a property to the shoreline was measured based on the property address. The mean distance from the coast is 15.61 kilometers (9.7mies). Figure 4 presents the histogram of the distance variable. As the distance from the coasts increases, the density of responses decreases. Therefore, most of the properties are located within 40km from the shoreline, and the highest density appears in the 0 and 4km interval.

Table 19 Summary Description of Geographic Characteristics (N=446)

Variable	Type	Description	Mean	Std. Dev.	Min	Max
State	Category	State where properties are located	2.11	1.71	1	5
		1=Florida	(67.7%)			
		2=Alabama	(3.1%)			
		3=Mississippi	(1.6%)			
		4=Louisiana	(5.2%)			
		5=Texas	(22.4 %)			
Metro	Binary	Whether a property is located in a metropolitan area (Yes=1, No=0)	0.95	0.22	0	1
Distance from the Coast(km)	Continuous	The distance from the nearest shoreline to a property	15.61	18.51	0	171.7

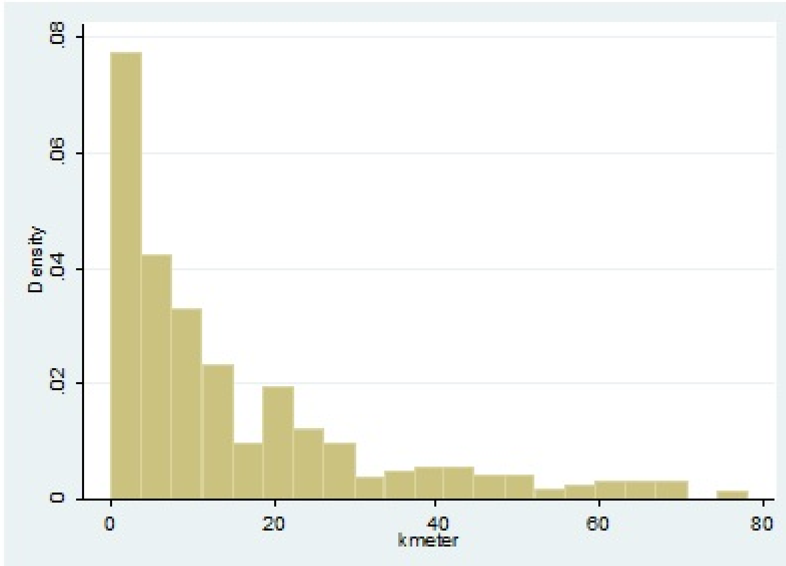

Figure 4 Histogram of Distances from the Coasts

In Table 20, the state with the largest responses, Florida, and the state with the smallest responses, Alabama/Mississippi show a larger uninsured group share while other states have a bigger insured group share. Since the largest number of flood insurance policies were issued in Florida, this result seems awkward.

Table 20 Distribution of Insurance Policy Holder by States

State	Has Insurance	No Insurance	Total
Florida	86 (28.48%)	216 (71.52%)	302
Texas	55 (55.00%)	45 (45.00%)	100
Louisiana	13 (56.52%)	10 (43.48%)	23
Alabama/Mississippi	7 (33.33%)	14 (66.67%)	21
Total	161	285	446

Table 21 shows the share by metropolitan area. In metro areas, insured group's share is larger than insured group's share in non-metro areas.

Table 21 Distribution of Insurance Policy Holder by Metro

Metropolitan	Has Insurance	No insurance	Total
Metro area	157 (37.03%)	267 (62.97%)	424
Non-metro area	4 (18.18%)	18 (81.82%)	22
Total	161	285	446

Table 22 describes the summary description of risk variables. Hurricane frequency, magnitude of damage, and expected damage are risk perception measuring variables. Hurricane frequency is the frequency of a major hurricane strikes in the next 50 years, and magnitude of damage measures the magnitude of damage on owned property from a major hurricane. The frequency responses range from 1 to 99 as a whole number while the magnitude of damage is expressed as a percentage of the total structure value. The respondents most likely expect the number of a major hurricane strikes in the next 50 years to be 6.08 times. The average expected severity of damage is 4.25; on average, people expect that 42.5 % of the total structure value will be destroyed once a major hurricane hits their properties. From two risk perception responses, expected damage is calculated by multiplying the frequency and magnitude. The number of frequency is divided by 50 to calculate the expected frequency of a given year, and the magnitude is divided by 10 to convert responses into a probability form. The most likely expected damage is 0.04, and that means that people expect their damage by a major hurricane in a given year as 4%.

Risk aversion is measured on a 1 to 6 scale with 6 meaning that the respondent is extremely risk-averse in both gain and loss scenarios. The means of the two scenarios are not very different. The means are 3.96 for the gain scenario and 3.93 for the loss scenario; these values show that, on average, people are risk-averse in both scenarios. About 36% of total respondents experienced flood damage before. Moreover, people have medium level (3.02) of confidence for an insurance company's compensation, and the expectation for government aid is slightly lower than medium level (2.68). The confidence for an insurance company is slightly stronger than expectation for governmental aid.

Table 22 Summary Description of Attitudes Toward Risk (N=446)

Variable		Type	Description	Mean	Std. Dev.	Min	Max
Hurricane Frequency	Mean	Continuous	Individual's perceived number of major hurricanes strikes in the next 50 years	6.08	8.61	1	75
	Most			9.52	12.64	1	99
	Least			2.71	4.72	0	45
Magnitude of damage	Mean	Continuous	Individual's perceived property magnitude of damage by a major hurricane in percentage (1=0 %, 11=100 %)	4.25	2.03	2	11
	Most			6.45	2.49	3	11
	Least			2.28	1.60	1	11
Expected Damage	Mean	Continuous	Product of frequency and magnitude calculated as the probability in a given year	0.04	0.06	0.02	0.7
	Most			0.10	0.16	0	1.50
	Least			0.01	0.03	0	0.54
Risk Aversion	Gain	Ordered Categorical	Risk aversion measured by gaining money lottery; larger number implies more risk aversion attitude	3.89	1.39	1	6
	Loss	Ordered Categorical	Risk aversion measured by losing money lottery; larger number implies more risk aversion attitude	3.96	1.27	1	6
Previous Damage		Binary	Individual's previous flood damage experience(1=experienced, 0=no experience)	0.36	0.48	0	1
Insurance Confidence		Ordered Categorical	Confidence for an insurance company's compensation once flooding (1=no confidence, 5=full confidence)	3.07	1.22	1	5
Expected Gov. Aid		Ordered Categorical	Expectation for Governmental aid once flooding(1=very unlikely, 5= very likely)	2.68	1.15	1	5

In risk aversion measurement, people make a decision based on their attitudes toward risks and the expected value of a choice. Between two choices, one choice always has a higher expected value than another. Table 23 shows the expected value of each choice in a lottery. For example, in Q1 choice A ($4.1) has a higher expected value than choice B ($1.4), and in Q4, choice B ($6.8) has a higher expected value than choice A ($4.7). Expected values of choice A do not changed a lot, but the expected values of choice B steeply increase. In the first question choice A has a higher expected value, but in third question expected value of choice B is higher than choice A.

Table 23 Expected Value of Each Lottery Question

	Expected Value of Choice A	Expected Value of Choice B
Q1	0.1*$5+0.9*$4= $4.1	0.1*$9.5+0.9*$0.5= $1.4
Q2	0.3*$5+0.7*$4= $4.3	0.3*$9.5+0.7*$0.5= $3.2
Q3	0.5*$5+0.5*$4= $4.5	0.5*$9.5+0.5*$0.5= $5.0
Q4	0.7*$5+0.3*$4= $4.7	0.7*$9.5+0.3*$0.5= $6.8
Q5	0.9*$5+0.1*$4= $4.9	0.9*$9.5+0.1*$0.5= $8.9

However, the choice is decided not only based on expected value but also based on one’s risk attitude. Because each prize has different probability, risk-averse people always prefer a lower risk choice in spite of a low expected value. Therefore, in the gain scenario, it is expected that risk-averse people choose choice A in Q1, and then depending on the magnitude of risk-averse people choose choice B in some points. The same is true for the loss scenario except vice versa. The following two graphs, Figure 5 and 6, show responses for risk aversion queries graphically. As shown below, the trend of selection change is in accordance with the hypothesis of the lottery experiment.

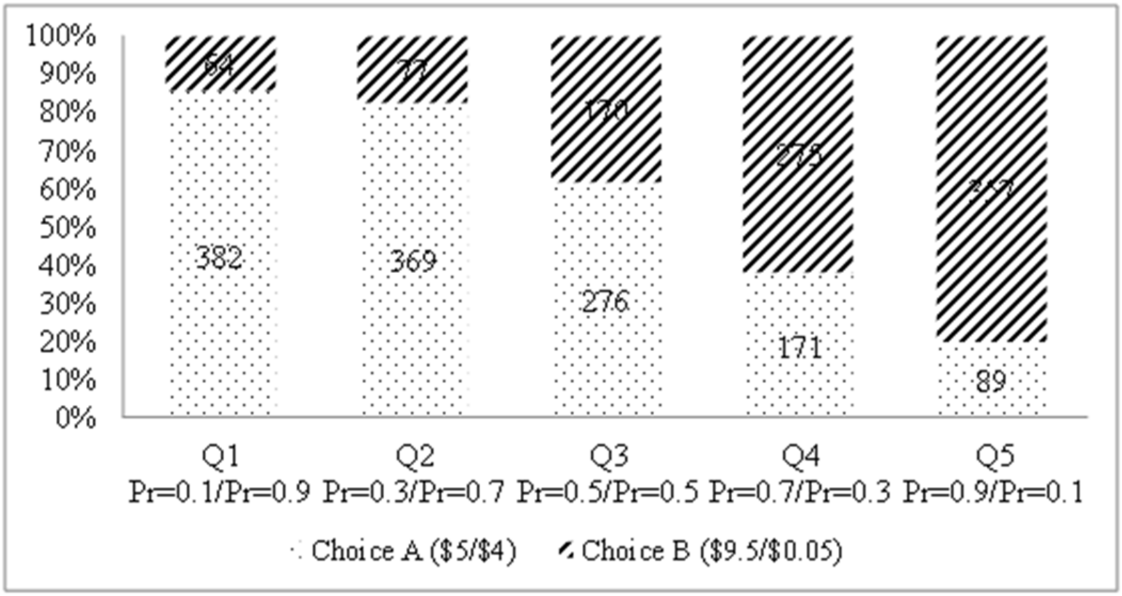

Figure 5 Proportion of Choices for the Gain Scenario (N=446)

