Transportation Research Part C 27 (2013) 108–116

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

A random-parameter hazard-based model to understand household evacuation timing behavior

Samiul Hasan, Rodrigo Mesa-Arango, Satish Ukkusuri *

School of Civil Engineering, Purdue University, 550 Stadium Mall Drive, West Lafayette, IN 47907, USA

ARTICLE INFO

Article history:
Received 28 November 2010
Received in revised form 22 June 2011
Accepted 23 June 2011

Keywords:
Hurricane evacuation timing
Hazard-based model
Random-parameter model
Hurricane evacuation behavior
Hurricane Ivan

ABSTRACT

The goal of this paper is to develop a random-parameter hazard-based model to understand hurricane evacuation timing by individual households. The choice of departure time during disasters is a complex dynamic process and depends on the risk that the hazard represents, the characteristics of the household and the built environment features. However, the risk responses are heterogeneous across the households; this unobserved heterogeneity is captured through random parameters in the model. The model is estimated with data from Hurricane Ivan including households from Alabama, Louisiana, Florida and Mississippi. It is found that the variables related to household location, destination characteristics, socio-economic characteristics, evacuation notice and household decision making are key determinants of the departure time. As such the developed model provides some fundamental inferences about hurricane evacuation timing behavior.

1. Introduction

Hurricanes cause extensive damage to property and loss of lives especially in the coastal areas. For instance, the 2005 Atlantic hurricane season in the United States had an estimated direct social cost of approximately 2300 deaths and record damages of over $130 billion (NHC, 2006). The experiences from these hurricanes compelled various stakeholders (agencies, emergency providers and researchers) to realize the critical role of evacuations (e.g., Houston evacuation during hurricane Rita caused considerable traffic delays). Effective evacuation management planning is therefore absolutely necessary for coastal regions as identified by many previous researchers (Dow and Cutter, 2002; Lindell et al., 2005; Gladwin et al., 2007; Lindell and Prater, 2007a). Evacuation problems in these regions are complicated by the limited growth of road network compared to the population growth and the diverse transportation needs (Dow and Cutter, 2002).

Hurricane evacuation is a complex dynamic process governed by many factors such as hurricane trajectory, household locations, hurricane warning system, and characteristics of the evacuees and their households (Baker, 1991; Gladwin et al., 2001; Urbaina and Wolshon, 2003; Gladwin et al., 2007; Lindell and Prater, 2007a; Carnegie and Deka, 2010). A significant research question is related to understanding and predicting household behavior before and after the disaster. However, despite significant research efforts on the issue of evacuation, the understanding of household evacuation decision-making issues are limited (Dash and Gladwin, 2007). One key question that should be understood with respect to household decision making is the evacuation departure time. An accurate estimate of the departure time will allow the prediction of dynamic evacuee demand and develop effective evacuation strategies.

The central idea of this paper therefore is to understand, using original data gathered from Hurricane Ivan, the causal factors which influence the household-level evacuation timing decision. There are a modest number of studies on evacuation

* Corresponding author. Tel.: +1 765 494 2296; fax: +1 765 496 7996.
E-mail addresses: samiul.hasan@gmail.com (S. Hasan), rmesaa@gmail.com (R. Mesa-Arango), sukkusur@purdue.edu (S. Ukkusuri).

0968-090X/$ - see front matter
doi:10.1016/j.trc.2011.06.005

departure time though most of them focus on deriving empirical distributions without considering the influences of different factors. For a detailed review on evacuation timing studies, the readers may refer to the study by Lindell and Prater (2007b). On the contrary there have been few attempts in literature to develop behavioral models for evacuation timing decisions. For example, Sorensen (1991) made one of the earliest attempts using path analysis for evacuation timing behavior. The process involved in this approach is a set of sequential decisions made over time with evolving hurricane forecasts. The study used ordinary least square regression to determine the relationship between departure time and other explanatory variables. Fu and Wilmot (2004) developed a sequential logit choice model, where each household reviews the conditions surrounding an approaching hurricane and makes the decision of whether to evacuate or not.

Fu and Wilmot (2006) developed a hazard-based modeling approach to understand decisions of whether to evacuate or not and when to evacuate as a joint model. While it provides important insights on individual's evacuation timing behavior, it has some limitations. First, one of the implicit assumptions of the model is that the decision of whether to evacuate and the decision of when to evacuate are made simultaneously and both decisions are influenced by the same set of variables. However, although these two decisions are linked, the factors and their associated influences for each kind of decision may be different. For example, the decision of whether to evacuate or not might be influenced by perception of danger of life (Hasan et al., 2011); while the decision of when to evacuate are influenced by the preparation time, the destination and perception of the required time to reach that destination, and the transportation system characteristics. Second, their model included the households who did not evacuate assuming the corresponding observations as right censored. However, this censoring assumption implicitly considers that every household will eventually evacuate which is not the case. As a result, this approach may overestimate the number of households who evacuate ignoring the factors that influence households who do not evacuate. Third, their model is estimated based on discrete time intervals with a coarse aggregation of six hour time durations. However individuals' evacuation timing decisions within this six hour interval (particularly the interval close to the hurricane landfall time) may be needed for developing efficient evacuation management strategies.

