University Transportation Research Center - Region 2

Final Report

A Decision Support Model to Understand Route Choice Decisions and Siting of Facilities in Emergency Evacuation

Performing Organization: The City College of New York/CUNY

October 2013

Sponsor:
University Transportation Research Center - Region 2

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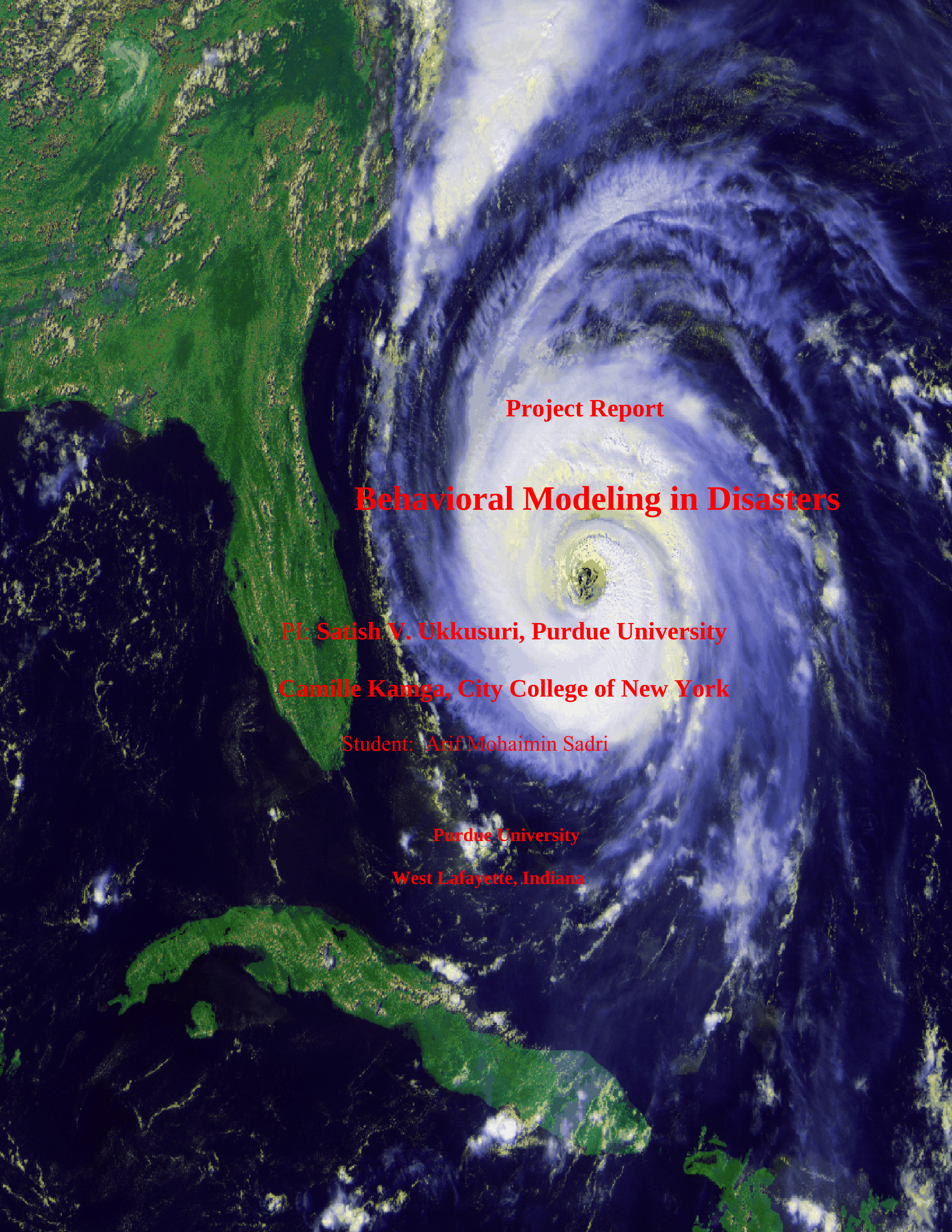

Project Report

Behavioral Modeling in Disasters

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16. Abstract

In this research, we present the results of a behavior model to capture different routing strategies executed by evacuees during hurricane evacuation by using a random-parameter logit-based modeling approach. To the best of our knowledge, this is the first attempt to model evacuees' strategic behavior for evacuation routing decisions using a random-parameter model. A probabilistic model incorporating the demographic characteristics of evacuees and evacuation related characteristics would predict the routing behavior of evacuees' in a better way. Several important factors, for example, household's geographic location, number of children, evacuees' income and age, timing and medium of evacuation notice, etc. influence household's evacuation routing decision which are found from our empirical analysis. In addition, we explain the results of a behavior model to capture the timing behavior of evacuees which elapses from the time of an evacuation decision making to the time of actual evacuation during a hurricane by developing a random-parameter ordered probit model. To the best of our knowledge, this is the first attempt to model evacuees' strategic behavior in terms of evacuation timing by developing a random-parameter ordered probit model. Different influential factors, such as, household's geographic location, socio-economic factors, evacuation related characteristics, trip time during normal condition, previous experience, etc. are found to be statistically significant which affect the time that is required by the evacuees for necessary arrangements during an evacuation.

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CHAPTER 1. INTRODUCTION

1.1 Motivation

Due to the vulnerability to hurricanes in the United States and its territories, comprehensive evacuation plans and strategies need to integrate transportation theory with evacuation behavior from a household level. Public agencies and emergency officials need to understand different dimensions of the overall evacuation process in order to mitigate devastating impacts of frequently occurring hurricanes. In United States (U.S.), hurricanes, occurring frequently in recent years, cause substantial damage to property damages and deaths. The average annual fatalities related to hurricanes increased to 116 from 2001 to 2010, which ranks hurricane as one of the deadliest natural hazards (NOAA 2011).

The 2005 hurricane season highlighted the critical role of evacuation in hurricane prone areas. For example, a great number of people were stuck in gridlock on the Houston freeways during Hurricane Rita. If their routes had run parallel to surge-prone bays, they would face significant danger. Gridlock could lead to massive loss of life if a storm makes landfall while thousands of motorists are waiting in areas subject to storm surge (Lindell et al. 2005). For this reason, emergency officials require a detailed understanding of the determinants of evacuation behavior so they can plan appropriately.

1.2 Research Contribution

Due to the emerging needs of public agencies and emergency managers to understand different dimensions of the overall evacuation process so as to mitigate devastating impacts of frequently occurring hurricanes, all key questions related to evacuees' behavior need to be addressed. This research develops two behavioral models which fit in the gap of existing hurricane evacuation literature in terms of behavioral modeling.

For the first model, by using data from Hurricane Ivan, a mixed (random parameters) logit model is estimated which captures the decision making process on what type of route to select while accounting for the existence of unobserved heterogeneity across households. Estimation findings indicate that the choices of evacuation routing strategy involve a complex interaction of variables related to household location, evacuation characteristics and socio-economic characteristics. Four variables(all found to be normally distributed) have been found to have random parameters that reflect the heterogeneous influences of the associated variables on evacuation routing strategy. These variables include the distance traveled during evacuation; number of years lived in the present home, destination type and time of evacuation. A logical interpretation of the routing strategies displayed by the drivers' would help planners and emergency managers to develop improved evacuation policies and control strategies.

For the second model, an ordered probit model has been developed by using Hurricane Ivan data and the estimation findings suggest that the mobilization time (elapsed from the time evacuees decide to evacuate to the time they actually evacuate) involves a complex interaction of variables related to household location, evacuation characteristics, socio-economic characteristics and some other important characteristics. In this model, six variables- source and time of evacuation notice to be received, work constraint, previous hurricane experience indicator, race and income- were found to be random and the random parameters (all found to be normally distributed) suggest that their effect varies across the observations.

The findings of this research are useful to determine different fractions of people in selecting a type of route and evacuees evacuating early or delaying for some time for a given socio-demographic profile once they actually decide to evacuate during a hurricane evacuation. The results from both of the models also provide some key insights regarding the two specific household level behaviors of the evacuees' during an active hurricane evacuation process.

1.3 Organization of Report

The remainder of this report is organized as follows. Chapter 2 provides an extensive review of the existing literatures related to hurricane evacuation and a brief overview of the state-of-the-art models of evacuation behavior. In Chapter 3, we discuss in details about the mixed logit model to capture the choice of routing strategies during evacuation. This chapter includes details about the methodology, data and estimation findings related to the mixed logit model. Similarly, Chapter 4 includes detailed presentation of the methodology, data and estimation findings related to the random parameters ordered probit model to capture the mobilization time from evacuation decision to the actual evacuation. We conclude the report in Chapter 5 by summarizing the completed work and providing some future research directions.