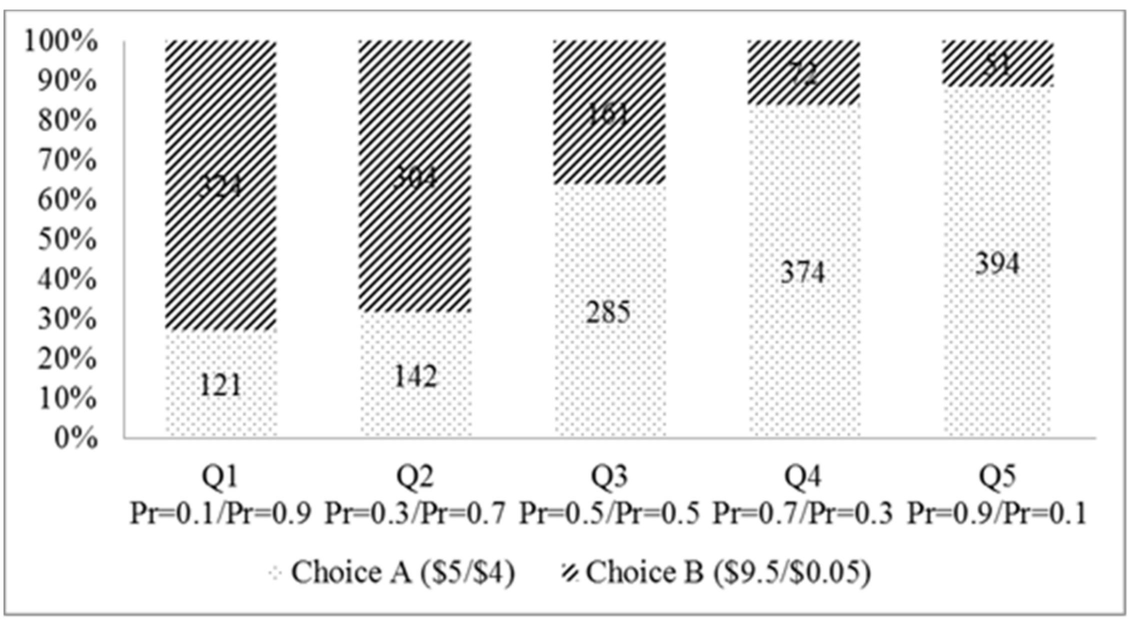

Figure 6 Proportion of Choices for the Loss Scenario (N=446)

Theoretically, the switch of a choice occurs one time because the risk increases or decreases if the respondent stays in one direction the entire time. Table 24 shows the first shifting point of the choice. Based on theoretical expectations, people have to shift their choices from choice A to choice B under the gain scenario and shift from choice B to choice A under the loss scenario. For example, 2nd (ABBBB) means that a person changes his choice from choice A to choice B in the second question and keeps choice B for the rest of questions. The number of people who changed their choices during the 1st or 2nd question (23.51 %) in the loss scenario is greater than the number in the gain scenario (11.64 %), and the number of people who changed their choices during the 3rd question in the loss scenario is also larger than the number in the gain scenario. Therefore, people tend to be more risk-neutral or risk-loving when they are confronted with potentially losing money.

However, an earlier mentioned problem appeared. Some people shift their choices again and again. For example, a person starts with choice A, shifts to choice B in the 3rd question, and then shifts to choice A in the 4th question. Here are examples of the possible choice sets which are not in accordance with the theory: ABABA, AABAB, AABAA, and ABBBA. These unexpected choice sets are counted into the inconsistent choice on the table. It is not clear why people make inconsistent choices, but we can only assume that they may not fully understand the concept of the lottery experiment and the logic of making choices. According to our results, more people have trouble understanding the lottery experiment under the loss scenario because there are more inconsistent choices under the loss scenario in comparison to the gain scenario. Generally, the 3rd question is a middle point and assumed to be the risk-neutral point; therefore, if a person changes his choice in the 3rd question (AABBB), he is identified as risk-neutral. In the gain scenario, people who change answers before the 3rd question (BBBBB and ABBBBB) are risk-loving, and people who change after the 3rd question

(AAABB and AAAAB) are risk-averse. Moreover, people who did not change to choice B from choice A (AAAAA) are extremely risk-averse. In the same manner, in the loss scenario, people who shift to choice A from choice B before the 3rd question (AAAAA and BAAAA) are risk-loving, and people who change latter than the 3rd question (BBBAA, BBBBA, and BBBBB) are risk-averse. In order to improve the quality of the data, the inconsistent choices from both scenarios are deleted for this variable used in the models, but in Table 24 the entire survey data is presented.

Table 24 Shifting Point of Lottery Choices (N=859)

	Gain (A to B)			Loss (B to A)	
Shifting point	N	Percentage	Shifting point	N	Percentage
1st(BBBBB)	60	6.98	1st(AAAAA)	139	16.18
2nd(ABBBB)	40	4.66	2nd(BAAAA)	63	7.33
3rd(AABBB)	154	17.93	3rd(BBAAA)	230	26.78
4th(AAABB)	169	19.67	4th(BBBAA)	148	17.23
5th(AAAAB)	113	13.15	5th(BBBBA)	29	3.38
No Change (AAAAA)	158	18.39	No Change (BBBBB)	60	6.98
Inconsistent Choice*	165	19.21	Inconsistent Choice*	190	22.12
Total	859	100	Total	859	100

CHAPTER VI

EMPIRICAL ANALYSIS AND ESTIMATION RESULTS

Empirical Analysis

Mean and range/variance of perceived risk are induced from the same queries, even though the latter is presenting one's risk ambiguity. Seemingly unrelated regression assumes the correlation of error terms in each equation and estimates two or more equations simultaneously by set of predictor variables. The set of predictor variables in each equation can be the same or different, and our mean perceived risk and range/variance perceived risk models have the same set of variables. This method is efficient than estimating OLS equations separately when there are stack of equations. There is an example of multiple equation structure:

$$\begin{aligned} \mathbf{y}_1 &= \mathbf{X}_1\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1 \\ \mathbf{y}_2 &= \mathbf{X}_2\boldsymbol{\beta}_2 + \boldsymbol{\varepsilon}_2 \\ &\vdots \\ \mathbf{y}_m &= \mathbf{X}_m\boldsymbol{\beta}_m + \boldsymbol{\varepsilon}_m \end{aligned} \tag{13}$$

Therefore, the seemingly unrelated regression (SUR) model is written as

$$\mathbf{y}_i = \mathbf{X}_i\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i, \quad i = 1,.....,m, \tag{14}$$

where

$$\boldsymbol{\varepsilon} = \left[\boldsymbol{\varepsilon}_1', \boldsymbol{\varepsilon}_2', ...\boldsymbol{\varepsilon}_m'\right]' \tag{15}$$

and

$$E\left[\boldsymbol{\varepsilon} \mid \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m\right] = 0$$
$$E\left[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}' \mid \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m\right] = \boldsymbol{\Omega}. \tag{16}$$

It is assumed that total of T observations are used in estimations of M equations. Each equation involves K_m regressors, for a total of $K = \sum_{i=1}^{n} K_i$. It is also assumed that disturbances are uncorrelated across observations, and thus,

$$E\left[\varepsilon_{it}\varepsilon_{js} \mid \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m\right] = \sigma_{ij}, \text{ if t=s and 0 otherwise.} \tag{17}$$

The disturbance formulation is

$$E\left[\boldsymbol{\varepsilon}_i\boldsymbol{\varepsilon}_j' \mid \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m\right] = \sigma_{ij}\mathbf{I}_T \quad \text{or}$$
$$E\left[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}' \mid \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m\right] = \Omega = \begin{bmatrix} \sigma_{11}\mathbf{I} & \sigma_{12}\mathbf{I} & \cdots & \sigma_{1m}\mathbf{I} \\ \sigma_{21}\mathbf{I} & \sigma_{22}\mathbf{I} & \cdots & \sigma_{2m}\mathbf{I} \\ \vdots & \vdots & & \\ \sigma_{m1}\mathbf{I} & \sigma_{m2}\mathbf{I} & \cdots & \sigma_{mm}\mathbf{I} \end{bmatrix} \quad \text{(a)} \tag{18}$$

By applying the generalized regression model to the stacked model,

$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_m \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{X}_2 & \cdots & 0 \\ & & \vdots & \\ 0 & 0 & \cdots & \mathbf{X}_m \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_m \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \vdots \\ \boldsymbol{\varepsilon}_m \end{bmatrix} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{19}$$

Thus, the efficient estimator of this regression is generalized least squares. For the *t*th observation, the m*m covariance matrix of the disturbance is

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1m} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2m} \\ \vdots & \vdots & & \\ \sigma_{m1} & \sigma_{m2} & \cdots & \sigma_{mm} \end{bmatrix}, \tag{20}$$

So, in (a), $\Omega = \Sigma \otimes \mathbf{I}$ and $\Omega^{-1} = \Sigma^{-1} \otimes \mathbf{I}$.

Denoting the *i* th element of $\sum^{-1}$ by σ^{ij}, general least square estimator is

$$\hat{\boldsymbol{\beta}} = \left[\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{X}\right]^{-1}\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{y} = \left[\mathbf{X}'(\Sigma^{-1}\otimes\mathbf{I})\mathbf{X}\right]^{-1}\mathbf{X}'(\Sigma^{-1}\otimes\mathbf{I})\mathbf{y} \text{ (Greene, 2005).} \tag{21}$$

For mean and range/variance of perceived risk estimations, seemingly unrelated regression is a good method. However, this may not be the best for the NFIP participation model since the dependent variable of the NFIP participation model is a binary variable. Therefore, we suggest another estimation method.

