A Behavioral Model to Understand Household Level Hurricane Evacuation Decision Making

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Abstract

Hurricanes are one of the most costly natural disasters in United States (U.S.) and have increased in frequency in the last few years. The critical role of evacuation, particularly for the vulnerable communities, has been realized from some disastrous evacuation experiences in some recent hurricanes (for instance, Hurricane Katrina and Rita in 2005). A thorough understanding of the determinants of evacuation behavior is therefore needed to protect the loss of lives especially in the vulnerable communities. However, a household's decision making process under a hurricane risk is a very complex process influenced by many factors. This paper presents a model of household hurricane evacuation behavior accounting for households' heterogeneous behavior in decision making using original data from Hurricane Ivan. It develops a mixed logit (also known as random-parameters logit) model of hurricane evacuation decision where random parameters reflect the heterogeneous responses of households due to a hurricane. We report several factors, consistent with some of the previous findings which are important for understanding household level evacuation decision making. We also explain the varied influences of some of the determining variables on the hurricane evacuation decision.

Introduction and Background

Hurricanes are one of the most costly natural disasters in United States (U.S.) and are particularly harmful in the coastal areas. For instance, the 2005 Atlantic hurricane season, the most active and harmful in recorded history, had an estimated direct social cost of approximately 2,300 deaths and record damages of over $130 billion (NHC 2006). The 2005 hurricane season has also provided a new level of awareness among researchers regarding the critical role of evacuation for many vulnerable communities; examples include the trapped citizens in floodwater in New Orleans due to Hurricane Katrina and a great number of people stuck in gridlock on the Houston freeways during Hurricane Rita. A significant danger, for example, lies for such communities waiting in traffic jams for a longer period of time if their evacuation routes run parallel to surge-prone bays. This type of situation could result in a massive loss of life if a storm makes landfall while thousands of motorists are waiting in vulnerable areas close to storm surge (Lindell et al. 2005). A thorough understanding of the determinants of evacuation behavior is therefore needed for emergency managers to protect the loss of lives especially in the vulnerable communities.

To understand hurricane evacuation behavior one has to understand and address the complexity involved in the household evacuation decision-making process. However, compared to the amount of research conducted on the issue of evacuation, understanding of household evacuation decision-making is limited. Dash and Gladwin (2007, p. 72) indicate that "those expected to evacuate often do not, and those who should not evacuate (at least in the estimation of emergency managers) often do". This is the consequence of the fact that a household's decision making process under such hurricane risk is a very complex process influenced by many factors (Gladwin et al. 2007). The central idea of this paper is to rigorously understand, using original data gathered from Hurricane Ivan, the causal factors which influence the household level evacuation decision making process.

Understanding who evacuates and who does not has been one of the principal questions of a large body of literature related to hurricane evacuation behavior. Research has focused on the characteristics of those who evacuate and those who do not (Baker 1979; Cross 1979; Baker 1991; Fischer et al. 1995, Dow and Cutter 1998, Drabek 1999). A recent review by Dash and Gladwin (2007) on hurricane evacuation behavior concluded that factors such as age of the decision maker, presence of children or elderly persons in the household, gender, disability, race and ethnicity, income, previous experience, and geographic location like proximity to highways and exit routes play important roles in evacuation decision making. These factors can either encourage or restrain evacuation depending on the situation; as for example, the presence of children in the household might influence parents to protect them from danger through evacuation, yet the presence of a disabled person may hinder their ability to take the essential steps for evacuation.

Previously, many researchers attempted to model evacuation behavior using statistical models (Perry 1994; Gladwin and Peacock 1997; Whitehead et al. 2000; Gladwin et al. 2001; Lindell et al. 2005; Fu and Wilmot 2004, 2006; Solis et al. 2009). In these studies, a diverse set of behavioral aspects has been addressed for modeling the evacuation decision. Gladwin and Peacock (1997), for example, focus on contextual indicators on evacuation behavior. They found that variables influencing evacuation include being in an evacuation zone, demographic factors such as household size, presence of either elders (negative effect) or children (positive effect), and living in a single-family dwelling unit (negative effect). However, specific measurements representing risk perception are not incorporated in their models.