CHAPTER 2. RELATED WORK

2.1 Introduction

This chapter provides a detailed literature review of the existing works related to hurricane evacuation mobilization time and evacuation routing strategy.

2.2 Choice of Routing Strategy

In terms of emergency planning and network level analysis, a number of research efforts could be mentioned. For example, Wilmot and Mei (2004) differentiated between the relative accuracy of different forms of trip generation for evacuating traffic. Another study explained and offered guidance on the development of dynamic traffic models for hurricane evacuations by Barrett et al. (2000). Murray-Tuite and Mahmassani (2004) developed a way to predict delays and traffic densities while accounting for family gathering behavior in evacuations by using trip chain simulations. Robinson et al. (2009) evaluated the impact of incidents on the time to complete an evacuation of a large metropolitan area. Research by Wolshon et al. (2005a, 2005b) focused on areas that are needed to be considered for a successful evacuation plan. Dixit and Radwan (2008) used microscopic modeling and introduced a process called “network breathing” for the external controls on entry and exit of evacuating vehicles into the evacuation network to improve overall outflow. Liu et al. (2006) developed a cell-based network model in order to determine optimal staging schemes to reduce congestion on an evacuation network by providing a more uniform distribution of demand. They assumed that the starting time for the evacuation of each staged zone could only be controlled.

As far as routing strategy during evacuation is concerned, Cova and Johnson (2003) developed a network flow model to identify optimal lane-based evacuation routing plans in a complex road network and the key idea is to reduce traffic delays at intersections in evacuations. Shen et al. (2008) proposed two models to address the highly uncertain and time-dependent nature of transportation systems during disruption. One of the models offered dynamic routing control in a stochastic time varying transportation network which routes the vehicles using the shortest path algorithm while accounting for the capacity of the links and delays due to congestion and they claimed that the proposed routing strategy minimizes evacuation time to the safety shelter locations. Lammel and Flotterod (2009) compared two different routing strategies in a multi-agent simulation of a real world evacuation environment. They claimed that the cooperative routing approach generates a substantially higher evacuation throughput than an alternative non-cooperative routing strategy. Chiu and Mirchandani (2008) showed that the route choice behavior of an evacuee, as opposed to selecting optimal routes, results in subsequent degradation of evacuation effectiveness. They introduced a FIR (Feedback Information Routing) strategy which could augment the evacuation effectiveness to an optimal situation. In this study, they applied an MNL-based route-choice model ERCM (Evacuation Route Choice Model) that is calibrated through the stated preference approach. However, an important point they emphasized is the fact that ERCM is not intended to serve as an exact representation of the actual route-choice behavior during evacuation but to devise a plausible route choice behavior to show how actual route choice results in evacuation performance deviating from the optimal route choice behavior.

Existing literature suggests that few studies have addressed the routing decisions made by evacuees during a hurricane evacuation. A recent study by Robinson and Khattak (2009) revealed that the preferences of evacuees whether or not to detour from a route when faced with congestion are predictable and controllable by using ATIS (Advanced Traveler Information Systems). Stated preferences analysis indicates that Hampton Roads drivers will be highly motivated to use an alternate route when longer than expected delays are observed on the intended route when ATIS information is available on alternate routes. The survey was intended to provide enough information to provide data for behavior based experiments but it was not possible to ensure a representative sample of the population of the whole region. This is why they emphasized that a demographically accurate survey must be obtained before employing the results in a real world situation.

However, in our model we consider detouring as one of the three major routing strategies during evacuation and capture the difference between the utilities evacuees receive in executing one of them by using a multivariate random parameters logit (mixed logit) approach. This study explores the variables associated with route choice decision-making and then provides some rational inferences about hurricane evacuation routing strategy.

2.3 Evacuation Mobilization Time

Several studies investigated evacuees' behavior in terms of hurricane evacuation decision making processes (Baker, 1979, 1991; Dow and Cutter, 1998; Gladwin et al., 2007; Dash and Gladwin, 2007; Hasan et al., 2011a; Murray-Tuite et al.,2012), hurricane evacuation destination choice (Cheng et al., 2008; Mesa-Arango et al., 2012) and hurricane evacuation routing strategy (Robinson and Khattak, 2009;Murray-Tuite et al.,2012; Sadri et al., 2012) and others.

Previous research efforts related to hurricane evacuation departure time mainly focused on deriving empirical distributions without the inclusion of different influential factors. Lindell and Prater (2007) and Murray-Tuite and Wolshon (Murray-Tuite and Wolshon, in press) provide detailed reviews on evacuation timing studies. However, as far as behavioral studies related to evacuation timing decisions are concerned, few attempts have been made to date. Sorensen (1991) used path analysis for evacuation timing behavior and included a set of sequential decisions made over time with evolving hurricane forecasts in this process. The study considered ordinary least square (OLS) regression to capture the relationship between departure time and several significant variables. A sequential logit choice model was developed by Fu and Wilmot (2004) to capture the decision of whether to evacuate or not when each household reviews the conditions surrounding an approaching hurricane. Later in 2006, they developed a hazard-based model to understand the evacuate/stay and evacuation timing decisions jointly, assuming that the decisions are made simultaneously and are influenced by similar variables. But these assumptions may not be valid because although these two decisions are connected, the factors affecting these two decisions may be different. Additionally, the model included the households who did not evacuate by considering the corresponding observations as right censored which may overestimate the number of households who actually evacuate.

The above evacuation timing models (Sorensen, 1991; Fu and Wilmot, 2004, 2006) mostly included environmental, social, and demographic factors. By following the work of Hensher and Mannering (1994), a hazard-based model to capture evacuation timing behavior was developed by Hasan et al. (2011b). The occurrence of the end of a duration, provided that the duration has lasted for a specified time, is the main focus of hazard-based models. In terms of hurricane evacuation, the end of the duration from the moment of receiving a hurricane warning to the moment of actual evacuation could be captured by a hazard-based approach. The hazard model developed in that study provides valuable insights to understanding the temporal dynamics of the household's evacuation decision making process. In addition, they captured the heterogeneous risk response in the modeling framework by including random parameters in the model. The key focus of this paper (Hasan et al.,2011b) was to understand the causal factors that influence the evacuation timing decision by using data from Hurricane Ivan.

From a different perspective, Dixit et al. (2008) explained different factors associated with the duration between the time that the evacuation decision is made and the time of evacuation by the evacuees of Hurricane Frances. They referred this duration as the "mobilization time." The study showed how the impact of a previous hurricane affects the mobilization time in a subsequent hurricane by estimating the two models simultaneously. Previously, the mobilization time was defined as the difference between the time of departure and the time of warning receipt (Sorensen, 1991).Some other studies referred mobilization time as the "evacuation delay," and revealed several factors affecting the delay by considering isolated hurricanes (Vogt, 1991; Heath et al., 2001;

Stopher et al., 2005).Later in 2012, Dixit et al. used mobilization time to structurally model risk attitudes which can predict the total number of evacuees along with the associated departure time.

However, to the best of our knowledge, no literature has used a random parameter model to estimate the mobilization time of evacuees. This is the time gap between the decision to evacuate and the actual departure from the home or from the evacuation zone when the evacuation warning is applicable. In addition to preparing for evacuation, this elapsed time may include time required for work constraint, shopping, or some other unobserved issues. In this study, a random parameter ordered probit model has been developed to understand the mobilization time required for an evacuee during a hurricane evacuation by using data specific to Hurricane Ivan.

CHAPTER 3. MODEL OF ROUTING STRATEGY DURING EVACUATION

3.1 Introduction

In this study, the problem of routing decisions during evacuation involves three possible outcomes. An evacuee could decide to take the usual or familiar route which they find as the shortest on the way to their destination. To achieve better performance in the transportation network, emergency officials recommend some specific routes prior to the evacuation which do not necessarily yield the best possible route in terms of travel time during non-evacuation scenarios. For example, US 231, SR 79 and SR 77 were recommended for the households in Bay County, Florida during hurricane Ivan. Similarly, some specific routes were assigned for different counties, both for inland and coastal, in Mississippi, Louisiana and Alabama (US Army Corps of Engineers 2005). This is because evacuation problems in hurricane prone regions are complicated by the limited growth of road network as compared to the growth of population in these areas (Dow and Cutter 2002). However, sometimes evacuees might switch to a different route depending on the current condition of the traffic stream to obtain better travel time. Evacuees have a preference for any of these three routing strategies while reaching a safe destination. The details of this model could be obtained from Sadri et al. 2013(a).

