Modeling Evacuation Behavior under Hurricane Conditions

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ABSTRACT
The understanding of evacuation behavior is critical to establish policies, procedures and organizational structure for effective response to emergencies. This study specifically investigated the evacuation behavioral responses under hurricane conditions. It aimed to explore the association between different contributing factors and the evacuation decision choices as well as evacuation destination choices. Unlike previous studies that model each response behavior separately, this paper proposed to use the structural equation modeling approach to examine the interrelationship between different response behaviors. A case study using the data set from a survey conducted in New Jersey was performed. With the Bayesian estimation approaches, the proposed structural equation models have been estimated and the effect of each predictive variable has been captured. An important finding is that the individuals’ preference to evacuate did not significantly affect their choices of evacuation destinations. In addition, other socio-economic and demographic characteristics that affected evacuation behavior have been identified.
INTRODUCTION

Hurricanes are among the most destructive natural disasters before which mass evacuations are highly likely. Especially in the post-Hurricane Irene and Sandy context, disaster preparedness has become a vital component of emergency management plans for many states in the Northeast United States that are vulnerable to flooding and other adverse effects of hurricanes (1, 2). Accuracy of the early warning information and timeliness of the response systems play a crucial role in mobilizing people under risk (3). In recent years, advanced information technologies enable decision-makers to evaluate risk factors and take necessary precautions hours before the storm makes landfall. However, mandatory evacuation orders by the authorities do not always mean the majority of people to start moving to safer places (4). Strong empirical evidence from literature shows that individual evacuation decisions are rather controlled by personal characteristics, features of the affected region and severity of the hurricane all of which need to be evaluated using statistical models.

A growing body of literature investigated the role of various factors in deciding whether to stay or to evacuate, mode, departure time, destination and route choice during evacuation. The majority of these studies were dedicated to identify the underlying factors in human decision-making. Statistical models that are employed to determine the significance of different factors are mostly calibrated using observed behavior in similar events. Parameters that are usually included in decision modeling are whether having a past experience in a similar disaster, proximity to coast, socio-economic and demographic characteristics. Although most of these models successfully mimic evacuation decisions and overall expected demand based on real world observed data, forecasting for life-threatening natural disasters such as hurricanes is generally very difficult. As pointed out by some recent studies, advanced statistical models can make an important improvement in accurate predictions for evacuation planning. For example it was showed that using models that allow including heterogeneity in model parameters to address the diverse causes behind the responses to survey questions can help better understanding evacuation decision (5), or route choice during evacuation (6).

Therefore, this paper aims to examine residents’ evacuation behavior. It contributes to the existing literature by developing a structural equation modeling (SEM) approach to jointly analyze evacuation decision and destination choices based on stated preference data. A Telephone survey data collected for Jersey City/Newark Urban Areas Security Initiative region in Northern New Jersey was used as a case study. For detailed description of survey design and descriptive statistics of responses readers are referred to Carnegie and Deka (7).

LITERATURE REVIEW

Emergency evacuation behavior modeling in the literature can be grouped in two main categories: 1) Post-event studies and 2) Pre-event studies. The main advantage of post-event studies over pre-event studies is the observed behavior of the affected population under real evacuation situations. Most of these studies try to identify the chief reasons behind the evacuation decisions of people. The results obtained from post-event studies are usually considered as inputs for predicting future behavior of the respondents. However, for events with high degree of uncertainty, such as hurricanes, it is not always possible to generalize the findings from a single situation to future events (8). Pre-event studies, on the other hand, facilitate analyses of a wide range of hypothetical scenarios based on different assumptions about spatial contiguity and severity of the hurricane. The major concern regarding the findings in pre-event studies is the accuracy of the respondents’ stated preferences with the actual behavior in a future real situation.