Most of the previously developed evacuation timing models (Sorensen, 1991; Fu and Wilmot, 2004, 2006; Lindell and Prater, 2007b) included environmental, social and demographic factors. However, in addition to these factors, "risk perception" is another key element to understand how households make decisions on when to evacuate. Dash and Gladwin (2007) pointed out that risk is not perceived in the same fashion for all decision makers but it is influenced by social dimensions and particular contexts. Therefore it is expected that individuals' actions are based on their perceptions of risk which may depend on their characteristics and the context or constraints they live in. However, it is difficult to model individuals' risk perception behavior for which no rigorous approach exists. One alternative would be to model the decision making behavior considering individuals' responses under risks. However, such individualized risk responses will be heterogeneous among the population and hence warrants techniques different than the traditional evacuation behavioral models that assume constant parameters for variables determining the time of evacuation.

In this paper, we examine the timing of evacuation for a household when impacted by a hurricane. We use a hazard-based modeling approach to model this evacuation time. Hazard-based models focus on occurrence of the end of duration (such as end of the duration from the moment of receiving a hurricane warning to the moment of actual evacuation) given that the duration has lasted for a specified time (Hensher and Mannering, 1994). This kind of model reports the conditional probability of the termination of the duration. This concept of conditional probability of the end of duration recognizes that the likelihood of evacuation time depends on the length of elapsed time since the start of the hurricane warning process. Thus the dynamics of the duration until evacuation is reflected through this conditional likelihood value. Therefore, the hazard model can provide valuable insights to understand the temporal dynamics of the household's evacuation decision making process. Furthermore to incorporate the heterogeneous risk response in the modeling framework, we introduce random parameters in our model. This paper also uses the continuous time approach to model evacuation time which overcomes the limitations associated with the coarse discrete time intervals mentioned above. Specifically this paper will make the following contributions:

- Develops a model of evacuation timing behavior using hazard-based duration modeling approach.
- Incorporates the random-parameter modeling to represent the unobserved heterogeneity across households particularly with respect to the risk response.
- Provides fundamental inferences on hurricane evacuation timing behavior based on empirical model using Hurricane Ivan evacuation data.

2. Methodology

Hazard-based duration models were originally developed for problems in biometrics and industrial engineering. More recently they were used to model duration times in economics, marketing and transportation. Hensher and Mannering (1994) provide a review of the applications of the hazard-based duration models in transportation up to the early 1990s. For instance, using hazard-based approach, Mannering and Hamed (1990) developed a model for the time duration that travelers delay their departure time from work to home to avoid congestion. Bhat (1996a,b) studied factors affecting shopping activity duration during the trip from work to home. As mentioned above, Fu and Wilmot (2006) studied hurricane evacuation timing as a function of household's socioeconomic characteristics, the characteristics of the hurricane and management practice (issuance of an evacuation order) using hazard-based model. In the following paragraphs we present the structure of the hazard-based duration models for modeling hurricane evacuation time.

Let T be a non-negative random variable representing the duration (in hours) between the beginning of a hurricane warning and the evacuation time for a household, and t is a specified time in the continuous time scale. Then the hazard function for household h at time t is defined as:

$$\lambda_h(t) = \lim_{\Delta t \to 0} \frac{prob[t + \Delta t > T \geqslant t | T \geqslant t]}{\Delta t} \tag{1}$$

where $\lambda_h(t)\Delta t$ is the conditional probability that household h will evacuate between time t and $t + \Delta t$ given that it has not evacuated up to time t.

To capture the influence of the covariates on the duration until the evacuation we use the accelerated life-time modeling approach. The accelerated life-time model assumes that the covariates rescale time directly (i.e., accelerate time) in a baseline hazard function, $\lambda_0(t)$. Assuming that covariates influence the process in the form $e^{\beta' \boldsymbol{X}}$, the hazard function for household h can be written as:

$$\lambda_h(t|\boldsymbol{X_h}) = \lambda_0[te^{\beta' \boldsymbol{X_h}}]e^{\beta' \boldsymbol{X_h}} \tag{2}$$

where $\boldsymbol{X_h}$ is a vector of the factors or covariates and $\boldsymbol{\beta}$ is a vector of estimable parameters.