The dependent variables of mean and range/variance of perceived risk models are included in the NFIP participation model as explanatory variables. This case is suitable to use a simultaneous equation model. The following model equations show the exact relationship of perceived risk models and the NFIP participation model.

$$\begin{aligned} &y_1^* = \boldsymbol{\beta}'\mathbf{x} + \alpha y_2 + \varepsilon, \quad y_1 = 1[y_1^* > 0], \\ &y_2 = \gamma'\mathbf{z} + u, \\ &(\varepsilon, u) \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}\right]. \end{aligned} \tag{22}$$

where y_1 is a binary variable and y_2 is a continuous variable. The problem with this model is that there is correlation between the y_2 and ε stemming from the correlation of u and ε, and that the probit estimation based on y_1 and $(\mathbf{x}_1, y_2)$ will not estimate consistent coefficients, $\boldsymbol{\beta}$ and α (Greene, 2007). Due to the structure of model, we suspect that there is an endogeneity problem. Empirically, an endogeneity problem can cause a measurement error, autocorrelation with autocorrelated errors, simultaneity, omitted variables, and sample selection error. Using an instrumental variable (IV) is one of the solutions to correct the endogeneity. We utilized a two-stage probit with IV estimation based on Newey's (1987) minimum chi-squared estimator. In our model, endogenous variables are mean perceived risk and range/variance of perceived risk variables because their values are elicited from the same survey questions. Some demographic variables are assumed to be correlated with endogenous variables, range/variance of perceive risk and mean perceived risk, but do not directly belong to the original equation. Those variables are instrumental variables because the correlation with the endogeneity variable and the lack of correlation with the regression equation is the condition to be an instrument. The model with the dichotomous dependent variables and endogenous regressors is

$$\begin{aligned} y_{1i}^{*} &= \mathbf{y}_{2i}\boldsymbol{\beta} + \mathbf{x}_{1i}\gamma + u_i \\ \mathbf{y}_{2i} &= \mathbf{x}_{1i}\boldsymbol{\Pi}_1 + \mathbf{x}_{2i}\boldsymbol{\Pi}_2 + \upsilon_{\imath} \end{aligned} \tag{23}$$

Where i=1,…….,N, $\mathbf{y}_{2i}$ is a vector of endogenous variables (mean and range/variance perceived risk variables), $\mathbf{x}_{1i}$ is a vector of exogenous variables (original explanatory variables in the equation of interest), $\mathbf{x}_{2i}$ is a vector of instruments (state, employment, marital status, ethnicity, and metro variables). It is assumed that $(u_i, \upsilon_i) \sim N(\mathbf{0}, \boldsymbol{\Sigma})$, where σ_{11} is normalized to one will identify the model. (u_i, υ_i) is i.i.d. multivariate normal for all i. With covariance matrix $\operatorname{var}(u_i, \upsilon_i) = \Sigma = \begin{bmatrix} 1 & \Sigma_{21}' \\ \Sigma_{21} & \Sigma_{21} \end{bmatrix}$. $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of the structural parameters, and $\boldsymbol{\Pi}_1$ and $\boldsymbol{\Pi}_2$ are matrices of the reduced-form parameters.

Instead of observing y_{1i}^{*}, we observe

$$y_{1i} = \begin{cases} 0, \text{ if } y_{1i}^{*} < 0 \\ 1, \text{ if } y_{1i}^{*} \geq 0 \end{cases} \tag{24}$$

The model is rewritten as

$$\begin{aligned} y_{1i}^{*} &= \mathbf{z}_i\boldsymbol{\delta} + u_i && \text{(1) structural equation of interest} \\ \mathbf{y}_{2i} &= \mathbf{x}_i\boldsymbol{\Pi} + \upsilon_i && \text{(2) set of reduced form equation of the endogenous explanatory variables} \end{aligned} \tag{25}$$

where $\mathbf{z}_i = (\mathbf{y}_{2i}, \mathbf{x}_{1i}), \mathbf{x}_i = (\mathbf{x}_{1i}, \mathbf{x}_{2i}), \boldsymbol{\delta} = (\boldsymbol{\beta}', \boldsymbol{\gamma}')',$ and $\boldsymbol{\Pi}=(\boldsymbol{\Pi}_1{}', \boldsymbol{\Pi}_2{}')'$. By substituting eq(2) into eq(1)

The reduced form equation of y_{1i}^* for two-stage estimation is

$$\begin{aligned} y_{1i}^* &= (\mathbf{x}_i \boldsymbol{\Pi} + \upsilon_i)\boldsymbol{\beta} + \mathbf{x}_{1i}\boldsymbol{\gamma} + u_i \\ &= \mathbf{x}_i \boldsymbol{\alpha} + \upsilon_i \boldsymbol{\beta} + u_i \\ &= \mathbf{x}_i \boldsymbol{\alpha} + v_i \end{aligned} \tag{26}$$

where $v_i = \upsilon_i \boldsymbol{\beta} + u_i$. v_i is normal because u_i and υ_i are jointly normal. For estimation,

$$\boldsymbol{\alpha} = \begin{bmatrix} \boldsymbol{\Pi}_1 \\ \boldsymbol{\Pi}_2 \end{bmatrix} \boldsymbol{\beta} + \begin{bmatrix} \mathbf{I} \\ \mathbf{0} \end{bmatrix} \boldsymbol{\gamma} = D(\boldsymbol{\Pi})\boldsymbol{\delta} \tag{27}$$

Where $D(\boldsymbol{\Pi}) = (\boldsymbol{\Pi}, \mathbf{I}_1)$ and I_1 is defined as $\mathbf{x}_i \mathbf{I}_1 = \mathbf{x}_{1i}$. Defining $\hat{\mathbf{z}}_i = (\mathbf{x}_i \hat{\boldsymbol{\Pi}}, \mathbf{x}_{1i}),\ \hat{\mathbf{z}}_i \boldsymbol{\delta} = \mathbf{x}_i D(\hat{\boldsymbol{\Pi}})\boldsymbol{\delta}$, where $D(\hat{\boldsymbol{\Pi}}) = (\hat{\boldsymbol{\Pi}}, \mathbf{I}_1)$. Thus one estimator of $\boldsymbol{\alpha}$ is $D(\hat{\boldsymbol{\Pi}})\boldsymbol{\delta}$, and this estimator is denoted by $\hat{\mathbf{D}}\boldsymbol{\delta}$.

$\boldsymbol{\alpha}$ could also be estimated directly as the solution to

$$\max_{\boldsymbol{\alpha}, \boldsymbol{\lambda}} \sum_{i=1}^{N} l(y_{1i}, \mathbf{x}_i \boldsymbol{\alpha} + \hat{\upsilon}_i \boldsymbol{\lambda}) \tag{28}$$

Where $l(\cdot)$ is the log likelihood for probit. Denote this estimator by $\tilde{\boldsymbol{\alpha}}$. Because the multivariate normality of the error terms (u_i, υ_i) implies the expected value of u_i is not zero, the $\hat{\upsilon}_i \boldsymbol{\lambda}$ term is included here. υ_i is an unobservable term, so the least-squares residuals from eq (2) is used.

Amemiya (1978) defined the estimator of $\boldsymbol{\delta}$ by

$$\max_{\boldsymbol{\delta}} (\tilde{\boldsymbol{\alpha}} - \hat{\mathbf{D}}\boldsymbol{\delta})' \hat{\Omega}^{-1} (\tilde{\boldsymbol{\alpha}} - \hat{\mathbf{D}}\boldsymbol{\delta}) \tag{29}$$

Where $\hat{\Omega}$ is a consistent estimator of the covariance of $\sqrt{N}(\hat{\boldsymbol{\alpha}} - \hat{\mathbf{D}}\boldsymbol{\delta})$, and the estimator of $\boldsymbol{\delta}$ is asymptotically efficient relative to all the other estimators that minimize the distance between $\hat{\boldsymbol{\alpha}}$ and $D(\hat{\boldsymbol{\Pi}})\boldsymbol{\delta}$. Therefore, an efficient estimator of $\boldsymbol{\delta}$ is defined as

$$\hat{\boldsymbol{\delta}} = (\hat{\mathbf{D}}'\hat{\Omega}^{-1}\hat{\mathbf{D}})^{-1}\hat{\mathbf{D}}'\hat{\Omega}^{-1}\tilde{\boldsymbol{\alpha}} \text{ and}$$

$$Var(\hat{\boldsymbol{\delta}}) = (\hat{\mathbf{D}}'\hat{\Omega}^{-1}\hat{\mathbf{D}})^{-1}. \tag{30}$$

To implement this estimator, $\hat{\Omega}^{-1}$ should be known.

The two-stage maximum likelihood estimator is obtained by solving

$$\max_{\boldsymbol{\delta},\boldsymbol{\lambda}} \sum_{i=1}^{N} l(y_{1i}, \mathbf{z}_i\boldsymbol{\delta} + \hat{\upsilon}_i\boldsymbol{\lambda}) \tag{31}$$

Residuals $\hat{\upsilon}_i = \mathbf{y}_{2i} - \mathbf{x}_i\hat{\boldsymbol{\Pi}}$ is computed by fitting equation (2) using OLS.

Newey(1987) induced $\sqrt{N}(\hat{\boldsymbol{\alpha}} - \hat{\mathbf{D}}\boldsymbol{\delta}) \xrightarrow{d} N(\mathbf{0}, \boldsymbol{\Omega})$; $\sqrt{N}(\hat{\boldsymbol{\alpha}} - \hat{\mathbf{D}}\boldsymbol{\delta})$ converges in distribution to $N(\mathbf{0}, \boldsymbol{\Omega})$, where

$$\Omega = \mathbf{J}_{\alpha\alpha}^{-1} + (\boldsymbol{\lambda} - \boldsymbol{\beta})'\sum\nolimits_{22}(\boldsymbol{\lambda} - \boldsymbol{\beta})\mathbf{Q}^{-1} \tag{32}$$

and $\sum_{22} = E\left\{\upsilon_i'\upsilon_i\right\}$. $\mathbf{J}_{\alpha\alpha}^{-1}$ is the covariance matrix of $\tilde{\boldsymbol{\alpha}}$, ignoring that $\hat{\boldsymbol{\Pi}}$ is an estimated parameter matrix. Also, Newey demonstrates that the covariance matrix from an OLS regression of $\mathbf{y}_{2i}(\hat{\boldsymbol{\lambda}} - \hat{\boldsymbol{\beta}})$ on $\mathbf{x}_i$ is a consistent estimator of $(\boldsymbol{\lambda} - \boldsymbol{\beta})'\sum_{22}(\boldsymbol{\lambda} - \boldsymbol{\beta})\mathbf{Q}^{-1}$. $\hat{\boldsymbol{\lambda}}$ can be obtained from solving equation (3), and the two-stage instrumental variables estimator yields a consistent estimate, $\hat{\boldsymbol{\beta}}$ (STATA, 2009).