Whitehead et al. (2000), on the other hand, consider storm intensity, by presenting hypothetical storm scenarios to respondents, in addition to objective and subjective risk variables in the development of their model. Their findings suggest that storm intensity is the most important determinant for households' evacuation decision. Regarding objective risk factors, households receiving a mandatory evacuation order instead of a voluntary order and households living in mobile homes are more likely to evacuate. On the other hand, subjective risk factors such as perceived risk from flooding are more important than risk from wind when making evacuation decisions. Influences of objective and subjective risk variables are measured through the coefficients of a logistic regression model. However, these coefficients are assumed constant across households ignoring their heterogeneity among the households; whereas such heterogeneity is more likely to happen because of the differences in the perception of risk among households. Similarly, models developed by Fu and Wilmot (2004, 2006), Solis et al. (2009) also suffer from the problems associated with ignoring heterogeneity among households.

Using correlation analysis, Lindell et al. (2005) found that evacuation decisions tended to be strongly correlated with geographic characteristics (e.g. proximity to the coast, proximity to inland waterways), utilization of information from peers and local authorities, social cues (e.g. official evacuation recommendations, observations of peers evacuating, and official watches and warnings), and demographic characteristics (e.g. younger, female, respondents with children at home). On the other hand, personal hurricane experience and previous experience of unnecessary evacuations were not significantly correlated with evacuation decisions. However, it is noteworthy to mention that such correlation-based analysis measures the influence of the variables on the evacuation decision separately instead of their combined effects.

In addition to the environmental, social and demographic factors, “risk perception” is another key element to understanding how households make decisions on evacuation. While knowledge about hazards such as hurricanes is important; it is not adequate enough to motivate action (i.e. evacuation). Information on hazard is actually transformed into a conception of impending danger within individuals’ own frames of reference (Dash and Gladwin 2007). Slovic (1987) asserts that while technically skilled analysts would employ risk assessment to evaluate hazards, the majority of people actually rely on their intuitive risk judgments or heuristics. There is a personalization effect involved in the way people make their intuitive judgments. Through the personalization process, individuals transform abstract notions of risk into concrete personalized assessments of risk for themselves, their families, and their households (Mileti and Sorenson 1987). Therefore individuals’ actions or responses are based on their individualized perceptions of risk which may depend on their characteristics and the context or constraints they live in. The key point is that models of decision making under such situations must include the concept of individualized responses based on the decision-makers’ frame of reference. However, such individualized responses will be heterogeneous among the population and hence warrants techniques different than the traditional evacuation behavior models that assume constant parameters for variables determining evacuation.

The purpose of this paper is to develop a model of household hurricane evacuation behavior accounting for the heterogeneity among households’ evacuation responses using original data from Hurricane Ivan. In particular, it develops a logit outcome model of hurricane evacuation decision using the random-parameters modeling technique of econometrics (known as mixed logit or random-parameters logit) where the random-parameters associated with different variables reflect the heterogeneity of households’ responses due to a hurricane threat. This paper reports several factors, consistent with previous findings, important for the evacuation decision providing insights for a better household decision making model for hurricane evacuation. However, it also explains the varied influences of some of the determining variables on the hurricane evacuation decision.

This paper is organized as follows. The next two sections present the methodological framework followed by a description of survey data. Then, we present and discuss the empirical results. The last section contains some concluding remarks along with some implications of the findings.

Methodology

The question of whether to evacuate or stay at home in advance of a hurricane involves a decision between these two possible outcomes. Discrete outcome models, such as logit, offer a rigorous analytical framework for modeling such situations; for the last several decades, the logit model has been extensively used to model this kind of discrete outcomes. However, one of the assumptions made in the derivation and application of the standard logit model is that the parameters or coefficients of variables are fixed across all observations. When this assumption does not hold, inconsistent estimates of parameters and outcome probabilities will result (Washington et al. 2003). To account for the possibility that the parameters may vary across observations the random-parameters or mixed logit model are usually considered. Following the work presented in Train (2003) and described in Washington et al. (2011) let us consider a function EV_{in} determining the outcome of the evacuation decision for household *n*,

$$EV_{in} = \boldsymbol{\beta}'\boldsymbol{X}_{in} + \varepsilon_{in} \quad (1)$$

where $\boldsymbol{\beta}$ is a vector of estimable parameters, $\boldsymbol{X}_{in}$ is a vector of the factors (covariates) that determine the evacuation decision outcome for household *n*, and ε_{in} is a disturbance term. If the disturbances ε_{in} are assumed as extreme value Type I distributed then the standard binomial logit form for the evacuation decision outcome is as following,

$$P_n(i) = \frac{e^{\boldsymbol{\beta}' \boldsymbol{X}_{in}}}{e^{\boldsymbol{\beta}' \boldsymbol{X}_{in}} + e^{\boldsymbol{\beta}' \boldsymbol{X}_{jn}}} \tag{2}$$

where $P_n(i)$ is the probability of household n evacuating and $\boldsymbol{X}_{in}$ and $\boldsymbol{X}_{jn}$ are the vectors of the factors that determine whether household n will evacuate and not evacuate respectively. To allow for parameter variations across households (represented by variations in $\boldsymbol{\beta}$) we define a mixed model (i.e. a model with a mixing distribution) in which the evacuation outcome probability is defined as $P_n^m(i)$ with

$$P_n^m(i) = \int P_n(i)\, f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{3}$$