3.2 Methodology

Logit models (discrete outcome models) provide an analytical framework for modeling such preferences. However, in the derivation and application of a standard logit model it is assumed that the parameters or coefficients of variables are fixed across all observations. When this assumption does not hold, inconsistent parameter estimates might be obtained along with erroneous outcome probabilities (Washington et al. 2003). In light of the above, it is important to apply a methodological approach that allows for the possibility that the influence of variables affecting routing strategy selection may vary across different households participating in evacuation. This is a significant consideration because, due to variations in evacuee's socio-economic characteristics and evacuation characteristics, it may be unrealistic to assume that the effects of selected variables are the same across all observations. Previous research conducted by Revelt and Train (1997), McFadden and Train (2000), etc., has demonstrated the effectiveness of a methodological approach (the mixed logit model) that can explicitly account for the variations (across households) of the effects that variables have on the categories (or choices) of routing strategies considered in this study.

Following the work presented in Train (2003) and described in Washington et al. (2011), consider a function determining the outcome of the routing strategy for evacuee ***n***,

$$RS_{i,n} = \beta_i X_{i,n} + \varepsilon_{i,n} \tag{3.1}$$

where, $RS_{i,n}$ is a route choice function determining the routing category ***i***; $X_{i,n}$ is the vector of explanatory variables (see Table 3.1); β_i is the vector of estimable parameters and $\varepsilon_{i,n}$ is an error term. If $\varepsilon_{i,n}$'s are assumed to be generalized extreme value distributed, it is shown (McFadden 1981) that the multinomial logit model results in:

$$P_n(i) = \frac{\exp[\beta_i X_{i,n}]}{\sum_I \exp[\beta_i X_{I,n}]} \tag{3.2}$$

where, $P_n(i)$ is the probability of route choice category ***i***(among all the categories *I*) for evacuee ***n*** (see Washington et al. 2003 for details). In order to account for the variations of parameters across different evacuees (variations in β), a mixing distribution is proposed giving route choice probabilities (Train 2003):

$$P_n(i) = \int \frac{\exp[\beta_i X_{i,n}]}{\sum_I \exp[\beta_i X_{I,n}]} f(\beta \mid \varphi) d\beta \tag{3.3}$$

where, $f(\beta \mid \varphi)$ is the density function of β with φ indicating a vector of parameters of the density function (mean and variance), and every other terms are as defined earlier. This β can now allow evacuee-specific variations of the effect of ***X*** on route choice probabilities and the density function $f(\beta \mid \varphi)$ used to determine β. The mixed logit probabilities are then obtained by a weighted average for different values of β across evacuees where some elements of the vector β may be fixed and some may be randomly distributed (see Gkritza and Mannering 2008).

Since they suggested that the estimation of maximum likelihood of mixed logit models is computationally cumbersome, a simulation-based maximum likelihood method is preferred. One of the simulation based techniques considers Halton draws, which was found to provide a more efficient distribution of draws for numerical integration than purely random draws (see Bhat 2003). For detailed understanding, McFadden and Ruud (1994), Stern (1997), etc. offer details about the simulation-based maximum likelihood methods. Previous studies have shown that 200 Halton draws is usually sufficient for accurate parameter estimation (see Bhat 2003, Anastasopoulos and Mannering 2009, etc.). In our study, we have also considered 200 Halton draws and random parameters are assumed to be normally distributed.

3.3 Data

In this study, data are used from a household survey conducted after the passage of Hurricane Ivan through the region of the west of Gulf Shores, Alabama in September 2004 (see Morrow and Gladwin 2005) in order to capture the choice of routing strategy during evacuation. Hurricane Ivan was the third and most dangerous storm to hit Gulf Shores in 2004 and it was the most destructive hurricane to impact this region within 100 years. 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, the Alabama and Mississippi coastline was included in the September 14th warning area followed by the New Orleans area of Louisiana and 1.4 million residents were provided evacuation notice to leave. Emergency officials hesitated in issuing a mandatory evacuation due to the large number of low-income residents without cars and it is estimated that about 600,000 people of New Orleans tried to evacuate (Morrow and Gladwin 2005).

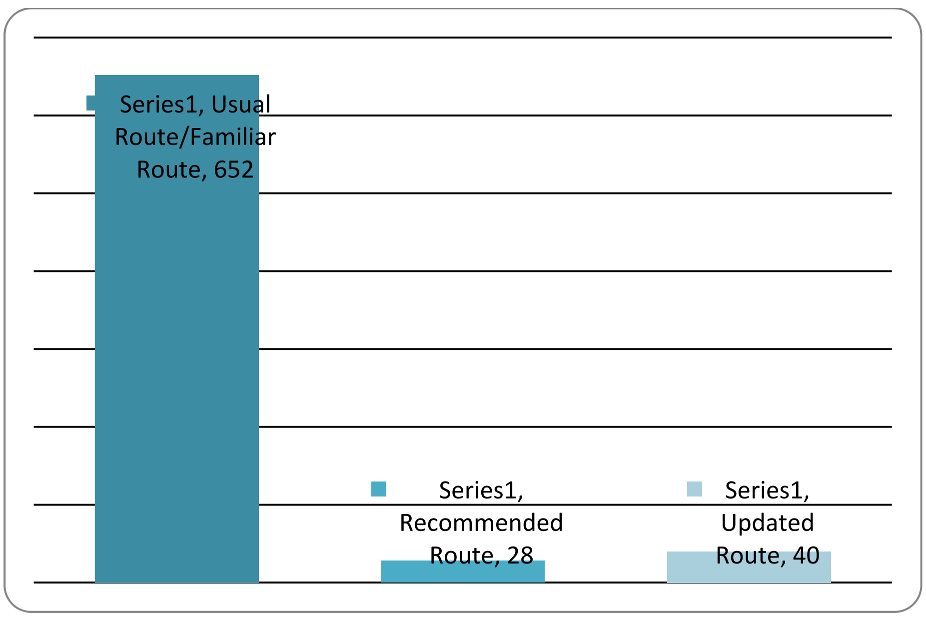

Figure 3.1 Frequency Distribution for the Route Type

The original data considered in this study were collected as part of the post-storm assessment of the impact of Hurricane Ivan on households in Florida, Alabama, Mississippi and Louisiana. A random sample of 3200 households was selected from these regions for telephone interviews and the data included household socio-demographic information, housing type and location, house ownership status, etc. Evacuation related features, such as, previous hurricane experience, time and type (mandatory or voluntary) of evacuation notice that was received, media through which the evacuation notice was received (i.e. TV/Radio, Friends, Relatives etc.), the time of evacuation, the destination, distance traveled to the destination, etc. were also included in the data. Out of 3200 households, 1443 households actually evacuated and due to missing data for some variables in the data set, the observations are reduced to 720 observations (See Figure 3.1). Table 3.1 provides additional information on the mean, standard deviation, minimum, and maximum of the explanatory variables.

3.4 Model Estimation Results

Since, a multivariate model is required to evaluate the influences of the combined effects of different variables on route choice behavior during evacuation; a mixed logit model is estimated in this study. However, in order to differentiate 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 3.2). A likelihood ratio test is then used to statistically test the overall significance of mixed logit model over the standard logit model. Here, the likelihood ratio (LR) can be calculated as following:

$$LR = -2[LL(\beta_{random}) - LL(\beta_{fixed})] \tag{3.4}$$

where, the $LL(\beta_{random})$ is the log-likelihood at convergence of the random-parameter logit model (mixed) and the $LL(\beta_{fixed})$ is the log-likelihood at convergence of the standard logit model (fixed). LR is χ^2 distributed with degrees of freedom equal to the difference in the number of parameters of both of the models. The value of LR is found as 11.336 (see Table 3.3). The critical value of $\chi^2_{0.05,4}$ (for 5% level of significance or 95% level of confidence and degrees of freedom equal to 4) is 9.488. Thus we reject the null

Table 3.1Model I: Descriptive Statistics of Explanatory Variables

Variables	Mean	Standard deviation	Min	Max
Location				
From Louisiana	0.3403	0.4739	0	1
From Alabama	0.1347	0.3415	0	1
Evacuation characteristics				
Received an evacuation notice early enough	0.5472	0.4979	0	1
Distance traveled during evacuation (miles)	194.9260	198.0280	0	998
Evacuated to a friend or relative's house	0.6319	0.4824	0	1
Evacuee left two days before the landfall	0.3014	0.4590	0	1
Received evacuation notice through radio or television	0.5083	0.5000	0	1
Socio-economic characteristics				
Annual household income less than $15,000	0.0583	0.2344	0	1
Annual household income $40,000 or over	0.5375	0.4987	0	1
Number of children aged under 18	0.7514	1.0781	0	7
Age of evacuee in years	51.6458	14.5805	18	92
Number of years lived in the present home	13.6208	13.2152	0	93

hypothesis of no random parameters (i.e. a fixed-parameter logit model) and the appropriateness of the mixed logit model over the standard fixed-parameter logit model is established. We also report the value of ρ^2 and adjusted ρ^2 to compare the goodness-of-fit measures for the random and fixed parameter logit models (Table 3.3).