The structure of the two-stage probit with IV estimation does not allow to exclude some unrelated variables from the first stage estimation if those variables have to be included in the second stage estimation. There is no supporting theories showing the relationship between range/variance of perceived risk and flood insurance policy related variables such as CRS, preFIRM, or house type variables, but the range/variance of perceived risk models have to include those variables because of the structure of the two-stage probit with IV estimation . Including unrelated variables in estimations would distort the result. Therefore, the estimation results of seemingly unrelated regression are reported for mean, range, and variance of perceived risk models while the results of probit with IV estimation are reported for the NFIP participation model. By combining range and variance of perceived risk and three different mean perceived risks, a total of six models will be estimated in each stage. Table 25 explains the summary statistics of the explanatory variables used in estimation models.

Table 25 Description of Explanatory Variables for Models Estimated (N=446)

Variables	Type	Description	Mean	Std.Dev.	Min	Max
Risk Perception		Perceived flood risk in different ways				
Hurricane Frequency	Continuous	Continuous between 0-99	6.08	8.61	1	75
Magnitude of Damage	Ordered Categorical	Between 0-10, 0 if no damage; 10 if complete damaged	3.25	2.03	1	10
Expected Damage	Continuous	Continuous between 0-198	3.67	6.40	0.2	70
Risk Aversion		One's risk preference toward risk				
Gain	Ordered Categorical	Between 1-6 scale, 1 if very risk loving; 6 if very risk aversion	3.89	1.39	1	6
Loss	Ordered Categorical	Between 1-6 scales, 1 if very risk loving; 6 if very risk aversion	3.96	1.27	1	6
CRS	Categorical	Between 1-10 scale, 1 if full participation; 10 if no participation	6.97	1.48	5	10
Flood Zone	Binary	1 if SFHA; 0 if otherwise	0.17	0.37	0	1
Previous Damage	Binary	1 if having flood damage experience; 0 if otherwise	0.36	0.48	0	1
preFIRM	Binary	1 if before FIRM; 0 if otherwise	0.37	0.48	0	1
Distance from coast	Continuous	The distance from the nearest coast in kilometer	15.61	18.51	0	171.68
Detached Single House	Binary	1 if a single family house detached from other houses; 0 if otherwise	0.85	0.36	0	1
Having a Mortgage	Binary	1 if having mortgage loan; 0 if otherwise	0.66	0.48	0	1
Insurance Confidence	Ordered Categorical	Between 1-5 scale, 1 if no confidence; 5 if full confidence	3.07	1.22	1	5

Table 25 (continued)

Expected Gov. Aid	Ordered Categorical	Between 1-5 scale, 1 if very unlikely; 5 if very likely	2.68	1.15	1	5
Florida	Binary	1 if Florida resident; 0 if otherwise	0.68	0.47	0	1
White	Binary	1 if white; 0 if otherwise	0.85	0.36	0	1
Work	Binary	1 if working in any employment types; 0 if otherwise	0.57	0.50	0	1
Marry	Binary	1 if having a spouse or cohabitating; 0 if otherwise	0.75	0.73	0	1
Metro	Binary	1 if metro area; 0 if otherwise	0.95	0.22	0	1
Age	Continuous	Continuous between 19-93	56.00	13.45	19	85
Male	Binary	1 if male; 0 if female	0.46	0.50	0	1
Income	Ordered Categorical	1 if less than $5K; 2 if $5K-less than $7.5K 3 if $7.5K-less than $10K; 4 if $10K-less than $12.5K; 5 if $12.5K-less than $15K; 6 if $15K-less than $20K; 7 if $20K-less than $25K; 8 if $25K-less than $30K; 9 if $30K-less than $35K; 10 if $35K- less than $40K; 11 if $40K-less than $50K; 12 if $50K-less than $60K; 13 if $60K-less than $75K; 14 if $75K-less than $85K; 15 if $85K-less than $100K; 16 if $100K-less than $125K; 17 is $125K-less than $150K; 18 if $150K-less than $175K; 19 if $175K or more	12.74	3.86	1	19
Education	Categorical	1 if less than high school; 2 if high school; 3 if some college; 4 if bachelor's degree or above	3.31	0.81	1	4

Range and variance of perceived risk variables are described separately

Results for Seemingly Unrelated Regression of Risk Ambiguity Model

This section describes the statistical analysis of risk ambiguity model. As mentioned before, risk ambiguity is measured in two ways: range and variance of perceived risk. Range simply measures the difference between the highest risk perception and the lowest risk perception (Range=H-L). Particularly, triangular variance is used as another risk ambiguity measurement, so the calculation for variance is

$$\text{Variance}=[(H^2+L^2+M^2)-(H*L)-(H*M)-(L*M)]/18 \tag{33}$$

when H is the highest value, L is the lowest value, and M is the mean value of an individual's risk perception. The two risk ambiguity models using different risk ambiguity measurement were separately estimated. Table 26 lists the summary statistics of the different risk ambiguity variables.

Table 26 Summary Description of Different Risk Ambiguity Variables (N=446)

Variable	Type	Description	Mean	Std. Dev.	Min	Max
Range of :		Risk ambiguity measured as range				
Hurricane Frequency	Continuous		6.82	9.78	0	89
Magnitude of Damage	Continuous		4.17	2.30	0	10
Expected Damage	Continuous		9.56	14.82	0.2	140
Variance of:		Risk ambiguity measured as triangular variance				
Hurricane Frequency	Continuous		6.45	25.87	0	353
Magnitude of Damage	Continuous		1.02	1.10	0	5.06
Expected Damage	Continuous		0.14	0.64	0.2	70

The perceived hurricane frequency is larger than actual hurricane frequency. According to NOAA's data (2012), actual numbers of major hurricane strikes in coastal counties between 1900 and 2010 by state are 4.5 times in Fl, 6.4 times in TX, 8 times in LA and 7.8 times in Al and MS. Despite our sample estimated the frequency of major hurricanes in 50 years, their expectations are obviously high: 6.1 times in FL, 5.7 times in TX, 7.4 times in LA, and 6 times in AL and MS. Therefore, the actual average in 50 years of all state is 3.3 times. It is almost twice larger than our sample average, 6.8 times. Although perceive risk is higher than actual risk, many people do not buy flood insurance (36% of total are insured).

In the result tables, observation numbers, R^2s , estimated parameters, standard errors, and significant levels of explanatory variables are presented. The dependent variable is range or variance of perceived risk variable, and the independent variables are risk aversion, mean risk perception, flood zone, damage experience, distance from the coast, state, ethnicity, work status, marital status, metro, age, gender, income, and education variables.

Table 27 shows the SUR estimation results of the range perceived risk models when risk perception is elicited by frequency, magnitude, and expected damage, respectively. The first column shows the estimates when range perceived risk is measured as the range of perceived hurricane frequency. In this model, the flood zone, state, education, and income variables are significant, but no risk variable is significant. Contrary to our expectation, the flood zone variable is negatively related to range perceived risk, so a person who lives in a high risk area has less risk ambiguity than a person who lives in a low flood risk area. A person who lives in Florida has more risk ambiguity than a person lives in other states. Lastly, education and income are positively related to risk ambiguity; a person with a higher education level or with a higher income level shows more risk ambiguity regarding flood risk.

The second column explains the results of the SUR estimates of the range perceived risk model when range perceived risk is measured as the range of magnitude of damage. The mean_risk perception, previous damage, distance from the coasts, education, and income variables are significant. The significant mean_risk perception variable means that as a person perceives greater risk, he is more ambiguous about risk. The previous damage variable has a negative relationship with range perceived risk; if a person experienced flood damage previously, his risk ambiguity decreases. Contrary to the hypothesis, when distance from the coast increases, one's risk ambiguity also increases. Ethnicity is positively related to range perceived risk, so if a person is white, he has more risk ambiguity than if he was another ethnicity. Education and income level are also positively related to risk ambiguity.

The third column shows the estimation results when range perceived risk is measured as a range of expected damage. The mean_risk perception, ethnicity, education and income variables are significant. All significant variables are positively related to range perceived risk. In sum, mean_risk perception shows significance when range perceived risk is measure as magnitude of damage and expected damage models, but other risk variables are not significant at all. Education and income variables are significant over all models.

Table 27 SUR Estimates of Range of Perceived Risks

Dependent Variable	Hurricane Frequency		Magnitude of Damage		Expected Damage	
	R^2 =0.5578		R^2 =0.0880		R^2=0.3859	
(N=446)	Parameter (Std. Err.)		Parameter (Std. Err.)		Parameter (Std. Err.)	
Risk Aversion (gain)	0.09(0.22)		0.03(0.07)		-0.14(0.38)	
Risk Aversion (loss)	0.16(0.23)		-0.02(0.08)		0.14(0.41)	
Mean_risk perception	1.08(0.03)		0.52(0.05)	**	2.12(0.07)	**
Flood Zone(SFHA)	-1.00(0.82)	**	-0.24(0.28)		-2.17(1.45)	
Previous Damage	0.58(0.64)		-0.54(0.22)	**	0.58(1.13)	
Distance from the Coast	0.01(0.02)		0.01(0.01)	**	0.02(0.03)	
Florida State	1.17(0.65)	*	0.17(0.22)		1.18(1.15)	
White	0.85(0.84)		0.60(0.29)	**	2.65(1.49)	*
Employed	0.66(0.72)		0.15(0.25)		1.15(1.27)	
Married or Cohabitating	-0.51(0.75)		0.09(0.26)		-2.06(1.32)	
Metro	0.55(1.39)		-0.47(0.48)		-2.42(2.45)	
Age	-0.03(0.03)		-0.002(0.01)		-0.06(0.05)	
Male	-0.08(0.62)		0.13(0.21)		0.36(1.09)	
Education	1.15(0.40)	**	0.47(0.14)	**	1.74(0.71)	**
Income	0.21(0.09)	**	0.07(0.03)	**	0.46(0.16)	**
Constant	-7.96(2.91)	**	-0.49(1.02)		-6.72(5.15)	

*, ** significant at p=0.1 and 0.05 respectively

Table 28 shows the SUR estimation results of the variance perceived risk models when risk perception is elicited by frequency, magnitude, and expected damage, respectively. Compared to the previous range perceived risk models, fewer variables are statistically significant.

