Study of Evacuation Behavior of Coastal Gulf of Mexico Residents

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1. Introduction:

People in the coastal south region of the U.S. are vulnerable to various natural disasters, most notably, to hurricanes. In any given year great losses may occur, either in terms of human life and/or property, due to the hurricanes. While timely evacuation from the site of disasters could save lives and properties, we have seen people fail to evacuate on a regular basis. In this study, we investigate the link between hurricane characteristics, demographics of the residents, including their household location, and their respective evacuation behavior. Our study is significantly different from the previously made studies on hurricane evacuation behavior in two ways. At first, the research data is collected through recording responses to a series of hypothetical situations which are quite identical, visually and content wise, to the set of information that people are used to see during the hurricane season. Previous studies on hurricane evacuation behavior have hardly used graphics to generate evacuation responses, and even when they used, e.g. Baker (1995), are not quite identical to what people are used to see in reality. Secondly, this study addresses and includes response heterogeneity while analyzing sample behavior, an issue which has not been addressed in previous research on hurricane evacuation behavior in spite of its importance.

Over the years, National Hurricane Center (NHC) keeps developing various graphic and non-graphic tools to inform the threat (area of possible damage and the path) of hurricane to the people of this region. Though these tools are developed using sophisticated computational techniques, and have good forecast value, however, they may not necessarily communicate people the information that it actually intends to do. For example, recently NHC starts issuing picture of “5-day cone”. Pictorially, a 5-day cone is just an extension of the 3-day cone that people were used to see, which informs people about a hurricane’s path and forward speed with a five-day lead-time forecast. A five-day pre-landfall forecast allow people more time to prepare for the pending storm than a three-day pre-landfall forecast. However, if people think that the longer term forecasts will likely deviate more from the storm's actual path than will forecasts of a shorter duration, or rather 5-day is too early to make any decision, then producing those two extra days of forecast would be of little worth. Evacuation decision is necessarily an economic (broadly speaking) decision making process under uncertainty, and the forecast information plays an important role to mitigate those uncertainties. In a recent study, Letson et al. (2007, page 83) found that, in spite of the fact that a great amount of economic value is attached to hurricane forecast and in its improvement, very little work has been done on this issue. One of the primary objectives of this study is to understand the factors going into the evacuation decision-making process using a set of forecast information which are quite similar to the information that NHC provides before a hurricane hits.

A good amount of previous applied research on hurricane evacuation had explored the relationships between individuals' evacuation decision behavior and various attributes of hurricanes. Those studies also assessed the role of individuals' risk perception, socio-economic and demographic information, including their location, on the impact of their evacuation decision. However, they do not consider peoples' heterogeneity in a structured way. The other primary objective of this study is to explore whether people from different social and geographical background show significantly different evacuation behavior under the similar hurricane situation. In other words, whether the hurricane response behavior is heterogeneous, and if so, the intent of this study is also to find the causes behind such heterogeneity and integrate into the data analysis process. Treating heterogeneity is important for two reasons; it gives us better understanding of the entire process, and also we may get biased result if heterogeneity remains untreated.

The empirical work presented in this paper is the result of an original survey. The survey was designed to understand coastal resident's possible evacuation decision under alternate hurricane scenarios. Compared to previous research, our survey instrument captures evacuation behavior quite differently. For example, Whitehead et al. (2000) study was based on a survey instrument where each individual responded to one hypothetical hurricane of a particular category (randomly chosen from category 1 to category 5). In contrast, our study is based on individual's responses to more than one type of hurricane (two or three depending on the design). Thus it enables us to gather more information about individual's probable actions to the variations in hurricane threats. Additionally, in Whitehead study, the risk information like evacuation notices (mandatory or advisable) were asked sequentially across the households (details are given in the literature review). Whereas in our survey instrument, evacuation notices are randomly assigned across individuals. A random assignment of evacuation notices is likely to reveal the behavioral response to evacuation notices more efficiently. Evacuation decision is a dynamic choice decision as opposed to a static choice decision like buying a commodity. Our survey instrument attempts to capture the dynamic element of evacuation decision by introducing a trend element in the threat scenario and allowing respondents to state their future action in a dynamic setup. In other words, considering evacuation, our survey instrument presents a set of hypothetical storm scenarios which represents reality in a more realistic manner than the previously made studies. Very few studies, if any have attempted to address these issues together. Our survey instrument is also designed to capture the distance between respondents' residence and the track of the hypothetical hurricane and thus enable us to include a spatial element in the analysis of evacuation behavior. It is useful for the policymakers to know how the perceived threats from a hurricane are spread across the area that is covered under the forecast graphics like a 3-day cone picture issued by NHC. Baker (1991) in his survey instrument randomly assigned hurricane characteristics, including hurricane intensities and evacuation notices, across respondents. However, his studies could not capture the impacts of household location with respect to storm track on evacuation behavior. The rest of the article is organized as follows. In the following section, we made a brief literature review of hurricane evacuation behavior. In section 3, we present the evacuation model. In section 4 the survey instrument and survey data are described. Section 5 describes the estimation process used and the subsequent analysis. Finally, section 6 concludes.

2. Literature Review

Research on evacuation has primarily focused on the following aspects of evacuation: namely, the attributes of hurricane scenario and other sources that disseminate the threat information and their respective impacts, the demographics of people who do and do not evacuate, and the way people perceive or assess the overall threat or risk of an impending hurricane. The attributes of hurricane and their impacts, individual demographics and the issues of risk perception are all intertwined and difficult to discuss them separately. However, we start our discussion with the issues related to risk perception.