Apart from considering the combined effects of selected variables, we report marginal effects of the corresponding variables in order to assess the importance of individual parameters (Table 3.2). Marginal effect is an appropriate quantity to demonstrate for dummy variables which can be computed as the difference in the estimated

Table 3.2ModelI: Estimation Results of the Mixed Logit Model

Variable Description	**Random Parameter Model**			**Fixed Parameter Model**		
	Parameter Estimate	**t-Ratio**	**Marginal Effect**	**Parameter Estimate**	**t-Ratio**	**Marginal Effect**
Fixed Parameters						
Constant	4.979	5.15		3.566	8.25	
Louisiana indicator variable (1 if household is from Louisiana, 0 otherwise)	-2.545	-3.29	-0.053	-1.267	-4.17	-0.06
Alabama indicator variable (1 if household is from Alabama, 0 otherwise)	-1.722	-1.88	-0.009	-0.788	-1.91	-0.011
Indicator variable for low income (1 if annual household income is less than $15,000, 0 otherwise)	-2.131	-1.83	-0.011	-1.045	-2.27	-0.011
Indicator variable evacuation notice (1 if the household received an evacuation notice early enough, 0 otherwise)	-1.779	-2.59	-0.047	-1.011	-2.88	-0.057
Indicator variable for high income (1 if annual household income is $40,000 and over, 0 otherwise, defined for recommended route utility function)	-0.621	-1.13	-0.241	-0.499	-1.23	-0.256
Number of children aged under 18 (defined for recommended route utility function)	0.443	1.81	0.199	0.235	1.45	0.161
Indicator variable for medium of evacuation notice (1 if evacuation notice is received through radio or television, 0 otherwise, defined for recommended route utility function)	0.813	1.35	0.281	0.831	1.74	0.404
Approximate distance traveled during evacuation in miles (defined for updated route utility function)	0.003	2.36	0.329	0.002	2.89	0.363
Age of evacuee in years (defined for updated route utility function)	0.017	1.42	0.506	0.013	1.58	0.624

Table 3.2 Continued.

Variable Description	Random Parameter Model			Fixed Parameter Model		
	Parameter Estimate	t-Ratio	Marginal Effect	Parameter Estimate	t-Ratio	Marginal Effect
Random Parameters						
Indicator variable for evacuation destination (1 if household evacuated to a friend or relative's house, 0 otherwise)	4.151	1.69	0.002	0.837	3.11	0.033
(Standard deviation of parameter distribution)	(3.845)	(1.93)				
Indicator variable for the time of evacuation (1 if the evacuee left two days before the landfall,0 otherwise)	3.981	1.36	0.006	0.703	2.17	0.014
(Standard deviation of parameter distribution)	(4.621)	(1.68)				
Indicator variable for medium of evacuation notice (1 if evacuation notice is received through radio or television, 0 otherwise)	4.148	2.29	0.02	1.408	3.45	0.06
(Standard deviation of parameter distribution)	(3.623)	(2.13)				
Number of years lived in the present home (defined for updated route utility function)	-0.111	-1.26	-0.272	-0.029	-1.79	-0.381
(Standard deviation of parameter distribution)	(0.104)	(1.56)				
Number of observations	720			720		
Log likelihood at zero	-806.381			-806.381		
Log likelihood at convergence	-237.616			-243.284		

Table 3.3 Model I: Goodness-of-fit Measures

	Random Parameters	**Fixed Parameters**
Number of parameters	18	14
Log likelihood at zero, $LL(0)$	-806.381	-806.381
Log likelihood at convergence, $LL(\beta)$	-237.616	-243.284
ρ2	0.705	0.698
Adjusted ρ2	0.683	0.681
Likelihood-ratio test	Random versus Fixed Parameters	
$LR = -2[LL(\beta_{random}) - LL(\beta_{fixed})]$	11.336	
Degrees of freedom	4	
Critical $\chi^2_{0.05,4}$ (0.95 level of confidence)	9.488	
Number of observations	720	

probabilities with the indicator variable changing from zero to one, while all other variables are equal to their means (see Washington et al. 2011). In our results, we only report the average marginal effect across all observations as each observation in the data has its own marginal effect. Since we are estimating a mixed logit model here, the probability of the outcome will be replaced by the corresponding simulated probability obtained from repeated Halton draws.

Table 3.2 indicates that most of the variables included in the mixed logit model are statistically significant with plausible signs. However, annual household income ($40,000 and over), medium of evacuation notice, age of evacuees, time of evacuation relative to landfall and number of years lived in the present home are a few interesting variables that are not statistically significant at the usual 5% or 10% levels of significance. Based on the discussion on criteria for omitting a variable by Ben-Akiva and Lerman (1985), we include these variables in our model since we believe that these variables have influences on the choices of routing strategy despite their relatively low t-ratio. Four parameters have been found to vary across the population according to the normal distribution. Parameters producing statistically significant standard deviations for their assumed distribution are treated as random and the remaining parameters are treated as fixed parameters as the standard errors are not significantly different from zero.

The constant term is defined for the usual route utility function when everything else remains same. All else being equal, the positive value of the constant term indicates that evacuees are more likely to take their familiar route which they usually take while evacuating towards a particular type of destination. It proves the preferences of evacuees in following the route they think would be fastest, shortest or least congested prior to the evacuation over the routes recommended by the emergency officials or the likelihood of switching from the route based on traffic condition. This is why subsequent gridlock occurred in the most popular routes during evacuation, for example, Hurricane Charley in 2004. Location specific indicator variables, Louisiana and Alabama, indicate that evacuees from these regions were less likely to prefer their usual route than the preference of following routes recommended by the emergency officials or updating routes from the one initially attempted based on prevailing traffic condition. This again validates the reason why gridlock was not observed in most of the routes located in these regions (US Army Corps of Engineers 2005).

Income related indicator variables were found to have plausible signs and show logical implications. For example, the indicator variable for low income (annual household income less than $15,000) has a negative sign as defined for the usual route utility function. This implies that low income people, who experience heightened levels of risk perception (Flynn et al. 1994), tend to follow routes recommended by officials or update their routes on the way to their destinations. From the average marginal effect, for low income group people, the probability for taking a usual route decreases by 0.011 compared to the other income group people. On the other hand, evacuees having an annual household income ($40,000 and over) are less likely to prefer the recommended evacuation routes as shown by the income indicator variable (defined for recommended route utility function) with a negative sign. It is expected because high income households are less sensitive to the possibility of hazards during evacuation and might stick to their own routing strategy rather than following recommendations.

When a household receives an evacuation notice early enough, they could find more information about the traffic conditions and learn the evacuation routes specified for that particular area. This is justified by the indicator variable for evacuation notice (defined for usual route utility function) as the parameter was estimated as -1.779 with a significant t-ratio of -2.59. Because of the predetermined routing strategy, evacuees are more likely to follow the recommended route or switch to the routes based on prevailing traffic conditions. The average marginal effect suggests that the probability of selecting usual or familiar route decreases by 0.047 for this type of evacuees. However, the variable indicating the households receiving evacuation notice from radio or television instead of any other source (friend, relative, newspaper, etc.) is treated as a fixed parameter for recommended route and a random parameter for usual route utility function. It shows that evacuees are more likely to take their familiar route to evacuate followed by the preference of taking the recommended evacuation routes. It is expected because there will be added influence on the evacuees of the information transferred from the media regarding the necessity of evacuation. For this reason, evacuees select a routing strategy which they think would yield better travel time. With a mean of 4.148 and a standard deviation of 3.623 (assuming a normal distribution of the parameter) of this variable (random parameter), it implies that 13 percent of the evacuees receiving evacuation notice from radio or television results in a lower probability to prefer the usual route while the remaining 87 percent results in a higher probability.

The variable for the number of children aged less than 18 years is defined for the utility function of the recommended route. Gladwin and Peacock (1997) reported that households with children lead to a higher likelihood of evacuation. This shows the inherent sensitivity of the households towards the safety of the children in terms of the risk associated with extreme weather conditions such as hurricanes. An interesting finding from the model here is that evacuees having children are more likely to follow the routes recommended by the emergency officials than any of the other two routing strategies. The average marginal effect implies that each additional child increases the probability of taking the recommended route by 0.199 which is quite significant.