Where $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\varphi}$ referring to a vector of parameters of that density function (i.e. mean and variance). Substituting Eq. (2) into Eq. (3) gives the mixed logit model for the probability of evacuation decision,

$$P_n^m(i) = \int \left(\frac{e^{\boldsymbol{\beta}' \boldsymbol{X}_{in}}}{e^{\boldsymbol{\beta}' \boldsymbol{X}_{in}} + e^{\boldsymbol{\beta}' \boldsymbol{X}_{jn}}} \right) f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{4}$$

Using Eq. (4), for model estimation, $\boldsymbol{\beta}$ can now account for household-specific variations of the effect of $\boldsymbol{X}$ on evacuation probability. For example, the household's heterogeneous responses related to a particular variable or information can be captured through the corresponding random parameter β. However, it should be noted that some elements of the vector $\boldsymbol{\beta}$ may be fixed parameters and some may be random parameters. Eq. (4) also suggests that mixed logit probabilities are a weighted average for different values of $\boldsymbol{\beta}$ across households. If the parameters are random, these mixed logit weights are determined by the density function $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$. Usually, a continuous form of the density function $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ (such as a normal distribution) is used for model estimation although a wide variety of density functions can be applied.

The mixed logit model as presented in Eq. (4) cannot generally be estimated using the usual maximum likelihood techniques as the integral of the logit function over the distribution of the random parameters does not have any closed form. A numerical integration of this function would make the estimation method computationally cumbersome and difficult (Gkritza and Mannering 2008). A simulation-based maximum likelihood method is therefore used to estimate the model. In this method, the mixed logit probabilities $P_n^m(i)$ are first approximated by drawing values of $\boldsymbol{\beta}$ from $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ given the values of $\boldsymbol{\varphi}$, and using these drawn values, a simple logit probability $P_n(i)$ is estimated. This procedure is repeated using many draws and the computed logit probabilities are averaged to a simulated probability $\hat{P}_n^m(i)$ which is used to compute a likelihood function. This likelihood function is finally maximized to estimate the parameter vectors $\boldsymbol{\beta}$ and $\boldsymbol{\varphi}$. For drawing values of $\boldsymbol{\beta}$ from $f\ (\boldsymbol{\beta}|\boldsymbol{\phi})$, usually random draws and Halton draws are considered. However, Bhat (2003) and Train (1999) have shown that Halton draws are more efficient and involve far fewer draws than purely random draws to find accurate probability approximations. McFadden and Ruud (1994), Geweke et al. (1994), Boersch-Supan and Hajivassiliou (1993), Stern (1997), Brownstone and Train (1999) and McFadden and Train (2000) offer the details of simulation-based maximum likelihood methods for estimating mixed logit models.

In order to assess the importance of individual parameters, elasticities or marginal effects of the corresponding variables are usually computed. Since most of our model variables are indicator or dummy variables, marginal effect is an appropriate quantity for this purpose. Marginal effect of an indicator variable is computed as the difference in the estimated probabilities with the indicator variable changing from zero to one, while all other variables are equal to their means (see Washington et al. 2011). As each observation in the data has its own marginal effect only the average marginal effect across all observations are reported in the results. Since we are estimating a mixed logit model here, the probability of the outcome will be replaced by the corresponding simulated probability as defined previously.

Data

To demonstrate the applications of the mixed logit modeling approach for modeling evacuation behavior, data are used from a household survey conducted after the passage of Hurricane Ivan through the region of the west of Gulf Shores, U.S. in September 2004 (Morrow and Gladwin 2005). Hurricane Ivan, the third and most dangerous storm to hit Gulf Shores in 2004, was a long-lived storm. Ivan reached Category 5 strength three different times before its first landfall in the United States as a Category 3 storm west of Gulf Shores Alabama at 2 AM CDT on September 16th (Stewart 2004). Hurricane warnings and evacuation orders for Hurricane Ivan varied from region to region. For example, a mandatory evacuation was ordered on September 10th in Florida Keys. However, on September 11th Ivan shifted westward from the Keys and Florida's southern coastline. On September 14th, a hurricane watch was issued for the northwestern panhandle of Florida; this hurricane watch soon became a hurricane warning for the area. Ivan was the most destructive hurricane to impact this region in more than 100 years. The Alabama coastline was included in the September 14th warning area. A mandatory evacuation was ordered for Gulf Shores, Orange Beach and Fort Morgan of Alabama. A mandatory evacuation was also ordered for the 78 miles of coastline of Mississippi. The New Orleans area of Louisiana was included in the warning on September 14th and 1.4 million residents were urged to leave. Officials hesitated to issue a mandatory evacuation due to the large number of low-income residents without cars. It is estimated that about 600,000 citizens of New Orleans tried to evacuate (Morrow and Gladwin 2005).