The way people perceive risk in the wake of hurricane is a complicated issue. With respect to economic theory, what people actually perceive is uncertainty rather than risk. Risky event has known probability distributions attached to its all possible outcomes, while under uncertainty, the probabilities of occurrences of the possible outcomes are not known. Since it is difficult even for a technically skilled analyst to measure and evaluate the objective risk of a particular outcome (e.g. probability of a damage of a particular amount at a particular place) in the wake of hurricane, people make their guesses and react upon that. In fact, majority of the people relied on intuitive risk judgment or heuristics (Slovic, 1987) to make those guesses. These heuristics usually work well, however they suffer from cognitive biases (Tversky and Kahneman, 1974). For example, residents' decisions might be influenced more by the events which they can remember more easily rather then the events that they could not be (availability bias) remembered so easily. Residents' decision about evacuation and risk perception is also necessarily a learning process, which could be thought as a part of cognitive evolution (readers are advised to see Meyer, 2005, for a comprehensive analysis of development of risk perception about catastrophe). In a laboratory experiment made on 189 individuals (students and staff from the University of Pennsylvania) Meyer (2005) looked at how far experiences help an individual to learn to make optimal mitigation investments in the context of hurricane hazards. He found that while the immediate past matters a lot, the earlier histories do not. The partial effect of lagged experiences showed that "the greater (or less) the loss a participant suffered from the just-previous storm, the more (or less) they were inclined to invest in protection against the current one. Losses from earlier storms (earlier lags) had a diminishingly small effect on current investments". Meyer study also revealed the fact the false-alarm need not necessarily have any significant negative effect. In fact, many researchers had analyzed the real data to study the impact of false alarms or "premature evacuations" on evacuation decisions. In the year of 1996, two hurricanes (Bertha and Fran) were thought to made landfall on South Carolina, but instead hit North Carolina. Early evacuations ordered were announced for the coastal people in South Carolina as well. Dow and Cutter (1998) assessed such impact. Study data were derived from interviewing residents of Hilton Head and Myrtle Beach, S.C. and Wilmington, N.C. to examine the "crying wolf" effect two weeks after Hurricane Fran. Bertha came two months earlier than Fran and the residents of Myrtle Beach and Hilton Head suffered "false alarm". Yet, the authors found that during Hurricane Fran, which was also a stronger hurricane than Hurricane Bertha, evacuation rate increased. The experience of "premature evacuations" during Bertha played only a minor role in evacuation decisions of the residents of South Carolina during Hurricane Fran. Also, in spite of wrong evacuation orders, the residents did not find that the officials were "crying wolf", however though the credibility of government officials and emergency managers reduced significantly, if not became irrelevant. Additionally, the authors also found that the residents sought other sources of information; particularly media and weather channel, to take evacuation decisions.

National Hurricane Center (NHC) is one of the primary information providers of hurricanes. Along with information about wind strength, storm track, landfall time etc., NHC also provide hurricane probabilities across a particular region. In particular, 1983 onwards, NHC began disseminating probability information. Baker (1995) did a study to assess the impact of information that conveyed the threat message, particularly the impact of probability information of a particular storm passing through a particular region within a particular time, on individual's evacuation decision. Research data were collected through a mail survey and the respondents were chosen from the coastal areas of Pinellas County, Florida. The total samples were divided into four groups. Respondents in each group were presented with sixteen hypothetical threat scenarios. However, one group did not get any information on threat probability and the other three groups got three different sets of supplemental information on the probability of the impending storm to cause hurricane conditions in their as well as other nearby locations. Evacuation responses were then compared. Threat scenarios were based upon four threat variables and they were designed in a way so that the four variables were statistically uncorrelated. The attributes and their respective levels were; 1) Severity of the storm (wind speed of 85 mph which represents a Category 1 hurricane and wind speed of 150 mph, which represents a Category 5 hurricane), 2) Track and position (the hypothetical storm was 500 away from the survey location and in other case the distance was 300 miles); 3) National Hurricane Center alert (hurricane watch, hurricane warning and neither) and 4) Officials' Evacuation Notice (evacuation advise, evacuation order and neither). Logistic regression models were fitted to each of the four groups to measure the partial impact of each variable on evacuation. The study found that local officials order or advice affect evacuation decision most significantly regardless of the presence or absence of probability information. The study found that people can understand and use probability information to a reasonable extent; however, the impact of probability information on evacuation response is not so significant.

Cross (1990) studied the behavior and evolution of hazard perceptions of Lower Florida Keys residents. His study data was collected over a period of twelve years, 1976 to 1988, from the same sample through mail surveys. Response rate was dropped form 525 in 1976 to 61 in 1988. His study findings suggest that over the years, awareness of hurricane threats remain high among the residents. In spite of the fact that the study area hadn't suffered from a major hurricanes, interestingly, he found that the majority of the residents kept thinking that their area will experience severe hurricane.

Whitehead et al. (2000) did a study to assess the determinants of evacuation of the residents from North Carolina coastal area those who were exposed to Hurricane Bonnie. Research data were collected through telephonic survey, where each respondent (usable sample size was 895) was faced with one hypothetical storm along with hurricane watch. Storm intensity (category 1 to category 5, following Saffir-Simpson scale) was randomly assigned to each respondent. For a particular storm category and hurricane watch, if respondents chose not to evacuate, then they were asked whether they would evacuate if there was a voluntary evacuation order from the officials. If the respondent still chose not evacuate, then they were asked what they would do if the officials issued mandatory order. Lastly, based on their negative response to mandatory order, respondents were asked what they would do if there was hurricane warning. Additionally, the respondents were also asked about their evacuation destination if they chose to evacuate. In orders to examine the impact of explanatory variables on evacuation decision and destination choice, authors employed logistic and multinomial logit regression models respectively. Their study found that the single most important predictor for evacuation is storm intensity. However, for those who live in mobile home and perceive flood risk, evacuation order by local officials also became an effective predictor. Whitehead (2005) did another study of the residents of North Carolina Coast based on their actual evacuation response to Hurricanes Dennis and Floyd in 1999 and revaluated their behavior with what they had said that they would do under hypothetical storm scenarios when they were interviewed in 1998, as mentioned earlier. He jointly estimated the revealed and stated behavior by employing a bivariate probit model. His study suggests that the hypothetical and real evacuation behavior is in fact driven by the similar choice processes. Dow and Cutter (1998) study also suggests that households are making use of information distributed by mass media.

