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Hurricane Evacuation Route Choice of Major Bridges in Miami Beach, Florida

Arif Mohaimin Sadri, Satish V. Ukkusuri, Pamela Murray-Tuite, and Hugh Gladwin

Evacuation is a typical recourse to prevent loss of life if a high storm surge occurs, especially in hurricane-prone regions. Bridges are the key locations of bottlenecks. Because of the specific geographic shape and roadway network of Miami Beach, Florida, residents need to evacuate over one of the six major bridges or causeways: MacArthur Causeway, Venetian Causeway, Julia Tuttle Causeway, John F. Kennedy Causeway, Broad Causeway, and Haulover Bridge. A mixed logit model is presented to identify the determining factors for evacuees from Miami Beach in selecting one of these bridges during a major hurricane. The model was developed by using data obtained from a survey that included a hypothetical Category 4 (major) hurricane scenario to reveal the most likely plans for evacuees from this area. The estimation findings suggest that the preference over a given bridge involves a complex interaction of variables, such as distance to reach the evacuation destination, evacuation-specific characteristics (evacuation day, time, mode, and destination), and evacuee-specific characteristics (gender, race, evacuation experience, and living experience). The normally distributed random parameters in the model account for the existence of unobserved heterogeneity across different observations. The findings of this study will help emergency officials and policy makers to develop efficient operational measures and better evacuation plans for a major hurricane by determining different fractions of people taking each of the six bridges.

Frequently occurring hurricanes are a major concern for coastal areas of the United States because of the devastating impacts, loss of lives, and property damage they cause. Barrier islands are a major area of risk in these coastal areas. These relatively low-elevation islands lie off much of the Atlantic and Gulf coastlines and expose large numbers of their residents to storm surge risk from hurricanes. Evacuation is the usual recourse to prevent loss of life if a high storm surge occurs, and most often evacuation from these islands depends on timely traffic flow over bridges and causeways. In the early morning of September 12, 2009, many residents of Galveston, Texas, had planned to evacuate for Hurricane Ike but woke to find that their causeway evacuation route was unavailable due to storm surge flooding (*1*). Hurricanes Irene (2011), Sandy (2012), and Arthur (2014) all resulted in large numbers of people evacuating from barrier islands at the last minute even as tropical storm force winds and a storm surge were coming onshore (*1, 2*). One often thinks of barrier islands as being isolated and having seasonal populations at most, but many are components of densely populated urban areas such as Galveston (population 47,762) and Miami Beach, Florida (population 91,026).

Evacuation problems in hurricane-prone regions are further complicated by the limited growth of the road network as compared with the growth of population in these areas (*3*). For example, during Hurricane Rita, many people were stuck in gridlock on Houston, Texas, freeways and a massive loss of life could be possible in similar situations (*4*). In short-notice disasters like hurricanes, evacuation management agencies usually identify alternate evacuation routes depending on the expected path of the hurricane before the evacuation, and official routing recommendations are provided to evacuees. Evacuation orders are supposed to allow clearance time for traffic to get past bottlenecks like bridges and roads with limited traffic capacity. However, evacuees often delay departure and wind up leaving together and on similar routes; this behavior shows synchronization in terms of evacuation behavior (*5*). As a consequence, traffic surges occur that result in gridlock on several evacuation routes. Route choice during evacuation is a complex process because evacuees can take the most familiar route or follow the routes recommended by emergency officials or those taken en route to obtain better travel time to reach a safe destination (*6*). In this regard, emergency officials require a detailed understanding of the determinants of evacuation routing behavior to control highly unpredictable vehicular traffic flows trying to evacuate in a short lead time.

Since bridges are main sources of bottlenecks, it is important to know how they are utilized during a disaster from the evacuees' point of view. Efficient operational and control measures, such as contraflow and bridge closure, need to be determined so that the system runs predictably and controllably in a situation different from that of regular traffic. This operation requires a behavioral model of route choice in the evacuation situation. The current research developed a random-parameter multinomial logit model (i.e., a mixed logit model) to understand the bridge choice strategies by Miami Beach residents during hurricane evacuation. The model contributes to hurricane evacuation research by determining the influential factors in selection of one of the six major bridges, such as distance to reach evacuation destination, evacuation-specific characteristics (evacuation day, time, mode, and destination), and evacuee-specific characteristics (gender, race, evacuation experience, and living experience). In addition, the distribution of random parameters accounts for the heterogeneous responses of the evacuees.