The following two indicator variables are the type of evacuation destination and the time of evacuation as defined for the usual route utility function and both of them are used as random parameters in the model. The indicator variable representing if an evacuee wants to evacuate to a friend or relative's house has a mean of 4.151 and a standard deviation of 3.845 (a normal distribution is assumed). This means that for 14 percent of the evacuees having their friend or relative's house as destination results in a lower probability to take the familiar or usual route while the 86 percent of the evacuees results in higher probability. This indicates that for the majority of the evacuees, when they evacuate to a familiar destination, they are likely to select their familiar routes from their previous visits to those destinations. The time of evacuation indicator variable indicates evacuees trying to evacuate two days before the landfall. With a mean of 3.981 and standard deviation (normal distribution) of 4.621, 19 percent of the evacuees evacuating two days before landfall result in a lower probability to take the usual route while the majority (81 percent) results in a higher probability. This again can be justified from intuition, because, when evacuees are departing well ahead of time, they need not necessarily follow the evacuation routes or switch routes, rather they would prefer to drive through the routes which they are familiar with.

Route updating strategy governs during an evacuation as suggested by the variables related to approximate distance traveled and evacuees' age. Average marginal effect shows that each additional mile increases the probability of detouring by 0.329. This is supported by Robinson and Khattak (2009) who noted that the propensity of an evacuee to detour might be related to the total planned distance of the evacuation from origin to destination. Likewise, as the age of the evacuees increases, they are more likely to switch their routes. Each additional year increases this probability by 0.506 as suggested by the marginal effect. This is an important finding because it addresses one of the limitations identified in Robinson and Khattak's (2009) study where they claim that no attempt was made to provide a representative sample of the region's population although the survey was initially intended to obtain enough information to provide data for behavior-based testing. This is why their analyses indicate no statistical evidence for relationships between demographics (e.g., age or gender) and driver's motivation to detour, for that sample. This is in contrast with our findings in this study. The variable representing number of years lived in the present home is also defined for the updated route utility function and used as a random parameter. With a mean of -0.111 and standard deviation as 0.104, it implies that for 86 percent of the evacuees, each additional year living in the present home results in lower probability to update or switch their route while for the remaining 14 percent results in a higher probability. The reason why the majority of the evacuees do not prefer to update their routes is because, as they live in the present home for years and gain experience over time, they become more confident in their preference of route selection.

3.5 Model Validation

In this section, a validation test is presented for the proposed model. To investigate the validity of the model specification, the data was first split into two parts (Sample 1 and Sample 2) each having about half of the observations. Then two separate models were estimated with the same specification using these two samples. The hypothesis for this specification test is that model parameters are equal for the models estimated on these two datasets. If we fail to reject the hypothesis then the validity of the model specification is established. We calculate a test statistics based on likelihood ratio (LR) as shown in the following equation:

$$LR = -2[\,LL(\beta_{FullData}) - LL(\beta_{Sample1}) - LL(\beta_{Sample2})\,] \tag{3.5}$$

where $LL(\beta_{FullData})$ is the log-likelihood at convergence of the model estimated using the full data, $LL(\beta_{Sample1})$ is the log-likelihood at convergence of the model estimated using Sample 1 which is equal to -112.403, and $LL(\beta_{Sample2})$ is the log-likelihood at convergence of the model estimated using Sample 2 which is equal to -119.387. The likelihood ratio is obtained as 11.652 with degrees of freedom equal to 18. Since, $\chi^2_{0.05,18} = 28.870,$ we fail to reject the hypothesis that the parameters across different samples are equal. Thus this test validates the model specification presented in this study.

3.6 Conclusion

The above findings provide some logical inference regarding route choice decisions for drivers while they try to evacuate to a safe destination. The distribution of random parameters accounts for the heterogeneous responses of the evacuees towards the routing decision. With the help of the proposed model, one could predict different fractions of people who would choose different types of routes for a given socio-demographic profile during an evacuation. In our study, we only consider the major three routing strategies, whereas, some other routing tactics could also be implemented by the evacuees during an evacuation. However, efforts need to be made to identify the set of characteristics for which evacuees have different routing behavior and more importantly to identify the variables that cause those differences to occur.

CHAPTER 4. MODEL OF MOBILIZATION TIME DURING EVACUATION

4.1 Introduction

In order to model the mobilization time, i.e. the elapsed time between evacuation decision and actual evacuation, we develop a random parameters ordered probit model where the dependent variable (time elapsed from evacuation decision to the actual evacuation) is modeled as ordinal data (i.e., elapsed time: 1 hour or less, 2 to 3 hours, 4 to 6 hours, 7 to 12 hours, 12 to 24 hours and more than 24 hours). The details of this model could be obtained from Sadri et al. 2013(b).

4.2 Methodology

In this study, the ordered probit approach has been used because it can explore relationship of explanatory variables (see Table 4.1) and a dependent variable (in this case, the lag time between evacuation decision and actual evacuation) as in case of ordinary least squares regression. However, unlike ordinary least squares regression, ordered probit accounts for the unequal differences among the ordinal categories in the dependent variable [see McKelvey and Zavoina 1975, Greene 1997, etc.). For example, it does not consider that the difference between two consecutive time intervals is the same as the difference between two other consecutive time intervals, provided a unit change in the explanatory variable. Here, ordered probit captures the qualitative differences between different consecutive time intervals. Following the work presented in Washington et al. (2011), Duncan et al. (1999),Anastasopouloset al. (2012), etc.,consider the following function:

$$y^* = \beta X + \varepsilon \tag{4.1}$$

where, y^* is the dependent variable (elapsed time between evacuation decision and actual evacuation) coded as 0, 1, 2, 3, 4, 5; β is the vector of estimated parameters and X is the vector of explanatory variables; ε is the error term, which is assumed to be normally distributed (zero mean and unit variance) with cumulative distribution denoted by $\Phi(\bullet)$ and density function denoted by $\phi(\bullet)$. Given a specific elapsed time, an individual falls in category *n*if $\mu_{n-1} < y < \mu_n$. The elapsed-time data, *y*, are related to the underlying latent variable *y**, through thresholds μ_n, where, *n* = 1 . . . 4. We have the following probabilities:

$$\text{Prob}(y = n) = \Phi(\mu_n - \beta X) - \Phi(\mu_{n-1} - \beta X) \tag{4.2}$$

where, $\mu_0 = 0$ and $\mu_5 = +\infty$ and $\mu_1 < \mu_2 < \mu_3 < \mu_4$ are defined as four thresholds between which categorical responses are estimated. The estimation of this model is relativelyeasy; the derivation of the likelihood is somewhat straight-forward [see McKelvey and Zavoina (1975) for details]. By using the economic software LIMDEP, thresholds μ and parameters β were estimated (see Table 4.2).

The thresholds μ show the range of the normal distribution associated with the specific values of the response variable. The remaining parameters, β', represent the effect of changes in the explanatory variables on the underlying scale. The marginal effects of factors ***X*** on the underlying elapsed-time can be evaluated in the following way:

$$\partial\,\text{Prob}(y = n) / \partial X = -[\Phi(\mu_n - \beta X) - \Phi(\mu_{n-1} - \beta X)]\beta', \qquad n = 1,......,5 \tag{4.3}$$

Computation of marginal effects is particularly meaningful for the ordered probit model where the effect of variables ***X*** on the intermediate categories is ambiguous if only the parameter estimates are available.

In addition to that, past research has considered random parameters to allow for the effect of the variables to vary across observations and to capture the unobserved heterogeneity present in the data. This is important because constraining the parameters to be constant when they actually vary across observations can lead to inconsistent, inefficient and biased parameter estimates. Greene (2007) developed estimation procedures (using simulated maximum likelihood estimation) for incorporating random parameters in the ordered probit modeling scheme by considering,

$$\beta_i = \beta + u_i \tag{4.4}$$

where β_i is a vector of different parameters and u_i is a randomly distributed term. One of the simulation based techniques considers Halton draws, which was found to provide a more efficient distribution of draws for numerical integration than purely random draws (see Bhat 2003). For detailed understanding, McFadden and Ruud (1994), Stern (1997), etc. offer details about the simulation-based maximum likelihood methods. Previous studies have shown that 200 Halton draws is usually sufficient for accurate parameter estimation (see Bhat 2003, Anastasopoulos and Mannering 2009, etc.). In our study, we have also considered 400 Halton draws and random parameters are assumed to be normally distributed.