The first column shows the estimates when variance perceived risk is measured as a variance of hurricane frequency. The mean_risk perception, state, and income variables are significant. They are all positively related to risk ambiguity. Their estimates are relatively larger than the previous range perceived risk model. It may because variance perceived risk has a smaller values and range than range perceived risk.

In the second column, the results of the variance perceived risk model utilizing the variance of magnitude of damage as risk ambiguity are presented. In this column, the mean_risk perception, previous damage, distance from the coast, and education variable are significant. The mean_risk perception, distance from the coast, and education variables are positively related to risk ambiguity while previous damage variable shows a negative relationship with risk ambiguity.

The estimation results of the variance perceived risk model utilizing a variance of expected damage as risk ambiguity are displayed in the third column. The mean_risk perception, marital status and education variables are statistically significant. The marital status variable first shows significance. If a person is married or cohabitating, he has less risk ambiguity. This is matched with our hypothesis. Overall, the mean_risk perception variable is significant over all models.

Table 28 SUR Estimates of Variance of Perceived Risks

Dependent Variable	Hurricane Frequency		Magnitude of Damage		Expected Damage	
	R^2=0.3775		R^2=0.0563		R^2=0.2569	
(N=446)	Parameter (Std. Err.)		Parameter (Std. Err.)		Parameter (Std. Err.)	
Risk Aversion (gain)	3.16(4.61)		0.14(0.26)		0.01(0.02)	
Risk Aversion (loss)	3.47(4.99)		-0.05(0.29)		-0.01(0.02)	
Mean_risk perception	18.75(0.63)	**	1.74(0.17)	**	0.09(0.003)	**
Flood Zone(SFHA)	-15.72(17.49)		-1.31(0.98)		-0.10(0.07)	
Previous Damage	4.87(13.57)		-1.64(0.77)	**	0.02(0.05)	
Distance from the Coast	-0.40(0.45)		0.04(0.02)	**	-0.001(0.001)	
Florida State	26.39(13.73)	*	0.49(0.79)		0.07(0.06)	
White	-0.49(17.98)		1.50(1.02)		0.06(0.07)	
Employed	9.16(15.29)		0.19(0.87)		0.05(0.06)	
Married or Cohabitating	-10.94(16.04)		0.33(0.91)		-0.15(0.06)	**
Metro	-1.26(29.57)		-1.81(1.68)		-0.15(0.12)	
Age	-0.05(0.56)		0.02(0.03)		0.001(0.003)	
Male	-8.67(13.16)		0.46(0.75)		0.01(0.05)	
Education	13.36(8.53)		1.27(0.48)	**	0.05(0.03)	
Income	3.67(1.94)	*	0.16(0.11)		0.02(0.01)	**
Constant	-184.92(62.14)	**	-6.35(3.58)	*	-0.40(0.24)	

*, ** significant at p=0.1 and 0.05 respectively

Results for Seemingly Unrelated Regression of Risk Perception Model

This section describes the statistical analysis of risk perception estimations. Risk perception is elicited as a number of major hurricane strikes in nest 50 years, one's property damage by a major hurricane strike, and expected damage on the property in a given year. In the result tables, observation numbers, R^2s , estimated parameters, standard errors, and significant levels of explanatory variables are presented. The dependent variable is one's perceived risk, and the independent variables are risk aversion, range or variance perceived risk, flood zone, damage experience, distance from the coast, state, ethnicity, work status, marital status, metro, age, gender, income, and education variables.

Table 29 shows the SUR estimation results of the frequency, magnitude, and expected damage risk perception models including range perceived risk. The range perceived risk, education, and income variables are statistically significant in all models. When one's risk ambiguity increases one's perceived risk also increases. Increased education level and income level decreases one's perceived risk. The state variable significant in the perceived risk from hurricane frequency model; the distance variable is significant in the perceived risk from magnitude of damage model; the flood zone variable is significant in the perceived risk from expected damage model.

Table 29 SUR Estimates of Mean Perceived Risks with Range Risk Ambiguity

Dependent Variable	Hurricane Frequency		Magnitude of Damage		Expected Damage	
	R^2 =0.5495		R^2 =0.0581		$R^{2=}$0.3869	
(N=446)	Parameter (Std. Err.)		Parameter (Std. Err.)		Parameter (Std. Err.)	
Risk Aversion (gain)	-0.10(0.19)		0.08(0.07)		0.08(0.16)	
Risk Aversion (loss)	-0.13(0.21)		0.06(0.07)		-0.07(0.18)	
Range of Risk Ambiguity	0.86(0.02)	**	0.42(0.05)	**	0.39(0.01)	**
Flood Zone(SFHA)	1.18(0.72)		0.21(0.25)		1.38(0.62)	**
Previous Damage	-0.48(0.57)		0.26(0.20)		-0.18(0.49)	
Distance from the Coast	-0.01(0.01)		-0.01(0.01)	**	-0.01(0.01)	
Florida State	-0.97(0.58)	*	-0.28(0.20)		-0.47(0.50)	
White	-0.69(0.75)		-0.02(0.26)		-0.96(0.65)	
Employed	-0.55(0.64)		-0.04(0.22)		-0.39(0.55)	
Married or Cohabitating	0.44(0.67)		0.11(0.23)		0.83(0.57)	
Metro	-0.42(1.23)		0.51(0.43)		1.09(1.06)	
Age	0.02(0.02)		-0.01(0.01)		0.03(0.02)	
Male	-0.05(0.55)		-0.31(0.19)		-0.37(0.47)	
Education	-1.01(0.36)	**	-0.32(0.12)	**	-0.71(0.31)	**
Income	-0.18(0.08)	**	-0.07(0.03)	**	-0.20(0.07)	**
Constant	7.17(2.59)	**	3.20(0.90)	**	3.04(2.22)	

*, ** significant at p=0.1 and 0.05 respectively

Table 30 shows the SUR estimation results of the frequency, magnitude, and expected damage risk perception models with variance perceived risk. The variance perceived risk and income variables are statistically significant across models. Like previous results, when risk ambiguity increases one's perceived risk also increases, and increased income level decreases one's perceived risk. The flood zone and state variables are significant in the perceived risk from hurricane frequency model; the distance and education variables are significant in the perceived risk from magnitude of damage model; the flood zone and marital status variable are significant in the perceived risk from expected damage model.

Table 30 SUR Estimates of Mean Perceived Risks with Variance Risk Ambiguity

Dependent Variable	Hurricane Frequency		Magnitude of Damage		Expected Damage	
	R^2=0.3747		R^2=0.0556		R^2=0.2655	
(N=446)	Parameter (Std. Err.)		Parameter (Std. Err.)		Parameter (Std. Err.)	
Risk Aversion (gain)	-0.19(0.22)		0.08(0.07)		-0.01(0.18)	
Risk Aversion (loss)	-0.14(0.24)		0.06(0.07)		0.08(0.20)	
Variance of Risk Ambiguity	0.04(0.001)	**	0.12(0.01)	**	8.42(0.34)	**
Flood Zone(SFHA)	1.44(0.85)	*	0.26(0.25)		1.74(0.68)	**
Previous Damage	-0.20(0.66)		0.22(0.20)		-0.11(0.53)	
Distance from the Coast	0.02(0.02)		-0.01(0.01)	**	0.01(0.01)	
Florida State	-1.11(0.67)	*	-0.27(0.20)		-0.59(0.54)	
White	0.11(0.87)		0.07(0.26)		-0.32(0.70)	
Employed	-0.38(0.74)		-0.0004(0.22)		-0.30(0.60)	
Married or Cohabitating	0.49(0.78)		0.12(0.23)		1.33(0.63)	**
Metro	0.18(1.44)		0.53(0.43)		1.52(1.16)	
Age	0.005(0.03)		-0.01(0.01)		0.01(0.02)	
Male	0.12(0.64)		-0.31(0.19)		-0.48(0.51)	
Education	-0.64(0.41)		-0.27(0.12)	**	-0.44(0.33)	
Income	-0.16(0.09)	*	-0.06(0.03)	**	-0.19(0.08)	**
Constant	9.01(3.02)	**	3.80(0.90)	**	-4.05(2.43)	*

*, ** significant at p=0.1 and 0.05 respectively

Results for Maximum Likelihood Estimation Using Instrumental Variable (IV) for NFIP Participation Model

In this part, the estimation results of the NFIP participation model are reported. As mentioned before, the perceived risk model and the NFIP participation model are estimated simultaneously. Since we assume that there is an endogeneity problem in the NFIP participation model, a two-stage probit with IV estimation is used. In order to check the validity of our assumption and of using a probit with IV estimation, we utilized two different tests. The first test is Newy's Over-ID test to check the validity of the instruments in the probit with IV estimation. The second test is the Wald test of exogeneity which checks the endogeneity in the estimation based on the assumption of valid instruments. Therefore, prior to testing the endogeneity problem of a model, the validity of instruments needs to be confirmed first. Newy's Over-ID test provides the overidentificaiton statistics of the probit with IV. Lee (1992) proved Newy's minimum distance for estimators in a probit with IV model to test the overidentifying restriction. The null hypothesis of an Over-ID test is that the excluded instruments are valid instruments. In other words, it tests the lack of correlation of the error term and excluded instruments. The rejection of the null means the invalidity of instruments, and thus, a problem of validity exists in using the instrumented variables if the test statistic is significant.