Similar to other kind of mixture models (e.g., mixed logit model), random parameters can also be introduced in the hazard model. To allow for random parameters to capture the unobserved heterogeneity, estimable parameters are written as (Washington et al., 2011)

$$\beta_h = \beta + \omega_h \tag{3}$$

where ω_h is a randomly distributed term. With this equation the hazard function for household h can be written as:

$$\lambda_h(t|\boldsymbol{X_h}, \boldsymbol{\omega_h}) = \lambda_0[te^{\beta'_{\boldsymbol{h}} \boldsymbol{X_h}}]e^{\beta'_{\boldsymbol{h}} \boldsymbol{X_h}} \tag{4}$$

Notice that, in the case of fixed parameters model, explanatory variables are included as $e^{\beta' \boldsymbol{X_h}}$ to hazard function as shown in Eq. (2) (i.e., all the households have the same parameter for a particular explanatory variable). However, in the case of random-parameters model, the explanatory variables act as $e^{\beta'_{\boldsymbol{h}} \boldsymbol{X_h}}$ allowing the parameters to vary across households. A simulation-based maximum likelihood method is usually used to estimate the parameters of such models. The simulation procedure involves drawing the values of $\boldsymbol{\beta}$ given a distribution. Previous studies (Train, 1999; Bhat, 2003) show that it is efficient to use Halton draws as compared to random draws. Our model estimation procedure (Greene, 2007) also uses Halton draws.

We assume that the baseline hazard function, $\lambda_0(t)$, follows a Weibull distribution which is widely used in duration modeling. The hazard function for Weibull distribution is (with parameters λ and P)

$$\lambda(t) = \lambda P[\lambda t]^{P-1} \tag{5}$$

Parameter P captures the duration dependence, if P is greater than 1 hazard increases with the increase of duration and if P is less than hazard decreases with the increase of duration. Typically few other duration distributions such as exponential, log–logistic and lognormal are available for parametric approach of duration modeling as followed in this paper. Weibull distribution is a generalization of exponential distribution and it's appropriateness over exponential distribution can be justified based on the significance of the P parameter. We also attempted log–logistic and lognormal distribution; however the estimation procedure fails to converge for these duration distributions.

3. Data

To demonstrate the applicability of the random-parameter hazard-based model for household-level evacuation timing behavior, data is used from a household survey conducted after the landfall of Hurricane Ivan in the region of Gulf Shores, Alabama, 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 that reached Category 5 strength three different times before its first landfall as a Category 3 storm in 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 Florida panhandle region; 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. It is estimated that about 600,000 citizens of New Orleans tried to evacuate during Ivan (Morrow and Gladwin, 2005).

The data was collected as part of the post-storm assessment of the impact of Hurricane Ivan on households in Florida, Alabama, Mississippi and Louisiana (Morrow and Gladwin, 2005). Several counties and parishes in and adjacent to the path of Hurricane Ivan in these 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 the summary statistics of the dependent variable and the explanatory variables selected for the model. Fig. 1 presents the distribution of the departure times of the households. The number of departures is not very high at the beginning of the evacuation; with the passage of time the departure rate increases significantly; however at hours very close to the landfall time the number of departures become very low.

4. Empirical results

In this section, the results of the estimation of a random-parameter hazard-based model for evacuation time are presented (Table 2). The model is estimated by specifying a distribution of the baseline hazard function, the functional form of the distributions of the random parameter and by using the simulation-based maximum likelihood estimation with 200 Halton draws (Bhat, 2003). For baseline hazard function Weibull, Weibull with gamma heterogeneity, log–logistic and lognormal distribution are tested. However, the model only converges for the Weibull duration distribution. The functional form of the distributions of the random parameters is tested with a normal, uniform and triangular distribution. For all the parameters that are found to be random, the normal distribution assumption provides the best statistical fit in terms of *t*-statistic of the parameters and the log-likelihood at convergence.

Regarding the interpretation of the results, a positive sign for the coefficient of a particular variable indicates that hazard increases with the increase of that variable and hence duration until evacuation decreases, i.e., the household will evacuate earlier. All the parameters of the model are found statistically significant and have reasonable signs. Table 2 indicates that three of the parameters are found as random. We also report the influence of the explanatory variables on the changes in duration.

The region specific indicator variables can capture the proximity to the projected path of the hurricane. The region-specific indicator variables associated with Alabama and Florida have positive parameters (Table 2). These positive parameters indicate that hazard for households located in Alabama and Florida increases implying earlier evacuation than those households located in Mississippi (i.e., indicator variable for households from Mississippi is treated as base in model specification).

Table 1
Summary statistics of explanatory variables.