Baker (9) compared hypothetical and actual hurricane evacuation behavior in Florida. The findings showed that logistic regression models using stated preference data precisely estimated the actual behavior of the respondents. In a more recent study, Kang et al. (10) found that a large portion of the population (80 per cent) who had stated that they would not evacuate actually did not evacuate during the Hurricane Lili. Same study also reported that 65 per cent of the users who had been expected to evacuate based on pre-event surveys did evacuate during the event. Murray-Tuite and Wolshon (8) provided an excellent summary of research efforts in general evacuation transportation modeling including specific studies dealing with hurricanes.
Logistic regression models are widely used for predicting evacuation behavior. Whitehead et al. (11) used telephone survey data from North Carolina to investigate evacuation decision-making of the respondents. Based on the survey data, the modeling results show that socio-economic characteristics along with the types of evacuation order played a key role in evacuation decision. As expected, in a voluntary evacuation order, people are more likely to stay and are not willing to go to a safer place compared to a mandatory evacuation order. Fu and Wilmot (12) used sequential logit models for estimating observed evacuation demand in Hurricane Andrew and concluded that their model produced reasonable prediction for the observed behavior. Brezina (13) highlighted the reasons for not evacuating during Hurricane Katrina using a survey data that is collected immediately after the disaster. Logistic regression model results showed that in contrast with common belief that welfare effects (i.e. employment status) are not among the significant effects in evacuation decision. Gudishala and Wilmot (14) developed logistic regression models to evaluate evacuation decisions for different types of natural and man-made disasters. The results showed that socio-economic characteristics of the respondents play a more decisive role in evacuation in hurricanes compared to the other types of emergency conditions.  

Random parameters models have been recently incorporated in the evacuation behavior context. Hasan et al. (5) used mixed logit models to estimate evacuation decision by addressing unobserved heterogeneity of survey responses. The reported model results were found to be consistent with previous studies in terms of significance of factors and it was concluded that including parameter heterogeneity in modeling can contribute to more informed decision-making during emergency conditions.  

Different modeling approaches employed to address risk-taking attributes and hierarchical nature of evacuation decision process. Dixit et al. (15) developed a model that incorporates risk aversion for departure time choice during evacuation. The model presented in this study was stated as useful for authorities in distinguishing factors that are related to risk taking behavior of the population and take necessary action to motivate them for evacuation. Huang et al. (16) analyzed household evacuation decision and departure time choice for Hurricane Ike using a Proactive-Action Decision Model. The results of this study showed that there is a hierarchical structure in evacuation decision, such that personal features play a role in deciding whether stay or to leave and storm characteristics and perceptions affect personal features.  

Table 1 gives a summary of selected literature on evacuation decision making along with data sources, sample sizes and modeling methodologies. All the existing studies modeled different evacuation behavior separately. The potential interactions among different evacuation behavior were not ignored. However, there is possibility that a person’s choice of one thing will be conditional upon the choices of other things. Therefore, it is necessary to investigate the possible relationship between different evacuation behavioral responses.
TABLE 1 Summary of selected evacuation decision modeling literature

<table>
<thead>
<tr>
<th>Author</th>
<th>Data Source</th>
<th>Sample Size</th>
<th>Modeling Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brezina (13)</td>
<td>Survey of Hurricane Katrina Evacuees, New Orleans</td>
<td>680</td>
<td>Logistic Regression Analysis</td>
</tr>
<tr>
<td>Whitehead et al. (11)</td>
<td>Telephone survey of North Carolina residents who were affected in Hurricane Bonnie</td>
<td>895</td>
<td>Logistic Regression Analysis for Evacuation Decision</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Multinomial Logit for Destination Choice</td>
</tr>
<tr>
<td>Gladwin et al. (4)</td>
<td>Interview with Miami residents who were affected in Hurricane Andrew and Erin</td>
<td>954</td>
<td>Ethnographic Decision Tree Analysis</td>
</tr>
<tr>
<td>Fu and Wilmot (12)</td>
<td>Interview with people from Southwest Louisiana after Hurricane Andrew</td>
<td>428</td>
<td>Sequential Logit Model</td>
</tr>
<tr>
<td>Hasan et al. (5)</td>
<td>Telephone survey of households that are affected in Hurricane Ivan</td>
<td>3,200</td>
<td>Mixed Logit Model</td>
</tr>
<tr>
<td>Dixit et al. (15)</td>
<td>Interview with people from Southwest Louisiana after Hurricane Andrew</td>
<td>429</td>
<td>Utility maximization with risk aversion</td>
</tr>
<tr>
<td>Gudishala and Wilmot (14)</td>
<td>Self-administered survey by mail in New Orleans area</td>
<td>300</td>
<td>Sequential Logit Model</td>
</tr>
<tr>
<td>Carnegie and Deka (7)</td>
<td>Survey of four hypothetical disaster scenarios in Northern New Jersey including a hurricane scenario</td>
<td>2,218</td>
<td>Logistic Regression</td>
</tr>
<tr>
<td>Huang et al. (16)</td>
<td>Mail survey of households in Houston- Galveston Study Area</td>
<td>200</td>
<td>Logistic Regression / Ordinary Least-squares Regression</td>
</tr>
</tbody>
</table>