Next, the Wald test of exogeneity checks whether there is an endogeneity problem or not. The null hypothesis of the Wald test of exogeneity is $H_0 : \boldsymbol{\lambda} = 0$; which means there is exogeneity. If $\boldsymbol{\lambda} = 0,$ the interaction term, $\hat{\upsilon}_i \boldsymbol{\lambda}$, is gone. This means that there is no term related to the error term in the estimation, so there is also no possibility of endogeneity. Therefore, if the test statistic is not significant, there is no endogeneity problem and using the instrumental variables are not appropriate. Consequently, an insignificant Newey's Over-ID test statistic confirms the validity of the instruments, and a significant Wald test statistic announces that there is an endogeneity problem in the model. In the bottom of each result table, the test statistics of Newy's Over-ID test and Wald test of exogeneity are reported.

To facilitate a comparison, each table includes the results of the six different models: probit with IV estimation, simple probit estimation, seemingly unrelated regression (SUR) estimation when risk ambiguity is measured as range and variance separately. Since the dependent variable is a binary variable (whether purchase flood insurance or not), OLS estimation from seemingly unrelated regression is not appropriate method. Moreover, if there is endogeneity, probit estimation is also not appropriate.

However, all estimation results are reported here for reference purpose, but due to the different derivation for estimated parameters, the direct comparison of estimates are not allowed among probit with IV, probit, and SUR estimations.

In the results table, the number of observation, log likelihoods of probit estimations, χ^2 s of Likelihood Ratio for probit estimations, χ^2 s of the Wald test for the coefficients of probit with IV estimations, estimated parameters, standard errors, significant levels, test statistics for instruments' validity (Newey's Over-ID test), and test statistics for endogeneity (the Wald test of exogeneity) are described.

Table 31 shows the results of the NFIP participation models when risk perception is elicited by hurricane frequency. Through the Newy's Over-ID test statistic and the Wald test of exogeneity statistic at the bottom, using the probit with IV estimation to fix the endogeneity problem seems appropriate in both NFIP participation model with range perceived risk and NFIP participation model with variance perceived risk; the over-ID test statistics are not significant, and the Wald test of exogeneity statistics are significant. The results of the probit with IV estimation are not very interesting because there are only one significant variable. In the probit with IV model using range perceived risk, the estimated parameter of income variable is only statistically significant, and in the probit with IV model using variance perceived risk, all estimated parameters are not significant. About this result, we can explain it in two ways; either risk perception as elicited by hurricane frequency does not explain an individual's flood insurance purchasing behavior or no significant relationship exists between the hypothesized variables and an individual's decision-making on flood insurance purchasing.

The results of both probit estimations show that the flood zone, risk aversion for loss scenario, confidence in insurance company compensation, expectation for government aid, and income variables are significant. The values of the estimated parameters are very close. It seems that using a different specification of risk ambiguity did not affect the estimation for the NFIP participation model. However, since the Wald test of exogeneity confirms that there is endogeneity, this similarity probably stems from the endogeneity problem.

The results of seemingly unrelated regression have many similarities with probit results. The flood zone, risk aversion for loss scenario, confidence in insurance company compensation, expectation for government aid, and income variables are significant.

Table 31 Estimated Parameters of Probit with IV, Probit, SUR Models When Risk Perception Elicited by Hurricane Frequency

Dep. Var.: Ins. Purchase Variables (N=446)	Probit with IV	Probit	SUR	Probit with IV	Probit	SUR
			Parameter (Std. Err.)			
Range of Frequency	-0.36(0.31)	-0.004(0.011)	-0.003(0.003)			
Variance of Frequency				-0.20(0.11)	-0.001(0.004)	-0.0001(0.000)
Mean Frequency	0.07(0.80)	0.02(0.01)	0.01(0.004)	-0.21(1.04)	0.01(0.01)	0.01(0.003)
Risk Aversion (gain)	-0.10(0.22)	-0.002(0.05)	-0.002(0.02)	-0.16(0.38)	-0.002(0.05)	-0.002(0.01)
Risk Aversion (loss)	0.17(0.13)	0.11(0.05)*	0.03(0.02)*	0.24(0.27)	0.10(0.05)*	0.03(0.02)*
CRS	-0.13(0.14)	-0.02(0.05)	-0.01(0.01)	-0.24(0.31)	-0.02(0.05)	-0.01(0.01)
Flood Zone(SFHA)	2.378(2.56)	1.39(0.20)**	0.47(0.06)**	4.23(3.90)	1.39(0.18)**	0.47(0.06)**
Previous Damage	0.40(0.40)	0.17(0.14)	0.05(0.04)	0.31(0.70)	0.17(0.14)	0.05(0.04)
PreFIRM	0.30(1.09)	0.02(0.15)	0.004(0.05)	0.36(1.81)	0.02(0.15)	0.004(0.05)
Distance from Coast	0.003(0.01)	-0.01(0.004)	-0.002(0.001)	-0.004(0.03)	-0.01(0.004)	-0.002(0.001)
Detached Single House	-0.29(0.63)	0.06(0.21)	0.01(0.06)	-0.10(1.27)	0.06(0.21)	0.01(0.06)
Having a Mortgage	0.08(0.51)	0.22(0.16)	0.07(0.05)	-0.01(0.92)	0.22(0.16)	0.07(0.05)
Insurance Confidence	-0.24(0.26)	0.11(0.06)*	0.03(0.02)*	-0.67(0.71)	0.11(0.06)*	0.03(0.02)*
Expected Gov. Aid	0.53(0.33)	0.21(0.06)**	0.06(0.02)**	1.03(0.76)	0.20(0.06)**	0.06(0.02)**
Age	-0.01(0.02)	0.004(0.01)	0.001(0.002)	0.01(0.03)	0.004(0.01)	0.001(0.002)
Male	-0.26(0.85)	0.08(0.14)	0.02(0.04)	-0.98(1.42)	0.08(0.14)	0.02(0.04)
Education	0.45(0.50)	0.11(0.09)	0.04(0.03)	0.29(0.60)	0.11(0.09)	0.03(0.03)
Income	0.19(0.09)**	0.06(0.02)**	0.02(0.01)**	0.29(0.21)	0.06(0.02)**	0.02(0.01)**
Constant	-2.54(3.37)	-3.45(0.80)**	-0.46(0.23)**	-2.63(6.03)	-3.46(0.80)**	-0.50(0.23)**
Log Likelihood		-242.5890			-242.6534	
LR χ^2 (17)		98.18**			98.05	
Wald χ^2 (17)	22.47			6.87		
Over-ID test χ^2 (3)	4.574			0.583		
Wald test of Exogeneity χ^2 (2)	18.45**			30.00**		

Table 32 shows the results NFIP participation models when risk perception is elicited by magnitude of damage to the home. From insignificant Newy's Over-ID test statistic and significant Wald test of exogeneity test statistic, it is confirmed that the used instruments in the probit with IV models are valid, and an endogineity problem exists in the NFIP participation models. Comparing with Table 31, the results of probit with IV model are very distinct. When risk ambiguity is measured as a range of perceived risk, range of magnitude of damage, mean magnitude, flood zone, detached single house, having a mortgage, education, and income variables are significant. The risk ambiguity variance of magnitude of damage, flood zone, and income level are significant when risk ambiguity is measure as a variance of perceived risk. The risk ambiguity, income, and education variables are significant in common. When a person has less risk ambiguity or has more perceived risk, the probability to flood insurance purchase increases. A person has a property in a SFHA or has a house detached from other houses, or has a mortgage, he has more probability to purchase flood insurance. With a higher income or a higher education level, one's probability of purchasing insurance increases. It is hard to decide for which is a better estimation, but when a model include a different risk ambiguity variable the result of two probit with IV models are different. In other words, the change in risk ambiguity measurements affects the estimation of the NFIP participation model.

The results of the probit estimations are very similar with the previous results. The mean magnitude, risk aversion for loss scenario, flood zone, having a mortgage, insurance compensation, expected government aid, education, and income variables show significant in both probit models.

The results of seemingly unrelated regression have significant mean magnitude, flood zone, having a mortgage, insurance compensation, expected government aid, and income variables in both models, and range of magnitude of damage and education variables are only significant in the NFIP participation model with range perceived risk

Table 32 Estimated Parameters of Probit with IV, Probit, SUR Models When Risk Perception Elicited by Magnitude of Damage

Dep. Var.: Ins. Purchase Variables (N=446)	Probit with IV	Probit	SUR	Probit with IV	Probit	SUR
			Parameter (Std. Err.)			
Range of Magnitude	-1.22(0.62)**	-0.04(0.03)	-0.02(0.01)*			
Variance of Magnitude				-3.48(2.08)*	-0.04 (0.06)	-0.003(0.003)
Mean Magnitude	1.12(0.60)*	0.16(0.04)**	0.05(0.01)**	1.39(0.86)	0.16(0.04)**	0.05(0.01)**
Risk Aversion (gain)	-0.01(0.13)	-0.02(0.05)	-0.01(0.02)	0.01(0.17)	-0.02(0.05)	-0.01(0.02)
Risk Aversion (loss)	0.03(0.13)	0.10(0.06)*	0.03(0.02)	0.003(0.17)	0.09(0.06)*	0.03(0.02)
CRS	0.18(0.14)	0.01(0.05)	0.002(0.01)	0.22(0.20)	0.005(0.05)	0.001(0.01)
Flood Zone(SFHA)	1.22(0.46)**	1.46(0.20)**	0.47(0.06)**	1.00(0.64)	1.46(0.20)**	0.47(0.06)**
Previous Damage	-0.75(0.54)	0.11(0.14)	0.03(0.04)	-0.91(0.74)	0.13(0.14)	0.04(0.04)
PreFIRM	0.05(0.34)	0.07(0.15)	0.01(0.04)	-0.05(0.45)	0.07(0.15)	0.01(0.04)
Distance from Coast	0.01(0.01)	-0.004(0.004)	-0.001(0.001)	0.01(0.02)	-0.004(0.004)	-0.001(0.001)
Detached Single House	1.31(0.76)*	0.21(0.22)	0.05(0.06)	1.44(1.01)	0.20(0.22)	0.05(0.06)
Having a Mortgage	0.80(0.44)*	0.30(0.16)*	0.09(0.05)*	1.01(0.63)	0.29(0.16)*	0.08(0.05)*
Insurance Confidence	0.03(0.16)	0.11(0.06)*	0.03(0.02)*	0.004(0.22)	0.12(0.06)*	0.04(0.02)**
Expected Gov. Aid	0.05(0.16)	0.21(0.06)**	0.06(0.02)**	0.05(0.21)	0.21(0.06)**	0.06(0.02)**
Age	0.02(0.02)	0.01(0.01)	0.002(0.002)	0.03(0.02)	0.01(0.01)	0.002(0.002)
Male	0.48(0.36)	0.09(0.14)	0.03(0.04)	0.52(0.48)	-0.08(0.14)	0.03(0.04)
Education	0.82(0.38)**	0.17(0.10)*	0.05(0.02)*	0.88(0.45)*	0.16(0.050)*	0.04(0.03)
Income	0.13(0.06)**	0.07(0.02)**	0.02(0.01)**	0.13(0.07)*	0.07(0.02)**	0.02(0.01)**
Constant	-7.97(3.87)**	-4.53(0.86)**	-0.79(0.23)**	-11.52(5.75)**	-4.55(0.86)**	-0.81(0.23)**
Log Likelihood		-233.1785			-233.7620	
LR χ^2 (17)		117.00**			115.83**	
Wald χ^2(17)	26.81*			17.09		
Over-ID test χ^2(3)	4.761			2.447		
Wald test of Exogeneity χ^2(2)	18.84**			21.92**		