The demographics of those who do and do not evacuate is another area of concerns among the researchers. Over the years, a considerable work has been done on these issues but influence of demographic features on evacuation is not very obvious yet. Baker (1991) revisited previously made studies on twelve different hurricanes[1] and integrated those findings to come up with a set of generalized results. His findings suggest that age and evacuation response are not strongly associated, although some evidence suggests elderly people in the retirement areas are morel likely to evacuate. Additionally, education, nature of job, marital status, gender, presence of children and/or pets at home, type of housing, whether is it owned or rented, are not typically associated with evacuation. In contrast, study made by Bateman and Edwards (2002), Whitehead et al. (2000) suggest a significant relationship between evacuation decision and these demographic characteristics. For example, Bateman and Edwards (2002) study suggests gender as an important factor. Their study data came from a cross sectional survey of 1050 coastal North Carolina residents who have been affected by Hurricane Bonnie, and they fit various multivariate analysis to get a better understanding of why women are more likely to evacuate for hurricane than men. Their findings suggest that the factors that influence evacuation decision significantly

[1] Carla, 1961, Texas and Louisiana; Camille, 1969, Mississippi; Eloise, 1975, Florida; Frederic, 1979, Louisiana, Mississippi and Florida; David, 1979, Florida; Allen, 1980, Texas; Alicia, 1983, Texas; Diana, 1984, South and North Carolina; Elena, 1985, Florida and Louisiana; Gloria, 1985, Virginia to Massachusetts and Hugo, 1989, South Carolina.

vary across the gender in a significantly different way. For example, risk perception is an important factor of evacuation, and "women have greater exposure to certain objective risks and they have more accurate perceptions of subjective risk compared to men". Gladwin and Peacock (1997) analyzed a survey data for the residents in South Florida collected after Hurricane Andrew. Their study suggests living in a single family house affects evacuation negatively. They also found that the presence of elderly people affect evacuation negatively while presence of children affects positively. Additionally, their study also suggests that people who receive evacuation information from friends, relatives, neighbors or authorities, rather than simply relying on the media are more likely to evacuate.

Solis et al. (2008) studied household evacuation behavior for a sample of 1,355 households collected from South East (Miami/Dade, Broward and Palm Beach counties) and North West (all counties west of the Apalachicola River) Florida, through an internet-based survey during March of 2007 and January of 2008. Participants from SE Florida were asked to reveal their experiences with hurricanes Katrina and Wilma and participants from North West Florida were asked to reveal their experiences with hurricanes Dennis and Katrina. Authors used probit procedure to estimate the impacts of various variables, namely respondents' previous experience with hurricanes, sources of hurricane forecast information, home ownership, mobile home residence, living in flood zone, preparations for the hurricane(s), family size, pet ownership, evacuation plans and experiences with their previous evacuation decisions. Their findings suggest that households living in mobile home are more likely to evacuate. Additionally, households with kids are more likely to evacuate whereas pet ownership affects evacuation decision adversely. Also, those who had experienced hurricane before are also more likely to evacuate. Interestingly, respondents from the South East Florida are found to be less likely to evacuate than the respondents from North West Florida. A comprehensive summary of social demographics in relation to evacuation could be found at Dash and Gladwin (2007).

Dow and Cutter (1998) find that the personal risk perception is the strongest determinants of evacuation behavior. In general, people tend to evacuate when they do not feel safe staying at home. The authors also found that type of housing as a good indicator of risk exposure. For example, they found chances of evacuation are higher for those who live in multi-unit buildings compared to those who live in single family dwellings.

Impact of length of residency on evacuation is not clear either. Some researchers have found that length of residence in a hurricane-affected area is negatively related to the likelihood of evacuation (Gladwin and Peacock, 1997). Also, in a study based on sample residents from the five Southern-most coastal counties in Texas, Zhang et al. (2004) found that the duration of residency on the Texas coast is negatively correlated with evacuation, though the relationship was not statistically significant. Baker (1979) revisited four previously made studies (based on three different hurricanes) and did not find any significant relationship between the length of residence and probability of evacuation. However, in contrast, in a study made on Florida coastal residents, Nelson et al. (1989) found that the longer individual leaves on the Florida coast, the higher is the chances of evacuation.

People usually rely on their past experiences about their overall safety during the time of hurricane. In a study made on twelve parishes in the south east Louisiana, Howell and Bonner (2005) found that more than two third of their sample think their home is safe up to a threat level of category 3 hurricane. The longer they live in a region, the safer they feel. The phenomenon is more pronounced usually for those who live more than thirty years in the same area. Additionally, if people believe that they live on high ground, which could be a factual error, and have never lived in a home which was damaged by hurricane, tend to feel safer either. However, as we know, having a well built house or living on high land does not necessarily make ones residence safe under a category 3 hurricane. Peoples' risk perception of hurricane is also affected by the type of hurricane someone previously experienced. Based on previously experienced hurricane category, people can update their risk perception for a hurricane of higher strength, whereas they find it difficult to adjust the threat perception for a hurricane of lower strength. The authors found no evidence that experiencing Hurricane Ivan, which is a category 4 hurricane, affected citizens' perception of risk for a Category 3 hurricane.

3. Empirical Model of Evacuation

Let us assume individual's utility is a function of overall safety (h) and net income (y - c) when y is individual's income/wealth and c is the cost associated with evacuation. Overall safety (h) is a function of a vector of controlled factors (**Z**) that define the threat scenario(j) at time period (t); specifically, hurricane category (z1), landfall time for the impending storm (z2), storm trend (z3), type of evacuation notice (z4), distance of individual's home from the hurricane track (z5), distance of individual's home from the landfall point (z6) and whether or not one's house is located on the east quadrant of the track(z7). Additionally, overall safety (h) also is a function of a vector of covariates, uncontrolled exogenous variables or individual demographics (**D**) like gender, race, education and previous experiences with hurricanes etc. Utility of an individual "i" associated with state "j' at scenario "t" could be written in the following manner;

$$V_{ijt} = h(\mathbf{D}_i, \mathbf{Z}_{jt}) + g(y_i - c_{ijt}), \qquad (1)$$

where $\mathbf{Z}_{jt}$ and c_{jt} is the vector of controlled factors and cost associated with state j at scenario t respectively. A specific functional form is required for the model estimation. Let individual i's utility function (V_{ijt}) be additively separable in terms of all (K number) control and exogenous variables (i.e. $X_{ijt} = D_i, Z_{ijt}, y_i, c_{ijt}$) present in the utility function, so that it could be written as

$$V_{ijt} = \beta_0 + \sum_{k=1}^{K} X_{k,ijt}\beta_k \; . \qquad (2)$$

In our study, we present every individual with 5 choice scenarios, and at every scenario individual was asked whether or not he will evacuate. At scenario t, individual chooses decision j iff by doing so he maximizes his utility. Individual utility could be represented using a typical RUM model framework, i.e.