Variables	Mean	Standard deviation	Min	Max
Duration*	51.4270	16.6782	1	126
Location				
From Alabama	0.1250	0.3308	0	1
From Florida	0.4063	0.4912	0	1
From Louisiana	0.2813	0.4497	0	1
From Mississippi	0.1875	0.3904	0	1
Evacuation characteristics				
Evacuated to a public shelter	0.0279	0.1646	0	1
Time to get to the destination (hours)	3.7166	4.4896	0	50
Evacuated to the neighborhood	0.1338	0.3406	0	1
1 or less hour duration between evacuation decision and actual evacuation	0.1498	0.3570	0	1
2–3 h duration between evacuation decision and actual evacuation	0.1780	0.3827	0	1
Received a non-mandatory evacuation notice	0.2996	0.4582	0	1
Received a mandatory evacuation notice	0.3381	0.4732	0	1
Socio-economic characteristics				
White race	0.8583	0.3488	0	1
Education status: high school graduate	0.2465	0.4311	0	1
Education status: post graduate	0.1597	0.3664	0	1
Annual household income less than $15,000	0.1036	0.3048	0	1
Lives in a mobile house	0.0677	0.2513	0	1
Has one child	0.1583	0.3651	0	1
Has two or more children	0.2071	0.4053	0	1

* Duration is the dependent variable in hours. Hour 0 corresponds to Monday September 13th 2004 at 0:00 h and hour 126 corresponds to Saturday September 18th 2004 at 6:00 h (24-h clock convention).

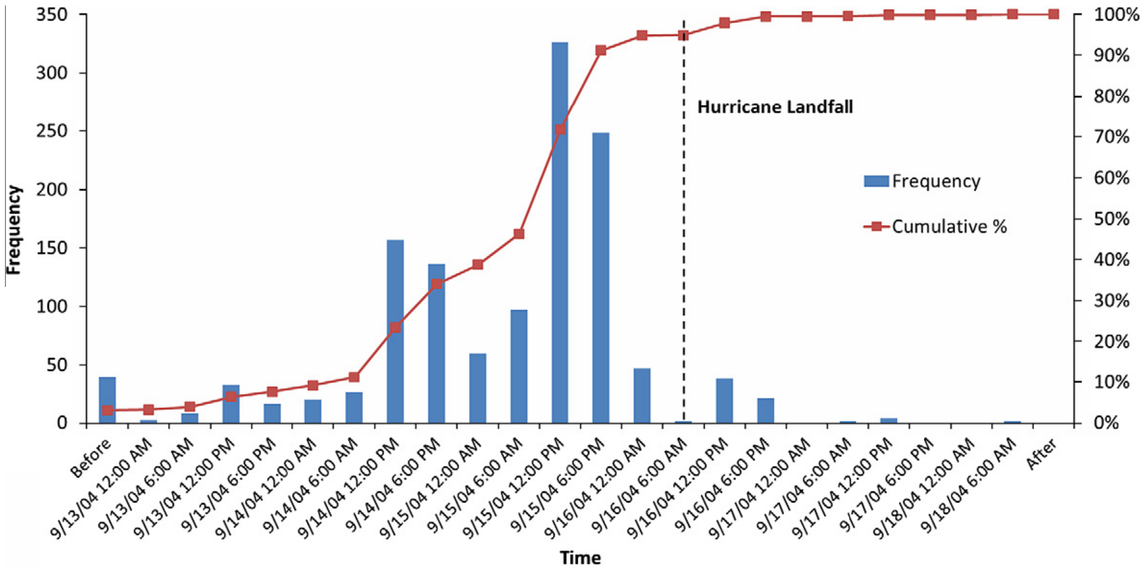

Fig. 1. Distribution of the departure times of the households.

Evacuation time also depends on the type and location of the destination. The indicator variable for the households who evacuate to public shelter has a negative parameter (Table 2) indicating that for such households hazard decreases and the duration until evacuation increases. This implies that household evacuating to public shelter are more likely to evacuate later compared to the households moving to other types of shelters; this may reflect the reluctance of the households to be in this kind of places and therefore waiting longer before evacuation. In other words this means that evacuees prefer to take the risk of staying longer at home than going to the public shelter. However, an alternative explanation could be that households that evacuate late are more likely to choose public shelter as their destinations as there are less time available to go to other types of places such as friend's or relative's house and hotels. Similarly, for those who evacuate to a neighborhood area hazard decreases and duration until evacuation increases (Table 2). This is expected since these households can wait longer period of time until evacuation as there would be less time involved to reach the neighborhood destinations.