EVACUATION BEHAVIOR SURVEY

A random digit dial telephone survey was conducted between August and October of 2008 in northern New Jersey (7). It covers a large urban region consisting of Passaic, Bergen, Hudson, Morris, Essex, Middlesex and Union Counties. The total population of the region is approximately 4.5 million. In total, 2,218 households were interviewed with a set of questions related to their evacuation experience, disaster preparedness (including hurricane, industrial accident and catastrophic nuclear explosion), evacuation decision choices, evacuation destinations, and evacuation mode choices. In addition, a series of questions regarding the characteristics of the household and household members, such as income, vehicle ownership, family size etc. were asked.

TABLE 2 lists the major questions interviewed in the evacuation behavior survey. The survey data were cleaned by removing those without full responses. In total, 1,221 households provided valid responses to the interviewed questions. The responses were coded in TABLE 2. The number in the in the parenthesis indicates the number of responses for each question.
TABLE 2 Defining variables for the evacuation survey

<table>
<thead>
<tr>
<th>Major Questions</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evacuation decision choice</td>
<td>very unlikely=0 (569); not very likely=1 (249); somewhat likely=2 (212); very likely=3 (191)</td>
</tr>
<tr>
<td>Evacuation destination</td>
<td>public shelter=1 (319); friend/relative’s home=2 (518); hotel/motel=3 (140); others=4 (244)</td>
</tr>
<tr>
<td>Gender</td>
<td>male=0 (554); female=1 (667)</td>
</tr>
<tr>
<td>Evacuation experience</td>
<td>yes=0 (100); no=1 (1121)</td>
</tr>
<tr>
<td>Employment status</td>
<td>employed=0 (681); not employed=1 (540)</td>
</tr>
<tr>
<td>Risk perception</td>
<td>not affected=0 (178); affected=1 (1043)</td>
</tr>
<tr>
<td>Years of current residence</td>
<td>≤ 1 years = 0 (114); 1 &lt; years ≤ 10 = 1 (527); &gt;10 years = 2 (580)</td>
</tr>
<tr>
<td>Type of residence</td>
<td>others=0 (319); house=1 (902)</td>
</tr>
<tr>
<td>House ownership</td>
<td>rent=0 (511); own=1 (710)</td>
</tr>
<tr>
<td>Age</td>
<td>age&lt;65 is 0 (969); age≥65 is 1 (252)</td>
</tr>
<tr>
<td>Household size</td>
<td>1 people =0 (262); ≥2 people =1 (959)</td>
</tr>
<tr>
<td>People under the age of 18</td>
<td>without =0 (779); with =1 (442)</td>
</tr>
<tr>
<td>Specific care needed</td>
<td>no =0 (1040); yes =1 (181)</td>
</tr>
<tr>
<td>Have pet</td>
<td>no =0 (795); yes =1 (426)</td>
</tr>
<tr>
<td>Educational level</td>
<td>≤ high school =0 (381); college and above =1 (840)</td>
</tr>
<tr>
<td>Household with vehicle</td>
<td>no =0 (217); yes =1 (1004)</td>
</tr>
<tr>
<td>Income level</td>
<td>&lt;$2500 =1 (201); $25000~$50,000 =2 (216); $50,000~$100,000 =3 (298); ≥$100,000 =4 (292); Unreported =5 (214)</td>
</tr>
<tr>
<td>Distance to shore</td>
<td>distance in miles (1221)</td>
</tr>
<tr>
<td>Language of interview</td>
<td>English =0 (1076); Others =1 (145)</td>
</tr>
<tr>
<td>Marital status</td>
<td>others =0 (653); married =1 (568)</td>
</tr>
<tr>
<td>Race / ethnic background</td>
<td>White not Hispanic =0 (507); others =1 (714)</td>
</tr>
</tbody>
</table>

METHODOLOGY

The surveyed evacuation responses include non-negative count data and the outcome of a set of contributing factors. To model such count data, a number of discrete choice models can be considered. The following sections describe the models used in this study.