$$U_{ijt} = \beta' X_{ijt} + \xi_{ijt} \tag{3}$$

and the impact of exogenous variables on his evacuation decision could be estimated by employing a standard logit model where ξ_{ijt} are the iid errors and assumed to follow extreme value distributions. Let P_{ijt} be the probability that individual i chooses evacuation decision j at scenario t. Following the standard logit formulation,

$$P_{ijt} = \frac{\exp(\beta' X_{ijt})}{\sum_j \exp(\beta' X_{ijt})}, \tag{4}$$

and the probability of respondents i's observed sequence of evacuation decision then becomes,

$$Q_i(\beta) = \prod_t P_{ijt} \tag{5}$$

Equations 2 to 5 assume the coefficients of variables to be same for the entire sample and the responses over the various scenarios are uncorrelated. However, it is unlikely to happen that way. Instead, for the entire sample, we randomize the parameter vectors ($\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_K)$) rather than treating them as fixed.

For our data set, which is non-hierarchical in nature, two types of model could be fit based on randomization; namely, Random effect (RE) model and Random Parameter (RP) model. RE model, in one way, is a restricted version of RP model. In a multifactor repeated observations sample study, RE model assumes the impact of each factor remains same across the entire sample, and specifically in a one-way RE model, it allows only the individual specific dummy or the intercept, that is the portion of "y" which could not be explained by the factors of the model, to vary. In case of two-way RE model, both the individual and time (scenario) specific dummy are allowed to vary across their respective mean value, however, the coefficient of the factors remain fixed. In contrast, in a RP model, we assume not only the intercept varies across the sample, so does the impact of each factor on the dependent variable. RP looks more appropriate over the RE model in our case because of the inherent uncertainty that is present in the decision making process of each individual. It is likely that the way these control variables are influencing individual's evacuation choice decision are not homogeneous. The vector β_i varies across all individuals in the following manner;

$$\beta_i = b + \eta_i, \qquad (6)$$

where b is the population mean vector and η_i represents individual deviation. We however do not vary β_i over the scenarios, primarily because there were no considerable time lapses between each hypothetical scenario. For the same reason, we do not fit two-way RE model where the additional randomization takes place over alternate scenarios. With randomized parameter vectors, the utility function now becomes;

$$U_{ijt} = b_i' X_{ijt} + \eta_i X_{ijt} + \xi_{ijt}, \qquad (7)$$

where $\eta_i X_{ijt} + \xi_{ijt}$ is the unobserved part of individuals utility and also correlated over the scenarios.

A general matrix form representation of the model could be the following;

$$g(\mu) = \log\left(\frac{\mu}{1-\mu}\right) = \mathbf{X\beta} + \mathbf{Z\gamma} = \boldsymbol{\eta}, \qquad (8)$$

where g(.) is a logit link, **X** is a (n*p) covariate matrix of rank k, **Z** is a (n*r) design matrix that captures the random effects. β and γ are the associated parameter vector. The random effects, γ_i (i = 1; : : : ;N), are assumed to be mutually independent and identically distributed with density function $f(\gamma_i \mid \boldsymbol{\alpha})$, where **α** denotes the parameter space, the mean and covariance vector.

Traditionally, we assume $\boldsymbol{\gamma} \sim \mathrm{MVN}(0, \mathbf{G})$. Correlation between observations on the same respondent arises because they share the same random effect γ_i. Matrix **Z** could be constructed such a way so that it can capture, 1) RE model, where the intercepts are allowed to vary but not the coefficients, 2) RP model, where the intercepts and other coefficients can vary across the sample. The RP specification could also capture the effect of exogenous variables (**D**) on the random coefficient, and in that situation equation 6 will become

$$\beta_i = b + \varphi(D) + \eta_i \qquad (9)$$

From equation 9 we can write

$$E(\mathbf{Y}|\boldsymbol{\gamma}) = g^{-1}(\mathbf{X}\boldsymbol{\beta}+\mathbf{Z}\boldsymbol{\gamma}) = g^{-1}(\boldsymbol{\eta}) = \mu \qquad (10)$$

Variance of **Y** conditioned on the random effects is $V[\mathbf{Y}|\gamma] = \mathbf{A}^{1/2}\mathbf{R}\mathbf{A}^{1/2}$. The matrix **A** is a diagonal matrix that contains variance of response, and the matrix R is a variance matrix. The variance of the random effect could contain **G** or **R** or both. However, a population –average or marginal model does not have the **G** part in its random effect. The likelihood function for the data ($\mathbf{Y} = ((\mathbf{Y}_1', \mathbf{Y}_2', \ldots\ldots, \mathbf{Y}_n')'$) is

$$\begin{aligned} L(\boldsymbol{\beta}, \boldsymbol{\theta}; \mathbf{Y}) &= \prod_{i=1}^{N} f(\mathbf{y}_i|\boldsymbol{\alpha},\boldsymbol{\beta}) \\ &= \prod_{i=1}^{N} \int \prod_{j=i}^{n_i} h(y_{ij}|\boldsymbol{\gamma}_i, \boldsymbol{\beta}) g(\boldsymbol{\gamma}_i|\boldsymbol{\alpha}) d\boldsymbol{\gamma}_i \end{aligned} \qquad (11)$$

The solutions of the estimations needs to be solved through either integral approximation or methods based on linearization. We chose the linearization approach primarily because of the presence of correlated errors and large number of random effects in our model. Integral approximation method becomes computationally difficult in presence of large number of random effects. Further, equation 11 was solved using pseudo-likelihood estimation (Wolfinger and O'Connell, 1993) based on linearization. The complete detail of the estimation process could be found from page 119 to 125 of SAS documentation set, The GLIMMIX Procedure. Estimation was carried out using GLIMMIX routine in SAS 9.2.