Data, analyzed in this paper, were collected as part of the post-storm assessment of the impact of Hurricane Ivan on households in Florida, Alabama, Mississippi and Louisiana. Several counties and parishes in and adjacent to the path of Hurricane Ivan in the four states were selected to be included in the original data collection. A random sample of 3200 households was selected from these regions for telephone interviews. Data collected included household socio-demographic information, housing type and location, house ownership status, past hurricane experience, reasons for evacuating or not evacuating, whether a hurricane evacuation notice was received, type of the notice received (mandatory or voluntary), media thorough which the evacuation notice was received (i.e. TV/Radio, Friends, Relatives etc.), the time of evacuation if evacuation occurred, the destination, the normal travel time to reach the destination and others. Table 1 provides summary statistics of some of the selected variables from the data.

Empirical Results

We first report the correlation matrix (Table 2) of the variables used in our model. This matrix is reported for future researches that may wish to derive specific conclusions about the relative influences of different factors on evacuation behavior. This correlation matrix also gives intuitive indications of possible predictors of evacuation. For example, the correlation matrix indicates that evacuation is positively correlated with variables such as word of mouth indicator variable, if the household receives a mandatory or voluntary evacuation notice, if the household lives in mobile type of house, high-income households and households having members with a post-graduate degree. On the other hand, evacuation is negatively correlated with previous hurricane experience, mandatory work requirement of a member of the households and if the home is owned by the household. However, it is important to note that the correlation provides the influence of only one variable at a time on evacuation. To assess the influences of the combined effects of different variables on evacuation behavior it is necessary to develop a multivariate model.

Therefore, to evaluate the determinants of households' evacuation decision a mixed logit is estimated. The model, as shown in Eq. (4), is estimated with simulation-based maximum likelihood. A functional form of the parameter density function (see $f\ (\boldsymbol{\beta}|\boldsymbol{\phi})$ in Eq. (4)) is specified first. For our analysis, the normal distribution is assumed which is a standard assumption for these models. Once the functional form is specified, values of $\boldsymbol{\beta}$ are drawn from $f\ (\boldsymbol{\beta}|\boldsymbol{\phi})$ and logit proportions are computed. The mixed logit model is estimated using 200 Halton draws as it has been found in literature that this number of Halton draws produces stable estimates of the parameters (Bhat 2003, Milton et al. 2008 and Gkritza and Mannering 2008). Due to missing data for some variables in the data set, after cleaning, the original 3200 observations are reduced to 1995 observations.

However, in order to demonstrate the differences between the estimated mixed logit (random-parameter logit) model and the standard logit (fixed-parameter logit) model, we report the estimation results of both models (Table 3). A likelihood ratio test is then used to statistically test the overall significance of mixed logit model over the standard logit model. The likelihood ratio (LR) can be calculated as following:

$$LR = -2[LL(\beta_R) - LL(\beta_U)] \quad (5)$$

where the $\mathrm{LL}(\beta_{\mathrm{R}})$ is the log-likelihood at convergence of the restricted model (in this case the standard logit model) and $\mathrm{LL}(\beta_{\mathrm{U}})$ is the log-likelihood at convergence of the unrestricted model (in this case the mixed logit model). LR is χ^2 distributed with degrees of freedom equal to the number difference in the number of parameters of the restricted and unrestricted model. The value of this likelihood ratio is found as 23.62. The critical value of $\chi^2_{0.05,5}$ (for 5% level of significance and degrees of freedom equal to 5) is 11.07. Thus the null hypothesis of no random parameters (i.e. a fixed-parameter logit model) is rejected and the appropriateness of the mixed logit model over the standard fixed-parameter logit model is established.