We also use the time between the evacuation decision and the actual evacuation as a variable for our model estimation (Table 2). This time could not be used as a continuous variable as the survey asked the respondents to categorize among various time intervals (i.e., 1 h, 2–3 h, 4–6 h, etc.); hence we include indicator variables representing these intervals. The values of the parameters associated with these indicator variables show that as this duration (time between the evacuation decision and the actual evacuation) increases hazard increases and duration until evacuation decreases. This suggests that the longer time a household takes between the evacuation decision and the actual evacuation the more likely is it to hasten its departure time. In literature, Sorensen (1991) reports that departure time is strongly influenced by mobilization time and time of warning receipt. Mobilization time was defined in Sorensen (1991) as the duration between warning receipt time and departure time. The variables used in our model represent a proxy of the mobilization time and provide interesting insights on its influences on evacuation timing behavior. For instance, households taking one hour time between evacuation decision and actual evacuation (i.e., leave shortly after making the evacuation decision) are more likely to evacuate later compared to the households taking longer time between evacuation decision and actual evacuation. This is intuitively plausible as households that evacuate late have less time available to spare and therefore have shorter mobilization time.

Socio-economic characteristics such as the race, income and education level of the respondent also influence the timing of evacuation. For example, the indicator variable for the respondent being white has a positive parameter value indicating an increase in hazard for households with such respondents and a decrease in the time until evacuation; that is such households respond to the risks by taking quick actions (i.e., earlier evacuation). Similarly the indicator variables representing the education level of the respondents (high school graduate, and post graduate) result in increase of hazard and decrease the time until evacuation. It is interesting to note that these groups represent both low (high school graduate) and high (post graduate) education level. Households with members from these education levels evacuate early. Also notice that for households with postgraduate members' hazard increases as compared to the households with high-school graduate members.

A particular group for income level of households is found to have significant influence on evacuation timing. Model results (Table 2) indicate that, for households having low income (less than $15,000 per year), hazard decreases with the passage of time and hence the duration until evacuation increases compared to the households with annual income more than $15,000. This reflects the fact that such households have lesser resources which facilitate evacuation (e.g., availability of personalized transport, resources to rent a hotel) and wait longer until evacuation. This may also reflect the fact that these households may have to depend on organized transport initiative which starts at the later stage of the evacuation process.

Table 2
Estimation results of the random-parameter hazard-based duration models for the decision of the timing of evacuation (random parameters are assumed to be normally distributed).

Variable description	Coeff.	*t*-Stat.	Change in duration (%)	Sample 1		Sample 2	
				Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Constant	−4.186	−179.859	–	−4.241	−128.071	−4.130	−104.542
Location							
Alabama indicator variable (1 if HH is From Alabama, 0 otherwise)	0.029	1.310	−2.8	0.039	1.319	0.025	0.779
Florida indicator variable (1 if HH is From Florida, 0 otherwise)	0.051	2.774	−5.0	0.097	3.698	0.021	0.770
Evacuation characteristics							
Indicator variable evacuated to a public shelter (1 if HH moved to a public shelter, 0 otherwise)	−0.120	−3.528	12.7	−0.056	−1.038	−0.183	−3.945
Indicator variable for neighborhood evacuation (1 if HH evacuated to a neighborhood area, 0 otherwise)	−0.070	−2.969	7.3	−0.128	−3.410	−0.044	−1.500
Indicator variable for 1 h duration between evacuation decision and actual evacuation (1 if HH took 1 h between evacuation decision and actual evacuation, 0 otherwise)	−0.068	−3.310	7.0	−0.019	−0.661	−0.107	−3.634
Indicator variable for 2–3 h duration between evacuation decision and actual evacuation (1 if HH took 2–3 h between evacuation decision and actual evacuation, 0 otherwise)	−0.042	−2.620	4.3	−0.062	−2.807	−0.027	−1.108
Indicator variable non-mandatory notice (1 if the HH received a non-mandatory evacuation notice, 0 otherwise)	0.068	4.758	−6.5	0.030	1.482	0.118	5.393
Indicator variable mandatory notice (1 if the HH received a mandatory evacuation notice, 0 otherwise)	0.068	4.394	−6.5	0.069	3.211	0.084	3.628
Socio-economic characteristics							
Indicator variable white (1 if the ethnicity is white, 0 otherwise)	0.029	1.711	−2.9	0.086	3.370	−0.027	−1.056
Indicator variable education status high school graduate (if the respondent was a high school graduate, 0 otherwise)	0.030	1.791	−2.9	0.045	1.877	0.025	1.044
Indicator variable education status post graduate (1 if the respondent was a graduate, 0 otherwise)	0.061	3.899	−5.9	0.072	3.063	0.035	1.530
Indicator variable for low income (1 if annual household income is less than $15,000, 0 otherwise)	−0.074	−2.874	7.7	−0.027	−0.753	−0.128	−3.313
Indicator variable mobile house (1 if HH is a mobile home, 0 otherwise)	−0.034	−1.530	3.5	−0.026	−0.845	−0.037	−1.065
More than one child indicator variable (1 if HH had more than one child below age 18, 0 otherwise)	0.035	2.386	−3.4	0.025	1.235	0.021	0.983
Random parameters							
Travel time to the evacuation area at normal time (hour)	0.023	13.466	−2.2	0.018	8.407	0.025	8.707
(Standard deviation of parameter distribution)	(0.005)	(3.546)	–	(0.001)	(0.728)	(0.004)	(1.723)
Louisiana indicator variable (1 if HH is from Louisiana, 0 otherwise)	0.050	3.201	−4.9	0.101	4.452	0.005	0.188
(Standard deviation of parameter distribution)	(0.055)	(5.331)	–	(0.022)	(1.539)	(0.001)	(0.064)
One Child indicator variable (1 if HH had one child below age 18, 0 otherwise)	−0.043	−2.611	4.4	−0.055	−2.493	−0.028	−1.086
(Standard deviation of parameter distribution)	(0.019)	(1.189)	–	(0.042)	(1.986)	(0.001)	(0.025)
P (distribution parameter)	3.906	71.768	–	4.016	48.203	3.922	52.160
Number of observations		751			383		368
Log-likelihood with constant only		−295.726			−146.098		−149.452
Log-likelihood at convergence		−230.456			−109.457		−110.004
Adjusted ρ_c^2		0.1463			0.1002		0.1167