4. Survey Design and Data collection:

A contingent valuation mail survey was developed to collect the required data. The survey was designed to better understand coastal resident's previous experiences with hurricanes, particularly Katrina and their possible evacuation decision under hypothetical hurricane scenarios. We generated 15 hypothetical hurricane scenarios based on four characteristics (factors) of hurricanes, namely wind speed (85 mph, 121 mph and 156 mph), storm trend (wind intensity likely to decrease, increase and remain same), estimated time to land-fall (3 days and 5 days), and evacuation notice (mandatory or advisable). The survey design was based on the fractional factorial design rationale (Dean and Voss, 2000). Measures were taken to make the design efficient (D-efficiency) and finally, the design was generated using SAS software. In order to avoid respondents' fatigue, we made three random blocks and present each individual a set of five unique threat scenarios rather than fifteen After a common introduction explaining these four factors and their respective levels, each respondent was given five scenarios to evaluate. Accompanying each scenario was a graphic map with a legend stating the hurricane conditions, similar to the NOAA hurricane maps the public is used to seeing (see appendix for a sample question). Graphic-map helps the respondent to asses the location of their home relative to the storm path. Under each hypothetical scenario, respondent was asked whether or not they will evacuate. Additionally, the survey instrument had questions to record respondents' demographic data, mainly the socio, economic and geographic variables that we discussed in the literature review section.

Surveys were sent to 2000 residents randomly selected across four Gulf of Mexico States, specifically Alabama, Florida, Louisiana, and Mississippi with greater sampling weight given to the coastal counties. In particular, 66% of the 2000 household samples are taken from the first two counties inland from the water's edge for all four states. Surveys were mailed during the first week of August 2008. We were ready to send the reminder letter two weeks after the first mailing; however, we had to wait two more weeks because of Hurricane Gustav and Ike. The replacement survey was sent during the last week of September and the first week of October.

2000 surveys were originally sent, out of which 320 returned after the first mailing and 218 returned following the second mailing. Six respondents responded to both mailing. We chose to use their first responses and thus the effective sample was reduced to 532 (a 30% response rate after adjusted for the undelivered mails). Table 1 contains the summary statistics of the data collected, and how each variable was specified in the econometric model. Our sample was skewed slightly in favor of middle-aged, educated, upper-middle-class white population. The mean age of our sample was 56. Twenty-one percent of our sample had a high-school degree or less, 22% had completed a bachelor's degree, and 16% had a graduate or professional degree. The mean household income level of our sample was about $60,000 and around 85% of our sample is white. Forty-five percent of our respondent was female. Seventeen percent of our sample lives in a flood zone (as defined by FEMA or some other organizations) and 15% of total sample are required to purchase flood insurance for their home. Ninety-one percent own their current residence and around 10% of total sample live in mobile home/trailer. Additionally, eighty-one percent have insurance against wind damage for their current home as well. Sixty-seven percent had experienced Hurricane Katrina in some ways and 48% of them had evacuated for Katrina.

Each respondent of the entire sample was given five unique hypothetical hurricane scenarios to respond. The entire sample was further divided into three subsamples of equal size. Each subsample was sent the same survey questionnaire except the set of 5 hypothetical scenarios. The first, second and the third sample had generated 176, 154 and 183 returns

respectively. In order to see whether the subsamples differ significantly, we estimate Kruskal-Wallis Tests for the ordinal variables and Chi-square tests for the categorical variables. As mentioned earlier, a significant amount of respondents had returned the survey after the second mailing. In order to see whether this set of people differ significantly, we estimate similar tests for the same set of the variables based on these two return types. Additionally, the interaction between sampling type and return type has been considered as well. Table 2 reports the results of all these tests. The result from Chi-square and Kruskal-Wallis Test indicates that in terms of demographics, hurricane experiences and residence type the subsamples do not vary significantly. However, as expected, the response variables under the five hypothetical scenarios vary significantly across sampling type but not across the return types. The primary reason for the variables Y1 to Y5 vary across sampling type is that each of the response profile corresponds to unique hurricane characteristics (see table 3). Distributions of responses to hypothetical scenarios (table 4) indicates the fact that though the rate of evacuation goes down from the first to fifth hypothetical scenario, the rate does not follow any pattern across the three sampling type.
[insert figure 1 here]

5. Estimation and Discussion:

Table 5 contains the results of mean evacuation responses for each control variables present in the model. We combine evacuation decisions for 3 different sample types to generate this table. The table shows the overall and not the partial relationship shared between each control variable and evacuation decision. The mean evacuation rate increases from .189 to .306 as the speed of the storm goes up to 121 mph or a category 3 storm from 85 mph or a category 1 storm. The rate goes up further to .505 as the storm becomes a category 5 hurricane. Two additional forecast-days lower the mean response by almost 10% whereas mandatory evacuation notice moves up the mean response rate by 10%. Interestingly, the impact of which side of the hurricane track an evacuees' house is, does not influence the evacuation rate that much. In fact, the table suggests that those who are on the left side of the track are slightly more inclined to evacuate than those who are on the right side, even though as a matter of fact, the storms are usually more destructive on its north east quadrant.

The relationship stated in table 5 does not show the partial impact of each control variables on evacuation rate, i.e. the impact of a particular control variable on the mean response rate while controlling other variables present in the model. In order to get the partial impacts, we estimated a logit model to estimate the impacts of the four controlled variables (SPEED, TREND, LANDFALL and NOTICE) and other covariates on evacuation response. Specifically, among the covariates, we included DISABLE, PETS, TRANSPORT, JOB_LEAVE, INCOME, LANDFALL_DIST, TRACK_DIST, YEARLIVING, HOMEOWN, RESI_TYPE (Base = other), FLOOD_ZONE (Base = don't know), INSUR_REQ (Base = don't know), RESCUED, NON BLACK, EDUCATION, SAMPLE TYPE (Base = third sample) and RETURN TYPE (base=late returns). SPEED, TREND and NOTICE were categorical variables with 3, 3 and 2 categories respectively, whereas LANDFALL was as a continuous variable. Distances from the landfall point (LANDFALL_DIST) as well as from the post landfall track (TRACK_DIST) are important factors of evacuation. LANDFALL_DIST was the Euclidean distance between residents location (Zip) and the landfall point, whereas, TRACK_DIST was the shortest distance of resident's location from the track.