Table 3 shows that most of the factors included in the mixed logit model are statistically significant with plausible signs. However, word of mouth, previous hurricane experience and house ownership are few interesting variables that are not statistically significant at usual 5% or 10% levels of significance. Despite their relatively low t-statistic, we include these variables in our model since we have a priori belief, based on our literature review, that these variables have influences on evacuation decisions (see Ben-Akiva and Lerman 1985 for discussion on criteria for omitting a variable). Five of these parameters have been found to vary across the households according to the normal distribution. Parameters producing statistically significant standard errors for their assumed distribution are considered as random. The remaining parameters are determined as fixed parameters as the standard deviations of their parameter distributions are not significantly different from zero.

The constant and region specific indicator variables are defined in the function determining the outcome of not evacuating. These variables capture the regional differences in evaluating the risk created by the direction of the hurricane. The constant term defined for the not evacuating outcome represents the determining function for not evacuating for the households from Mississippi when everything else remains same. A positive value of it indicates that, given that everything else remains the same, a household from Mississippi is less likely to evacuate. Similarly, the parameter of the indicator variable for the households of Alabama has a positive value suggesting that being from Alabama results in a lower probability to evacuate. However, it should be noted that although this parameter is not statistically significant we include it so that we can infer about the evacuation decisions for the households from Mississippi. From average marginal effect, for households from Alabama, the probability for not evacuating increases by 0.0033 compared to the households from other states.

It is expected that if a household receives an evacuation notice, either mandatory or voluntary, then it is more likely to evacuate. However, it is interesting to note that the variable for the households receiving mandatory notice has a fixed parameter; whereas a similar variable for the households receiving voluntary notice has a random parameter with a mean of 1.656 and a standard deviation of 1.821 (assuming a normal distribution of the parameter). This indicates that those who receive mandatory notice are more likely to evacuate and the response is uniform across households. On the other hand, for 18 percent of the households, receiving voluntary evacuation notice results in a lower probability to evacuate while for 81 percent of households receiving such notice results in a higher probability to evacuate. This indicates that households' responses are non-uniform if they receive a voluntary evacuation notice. For households receiving mandatory notice, the probability to evacuate increases by 0.0653 and similarly for households receiving an evacuation notice as a recommended option, the probability to evacuate increases by 0.0402. In the literature (Whitehead et al. 2000), it is also found that households that receiv voluntary or mandatory evacuation orders are more likely to evacuate than those who do receive any order.

The fact that a household first hears about the evacuation notice from a friend or relative instead of any other source (e.g. TV, Radio, Internet) results in higher probability to evacuate. This fact actually supports previous findings; Gladwin and Peacock (1997) and Lindell et al.

(2005) also suggest that people who receive evacuation information from friends, relatives, neighbors or authorities, rather than simply relying on the media are more likely to evacuate. From average marginal effect, for such households the probability to evacuate increases by 0.0022 compared to the households who hear the evacuation notices from other sources.

Evacuation behavior is found to be related to the previous experience to similar events. Previous hurricane experience was measured through this specific question "Before the summer of 2004, had you ever experienced a major hurricane?" Though not highly significant, the indicator variable for previous major hurricane experience has produced a fixed parameter with a value of -0.281 suggesting that prior experience with a major hurricane results in lower probability to evacuate. However, there exist inconsistent findings in the literature related to the influence of previous experience on the evacuation decision. Baker (1991) and Lindell et al. (2005), for example, found that previous hurricane experience is not significantly correlated with the evacuation decision. On the other hand, Riad et al. (1999) reported evacuation experience as the single best predictor of evacuation in Hurricanes Hugo and Andrew. However, Baker (1991) provides the methodological explanations for these conflicting findings about the effect of experience on evacuation decision. One of the reasons is that there are different ways of measuring experience—examples include the number of hurricanes experienced, the most recent hurricane experienced, the severity of the hurricanes experienced, the amount of property damage experienced, whether any family injuries were experienced, and whether or not an unnecessary evacuation was experienced. Another contributing factor is the presence of "false" experience where people assume that the maximum storm conditions, reported in the media, occurred in their locations, and as their homes withstood these storm conditions these structures would be able to withstand similar storms in the future. However, the fallacy in the reasoning lies in the fact that most people experience wind forces that are much weaker than the maximum wind speeds reported in the news media.