4.3 Data

In this study, data are used from a household survey conducted after the passage of Hurricane Ivan through the region of the west of Gulf Shores, Alabama in September 2004 (see Morrow and Gladwin 2005) in order to capture the choice of routing strategy during evacuation. Hurricane Ivan was the third and most dangerous storm to hit Gulf Shores in 2004 and it was the most destructive hurricane to impact this region within 100 years. 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, the Alabama and Mississippi coastline was included in the September 14th warning area followed by the New Orleans area of Louisiana and 1.4 million residents were provided evacuation notice to leave. Emergency officials hesitated in issuing a mandatory evacuation due to the large number of low-income residents without cars and it is estimated that about 600,000 people of New Orleans tried to evacuate (Morrow and Gladwin 2005).

The original data considered in this study were collected as part of the post-storm assessment of the impact of Hurricane Ivan on households in Florida, Alabama, Mississippi and Louisiana. A random sample of 3200 households was selected from these regions for telephone interviews and the data included household socio-demographic information, housing type and location, house ownership status, etc. Evacuation related features, such as, previous hurricane experience, time and type (mandatory or voluntary) of evacuation notice that was received, media through which the evacuation notice was received (i.e. TV/Radio, Friends, Relatives etc.), the time of evacuation, the destination, distance traveled to the destination, etc. were also included in the data. Out of 3200 households, 1443 households actually evacuated and due to missing data for some variables in the data set, the observations are reduced to 457 observations(See Figure 4.1). Table 4.1 provides additional information on the mean, standard deviation, minimum, and maximum of the explanatory variables.

4.4 Model Estimation Results

In order to determine the best possible estimation of the ordered probit model, a number of variable interactions were incorporated and tested, and the best model specification

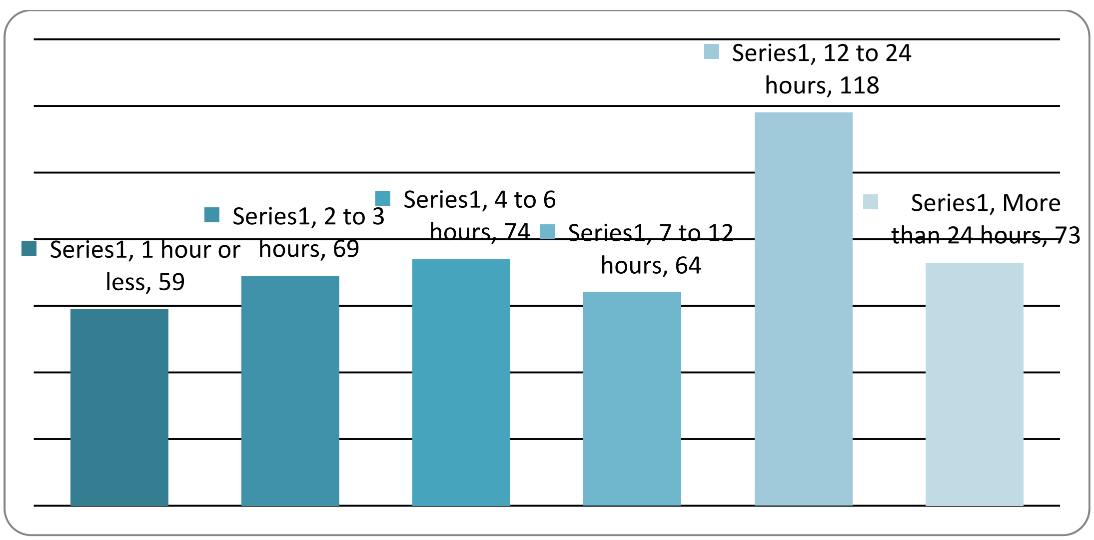

Figure 4.1Frequency Distribution for the Mobilization Time

results are presented in Table 4.2 to understand the elapsed time between evacuation decision and actual evacuation of the evacuees during an evacuation process. To statistically compare the random parameters ordered probit model with its fixed parameters counterpart, we report the estimation results of both models (Table 4.2). A likelihood ratio test is used to statistically test the overall significance of random parameters model over the fixed parameters model. The likelihood ratio (LR) can be calculated as following:

$$LR = -2[LL(\beta_{random}) - LL(\beta_{fixed})] \tag{4.5}$$

where, the $LL(\beta_{random})$ is the log-likelihood at convergence of the random-parameter ordered probit model and the $LL(\beta_{fixed})$ is the log-likelihood at convergence of the fixed-parameter ordered probit model. LR is χ^2 distributed with degrees of freedom equal to the difference in the number of parameters of both of the models. The value of LR is found as 19.184 (see Table 4.4). The critical value of $\chi^2_{0.01,6}$ (for 1% level of significance or 99% level of confidence and degrees of freedom equal to 6) is 16.810. Thus we reject the null hypothesis of no random parameters (i.e. a fixed-parameters ordered probit model) and the appropriateness of the random-parameters ordered probit model over the standard fixed-parameters ordered probit model is established.

In addition to the consideration of the combined effects of selected variables, we report marginal effects of the corresponding variables in order to assess the importance of individual parameters (Table 4.3). Marginal effect is an appropriate quantity to demonstrate indicator or dummy variables which can be 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). In our results,

Table 4.1 Model II: Descriptive Statistics of Explanatory Variables.

Variables	Mean	Standard deviation	Min	Max
Location				
From Louisiana	0.4070	0.4918	0	1
Evacuation characteristics				
Received an evacuation notice early enough	0.8840	0.3205	0	1
Evacuated to a public shelter or Church	0.0328	0.1784	0	1
Evacuee left two days before the landfall	0.3173	0.4659	0	1
Received evacuation news through radio or television	0.8140	0.3895	0	1
Received evacuation notice from friend/relative/neighbor	0.0766	0.2662	0	1
Socio-economic characteristics				
Annual household income less than $15,000	0.0722	0.2591	0	1
Age: over 50 years	0.5077	0.5005	0	1
Education status: high school graduate	0.1926	0.3947	0	1
Home-materials made of woods	0.3720	0.4839	0	1
White race	0.8752	0.3308	0	1
Others				
Approximate trip time under normal circumstance (hours)	3.8031	4.3715	0	50
Evacuee left during afternoon, evening or noon until midnight	0.5120	0.5004	0	1
Had a major hurricane experience previously	0.7834	0.4124	0	1
Work constraint during evacuation	0.3151	0.4651	0	1

Table 4.2Model II: Estimation Results of Ordered Probit Model

	Random Parameters		Fixed Parameters	
Variable Description	***Coefficient***	***t-stats***	***Coefficient***	***t-stats***
Fixed Parameters				
Constant	1.078	3.53	0.779	2.68
Indicator variable for location (1 if household is from Louisiana, 0 otherwise)	-0.396	-3.45	-0.307	-2.84
Indicator variable for source of evacuation notice (1 if household received evacuation notice from radio/television, 0 otherwise)	0.435	2.64	0.323	2.00
Indicator variable for education status (1 if respondent was a high school graduate, 0 otherwise)	-0.418	-3.06	-0.278	-2.17
Home-materials indicator variable (1 if respondent's home is mostly made of woods, 0 otherwise)	0.390	3.57	0.255	2.43
Indicator variable for destination type during evacuation (1 if respondent evacuated to a public shelter or Church, 0 otherwise)	-1.149	-3.72	-0.755	-2.57
Approximate trip time under normal circumstance in hours	0.063	4.63	0.044	3.48
PM indicator variable (1 if the respondent left during afternoon, evening or noon until midnight , 0 otherwise)	-0.524	-4.80	-0.392	-3.82
Age indictor variable (1 if respondent is over 50 years , 0 otherwise)	-0.299	-2.77	-0.223	-2.13
Indicator variable for the time of evacuation (1 if the evacuee left two days before the landfall, 0 otherwise)	0.155	1.25	0.143	1.26

Table 4.2 Continued.

Variable Description	Random Parameters		Fixed Parameters	
	Coefficient	***t-stats***	***Coefficient***	***t-stats***
Random Parameters				
Indicator variable for source of evacuation notice (1 if household received evacuation notice from friend/relative/neighbor, 0 otherwise)	0.593	2.41	0.410	1.75
(Standard deviation of parameter distribution)	(1.086)	(5.10)		
Indicator variable for work constraint (1 if anyone in the household had to go to work while the evacuation was going on)	-0.245	-2.16	-0.183	-1.67
(Standard deviation of parameter distribution)	(0.470)	(5.01)		
Indicator variable for hurricane experience indicator (1 if the respondent experienced a major hurricane previously, 0 otherwise)	0.201	1.59	0.126	1.04
(Standard deviation of parameter distribution)	(0.876)	(12.98)		
Race indicator variable (1 if the respondent is white, 0 otherwise)	0.242	1.50	0.179	1.17
(Standard deviation of parameter distribution)	(0.265)	(4.85)		
Income indicator variable (1 if the total household income of the respondent less than $15,000)	-0.403	-1.95	-0.318	-1.61
(Standard deviation of parameter distribution)	(0.364)	(1.87)		
Indicator variable for early evacuation notice (1 if household received evacuation notice early enough, 0 otherwise)	0.241	1.44	0.210	1.30
(Standard deviation of parameter distribution)	(0.377)	(6.74)		

Table 4.2 Continued.