Structural Equation Modeling

Instead of modeling different aspects of evacuation behavior separately, an alternative interesting approach is to investigate whether one behavior/decision will affect the others. Specifically, whether the individuals’ evacuation decisions will affect their choice of evacuation destination?

In order to address the aforementioned question, the structural equation modeling (SEM) approach is used in this study. In general, the structural equation modeling involves two components: a measurement model and a structural model. Former component describes how well the observed indicators measure the latent (unobserved) variables and the later one is used to relate all of the variables (both latent and manifest). FIGURE 1 shows the SEM model considered in this study. Some of the survey questions are considered to be explanatory variables that only affect the evacuation decision choices or evacuation destination choices whereas others (i.e. survey question k and h) are considered to be influential in both responses.
The proposed model assumes that the evacuation decision choice will affect the choices of evacuation destination. In other words, if the individual chooses to evacuate, his/her choice to evacuation destination is bounded by certain options. The SEM approach can integrate different statistical modeling procedures into single statistical program, which provides us unparalleled flexibility in modeling other scenarios (if needed). Within the structural modeling framework, the individual components will be modeled in the following sections.

Modeling Evacuation Decision Behavior

The personal responses to the evacuation decision in the survey are described by four categorical answers, including very unlikely, not very likely, somewhat likely, and very likely. Thus these four choices can be considered as a discrete and ordinal response variable of the evacuation decision. Given the discrete natural order of the tendency of choice, the ordered probit regression (OPR) model is considered to capture the relationship between a list of exogenous factors and the interviewed person’s evacuation decision choice. The modeling approach is described below.

Assume there is an unobserved latent continuous metric \( y_i' \) underlying the observed tendency of evacuation decision \( y_i \) of the \( i \)th interviewed person. \( y_i' \) is assumed to depend linearly on the exogenous factors \( X_i \) plus a random error term \( e_i \) as follows:

\[
y_i' = X_i'\beta + e_i
\]

(1)

where \( y_i' \) denotes the latent variable measuring the evacuation decision of the \( i \)th interviewed person; \( X_i \) is a \( k \times 1 \) vector of observed non-random explanatory variables; \( \beta \) is a \( k \times 1 \) vector of unknown parameters; and \( e_i \) is the random error term.

The latent variable \( y_i' \) is mapped onto the observed variable \( y_i \) according to the following scheme:

\[
y_i = j \text{ if } \tau_{j-1} < y_i' \leq \tau_j \text{ for } j = 1 \text{ to } J
\]

(2)

where \( j \) is the observed tendency of evacuation decision of person \( i \); \( y_i' \) is dissected by \( J - 1 \) thresholds into \( J \) partitions; \( \tau_j \)'s are constant and unknown threshold parameters to define partitions, denoted as \( \tau_{j-1} < \tau_j \text{, } \tau_0 = -\infty \text{, and } \tau_J = +\infty \). The partitions are not in general equally spaced.

Defining evacuation decision of four levels according to the person’s response to the question, equation (2) can be represented by the following decision model:

\[
y_i =
\begin{cases}
1 & \text{if } \tau_0 < y_i' \leq \tau_1 \text{ (Response = very unlikely)} \\
2 & \text{if } \tau_1 < y_i' \leq \tau_2 \text{ (Response = not very likely)} \\
3 & \text{if } \tau_2 < y_i' \leq \tau_3 \text{ (Response = somewhat likely)} \\
4 & \text{if } \tau_3 < y_i' \leq \tau_4 \text{ (Response = very likely)}
\end{cases}
\]

(3)
Using the above equation (3) we can determine the cumulative probability of \( y_i \) as equation (4):
\[
\Pr(y_i \leq j) = \Pr(y_i^* \leq \tau_j) = \Pr(X_i\beta + \epsilon_i \leq \tau_j) = \Pr(\epsilon_i \leq \tau_j - X_i\beta) = F(\tau_j - X_i\beta)
\]
where \( F \) is the cumulative distribution function (CDF) of the unobserved error term \( \epsilon_i \).