Our model results also show the impacts of some of the socio-economic variables influencing household evacuation decision. For example, if a family lives in a mobile house then they are more likely to evacuate. For such households, the probability to evacuate increases by 0.0146 compared to the households living in other type of houses. On the other hand, families who own their house are less likely to evacuate; the probability to evacuate for such households decreases by 0.0486. This might indicate the fact that such households might have concerns for leaving the house that they own (*e.g.* concern about looters) and thereby have less likelihood to evacuate. High income households (annual household income above 80,000 USD in 2004) are more likely to evacuate. Similarly, if the respondent from a household has a post graduate degree then the household is more likely to evacuate. The probabilities to evacuate for high-income households and households with post-graduate respondents increase by 0.0118 and 0.0139 respectively. One might raise the issue of multicollinearity between the indicator variables for high income and post graduate degree for estimation of the model. In such cases, usually excluding one of the correlated variables change the parameters significantly (Washington et al. 2003). Though the correlation between these two variables is not significant to cause this problem (see Table 2), we investigate this issue by implementing the model excluding one of the correlated variables; however the parameters do not change significantly. Therefore, the multicollinearity issue should not be of concern for this problem. However, it should be noted here that the interpretations from the model concerning these two variables will be limited. All of these socio-economic variables have been found to have fixed-effects indicating a uniform risk response among these households having these particular socio-economic characteristics.

Two of the region specific indicator variables (indicator variables for households from Florida and Louisiana) have significant random parameters. For example, the parameter for the indicator variable for the households from Florida is found as random with mean 1.522 and standard deviation 1.75 (a normal distribution is assumed). Given these estimates, this parameter is less than zero for 19% of the households and greater than zero for 81% of the households. This indicates that for 19 percent of the households, being from Florida results in a higher probability to evacuate, while for 81 percent of households, being from Florida results in lower probability to evacuate when everything else remains the same. This suggests that the majority of the households from Florida responded negatively towards evacuation while for a fraction of the households from this state other unobserved factors influenced to evacuate and hence increased the likelihood of evacuation. Similarly, the indicator variable for Louisiana households has a random parameter with a mean of -0.498 and a standard deviation of 2.032 (a normal distribution is assumed). This means that, given that everything else remains the same, for 60 percent of the households, being from Louisiana results in a higher probability to evacuate while for 40 percent of households being from Louisiana results in a lower probability to evacuate. This variability is likely capturing the heterogeneity in responses due to the unobserved factors such as category of the risk zone that a household is living in and distance between the house and the center of the storm track. From average marginal effect results, for households from Florida the probability for not evacuating increases by 0.0387 and for households from Louisiana the probability for not evacuating decreases by 0.0082.

The indicator variable representing if a member of a household had to work during the evacuation period has a random parameter with a mean of -0.586 and a standard deviation of 2.104 (a normal distribution is assumed). This means that for 61 percent of the households, having a member who has to go to work during the evacuation period results in a lower probability to evacuate while for 39 percent of households such a fact results in higher probability to evacuate. This indicates that for the majority of the households such a work requirement affects negatively towards evacuation, while for the rest of the households this job requirement is compensated by other risk factors resulting in higher probability for evacuation.

The variable for the number of children under 18 years has a random parameter with a mean of 0.201 and a standard deviation of 0.694 (a normal distribution is assumed). This means that for 39 percent of the households, each additional child results in a lower probability to evacuate while for 61 percent of households each additional child results in a higher probability to evacuate. In the literature (Gladwin and Peacock 1997, Solis et al. 2009), it has been reported that households with children display a higher probability of evacuation. However, the interesting finding from the model here is that households with children respond differently. This suggests that the majority of the households respond positively towards evacuation with each additional child while other households show negative responses to evacuation. The differences in evacuation responses might also be attributed to the age of children. For example, households with children aged less than six years might perceive the risk more seriously than households with children aged above six years. To investigate this with further details we require the distribution of the age of the children in the sample. However, the survey questionnaire does not include the specific ages of the children; rather they are included under a broad category of children under 18 years.

The above findings related to the random parameters of the model have important implications. First, the random parameter of a variable indicates that households respond to that variable in fundamentally different ways with respect to their evacuation decisions. Therefore the statistically significant random parameter of a variable might explain the conflicting results across different studies that assume fixed parameters. Second, it would be difficult for emergency managers and transportation officials to determine which households with a given characteristic will respond by evacuating and which will respond by staying. However, it would be better for them to understand the heterogeneity of responses among the households instead of assuming a uniform response towards evacuation decision due to a given characteristic of the household. Such heterogeneous responses (reflected by the distribution of a random parameter) can provide a better prediction of the share of evacuated population. The challenge for future research however would be to identify the set of characteristics for which households have different evacuation responses and more importantly to identify the variables that cause those differences to occur.

Summary and Conclusions

In this paper, we report the results of a mixed logit model of the decision of whether to evacuate or stay at home as a hurricane approaches. The modeling approach followed in this paper offers a methodological flexibility that can be used to model household-based evacuation decisions by taking into account the unobserved heterogeneity present in households' evacuation responses.