Variable Description	Random Parameters		Fixed Parameters	
	Coefficient	***t-stats***	***Coefficient***	***t-stats***
Thresholds				
μ_1	0.821	9.11	0.595	11.30
μ_2	1.466	13.81	1.065	19.09
μ_3	1.999	17.18	1.454	24.81
μ_4	3.190	22.24	2.310	30.25
Number of observations		457		457

Table 4.3 Model II: Marginal Effects of Explanatory Variables

	Marginal Effects					
Variable Description	1 hour or less	2 to 3 hours	4 to 6 hours	7 to 12 hours	12 to 24 hours	More than 24 hours
Indicator variable for location (1 if household is from Louisiana, 0 otherwise)	0.041	0.071	0.043	-0.007	-0.099	-0.049
Indicator variable for source of evacuation notice (1 if household received evacuation notice from radio/television, 0 otherwise)	-0.053	-0.080	-0.039	0.016	0.110	0.046
Indicator variable for education status (1 if respondent was a high school graduate, 0 otherwise)	0.050	0.077	0.038	-0.014	-0.106	-0.045
Home-materials indicator variable (1 if respondent's home is mostly made of woods, 0 otherwise)	-0.035	-0.067	-0.047	0.000	0.095	0.055
Indicator variable for destination type during evacuation (1 if respondent evacuated to a public shelter or Church, 0 otherwise)	0.240	0.174	0.002	-0.101	-0.248	-0.067
Approximate trip time under normal circumstance in hours	-0.006	-0.011	-0.007	0.001	0.016	0.008
PM indicator variable (1 if the respondent left during afternoon, evening or noon until midnight , 0 otherwise)	0.051	0.092	0.059	-0.004	-0.128	-0.069
Age indictor variable (1 if respondent is over 50 years , 0 otherwise)	0.029	0.053	0.034	-0.003	-0.074	-0.039

Table 4.3 Continued.

Variable Description	Marginal Effects					
	1 hour or less	2 to 3 hours	4 to 6 hours	7 to 12 hours	12 to 24 hours	More than 24 hours
Indicator variable for the time of evacuation (1 if the evacuee left two days before the landfall, 0 otherwise)	-0.014	-0.027	-0.018	0.001	0.038	0.021
Indicator variable for source of evacuation notice (1 if household received evacuation notice from friend/relative/neighbor, 0 otherwise)	-0.038	-0.090	-0.082	-0.024	0.124	0.109
Indicator variable for work constraint (1 if anyone in the household had to go to work while the evacuation was going on)	0.025	0.044	0.026	-0.005	-0.062	-0.030
Indicator variable for hurricane experience indicator (1 if the respondent experienced a major hurricane previously, 0 otherwise)	-0.021	-0.036	-0.021	0.004	0.051	0.024
Race indicator variable (1 if the respondent is white, 0 otherwise)	-0.027	-0.044	-0.024	0.007	0.062	0.027
Income indicator variable (1 if the total household income of the respondent is less than $15,000)	0.052	0.075	0.034	-0.017	-0.102	-0.040
Indicator variable for early evacuation notice (1 if household received evacuation notice early enough, 0 otherwise)	-0.027	-0.044	-0.024	0.007	0.062	0.027

Table 4.4 Model II: Goodness-of-fit Measures

	Random Parameters	**Fixed Parameters**
Number of parameters	26	20
Log likelihood at convergence, $LL(\beta)$	-767.140	-776.732
Likelihood-ratio test	Random versus Fixed Parameters	
$LR = -2[LL(\beta_{random}) - LL(\beta_{fixed})]$	19.184	
Degrees of freedom	6	
Critical $\chi^2_{0.01,6}$ (0.99 level of confidence)	16.810	
Number of observations	457	

we only report the average marginal effect across all observations as each observation in the data has its own marginal effect. The estimation and the reporting of marginal effects are particularly meaningful for the ordered probit model because, the effect of variables *X* on the intermediate categories is ambiguous if only the parameter estimates are available without marginal effects (Duncan et al. 1999).

Most of the variables included in the ordered probit model are statistically significant with plausible signs as presented in Table 4.2. However, indicator variable for time of evacuation relative to landfall is not statistically significant at the usual 5% or 10% levels of significance. Based on the discussion on criteria for omitting a variable by Ben-Akiva and Lerman (1985), we include this variable in our model despite the relatively low t-ratio. Six parameters have been found to vary across the population according to the normal distribution. Parameters producing statistically significant standard deviations for their assumed distribution are treated as random and the remaining parameters are treated as fixed parameters as the standard errors are not significantly different from zero. Turning to the estimation results of the random parameters model, there are six variables in the model (source and time of evacuation notice to be received, work constraint, previous hurricane experience indicator, race and income) that are normally distributed random parameters. This suggests that the effect of these variables on the mobilization time between evacuation decision and actual evacuation varies across the observations – for some observations the effect may be positive while for others it may be negative.

Regarding the fixed parameters that affect evacuees' decision either to evacuate early or delay for a while (see Table 4.2), Louisiana indicator variable shows that households from Louisiana are more likely to evacuate early (in an hour or less) as opposed to evacuating later (more than 24 hours) once they decide to evacuate. More specifically, by considering the average marginal effects from Table 4.3, households from Louisiana are more likely to take no more than 6 hours to evacuate. This can be justified from the fact that after making landfall as a major hurricane just west of Gulf Shores, Alabama, Ivan weakened as it moved inland, producing over 100 tornadoes and heavy rains. But the remnant low re-acquired tropical characteristics, became a tropical storm for the second time, and made its final landfall in southwestern Louisiana as a tropical depression on the 24th September, 2004 (NHC 2011). This could be a reason why people from Louisiana took less time to evacuate and they did not get enough time for preparation during Ivan.
Evacuees who receive evacuation notice from media (radio, television, etc.) are more likely to take more than 24 hours to evacuate after they decide to evacuate. This is intuitive because, media updates evacuation related news fast enough that people get enough time to take evacuation decision and prepare themselves. The indicator variable representing group of evacuees who receive evacuation notice from their friends, relatives or neighbors also found to be statistically significant and shows that this category people usually take more than 24 hours to evacuate once they decide to go someplace safer during an evacuation. However, this is a random parameter implying that there is a substantial portion of evacuees receiving evacuation notice from friends or relatives (29.25%) that are more likely to evacuate in less than 6 hours as opposed to the rest of households. On the other hand, similar insight is obtained from the indicator variable representing households who receive evacuation notice early enough. This is again a random parameter showing that 73.87% households receiving evacuation notice early enough take more than 7 hours to evacuate as they get enough time to prepare for the evacuation process. All these findings suggest the significant influence of the source

and the timing of evacuation notice on the evacuees' evacuation behavior in terms of decision making and subsequent evacuation timing.

The model results also show the impacts of some of the socio-economic variables influencing the mobilization time in between evacuees' evacuation decision and actual evacuation. For example, if the respondent from a household is a high school graduate then the household is more likely to take one hour or less to evacuate. In addition to that, age indicator variable representing the respondents being over 50 years old show that they are more likely to take no more than 6 hours as opposed to the evacuees aging below 50 years. This is expected because elder people who may live alone and do not have any children living with them, they might take less time to prepare during an evacuation. Also, they might feel so concerned about the threat created by the hurricane and evacuate as early as possible before the hurricane makes its landfall. An interesting finding is that households having their home made mostly of woods are more likely to evacuate more than 24 hours after they decide to evacuate. This is an intuitive result because if the house is made of only woods and hurricane threat is in progress, evacuees might take some time to fix how much damage would be caused in their homes and act accordingly. Indicator variables related to the race and income were incorporated in the model as random parameters. White race indicator variable suggests that the evacuees being white by race are more likely to take more than 24 hours while the evacuees having annual household income less than $15,000 are more likely to evacuate in an hour or less once they decide to evacuate. By considering marginal effects and the mean and the standard deviation of the random parameter (income indicator), it is found that 86.59% of the low income group people would evacuate as early as possible (in no more than 6 hours) who experience heightened levels of risk perception (Flynn et al. 1994).