Table 33 shows the results of NFIP participation models when risk perception is elicited by expected damage. Because the Over-ID test statistics are significant, one cannot be sure the validity of the instruments in both probit with IV models. The validity of the Wald test of exogeneity is also doubtful because the Wald test of exogeneity is conducted based on the assumption of valid instruments. In sum, the estimated parameters are considered inaccurate because the selection of the estimation method is not credible. In order to find a valid model, we manipulated the instrumental variables in several ways, but the trials were failed.

If there was no endogeneity, using a simple probit estimation would be a more accurate estimation method. Therefore, when risk perception is elicited by expected damage, the simple probit results are more useful to interpret the behavior of flood insurance purchase. The significant LR χ^2 statistics report that their estimate parameters are not simultaneously zero in both probit models. The mean expected damage, risk aversion for loss scenario, flood zone, insurance confidence, expected government aid, and income variables have significant values in both. When one's perceive risk increases, the probability to purchase insurance also increases. When a property is located in a SFHA, the property owner's probability to purchase flood insurance increases. As the confidence for an insurance company's compensation increases or the expectation of government aid increases, one's probability to purchase flood insurance increases. Also, with increased income the probability of purchasing flood insurance increases. Insurance confidence and expected gov. aid variables are statistically significant only in this models. There is evidence that the probit method provides an appropriate estimation when the risk perception is elicited as expected damage. Nevertheless, the list of significant variables is very similar with those of previous models.

Table 33 Estimated Parameters of Probit with IV, Probit, SUR Models When Risk Perception Elicited by Expected Damage

Dep. Var.:Insurance Purchase	Probit with IV	Probit	SUR	Probit with IV	Probit	SUR
Variables (N=446)	Parameter (Std. Err.)					
Range of Expected Damage	-0.12(0.07)*	0.001(0.01)	-0.001(0.002)			
Variance of Expected Damage				-1.32(1.14)	0.05(0.15)	-0.02(0.04)
Mean Magnitude	0.30(0.38)	0.03(0.01)**	0.01(0.004)**	-0.02(0.25)	0.03(0.01)**	0.01(0.004)**
Risk Aversion (gain)	-0.03(0.08)	-0.01(0.05)	-0.004(0.02)	0.02(0.07)	-0.01(0.05)	-0.004(0.02)
Risk Aversion (loss)	0.11(0.09)	0.11(0.06)*	0.03(0.02)*	0.07(0.08)	0.11(0.06)*	0.03(0.02)*
CRS	-0.001(0.12)	-0.01(0.05)	-0.004(0.01)	-0.07(0.10)	-0.01(0.05)	-0.004(0.01)
Flood Zone(SFHA)	1.05(1.01)	1.37(0.20)**	0.45(0.06)**	1.70(0.78)**	1.37(0.20)**	0.45(0.06)**
Previous Damage	0.19(0.26)	0.15(0.14)	0.05(0.04)	0.26(0.23)	0.15(0.14)	0.05(0.04)
PreFIRM	-0.56(0.37)	0.01(0.15)	0.002(0.05)	0.08(0.31)	0.01(0.15)	0.001(0.05)
Distance from Coast	-0.004(0.01)	-0.01(0.004)	-0.002(0.001)	-0.01(0.01)	-0.01(0.004)	-0.002(0.001)
Detached Single House	0.10(0.44)	0.11(0.21)	0.01(0.06)	-0.05(0.38)	0.11(0.21)	0.01(0.06)
Having a Mortgage	0.20(0.24)	0.22(0.16)	0.07(0.05)	0.22(0.21)	0.22(0.16)	0.07(0.05)
Insurance Confidence	-0.001(0.15)	0.12(0.06)*	0.03(0.02)*	-0.02(0.14)	0.12(0.06)*	0.03(0.02)*
Expected Gov. Aid	0.21(0.16)	0.21(0.06)**	0.06(0.02)**	0.28(0.13)**	0.21(0.06)**	0.06(0.02)**
Age	-0.004(0.01)	0.01(0.01)	0.001(0.002)	0.01(0.01)	0.01(0.01)	0.001(0.002)
Male	0.22(0.43)	0.09(0.14)	0.03(0.04)	-0.07(0.34)	0.09(0.14)	0.03(0.04)
Education	0.36(0.21)*	0.12(0.09)	0.03(0.03)	0.18(0.14)	0.12(0.09)	0.03(0.03)
Income	0.11(0.04)**	0.07(0.02)**	0.02(0.01)**	0.08(0.03)**	0.07(0.02)**	0.02(0.01)**
Constant	-4.15(2.18)*	-3.70(0.81)**	-0.53(0.23)**	-3.03(1.79)*	-3.71(0.81)**	-0.53(0.23)**
Log Likelihood		-239.8941			-239.8441	
LR χ^2 (17)		103.57**			103.67**	
Wald χ^2 (17)	43.54**			50.48**		
Over-ID test χ^2 (3)	16.873**			24.735**		
Wald test of Exogeneity χ^2 (2)	7.00**			3.08		

For an economic aspect, the estimated parameters from a probit estimation including a probit with IV estimation do not have any economic meanings by themselves. Due to the unavailability of the direct interpretation of probit estimates, marginal effects (MEs) are additionally calculated in Table 34, 35, and 36. In STATA, there is an option to calculate marginal effects, but in the case of using a two-stage probit with IV estimator, it is not provided. Thus the marginal effects are calculated by hand based on the same formula of the STATA. The calculation for marginal effects is shown below.

When $\hat{\boldsymbol{\theta}}$ is the vector of parameter estimates, marginal effect, $p(\boldsymbol{\theta})$, is estimated using

$$\hat{p} = \frac{1}{\omega.} \sum_{j=1}^{N} \delta_j (S_p) \omega_j f(\mathbf{z}_j, \hat{\boldsymbol{\theta}}) \tag{34}$$

where $\omega. = \sum_{j=1}^{N} \delta_j (S_p) \omega_j$.

$\delta_j (S_p)$ shows whether observation j is in subpopulation S_p, ω_j is the weight for the j th observation, and N is the sample size (Stata, 2009).

These following tables report the marginal effect (ME) of probit with IV, probit, and estimates of SUR. ME shows the probability change of NFIP participation according to a unit change of variables. For NFIP participation models using perceived risk from hurricane frequency and magnitude of damage, probit with IV is an appropriate method while for models using perceived risk from expected damage, probit is a proper method. Therefore, meaningful interpretation of ME is only from the valid models and their significant variables. In ME tables, additional information is included for reference, like estimation result tables. Table 34 notes the MEs of NFIP participation models when risk perception elicited by hurricane frequency. From probit with IV models, only income variable of the NFIP participation with range of perceived risk model is statistically significant and has a valuable interpretation. When one category of the income variable increases, the probability of flood insurance purchasing increases by 6.4%.

Table 34 Marginal Effects of Probit with IV and Probit Models and Estimates of SUR Model When Risk Perception Elicited by Hurricane Frequency

Dependent Variable: Insurance Purchasing (N=446)	Probit with IV	Probit	SUR	Probit with IV	Probit	SUR
			Marginal Effect			
Range of Hurricane Frequency	-0.121	-0.001	-0.003			
Variance of Hurricane Frequency				-0.074	-0.0002	-0.0001
Mean Hurricane Frequency	0.024	0.005	0.006	-0.077	0.004	0.005
Risk Aversion (gain)	-0.032	-0.001	-0.002	-0.057	-0.001	-0.002
Risk Aversion (loss)	0.059	0.032	0.030	0.086	0.032	0.029
CRS	-0.042	-0.007	-0.007	-0.084	-0.07	-0.007
Flood Zone(SFHA)	0.734	0.426	0.464	0.854	0.427	0.466
Previous Damage	0.150	0.052	0.053	0.118	0.051	0.051
PreFIRM	0.109	0.007	0.004	0.135	0.007	0.004
Distance from Coast	0.001	-0.002	-0.002	-0.002	-0.002	-0.002
Detached Single House	-0.108	0.018	0.007	-0.036	0.019	0.008
Having a Mortgage	0.029	0.066	0.066	-0.002	0.066	0.066
Insurance Confidence	-0.079	0.033	0.030	-0.241	0.034	0.030
Expected Gov. Aid	0.177	0.063	0.060	0.372	0.063	0.059
Age	-0.002	0.001	0.001	0.003	0.001	0.001
Male	-0.093	0.023	0.023	-0.350	0.023	0.022
Education	0.152	0.035	0.036	0.104	0.034	0.033
Income	0.064	0.019	0.018	0.103	0.019	0.018

Table 35 reports the MEs of the NFIP participation models when risk perception is elicited by magnitude of damage. Only MEs of probit with IV models are explicitly explained in this section. With a level higher education variable, an individual has 63.3 % increased probability to purchase flood insurance in the NFIP participation model with range of perceived risk and 29.2% increased probability in the NFIP participation model with variance perceived risk. Moreover, when one unit of risk ambiguity increases, the probability of insurance purchasing decreases by 94.8 % in the NFIP participation model with range of perceived risk and decreases by 115 % in the NFIP participation model with variance perceived risk. These huge MEs are caused by a small value of perceived risk from magnitude of damage, and thus one unit change of range/variance of perceived risk is huge change in this model. When a property is located in a high flood risk area (SFHA), the property owner has 25.2 % higher probability of insurance purchasing in the NFIP participation model with range of perceived risk. In the NFIP participation model with range of perceived risk, if a unit of mean risk perception increases, the probability to purchasing insurance increases by 86.7 %; if the house type is a detached single family house, the home owner has 47 % increased probability for insurance purchasing; if a property owner currently holds outstanding mortgage principal, he has 25.9 % more probability to purchase flood insurance. When one category of the income variable increases, the probability of insurance purchasing increases by 10.2 % in t the NFIP participation model with range perceived risk, and 4.4 % in the NFIP participation model with variance perceived risk. Considering that the interval of income category is about \$2,500 to \$25,000, the increased probability is small.