Several important factors are found to influence a household's decision to evacuate or stay at home. These factors include the household's geographic location, source of the news of evacuation notice, whether or not a member in the household has to go to work during the evacuation, number of children, living in a mobile house, house ownership status, type of evacuation notice (mandatory or optional) received, previous hurricane experience and whether the household has high income or a post-graduate member. Several of these variables such as indicator variable for households having voluntary notice, indicator variable for mandatory work requirement and number of children aged under 18 are identified to have random parameters to represent the associated heterogeneities in households' evacuation behavior.

This study provides useful insights for a better understanding of household hurricane evacuation decision. For forecasters and emergency managers it confirms the large number of factors people have to consider in their evacuation decision. This complexity adds to the dilemma over whether to give evacuation orders earlier when the location of hurricane landfall is less certain, or later with more certainty but also less time available for evacuees to get ready and leave. However, a new finding of this study points to a partial solution. For example, the fact that households respond non-uniformly if they receive a voluntary evacuation notice suggests that the voluntary notice gives further information that gets weighed along with their other considerations. What this could mean for emergency managers is that giving a voluntary evacuation order before the required order is a good thing, but it needs to be given with additional information via the media on its rationale. This would enable potential evacuees to better weigh it against the other factors they are considering and thus make a decision better informed about the timing and necessity of evacuating.

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Table 1 Summary statistics of some selected variables

Variables	Percent of Households
Evacuated	45.1
Household Location	
Alabama	12.5
Florida	40.6
Louisiana	28.1
Mississippi	18.8
Housing Type	
Single family home	82.4
Multiple family unit	3.7
Mobile home	6.8
House Ownership Status	
Own home	88.6
Rent	9.9
Type of evacuation notice received	
Received recommended notice	23.5
Received mandatory notice	19.3
Source of evacuation notice	
First heard evacuation notice from TV/Radio	37.2
First heard evacuation notice from word of mouth	2.6
Had a major hurricane experience previously	79.5
Education	
Some High School or Graduate	29.6
Some College	26.0
College Graduate	25.5
Post-Graduate	15.4
Children under 18	
None	53.3
1 – 2	24.4
3 or more	6.2
Income	
Less than $15,000	8.0
$15,000-$24,999	9.2
$25,000 - $39,999	14.8
$40,000 - $79,999	25.7
$80,000 or More	19.7

Note: Percentages do not add up to 100% due to missing data or omission of some categories from the table.

Table 2 Correlation Matrix of the Variables Used in the Model

	EVAC	MOUTH	MAND	SHOULD	PREVEXP	MWORK	MHOME	OWN	HINC	GRAD	NCHILD	AL	FL	LA
EVAC	1.0000													
MOUTH	0.1038	1.0000												
MAND	0.3136	0.1302	1.0000											
SHOULD	0.1391	0.0852	-0.2890	1.0000										
PREVEXP	-0.0396	-0.0369	-0.0345	0.0140	1.0000									
MWORK	-0.0086	-0.0103	0.0192	0.0422	0.0129	1.0000								
MHOME	0.1103	0.0216	0.0621	-0.0085	-0.0135	-0.0073	1.0000							
OWN	-0.0443	0.0053	-0.0308	-0.0006	0.1215	-0.0534	-0.0191	1.0000						
HINC	0.0462	-0.0040	0.0141	-0.0140	0.0150	0.0724	-0.1400	0.1418	1.0000					
GRAD	0.0886	0.0244	0.0149	0.0404	-0.0177	-0.0231	-0.0988	0.0600	0.2376	1.0000				
NCHILD	0.0956	-0.0018	0.0878	0.0236	-0.0332	0.1361	0.0801	-0.1219	0.0007	-0.0311	1.0000			
AL	0.0191	0.0041	0.0419	-0.0796	0.0448	-0.0295	-0.0106	0.0281	0.0151	-0.0254	0.0048	1.0000		
FL	-0.2446	-0.0288	-0.0938	-0.1563	-0.0560	-0.0390	0.0865	0.0020	-0.0239	-0.0232	-0.0289	-0.3146	1.0000	
LA	0.1845	-0.0030	0.0231	0.2202	-0.0354	0.0798	-0.0710	-0.0069	0.0317	0.0168	0.0184	-0.2414	-0.5137	1.0000