Adjusted $\rho_c^2 = 1 - \frac{\text{Log-likelihood at convergence} - \text{Number of parameters}}{\text{Log-likelihood with constant only}}$.

Receiving evacuation notice either mandatory or optional also results in the increase of hazard and thereby results into an earlier evacuation than those who have not received any form of evacuation notice. These variables also represent the proximity of households to the landfall sites. Clearly households receiving notices can be assumed to be closer to hurricane landfall sites. Therefore these households would respond to the risk or threat quickly and hence leave early.

Similar to the low-income households, the parameter for the households living in a mobile home has negative values (Table 2). However, it is usually expected that these households will evacuate earlier; but our model results indicate that for such households, hazard decreases and time until evacuation increases. This may reflect the fact that such households might wait longer to observe the direction of the hurricane; therefore their duration until evacuation increases.

Travel time to the evacuation area under normal situation produces a normally distributed parameter with a mean of 0.023 and a standard deviation of 0.005 (Table 2). This implies that most of the households have a positive value for this parameter which is intuitively plausible. But the distribution shows that there is a variable perception of the distance to the destination (due to the congestion while evacuation) resulting in a variable increase of hazard across the households. The travel time under normal situation can be used as a proxy for the distance that the household has to travel when evacuating. The positive value for all the households suggests that with the increase of distance to the safe destinations, hazard will increase and duration until evacuation will decrease. This implies that those households which decided to evacuate to places that usually require longer time to be reached (i.e., places far away) will evacuate earlier than those household that decided to evacuate to places that require shorter time.

The indicator variable for Louisiana households also produces a normally distributed parameter with a mean of 0.05 and a standard deviation of 0.055 (Table 2). This means that, given that everything else remains the same, for a majority (81.83%) of Louisiana households, it results in an increase of hazard implying earlier evacuations. The variability in parameters captures the unobserved heterogeneity in the responses of households from Louisiana. As Louisiana was on the safe side of the storm but with evacuation orders (possibly overreaction from past hurricanes) and prior experience of the households to past hurricane evacuation, households from this state are expected to behave heterogeneously in terms of their evacuation time choice.

For majority of the households, the presence of one child decreases hazard and thereby increases duration until evacuation. The indicator variable related to this produces a normally distributed parameter with a mean of -0.043 and a standard deviation of 0.019 (Table 2). This means that for majority (98.8%) of the households having one child result in decrease of hazard and duration until evacuation increases; these household will evacuate later than households with no children. However, the interesting finding from the model is that households with one child respond to the risks differently. This suggests that the majority of the households with one child respond to evacuation warning lately while for other households such risk is compensated by other considerations resulting in early departure. The risk response due to one child is not uniform across the households. The differences in risk responses might be attributed to the age of the child. For example, households with a child aged less than six years may respond to the risk more seriously than households with children aged above six years. To investigate this further, 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. Finally, this parameter indicates the strength of our modeling methodology through capturing the unobserved heterogeneity in the evacuation behavior. In contrast to the above finding related to the household with one child, the indicator variable representing households with more than one child is found to be fixed with a positive parameter. This suggests that households with more than one child would perceive the risk uniformly resulting into an earlier evacuation.

Fig. 2 presents the actual and predicted hazard for the households. The predicted hazard captures the trends of the actual hazard values. The unusual drop in the hazard is due to the hurricane landfall event when no households actually evacuate.