Based on equation (4), the probability that the \( i^{th} \) person choosing \( j^{th} \) response level can be described by equation (5):
\[
\Pr(y_i = j | X_i) = F(\tau_j - X_i\beta) - F(\tau_{j-1} - X_i\beta)
\]

Given the assumption that the error term \( \epsilon_i \) in equation (1) is independently distributed according to standard normal distribution \( \epsilon_i \sim N(0,1) \), then equation (1) represents the ordered probit model structure and the probability equation (5) can be specified as follows:
\[
\Pr(y_i = j | X_i) = \Phi(\tau_j - X_i\beta) - \Phi(\tau_{j-1} - X_i\beta)
\]
where \( \Phi \) is the CDF of the standard normal distribution.

Specifically, the probability that the person is very unlikely to evacuate is:
\[
\Pr(y_i = 1 | X_i) = 1 - \Phi(\tau_1 - X_i\beta)
\]
The probability that the person is very likely to evacuate is:
\[
\Pr(y_i = 4 | X_i) = \Phi(\tau_3 - X_i\beta)
\]

We are concerned with how changes in the independent variables \( X_i \) translate into the probability of observing a particular level of severity. Equation (7) and (8) indicate that a positive coefficient \( \beta_j \) decreases \( \Pr(y_i = 1 | X_i) \) and increases \( \Pr(y_i = 4 | X_i) \), respectively. Alternatively, it can be said unambiguously that an increase in the variable implies the increases in the probability of deciding to evacuate under hurricane condition.

### Modeling Evacuation Destination Choices

The individual responses regarding the evacuation destinations are described by a set of unordered discrete outcomes: public shelter = 1, friend or relative’s home = 2, hotel or motel = 3, and somewhere else = 4. Naturally, a multinomial logit (MNL) model is a suitable candidate to describe the relationships that may exist between the independent variables and the destination choices. In general, the MNL model aims to estimate a function that determines choice probabilities. Given one choice as a reference (i.e., public shelter), the probability of each choice \( \pi_j \) is compared to the probability of the reference choice \( \pi_J \). For choices \( j = 1, 2, ..., J - 1 \), the log-odds of each choice is assumed to follows linear model:
\[
\eta_j = \log\left(\frac{\pi_j}{\pi_J}\right) = X_i\alpha_j
\]
where \( \alpha_j \) is a \( k \times 1 \) vector of regression coefficients for each choice \( j = 1, 2, ..., J - 1 \).

Based on equation (9), the probability of choosing \( i^{th} \) choice is \( \pi_j = \exp(\eta_j) \times \pi_J \). Note the fact that \( \eta_J = 0 \) and \( \sum_{j=1}^{J-1} \pi_j = 1 \), we can obtain \( \pi_j = \exp(\eta_j) \sum_{j=1}^{J-1} \exp(\eta_j) \). Therefore, the probability \( \pi_j \) can be rewritten as follows:
\[
\pi_j = \frac{\exp(\eta_j)}{\sum_{j=1}^{J-1} \exp(\eta_j)} \frac{\exp(X_i\alpha_j)}{\sum_{j=1}^{J-1} \exp(X_i\alpha_j)}
\]

The MNL model is reduced to a logistic regression model if there are only two destination choices \( J = 2 \). For \( J > 2 \), the probability distributions of the destination choices are multinomial instead of binomial.
Bayesian Modeling Procedure