Variable Code	**Variable Description**
EVAC	The indicator variable for evacuation decision (1 the household evacuated, 0 otherwise)
MOUTH	Word of mouth indicator (1 if evacuation notice is received through friends or relatives, 0 otherwise)
MAND	Indicator variable for mandatory notice (1 if the household received a mandatory evacuation notice, 0 otherwise)
SHOULD	Indicator variable for voluntary notice (1 if the household received a voluntary evacuation notice, 0 otherwise)
PREVEXP	Previous hurricane experience indicator variable (1 if household has experienced a major hurricane before 2004, 0 otherwise)
MWORK	Mandatory work indicator variable (1 if someone in the house had to work during the evacuation period, 0 otherwise)
MHOME	Indicator variable mobile house (1 if household lived in a mobile home, 0 otherwise)
OWN	Indicator variable for house owner (1 if houses are owned, 0 otherwise)
HINC	Indicator variable high income (1 if annual household income is greater than $80,000, 0 otherwise)
GRAD	Indicator variable for post graduate (1 if the respondent has a post graduate degree, 0 otherwise)
NCHILD	Number of children aged under 18

Variable Code	Variable Description
AL	Alabama indicator variable (1 if household is from Alabama, 0 otherwise)
FL	Florida indicator variable (1 if household is from Florida, 0 otherwise)
LA	Louisiana indicator variable (1 if household is from Louisiana, 0 otherwise)

Table 3 Estimation results of logit models for the decision of whether or not to evacuate (random parameters are assumed normally distributed, all the variables are defined for evacuation outcome except mentioned otherwise)

	Random Parameter Model			Fixed Parameter Model		
Variable Description	**Estimated Coefficient**	**t-Statistic**	**Marginal Effect**	**Estimated Coefficient**	**t-Statistic**	**Marginal Effect**
Fixed Parameters						
Constant (defined for the outcome of not evacuating)	0.559	1.565		0.439	1.989	
Alabama indicator variable (1 if household is from Alabama, 0 otherwise, defined for the outcome of not evacuating)	0.183	0.749	0.0033	0.141	0.786	0.0272
Indicator variable for mandatory notice (1 if the household received a mandatory evacuation notice, 0 otherwise)	3.029	7.821	0.0653	1.919	13.785	0.3714
Word of mouth indicator (1 if evacuation notice is received through friends or relatives, 0 otherwise)	0.962	1.418	0.0022	0.527	1.514	0.1020
Previous hurricane experience indicator variable (1 if household has experienced a major hurricane before 2004, 0 otherwise)	-0.281	-1.314	-0.0263	-0.188	-1.451	-0.0364
Indicator variable mobile house (1 if household lived in a mobile home, 0 otherwise)	2.042	4.542	0.0146	1.245	5.731	0.2409
Indicator variable for house owner (1 if houses are owned, 0 otherwise)	-0.466	-1.614	-0.0486	-0.277	-1.661	-0.0537
Indicator variable high income (1 if annual household income is greater than $80,000, 0 otherwise)	0.346	1.833	0.0118	0.268	2.280	0.0518
Indicator variable for post graduate (1 if the respondent has a post graduate degree, 0 otherwise)	0.706	3.017	0.0139	0.489	3.456	0.0947
Random Parameters						
Florida indicator variable (1 if household is from Florida, 0 otherwise, defined for the outcome of not evacuating)	1.522	4.284	0.0387	0.896	6.231	0.1734
(Standard deviation of parameter distribution)	(1.750)	(2.955)				
Louisiana indicator variable (1 if household is from Louisiana, 0 otherwise, defined for the outcome of not evacuating)	-0.498	-1.891	-0.0082	-0.241	-1.630	-0.0467
(Standard deviation of parameter distribution)	(2.032)	(2.428)				
Indicator variable for voluntary notice (1 if the household received a voluntary evacuation notice, 0 otherwise)	1.656	5.108	0.0402	0.995	8.145	0.1925
(Standard deviation of parameter distribution)	(1.821)	(1.715)				

Variable Description	Random Parameter Model			Fixed Parameter Model		
	Estimated Coefficient	**t-Statistic**	**Marginal Effect**	**Estimated Coefficient**	**t-Statistic**	**Marginal Effect**
Mandatory work indicator variable (1 if someone in the house had to work during the evacuation period, 0 otherwise)	-0.586	-2.496	-0.0127	-0.227	-2.082	-0.0440
(Standard deviation of parameter distribution)	(2.104)	(3.466)				
Number of children aged under 18	0.201	2.078	0.0147	0.121	2.539	0.0234
(Standard deviation of parameter distribution)	(0.694)	(2.657)				
Number of observations	1995			1995		
Log likelihood at zero	-1382.829			-1382.829		
Log likelihood at convergence	-1127.348			-1139.156		
Adjusted ρ2	0.171			0.166		