Logit model fits the data reasonably well with Max-rescaled R-Square value of 0. 2377 and the P-value of 0. 6705 for the Hosmer and Lemeshow Goodness-of-Fit test statistics. The Hosmer and Lemeshow Goodness-of-Fit Test divides subjects into deciles based on predicted probabilities and then computes a chi-square from observed and expected frequencies. The higher is the P-value, the better it is as a model. Higher P-value indicates that we fail to reject the null hypothesis that there is no difference between the observed and predicted values of the dependent variable. Table 6 reports the results of logit estimation. The evacuation probability decreases as the storm loses it strength and the landfall time increases. The evacuation probability also decreases as the distance from the landfall point increases. However, the distance from the post landfall hurricane track, affects the evacuation probability positively. It is most likely that given the shape of the cone and the sampling area, the further one moves away from the track, the closer it gets to the landfall point. Education affects evacuation probability negatively. Having disabled person at home increases the evacuation chances whereas the pet owners are less likely to evacuate. As expected, chances of evacuation go down as respondents' confidence in being rescued after the storm increases. The result also suggests that non African Americans or non Blacks are less likely to evacuate and the type of job is an influential factor in evacuation decision. For those whose current job allow taking leave during the storm are more likely to evacuate. Residents who are required to buy flood insurance are significantly less likely to evacuate compared to those who are not required to buy and those who are not sure about the requirements. Residents' evacuation probabilities do not significantly depend on whether or not they live in a FEMA designated flood zone. Additionally, those who live longer in the same place are less likely to evacuate

The logit model we fit assumes fixed intercept and fixed parameters. As stated earlier, assumption of fixed parameter not only may understate the inherent variability of individuals' decision making process, but also it may result in biased parameter estimates. We estimate a generalized linear mixed model where we randomize the intercept, speed and trend parameter. The result differs significantly in terms of parameter significance. The parameter associated with "decreasing trend" becomes significant when the same parameter was insignificant under the regular Logit model. Furthermore, JOB_LEAVE, TRACK_DIST, YEARLIVING and EDUCATION becomes insignificant under the RP model. Table 6 reports the covariance parameter estimate. The values are significantly different than zero, and table 7 shows the tests results of no G-side effect. The results in table 7 are based on the residual pseudo-likelihood. The associated p-vale shows the significance of random parameters.

Conclusion:

Based on a sample of 530 observations collected from the four Gulf of Mexico states, this study analyzes the relationships between individuals' evacuation decision behavior and various attributes of hurricanes. The study also assesses the role of individuals' demographic information, including their household location, on the impact of their evacuation decision given specified hurricane attributes. We would like to restate that our survey had a response rate of 30%; thus around two-third of the possible respondents did not contribute their opinions, and thus our results may not necessarily be representative of the general public. However, in as much as our sample represents the general population, the following can be said.

The results of this study indicate that the determinants of storm threat, especially wind speed and expected changes in wind trend affects individual's perception of threat in a non-homogenous manner. Additionally, results indicate that those who have pets at are less likely to evacuate than their counterparts, whereas, those who have individuals at home with physical disability are more likely to evacuate than their counterparts. Results also indicate that the non-blacks are less likely to evacuate than the black people.

Our study explored the evacuation behavior of Gulf of Mexico coastal and inland residents. By doing this now, our study will help us understand the relationship between environment and human life in and around the coastal region to a finer degree and provide evidence of important factors used by respondents in deciding to evacuate or not.

Table 1: Summary Statistics

Variable	Variable Type and Description	Frequency	Mean	Std. Dev
Y1		513	0.388	0.488
Y2		508	0.374	0.484
Y3	Evacuation decision to 5 hypothetical scenarios: Yes=1, No=0	506	0.350	0.477
Y4		505	0.305	0.461
Y5		509	0.299	0.458
LANDFALL_DIST	Distance from the landfall point, measured in statute miles	518	76.644	58.661
TRACK_DIST	Distance from the hurricane track measured in statute miles	518	65.702	55.142
YEARLIVING	No. of years a resident is living at current ZIP	513	20.819	18.095
HOMEOWN	Owned =1 and rented =0	519	0.915	0.279
RESI_TYPE	Type of residence: House=1, Mobile Home/Trailer=2, Apartment=3, Other=4	519	1.245	0.649
FLOOD_ZONE	Living in flood zone: Yes=1, No=2, Don't Know=3	520	1.921	0.511
INSUR_REQ	Flood insurance required: Yes=1, No=2, Don't Know=3	520	1.896	0.440
WIND_INSUR	Having insurance against wind damage: yes=1, no=0	507	0.817	0.387
WORRIED	Worried that major hurricane will hit this season: Extremely Worried =3, Somewhat Worried=2, Not Worried=3	519	2.135	0.631
EXP_KATRINA	experience Hurricane Katrina: Yes=1, No=0	510	0.671	0.470
EVACUA_KATRINA	evacuated for Hurricane Katrina: Yes= 1, No=0	363	0.482	0.500
EDUCATION	Less than 9th grade=1, 9th to 12th grade or no diploma=2, high school graduate=3, some college but no degree=4, associate degree=5, bachelor's degree=6, graduate or professional=7	521	4.674	1.583
WEEKEND	Evacuation decision depends on weekend: Positively=3, Negatively=2, No Effect=1	532	2.968	0.525
RESCUED	Confident of being rescued no matter what: Very confident=3, Somewhat Confident =2, Not At All Confident=1	502	2.072	0.744
JOB_LEAVE	Job allowed to leave if evacuation chosen: Ye=1, No=0	483	0.899	0.302
TRANSPORT	Adequate transportation to evacuate: Yes=1, No=0	517	0.971	0.235
PETS	Pets owned: Yes=1, No=0	518	0.602	0.490
DISABLE	Physically disabled at home: Yes=1, No=0	514	0.140	0.347
HHSIZE	Household size	515	2.561	1.404
AGE		511	56.125	14.301
GENDER	Female=1	516	0.453	0.498
INCOME	Annual Income: <$10K=1, $10K up to $15K=2, $15K up to $25K=3, $25K up to $35K=4, $35K up to $50K=5, $50K up to $75K=6, $75K up to $100K=7, $100K up to $150K=8, $150K up to $200K=9, >$200K=10 and won't say=11	440 (another 55 chose not to say)	6.242	2.640
WIND_SUSTAIN	Wind speed that current home can sustain: up to 55 mph=1, up to 85 mph=2, up to 12 mph=4, up to 155 miles=4, don't know=5	513	3.433	1.040
RACE	White=1, Black=2, Person of Hispanic Origin=3, Asian=4, Other=5, Won't say=6	507	1.215	0.656