Other MEs also can be interpreted in the same way, but we only emphasize and interpret the MEs for significant variables from the valid model.

Table 35 Marginal Effects of Probit with IV and Probit Models and Estimates of SUR Model When Risk Perception Elicited by Magnitude of Damage

Dependent Variable: Insurance Purchasing (N=446)	Probit with IV	Probit	SUR	Probit with IV	Probit	SUR
	Marginal Effect					
Range of Magnitude of Damage	-0.948	-0.012	-0.018			
Variance of Magnitude of Damage				-1.151	-0.012	-0.003
Mean Magnitude of Damage	0.867	0.049	0.054	0.459	0.047	0.051
Risk Aversion (gain)	-0.011	-0.005	-0.008	0.002	-0.006	-0.008
Risk Aversion (loss)	0.026	0.028	0.026	0.001	0.028	0.026
CRS	0.135	0.002	0.002	0.071	0.001	0.001
Flood Zone(SFHA)	0.252	0.431	0.471	0.381	0.432	0.471
Previous Damage	-0.238	0.033	0.031	-0.303	0.037	0.036
PreFIRM	0.098	0.020	0.014	-0.019	0.020	0.015
Distance from Coast	0.009	-0.001	-0.001	0.005	-0.001	-0.001
Detached Single House	0.470	0.062	0.050	0.363	0.059	0.045
Having a Mortgage	0.259	0.089	0.086	0.329	0.087	0.085
Insurance Confidence	0.019	0.033	0.034	0.001	0.034	0.035
Expected Gov. Aid	0.380	0.062	0.059	0.017	0.063	0.060
Age	0.016	0.002	0.002	0.010	0.002	0.002
Male	0.141	0.025	0.033	0.190	0.023	0.031
Education	0.633	0.049	0.048	0.292	0.046	0.044
Income	0.102	0.021	0.019	0.044	0.021	0.019

Table 36 describes the MEs when risk perception is elicited by expected damage. For the case risk perception is elicited by expected damage, MEs of the probit is worthy to interpret. A unit increase of mean expected damage increases the probability of insurance purchase by 1% in both NFIP participation models. A unit increase in risk aversion of loss scenario increases 3.2% of insurance purchasing probability in both models. That means a risk-averse person has a higher probability of insurance purchase. When a property located in a SFHA, the property owner has 41.6% higher probability of flood insurance purchase in both. Whether a property is located in a SFHA leads a huge change of probability of insurance purchase compared to other variables. A unit increase of confidence for an insurance company's compensation and of expectation for government aid increase the probability of insurance purchase 3.5% and 6.4%, respectively, in the NFIP participation model with range perceived risk and 3.6% and 6.4% in the NFIP participation model with variance perceived risk. Moreover, an unit increase in the income variable increases the probability of flood insurance purchasing by 2% equally in both models. The MEs of both probit models are very close. It is possible to explain that there is not significant impact of using different methods of risk ambiguity in a probit estimation. However, to confirm this assumption, further research is required to exam details. Estimates of SUR have similar values of estimates with MEs of probit models even though they are derived differently.

Table 36 Marginal Effects of Probit with IV and Probit Models and Estimates of SUR Model when Risk Perception Elicited by Expected Damage

Dependent Variable: Insurance Purchasing (N=446)	Probit with IV	Probit	SUR	Probit with IV	Probit	SUR
			Marginal Effect			
Range of Expected Damage	-0.042	0.0002	-0.001			
Variance of Expected Damage				-0.456	0.016	-0.022
Mean Expected Damage	0.104	0.010	0.010	-0.007	0.010	0.010
Risk Aversion (gain)	-0.009	-0.002	-0.004	0.007	-0.002	-0.004
Risk Aversion (loss)	0.038	0.032	0.030	0.023	0.032	0.030
CRS	-0.0003	-0.004	-0.004	-0.024	-0.004	-0.004
Flood Zone(SFHA)	0.399	0.416	0.453	0.599	0.416	0.453
Previous Damage	0.073	0.046	0.047	0.095	0.046	0.047
PreFIRM	-0.021	0.003	0.002	0.030	0.003	0.001
Distance from Coast	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
Detached Single House	0.036	0.033	0.014	-0.018	0.034	0.014
Having a Mortgage	0.074	0.066	0.067	0.079	0.065	0.067
Insurance Confidence	-0.002	0.035	0.032	-0.005	0.036	0.032
Expected Gov. Aid	0.070	0.064	0.057	0.097	0.064	0.057
Age	-0.001	0.001	0.001	0.002	0.001	0.001
Male	0.081	0.026	0.029	-0.027	0.027	0.029
Education	0.122	0.036	0.034	0.062	0.035	0.033
Income	0.039	0.020	0.018	0.028	0.020	0.018

CHAPTER VII

CONCLUSION AND DISCUSSION

This research was conducted to identify the factors that influence subjective risk perceptions, particularly risk ambiguity, regarding hurricane frequency and property damage, and how these subjective perceptions influence NFIP participation. The data were collected via online survey from a sample of coastal residents in Alabama, Florida, Louisiana, Mississippi, and Texas.

The main contribution of this research is that this is the first study which collected range/variance of perceived flood risk of hurricane strike and property damage. Range/variance of perceived risk is interpreted as a measure of one's risk ambiguity.

We also collect data on perceived confidence in insurance companies to pay the full amount of claims and to test if and to what degree this factor affects NFIP participation. Additionally, we introduced new demographic indicators in the mean and range/variance of perceived risk models such as metropolitan living status, working status, marital status, ethnicity, and state. These demographic characteristics were not accounted for flood risk in previous research. Marital status, ethnicity, and state show significance in some models.

Key findings are as follows. The mandatory purchase requirement seems to operate well. We find that among sample respondents who live in a SFHA, 76% hold a flood policy. Furthermore, we find that in our sample, participation rate of mortgage holders in a SFHA is 90% of total mortgage holders in a SFHA purchased flood insurance. Enhancement of implementation of mandatory purchase requirement for flood insurance would increase NFIP participation, but with an already high participation rate, achieving yet higher via additional regulations may prove difficult. Therefore, it is better to find a feasible way to increase NFIP participation through other regulations sources, for example, a stronger regulation for new constructions in coastal areas.

Regarding the role of risk factors on the decision to purchase flood insurance, mean perceived risk, range/variance of perceived risk, and risk aversion are statistically significant in some NFIP participation models. Even though they are not consistently significant across all models, they provide some evidence that these factors influence one's decision to purchase flood insurance. For future studies of NFIP participation, it is recommended that researchers account for these risk factors.

When risk perception is elicited as expected damage to the homes in a given year, the confidence in insurance companies and expectation of government aid are significant. As one's confidence for compensation from an insurance company increases, the probability of flood insurance purchase increases. Thus, efforts to increase confidence in insurance companies will help encourage people to buy flood insurance. On the other hand, we hypothesized that the expectation of government aid has a negative relationship with NFIP participation, but with high expectation the probability of insurance purchase also increases. Since NFIP is a government program, the increase of confidence for government would result in the increase of NFIP participation. Also, it is expected from positively related expectation for government aid that the intention of confidence for payable ability of government would help NFIP implementation.

The follow is a discussion of potential direction for future research. The comparison of NFIP models' results when perceived risk is elicited as hurricane frequency, magnitude of damage, and expected damage confirmed that the change of variable specifications leads to differences in explanatory power of related variables. For example, in the NFIP participation model when risk is perceived as hurricane frequency, one's decision to purchase flood insurance was significantly related to the state where he resides, while this relationship was not significant in the NFIP participation model when risk perceived as magnitude of damage. Therefore, a researcher should carefully select his risk perception measurement carefully depending on his objective.

Due to some misunderstandings over survey questions, many observations were dropped, and thus, the applicable observation number for statistical analysis was limited although many people participated in the survey. It is possible that our risk perception queries were misunderstood by respondents. Many significant variables existed in NFIP models when risk perception is elicited as magnitude of damage while a few hypothesized variables were statistically significant in other NFIP models. This result may results from that measurement of particular perceived risk is poor. Therefore, development of precise questions related to risk perception will improve the data quality for further research.

NFIP participation models when risk perception is elicited as expected damage did not have endogeneity although measurement of perceived expected damage was derived from the measurement of other two perceived risks. It could be a problem of the estimation specification or a problem of the risk perception measurement. In order to find a precise reason of this result, additional research is recommended.

Research regarding one's attitude toward flood risk was rarely conducted, and risk attitude is not an easily measurable characteristic. In spite of some caveats, this research provides more understanding for an individual's attitude related to flood risk to policymakers. Since risk attitude affects one's decision for NFIP participation, policymakers may wish to find to better understand and account for attitudes regarding risk in order to improve the quality of the National Flood Insurance Program and to encourage NFIP participation. However, developing practical means of collecting reliable information on subjective risk information may prove difficult.

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