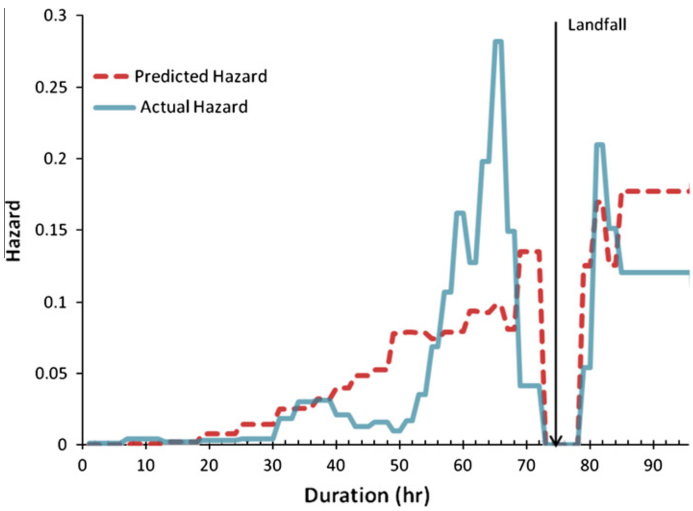

Fig. 2. Actual and predicted hazard at different departure times.

Given the complexity involved in the decision making process during hurricane evacuation, our model performs reasonably in terms of predicting the hazard values.

5. Model validation

In this section we present a validation test for our proposed model. To investigate the validity of the model specification, we first split the data into two parts (Sample 1 and Sample 2) each having about half of the observations. We estimate two separate models with the same specification using these two samples.

Table 2 presents the estimation results for 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 our specification is established. We calculate a test statistics based on likelihood ratio (LR) as shown in Eq. (6):

$$LR = -2[LL(\beta_{FullData}) - LL(\beta_{Sample1}) - LL(\beta_{Sample2})] \tag{6}$$

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, and $LL(\beta_{Sample2})$ is the log-likelihood at convergence of the model estimated using Sample 2. The likelihood ratio is obtained as 21.99 with degrees of freedom equal to 22. Since $\chi^2_{22,0.05} = 33.924$, we fail to reject the hypothesis that the parameters across different samples are equal. Thus this test validates the model specification presented in the paper.

6. Summary and conclusions

In this paper, we present the results of a hurricane evacuation timing model using a random-parameter hazard-based modeling approach. To the best of our knowledge, this is the first attempt to model household's heterogeneous risk response behavior for evacuation timing decisions using a random-parameter model. Traditionally evacuation planners use response curves showing the distribution of departure time of evacuees to predict the departure rate in each time interval. However, a probabilistic model incorporating the socio-economic characteristics of household and evacuation destination characteristics would predict the temporal distributions of evacuation in a better way. Therefore the proposed quantitative model of evacuation timing behavior would help planners and managers to develop better evacuation strategies.

Findings from the model also contribute to a better understanding of household evacuation timing behavior. Several important factors that influence a household's evacuation timing decision are found from our empirical analysis. These factors include household's geographic location, type of the shelter, location and time to reach the destination in normal time, time between decision and actual evacuation, whether or not to live in a mobile house, education status, income, type of evacuation notice (mandatory or optional) received. Three variables have been found to have random parameters. These variables include usual travel time to reach the destination, location of household and the number of children. These parameters reflect the heterogeneous influences of the associated variables on evacuation departure time. The findings from this study provide us useful insights to understand hurricane evacuation timing behavior. Such insights include:

- Travel time to destinations under normal condition influences the timing decision. Households moving to places that usually require longer time to be reached in normal situations will evacuate earlier.
- Households that evacuate late are likely to leave shortly after making the evacuation decision (i.e., low mobilization time) compared to the households evacuating earlier.
- Socio-economic characteristics such as the race, income, education level, and housing type of the respondent also influence the timing of evacuation. For example, low-income households are likely to evacuate later.
- Households receiving evacuation notice (either mandatory or optional) are likely to evacuate early.

The above findings have important implications for effective evacuation planning. For example, since travel time information significantly influences the evacuation time of a household, provision of a real-time traffic information source can play an important role for distributing the evacuation demand over time. Strategies can also be devised so that low-income households or families living in mobile homes can evacuate early. Thus the study, using sophisticated methodological approach, provides some fundamental insights on hurricane evacuation timing behavior.

Acknowledgments

This research presented in this paper was supported by National Science Foundation Award SES-0826874 "Incorporating Household Decision Making and Dynamic Transportation Modeling in Hurricane Evacuation: An Integrated Social Science-Engineering Approach" for which the authors are grateful. However, the authors are solely responsible for the findings of the research work. The writers also acknowledge Prof. Fred Mannering of Purdue University for his valuable suggestions on estimating the hazard-based model and three anonymous referees, who provided useful comments on an earlier draft of the paper.