Table 2: P-values of the Chi-square and Kruskal-Wallis Tests[2]

Variable	Sampling Type	Return Type	Interaction of Sampling Type and Return Type
Evacuation decision to 1st scenario	<.0001	0.2631	<.0001
Evacuation decision to 2nd scenario	0.0804	0.5024	0.3107
Evacuation decision to 3rd scenario	<.0001	0.88	<.0001
Evacuation decision to 4th scenario	<.0001	0.1163	<.0001
Evacuation decision to 5th scenario	<.0001	0.8624	<.0001
LANDFALL_DIST	0.5953	0.9666	0.9269
TRACK_DIST	0.6364	0.4274	0.7248
YEARLIVING	0.7314	0.0347	0.2325
HOMEOWN	0.2301	0.863	0.1666
RESI_TYPE	0.4171	0.8419	0.5246
FLOOD_ZONE	0.662	0.3822	0.8249
INSUR_REQ	0.6136	0.1961	0.4373
WIND_INSUR	0.7195	0.5564	0.3106
WORRIED	0.5963	0.9395	0.453
EXP_KATRINA	0.9784	0.2381	0.6855
EVACUA_KATRINA	0.5768	0.4492	0.6849
EDUCATION	0.2243	0.0051	0.0072
WEEKEND	0.2711	0.0098	0.1147
RESCUED	0.5386	0.1206	0.1587
JOB_LEAVE	0.4995	0.9928	0.5205
TRANSPORT	0.5975	0.6722	0.8355
PETS	0.1733	0.5235	0.311
DISABLE	0.3011	0.5289	0.2878
HHSIZE	0.6465	0.2336	0.715
AGE	0.7947	0.8359	0.8363
GENDER	0.1857	0.1465	0.1654
INCOME	0.1615	0.6917	0.1135
WIND_SUSTAIN	0.0135	0.2441	0.0853
RACE	0.7015	0.3754	0.739

[2] Kruskal-Wallis Tests were performed for the italicized variables. These variables are either continuous or considered ordinal. Whereas the rest of the variables are treated as categorical variables and Chi-square tests were performed.

Table 3: Factor Profiles of Hypothetical Scenarios

Scenarios	Sampling Type	Speed of impending storm (mph)	Storm Trend or change in wind intensity	Landfall time (days)	Evacuation notice
Scenario 1		121	Remains same	5	Mandatory
Scenario 2		156	Decreasing	5	Advisable
Scenario 3	1st unit	156	Increasing	3	Advisable
Scenario 4		85	Remains same	3	Advisable
Scenario 5		85	Increasing	3	Mandatory
Scenario 1		156	Remains same	3	Mandatory
Scenario 2		121	Increasing	3	Advisable
Scenario 3	2nd unit	121	Increasing	5	Mandatory
Scenario 4		85	Increasing	5	Mandatory
Scenario 5		85	Remains same	5	Advisable
Scenario 1		121	Decreasing	3	Mandatory
Scenario 2		121	Remains same	3	Advisable
Scenario 3	3rd unit	121	Decreasing	5	Advisable
Scenario 4		156	Decreasing	3	Mandatory
Scenario 5		156	Increasing	5	Advisable

Table 4: Distributions of Mean Evacuation Responses across Hypothetical Scenarios

	entire sample		Sampling Type					
			1st unit		2nd unit		3rd unit	
	# obs.	Mean	# obs.	Mean	# obs.	Mean	# obs.	Mean
Evacuation decision to 1st scenario	513	0.388	176	0.290	154	0.552	183	0.344
Evacuation decision to 2nd scenario	508	0.374	174	0.414	153	0.405	181	0.309
Evacuation decision to 3rd scenario	506	0.350	175	0.549	152	0.329	179	0.173
Evacuation decision to 4th scenario	505	0.305	175	0.149	151	0.192	179	0.553
Evacuation decision to 5th scenario	509	0.299	176	0.273	154	0.136	179	0.464

Figure 1: Distributions of Mean Evacuation Responses across Hypothetical Scenarios