The structural equation model in this study was calibrated within the Full Bayesian context, which uses Monte Carlo Markov Chain (MCMC) sampling methods to estimate the parameters. The proposed model was constructed and implemented in the WinBUGS (“BUGS” stands for Bayesian inference using Gibbs sampling) statistical software. Such model estimation approach has been frequently used in travel behavior studies (17, 18). MCMC approach draws samples from the posterior distribution and generates chains of random points. Once the distribution of the simulated chains is observed to converge to the target posterior distribution, full Bayesian estimates of the model parameters are obtained from the remaining iterations. The Brooks–Gelman–Rubin (BGR) statistic and trace plots of the chains can be used to check the convergence. The iterations up to the convergence point are excluded as burn-in samples and the remaining iterations are used for the posterior estimates. The accuracy of the posterior estimates is assessed by calculating the Monte Carlo error for each parameter. The Monte Carlo error is an estimate of the difference between the mean of sampled values and the true posterior mean. In general, an inference is considered to be reliable when the Monte Carlo error for each parameter of interest is less than about 5 percent of the sampled standard deviation (19). In order to implement the Bayesian estimation procedure, prior distribution of each variable has to be defined. Since there is no known information about the distribution of each parameter, uninformative priors are considered. Usually, the normal distribution with zero mean and a large variance is used to define the prior distribution for the regression parameters. In addition, Gamma distribution [i.e., \( \text{Gamma}(0.001,0.001) \)] was used as the uninformative priors for other parameters such as the precision in specifying a normal distribution.

The Deviance information criterion (DIC) is used to assess the model fitting and complexity. DIC is calculated by the following equation:

\[
DIC = \bar{D}(\theta) + p_D
\]  

(11)

where \( D(\theta) \) represents the Bayesian deviance of the estimated parameter \( \theta \). \( \bar{D}(\theta) \) is the posterior mean of \( D(\theta) \), \( \bar{D}(\theta) = E[D(\theta)] = -2\log(L(Y|\theta)) \). \( p_D = \bar{D}(\theta) - D(\theta) \) defines the effective number of parameters and can be denotes as a measure of model complexity. \( \bar{D}(\theta) \) is the point estimate that describes how well the model fits the data and \( L(Y|\theta) \) is the likelihood function. As a rule of thumb, a DIC difference of 10 would be used to rule out the model with the higher DIC (20, 21).

RESULTS AND DISCUSSION

Based on the defined variables in TABLE 2, the original data set was cleaned by removing those with missing values. In total, data related to 1,221 households were used for the final modeling analysis.