References

Baker, E.J., 1991. Hurricane evacuation behavior. International Journal of Mass Emergencies and Disasters 9 (2), 287–310.

Bhat, C.R., 1996a. A hazard-based duration model of shopping activity with nonparametric baseline specification and nonparametric control for unobserved heterogeneity. Transportation Research Part B: Methodological 30 (3), 189–207.

Bhat, C.R., 1996b. A generalized multiple durations proportional hazard model with an application to activity behavior during the evening work-to-home commute. Transportation Research Part B: Methodological 30 (6), 465–480.

Bhat, C.R., 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transportation Research Part B: Methodological 37 (1), 837–855.

Carnegie, J.A., Deka, D., 2010. Using hypothetical disaster scenarios to predict evacuation behavioral response. In: Proceedings of the 89th Annual Meeting of the Transportation Research Board, Washington, DC, USA.

Dash, N., Gladwin, H., 2007. Evacuation decision making and behavioral responses: individual and household. Natural Hazards Review 8 (3), 69–77.

Dow, K., Cutter, S.L., 2002. Emerging hurricane evacuation issues: Hurricane Floyd and South Carolina. Natural Hazards Review 3 (6), 12–18.

Fu, H., Wilmot, C.G., 2004. Sequential logit dynamic travel demand model for hurricane evacuation. Transportation Research Record: Journal of the Transportation Research Board 1882, 19–26.

Fu, H., Wilmot, C.G., 2006. Survival analysis-based dynamic travel demand models for hurricane evacuation. Transportation Research Record: Journal of the Transportation Research Board 1964, 211–218.

Gladwin, C.H., Gladwin, H., Peacock, W.G., 2001. Modeling hurricane evacuation decisions with ethnographic methods. International Journal of Mass Emergencies and Disasters 19 (2), 117–143.

Gladwin, H., Lazo, J.K., Morrow, B.H., Peacock, W.G., Willoughby, H.E., 2007. Social science research needs for the hurricane forecast and warning system. Natural Hazards Review 8 (3), 87–95.

Greene, W., 2007. Limdep, Version 9.0. Econometric Software Inc., Plainview, New York.

Hasan, S., Ukkusuri, S., Gladwin, H., Murray-Tuite, P., 2011. A behavioral model to understand household-level hurricane evacuation decision making. Journal of Transportation Engineering 137 (5), 341–348.

Hensher, D.A., Mannering, F.L., 1994. Hazard-based duration models and their application to transport analysis. Transport Reviews 14 (1), 63–82.

Lindell, M.K., Lu, J.C., Prater, C.S., 2005. Household decision making and evacuation in response to Hurricane Lili. Natural Hazards Review 6 (4), 171–179.

Lindell, M.K., Prater, C.S., 2007a. A hurricane evacuation management decision support system (EMDSS). Natural Hazards 40 (3), 627–634.

Lindell, M.K., Prater, C.S., 2007b. Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: examples from hurricane research and planning. Journal of Urban Planning and Development 133 (1), 18–29.

Mannering, F.L., Hamed, M., 1990. Occurrence, frequency, and duration of commuters' work-to-home departure delay. Transportation Research Part B: Methodological 24 (2), 99–109.

Morrow, B.H., Gladwin, H., 2005. Hurricane Ivan Behavioral Analysis, 2004 Hurricane Assessments. US Army Corps of Engineers. <http://chps.sam.usace.army.mil/USHESdata/Assessments/2004Storms/2004_hurricane_season_page.htm> (accessed 10.12.09).

NHC, National Hurricane Center, 2006. Tropical Cyclone Report: 2005 Atlantic Hurricane. Washington, DC: NOAA.

Sorensen, J.H., 1991. When shall we leave? Factors affecting the timing of evacuation departures. International Journal of Mass Emergencies and Disasters 9 (2), 153–165.

Stewart, S.R., 2004. Tropical Cyclone Report: Hurricane Ivan. National Hurricane Center. <www.nhc.noaa.gov/2004ivan.shtml> (accessed 10.12.09).

Train, K., 1999. Halton Sequences for Mixed Logit. Working Paper, University of California Berkley, Department of Economics.

Urbaina, E., Wolshon, B., 2003. National review of hurricane evacuation plans and policies: a comparison and contrast of state practices. Transportation Research Part A: Policy and Practice 37 (3), 257–275.

Washington, S.P., Karlaftis, M.G., Mannering, F.L., 2011. Statistical and Econometric Methods for Transportation Data Analysis, second ed. Chapman Hall/CRC, Boca Raton, FL.