If the evacuees leave for someplace safer two days before the landfall during an evacuation, the time that elapses from evacuation decision to the actual evacuation of the evacuees' is more likely to be more than 24 hours and less likely to be an hour or less. This finding is intuitive because the evacuees' perceive sufficient amount of time to prepare themselves as they evacuate well ahead of time before the landfall. On the other hand, the variable indicating group of evacuees' who decide to evacuate to a public shelter or a Church, suggests that they are more likely to depart within an hour and take least amount time to prepare for the evacuation. This finding is justified because evacuees' planning to go to a public shelter might think that they would receive proper arrangements of facilities equipped with water, nonperishable food, blankets, and basic toiletries, etc. (ARC 2001, Smitherman and Soloway-Simon 2002, etc.). Among the evacuees who prefer to evacuate during afternoon, evening or noon until midnight, they are more like to evacuate shortly (within an hour or less) after they decide to go someplace safer. This is again intuitive because these evacuees may have some other constraints in the daytime and once they decide to evacuate they do not get sufficient amount time to prepare for evacuation.

Approximate trip time (in hours) that is required under normal circumstance to reach to a type of destination from the household also has a significant influence over the mobilization time in between evacuation decision and actual evacuation. Table 4.2 suggests that as trip time increases, they are more likely to take more than 24 hours to evacuate once they actually decide to evacuate. More specifically, by considering the average marginal affects from Table 4.3, an hour increase in the trip time required to reach the destination results in an average 0.008 increase in the probability for the evacuees to take more than 24 hours, a 0.016 increase to evacuate in 12 to 24 hours, a 0.001 increase to evacuate in 7 to 12 hours, a 0.007 decrease to evacuate in 4 to 6 hours, a 0.001 decrease to evacuate in 2 to 3 hours, and a 0.006 decrease to evacuate in an hour or less. This is an interesting finding because the more the trip time is required, the more is the distance to travel and this is why evacuees need more time to prepare and arrange necessary things accordingly which need to be considered during an evacuation.

For the evacuees who have to go to work while the evacuation is going on, it is found to increase the likelihood of evacuating in an hour or less once they decide to evacuate. However, its effect varies across the observations (30.11% of respondents are more likely to take more than 7 hours to evacuate and less likely to take less than 6 hours). In contrast, households with previous major hurricane experience are more likely to evacuate more than 24 hours after they decide to evacuate. However, the effect of previous hurricane experience also varies across the observations, suggesting that for about 59.07% of households with major hurricane experience are more likely to take more than 7 hours from their decision to evacuate. This is another important insight that evacuees having past experience know how to react in emergency situation and plan accordingly which might let them require more time to evacuate.

4.5 Model Validation

In this section, a validation test is presented for the proposed model. To investigate the validity of the model specification, the data was first split into two parts (Sample 1 and Sample 2) each having about half of the observations. Then two separate models were estimated with the same specification using these two samples. The hypothesis for this specification test is that model parameters are equal for the models estimated on these two datasets. If we fail to reject the hypothesis then the validity of the model specification is established. We calculate a test statistics based on likelihood ratio (LR) as shown in the following equation:

$$LR = -2[LL(\beta_{FullData}) - LL(\beta_{Sample1}) - LL(\beta_{Sample2})] \tag{4.6}$$

where $LL(\beta_{FullData})$ is the log-likelihood at convergence of the model estimated using the full data, $LL(\beta_{Sample1})$ is the log-likelihood at convergence of the model estimated using Sample 1 which is equal to -336.828, and $LL(\beta_{Sample2})$ is the log-likelihood at convergence of the model estimated using Sample 2 which is equal to -411.861. The likelihood ratio is obtained as 36.903 with degrees of freedom equal to 26. Since, $\chi^2_{0.05,26}$ =38.890, we fail to reject the hypothesis that the parameters across different samples are equal. Thus this test validates the model specification presented in this study.

4.6 Conclusion

The above findings provide some logical inference in terms of evacuees' response to the timing behavior starting from the decision to evacuate and the actual evacuation to a safe destination during a hurricane. The distribution of random parameters accounts for the heterogeneous responses of the evacuees towards this type of timing behavior. With the help of the proposed model, one could predict different fractions of people who would either evacuate early or delay for some time on purpose to evacuate. However, efforts need to be made to identify the set of characteristics for which evacuees execute different timing behavior and more importantly to identify the variables which are responsible for the changes in that type of a behavior.

CHAPTER 5. CONCLUSION AND FUTURE WORK

In this research, we present the results of a behavior model to capture different routing strategies executed by evacuees during hurricane evacuation by using a random-parameter logit-based modeling approach. To the best of our knowledge, this is the first attempt to model evacuees' strategic behavior for evacuation routing decisions using a random-parameter model. A probabilistic model incorporating the demographic characteristics of evacuees and evacuation related characteristics would predict the routing behavior of evacuees' in a better way. Several important factors, for example, household's geographic location, number of children, evacuees' income and age, timing and medium of evacuation notice, etc. influence household's evacuation routing decision which are found from our empirical analysis.In addition, we explain the results of a behavior model to capture the timing behavior of evacuees which elapses from the time of an evacuation decision making to the time of actual evacuation during a hurricane by developing a random-parameter ordered probit model. To the best of our knowledge, this is the first attempt to model evacuees' strategic behavior in terms of evacuation timing by developing a random-parameter ordered probit model. Different influential factors, such as, household's geographic location, socio-economic factors, evacuation related characteristics, trip time during normal condition, previous experience, etc. are found to be statistically significant which affect the time that is required by the evacuees for necessary arrangements during an evacuation.

In the mixed logit model, four variables have been found to have random parameters which reflect the heterogeneous influences of the associated variables on evacuation routing strategy. These variables include the distance traveled during evacuation; number of years lived in the present home, destination type and time of evacuation. The findings from this study provide some key insights regarding hurricane evacuation routing behavior. Such insights include:

- The more distance the evacuees need to travel during evacuation, the more likely that the evacuees will update or switch routes.
- If the evacuees evacuate to a friend or relative's house, they are likely to take their familiar route. Similar situation is observed when they evacuate two days before the landfall.
- Socio-economic characteristics such as the income, age and number of children also influence the routing decision. For example, the preference of following emergency evacuation routes increases with the number of children in the household while evacuees are likely to detour or update their routes as their age increases.

In addition, six variables have been found to have random parameters in the ordered probit model which reflect the heterogeneous influences of the associated variables on evacuation timing behavior. These variables include- source and time of evacuation notice to be received, work constraint, previous hurricane experience indicator, race and income- were found to be random and the random parameters (all found to be normally distributed) suggest that their effect varies across the observations. The findings from this study provide some key insights regarding hurricane evacuation routing behavior. Such insights include:

- The source and the timing of evacuation notice have significant impact on the evacuees' evacuation behavior in terms of decision making and subsequent evacuation timing. For example, evacuees, receiving evacuation notice from media (radio, television, etc.), are more likely to take more than 24 hours to evacuate once the evacuation decision is made. Similar insight is found for the households who receive evacuation notice early enough.

- The more the trip time is required to reach a type of destination under normal circumstance, the more likely that the evacuees would take more than 24 hours to evacuate once they actually decide to evacuate.
- Socio-economic characteristics such as the income, age, race, education, etc. also influence the mobilization time framework. For example, respondents aging over 50 years are more likely to take no more than 6 hours to evacuate. Similarly, low income group people would evacuate as early as possible (in no more than 6 hours) because of higher risk perception.

The two proposed quantitative models of evacuation routing strategy and mobilization time would help practitioners and emergency planners to develop better evacuation policies. Researchers in the field of evacuation simulations may also find this study useful. The route type choice model can be used as an important input in terms of routing to determine the evacuation clearance time by building more credible simulation models than what is currently being done. However, the model only helps to determine a type of route an evacuee would select but it does not specifically capture the route choice. For the model to be more useful, we need to have more disaggregated data, such as, what routes evacuees actually take, the reasons and the locations where evacuees update their routes both in space and time, etc. One future research should focus on getting detailed path information of evacuees to develop a more robust route choice model for evacuation. Another way of doing that could be to collect GPS (global positioning system) trajectories of evacuees while they evacuate in order to calibrate more accurate evacuation route choice models. Likewise, the ordered probit model only helps to capture the time interval that elapses from evacuees' evacuation decision and actual decision. For the model to be more specific, we need to have more accurate data so as to develop a model that can predict the timing behavior with respect to evacuation decision making. In future, efforts need to be made to focus on developing such a model of evacuation decision jointly with evacuation timing to estimate more accurate departure time choices of the evacuees.

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