In order to specify the potential model structures, various relationships between response variables and independent variables have been explored. Those with small correlation coefficients have been excluded from initial consideration. Then an iterative procedure was employed to add/remove each variable to/from the candidate models. For the final evacuation decision choice model, seven variables, including gender, risk perception, age, education level, income level, distance to shore, and race / ethnic backgrounds, were specified in the final models. Other than the evacuation decision choice, other three variables namely, house ownership, evacuation experience, and employment status, were also included in the final model for evacuation destination choice. After a burn-in period of 20,000 iterations, we ran each chain (two chains in total for additional 10,000 iterations. Setting aside the results from the burn-in period, the estimated posteriors have been presented in TABLE 3. The accuracy of the estimation was verified as the Monte Carlo errors were less than 5 percent of the sampled standard deviation. The DIC for the structural equation model is 6038.94 (consisting of which Evacuation decision choice model DIC =2947.32 and evacuation destination choice model DIC=3091.62). No other model specifications were found to yield significantly smaller DIC value.
<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>sd</th>
<th>2.5%</th>
<th>97.5%</th>
<th>Variable</th>
<th>mean</th>
<th>sd</th>
<th>2.5%</th>
<th>97.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_1)</td>
<td>0.106</td>
<td>0.067</td>
<td>-0.024</td>
<td>0.237</td>
<td>(\alpha_{1,2})</td>
<td>0.644</td>
<td>0.361</td>
<td>-0.043</td>
<td>1.362</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>0.345</td>
<td>0.091</td>
<td>0.165</td>
<td>0.520</td>
<td>(\alpha_{1,3})</td>
<td>-0.821</td>
<td>0.495</td>
<td>-1.764</td>
<td>0.136</td>
</tr>
<tr>
<td>(\beta_3)</td>
<td>-0.278</td>
<td>0.083</td>
<td>-0.439</td>
<td>-0.116</td>
<td>(\alpha_{1,4})</td>
<td>-0.124</td>
<td>0.438</td>
<td>-0.989</td>
<td>0.734</td>
</tr>
<tr>
<td>(\beta_4)</td>
<td>-0.208</td>
<td>0.082</td>
<td>-0.368</td>
<td>-0.048</td>
<td>(\alpha_{2,2})</td>
<td>0.783</td>
<td>0.150</td>
<td>0.490</td>
<td>1.079</td>
</tr>
<tr>
<td>(\beta_5)</td>
<td>-0.088</td>
<td>0.117</td>
<td>-0.318</td>
<td>0.140</td>
<td>(\alpha_{2,3})</td>
<td>0.785</td>
<td>0.215</td>
<td>0.369</td>
<td>1.206</td>
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<tr>
<td>(\beta_6)</td>
<td>-0.262</td>
<td>0.114</td>
<td>-0.488</td>
<td>-0.043</td>
<td>(\alpha_{2,4})</td>
<td>0.787</td>
<td>0.182</td>
<td>0.432</td>
<td>1.146</td>
</tr>
<tr>
<td>(\beta_7)</td>
<td>-0.242</td>
<td>0.123</td>
<td>-0.487</td>
<td>-0.002</td>
<td>(\alpha_{3,2})</td>
<td>0.580</td>
<td>0.271</td>
<td>0.057</td>
<td>1.115</td>
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<tr>
<td>(\beta_8)</td>
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<td>0.119</td>
<td>-0.377</td>
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<td>(\alpha_{3,3})</td>
<td>0.136</td>
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</tr>
<tr>
<td>(\beta_9)</td>
<td>-0.341</td>
<td>0.051</td>
<td>-0.442</td>
<td>-0.242</td>
<td>(\alpha_{3,4})</td>
<td>0.188</td>
<td>0.305</td>
<td>-0.400</td>
<td>0.789</td>
</tr>
<tr>
<td>(\beta_{10})</td>
<td>0.486</td>
<td>0.071</td>
<td>0.348</td>
<td>0.627</td>
<td>(\alpha_{4,2})</td>
<td>0.261</td>
<td>0.250</td>
<td>-0.228</td>
<td>0.752</td>
</tr>
<tr>
<td>(c_1)</td>
<td>-1.483</td>
<td>0.170</td>
<td>-1.829</td>
<td>-1.160</td>
<td>(\alpha_{4,3})</td>
<td>0.126</td>
<td>0.342</td>
<td>-0.537</td>
<td>0.810</td>
</tr>
<tr>
<td>(c_2)</td>
<td>-0.857</td>
<td>0.168</td>
<td>-1.195</td>
<td>-0.535</td>
<td>(\alpha_{4,4})</td>
<td>-0.169</td>
<td>0.287</td>
<td>-0.725</td>
<td>0.401</td>
</tr>
<tr>
<td>(c_3)</td>
<td>-0.265</td>
<td>0.167</td>
<td>-0.600</td>
<td>0.054</td>
<td>(\alpha_{5,2})</td>
<td>0.052</td>
<td>0.218</td>
<td>-0.380</td>
<td>0.478</td>
</tr>
</tbody>
</table>

**Note:**
- \(\beta_i\) - gender
- \(\alpha_{j,i}\) - intercept
- \(\beta_2\) - risk perception
- \(\alpha_{j,2}\) - house ownership
- \(\beta_3\) - age
- \(\alpha_{j,3}\), \(\alpha_{j,4}\), \(\alpha_{j,5}\) - evacuation decisions
- \(\beta_4\), \(\beta_6\), \(\beta_7\), \(\beta_8\) - income
- \(\alpha_{j,6}\) - with people under 18
- \(\beta_9\) - distance to shore
- \(\alpha_{j,7}\) - evacuation experience
- \(\beta_{10}\) - race / ethic
- \(i\) - specific destination choice
- \(c_1\), \(c_1\), \(c_1\) - cutoff values