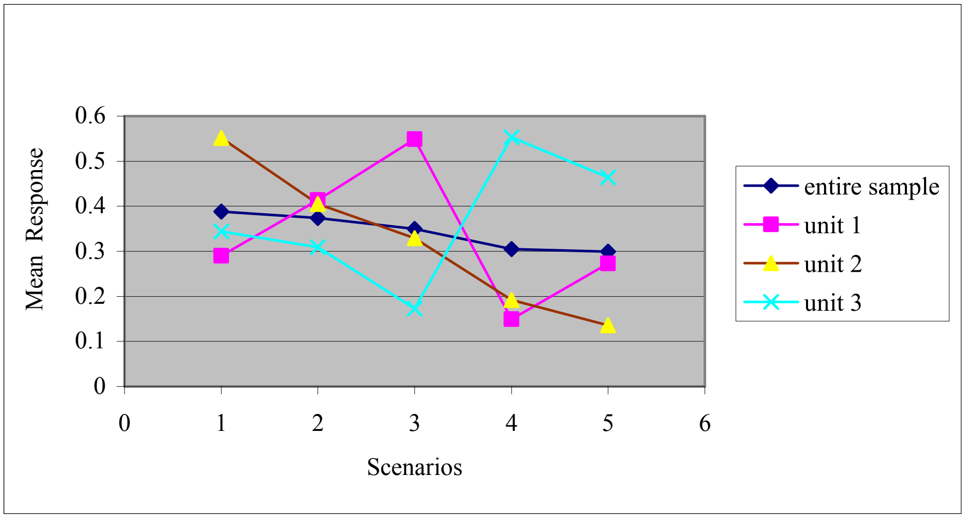

Table 5: Mean Evacuation Response vs. Control Variables

Wind Speed	Mean Evacuation Response	Trend	Mean Evacuation Response	Forecast Period	Mean Evacuation Response	Evacuation Notice	Mean Evacuation Response
85 mph	0.189	Decreasing	0.371	3 days	0.389	Advisable	0.326
121 mph	0.306	Same	0.285	5 days	0.289	Mandatory	0.363
156 mph	0.505	Increasing	0.373				

Table 6: Parameter Estimates of Logit and Random parameter Logit Model.

Variables		Logit Estimates	Random Parameter Logit Estimates
Intercept		3.8531***	12.9301***
SPEED (Base = 156 MPH)	85 MPH	-1.6905***	-5.568***
	121 MPH	-0.9247***	-2.6862***
TREND (Base = Increasing)	Decreasing	-0.3524	-1.1887***
	Remain same	-0.3647***	-1.179***
LANDFALL		-0.2115***	-1.1046***
NOTICE (Base = Mandatory)		-0.2594**	-0.7471***
SIDE (Base = West)		-0.0567	-0.1089
DISABLE		0.7164***	2.4451**
PETS		-0.5094***	-1.3917**
TRANSPORT		-0.068	-0.3057
JOB_LEAVE		0.3904**	1.0978
INCOME		-0.0682	-0.212
LANDFALL_DIST		-0.00975***	-0.02577*
TRACK_DIST		0.00818**	0.02155
YEARLIVING		-0.00652**	-0.01534
HOMEOWN		0.2225	0.717
RESI_TYPE (Base = other)	House	-0.1267	-0.3635
	Mobile/trailer	0.1435	0.4104
	Apartment	-0.945	-3.3433
FLOOD_ZONE (Base = don't know)	Yes	0.1991	0.8282
	No	0.1683	0.5559
INSUR_REQ (Base = don't know)	Yes	-0.0849	0.01002
	No	-0.7708***	-1.9103
RESCUED		-0.1603**	-0.4673
NON BLACK		-0.8058***	-2.5786**
EDUCATION		-0.0811**	-0.2397
SAMPLE TYPE (Base = third unit)	1st unit	0.0223	0.257
	2nd unit	0.1356	0.4753
HURRICANEDATE (Base = late returns)		-0.0476	-0.02143

*** indicates variables are significant at 1% level, ** indicates variables are significant at 5% level and *** indicates variables are significant at 10% level respectively

Table 7: Covariance Parameter Estimate

Cov Parm	Estimate	Std. Error
Intercept	17.15	2.4071
speed	9.2189	0.9493
trend	6.4122	0.6718
Residual (VC)	0.0953	0.0043

Table 8: Tests of No G-side effect (Based on the Residual Pseudo-Likelihood)

DF	-2 Res Log Pseudo-Likelihood	ChiSq	Pr > ChiSq
3	13899	445.62	<.0001

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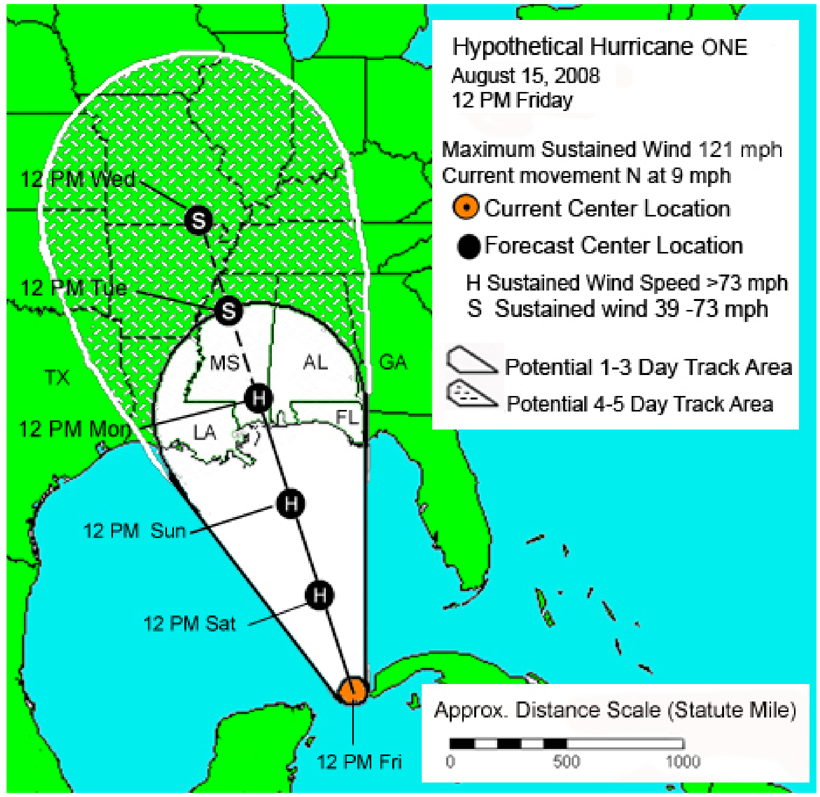
Appendix 1: Sample question

Refer to the following hurricane characteristics and map and answer the questions at the bottom of the page.

Hypothetical Scenario 1

Factors

1. Wind speed - **121 miles per hour** at current position, average speed of Category 3 hurricane
2. Storm trend – **Wind intensity** likely to **decrease**
3. Landfall time - **3 days**
4. Official evacuation notice –**Mandatory**



1. Given where you presently live, <u>would you evacuate</u> under the hypothetical hurricane scenario presented above?

- ☐ 1-Yes, I would evacuate.
- ☐ 2- No, I would not choose to evacuate at this point.