The 95% Bayesian credible interval (BCI) was used to examine whether a variable is significant or not. This is defined by the lower 2.5 percentile estimate and the upper 97.5 percentile estimate shown in the above table. If the estimated BCI covers zero, it suggests that the variable is not significant. Otherwise, the variable is considered to be significant. The estimation results in TABLE 3 show that females tend to be more likely to evacuate than males (reference group) as the posterior mean of gender is 0.106 (The lower bound (2.5 percentile) of its BCI is close to zero). If the person feels his/her family will be affected by the hurricane, his/her family is more likely to evacuate (\(\beta_2 = 0.345\)). Elder person (age over 65) is less likely to evacuate than younger ones (reference group). These findings are consistent with Carnegie and Deka (7). Interestingly, there is significant association between education levels and evacuation decision choices. \(\beta_4 = -0.208\) suggests that the ones with college or higher education are less likely to evacuate than others (reference group). Though the sign of this variable is consistent with the findings of Carnegie and Deka (7), they did not find it is significant. Other than \(\beta_4\), the other three coefficients of income are not found to be significant in our study. This suggests that there is no significant difference between people with different income levels in terms of their evacuation decision choices. It was found that a family living close to shore is more likely to evacuate as \(\beta_9 = -0.976\). The
race/ethnic background also affects the evacuation decisions. Compared to “White but not Hispanic” residents, others are more likely to evacuate.

The multinomial logistic regression model treated public shelters as the reference group and estimated three models for different destinations relative to public shelters. The standard interpretation of each estimated coefficient is that for a unit change in the explanatory variable, the logit of \( i^{th} \) destination choice relative to the reference group is expected to change by the corresponding estimate (in log-odds units) while holding all other variables in the model constant. For example, if the interviewed subject owns the house / apartment, the logit of choosing friend/relative’s home, hotel/model, and other places as their destination in relative to public shelters is expected to increase 0.783, 0.785, and 0.787 units respectively, given all other variables in the model are held constant. Likewise, if the family has members under 18, it is more likely to choose their friend / relative’s home or hotel / motel as their destinations. Interestingly, previous experience with evacuation did not significantly change the logit of choosing friend/relative’s home, hotel/model, or other places of destinations in relative to public shelters. The estimated \( \alpha_{3i}, \alpha_{4i}, \) and \( \alpha_{5i} \) examined the association between the evacuation decision choices and the evacuation destination choices. Other than \( \alpha_{12} \), the results suggest that there was no obvious link between the evacuation decisions and destination choices. In other words, the subject’s attitude to evacuate does not necessarily affect their choice of candidate destinations.

**CONCLUSIONS**

This study examined evacuation behavioral responses under hurricane conditions. The stated preferences for evacuation decision choices and evacuation destinations have been investigated based on a survey in New Jersey. A structural equation model has been developed to jointly model: (a) the potential factors that affect the choice behavior and (b) the relationship between the evacuation decision choices and the evacuation destination. It was found that age, education levels, distance to shore, and race/ethnic background tend to affect the evacuation decisions. Nevertheless, gender and income levels did not significantly affect the decisions of evacuation. Regarding the evacuation destination choices, it was found that house ownership is a key factor that changes the preference of other types of destinations in relative to public shelters. The individuals who own the house/apartment are more likelihood to evacuate to their friend / relative’s home as well as hotel. Evacuation experience did not significantly affect their choices of destinations. In addition, there was no strong relationship between evacuation decision choices and evacuation destination choices. In other words, whether or not the individuals consider to evacuate, there is no significant difference between choosing public shelters and other places.

Unlike other previous studies that modeled each evacuation behavior separately, this study offered a way to employ structural equation model for modeling different evacuation behavioral responses together. It suggests the need to consider the potential relationship between some response variables. However, this study is not free from limitations. First, the sample size of the survey should be further enlarged so that the heterogeneity of surveyed individuals across the state can be captured. A larger sample size will also be helpful in training the SEM models. Second, a comparative analysis with post-evacuation data collected after real hurricanes such as Sandy and Irene should be performed. Most of current surveyed population did not have experience of severe hurricanes in their local areas. Finally, other structural equation models can be considered by assuming different relationship among the contributing factors.

We have to mention that the SEM approach cannot test directionality in relationships. In other words, it requires users to hypothesize the causality (i.e., which evacuation behavior may affect the others). In addition, SEM requires well-specified measurement and conceptual models. The choice of variables and pathways will affect the SEM’s ability to capture the sample covariance and variance patterns observed in field. Thus, the sensitivity of the model specification should be tested to help find more rational models.
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