In this study, the choice of a major bridge by Miami Beach residents during hurricane evacuation is modeled with the data obtained

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Transportation Research Record: Journal of the Transportation Research Board, No. 2532, Transportation Research Board, Washington, D.C., 2015, pp. 164–173.
DOI: 10.3141/2532-18

FIGURE 1 Respondents from Miami Beach, who are most likely to use one of six major bridges.

from a survey that included a hypothetical Category 4 (major) hurricane scenario. The survey was designed so that the respondents provided their most likely evacuation plans during a major hurricane. Miami Beach is a coastal city in Miami–Dade County, Florida, with a total population of 91,026 (*7*). This city has a unique geographical shape and road network (Figure 1), and residents need to evacuate over one of the six major bridges or causeways: MacArthur Causeway, Venetian Causeway, Julia Tuttle Causeway, John F. Kennedy Causeway, Broad Causeway, and Haulover Bridge. In particular, the purpose of this study is to model the preference of evacuees for selection of any of these six bridges to reach a safe destination during a major hurricane. The findings of this study provide a logical inference in terms of evacuees' bridge choice strategy and would help practitioners to take efficient measures by determining the level of congestion on these bridges and causeways.

BACKGROUND AND RELATED WORK

A number of existing studies have considered the overall hurricane evacuation process. In general, the importance of effective evacuation management planning in coastal regions has been duly addressed in some of the studies (*4, 8–10*). To explain the complex dynamic process of hurricane evacuation, several studies identified different governing factors, such as hurricane trajectory and warning systems, household locations and types, and characteristics of the evacuees, among others (*9–14*). In particular, several studies focused on individual-level decision making during the process of evacuation. These studies include those on evacuation decision making (*9, 13, 15–19*); evacuation timing behavior (*20–24*); mobilization time, that is, time elapsed from the decision to evacuate to the actual evacuation (*20, 25–30*); destination choice (*31–38*); travel mode to evacuate (*39, 40*); and preevacuation preparation activities (*41*).

Several other studies contributed to the area of emergency planning and network-level analysis. Barrett et al. provided guidance on the development of dynamic traffic models for hurricane evacuations (*42*). The relative accuracy of different forms of trip generation for evacuating traffic was examined by Wilmot and Mei (*43*). With the help of trip chain simulations, Murray-Tuite and Mahmassani presented a method to predict delays and traffic densities during evacuation (*44*). Wolshon et al. emphasized the areas to be considered for a successful evacuation plan (*45–46*). Liu et al. proposed a cell-based network model to determine optimal staging schemes to reduce congestion on an evacuation network with a more uniform distribution of demand (*47*). Within a microscopic modeling framework, Dixit and Radwan introduced the "network breathing" process for the external controls on entry and exit of evacuating vehicles into the evacuation network to improve overall outflow (*48*). The impact of incidents on the time to complete an evacuation of a large metropolitan area was evaluated by Robinson et al. (*49*). Yazici and Ozbay proposed a system-optimal dynamic traffic assignment model with probabilistic demand and capacity constraints while accounting for the randomness in evacuation demand and roadway capacity (*50*).

Research related to evacuation routing strategy includes several other studies. For example, Cova and Johnson proposed a network flow model to identify optimal lane-based evacuation routing plans in a complex road network in order to reduce traffic delays at intersections in evacuations (*51*). Chiu and Mirchandani showed that the route choice behavior of an evacuee results in subsequent degradation of evacuation effectiveness (*52*). The study introduced a "feedback information routing" strategy that increases the evacuation effectiveness to an optimal condition. In this regard, the multinomial logit-based route choice model ERCM was calibrated through the stated-preference approach. However, ERCM is not intended to serve as an exact representation of the actual route choice behavior during evacuation according to this study but to show how actual route choice results in the deviation of evacuation performance as compared with optimal route choice behavior. Shen et al. proposed two models to address the highly uncertain and time-dependent nature of transportation systems during disruption (*53*). By using the shortest-path technique, one of the two models offered dynamic routing control in a stochastic time-varying transportation network that routes the vehicles. The study also found that the proposed routing strategy minimizes evacuation time to the safety shelter locations. Lammel and Flotterod compared two different routing strategies within a multiagent simulation framework and found that the cooperative routing approach generates a substantially higher evacuation throughput than an alternative noncooperative routing strategy (*54*).

However, only a few studies addressed the evacuation routing decisions made by evacuees during a hurricane at the household or individual level. Carnegie and Deka found that 81% of the survey respondents who were "very likely" or "somewhat likely" to voluntarily self-evacuate would be "very willing" to follow the evacuation instructions in terms of their route choice and departure time (*14*). Robinson and Khattak showed that evacuees' preference of whether or not to detour from a route when faced with congestion can be controlled by using advanced traveler information systems (*55*). The study conducted a stated-preference approach to show that drivers in Hampton Roads, Virginia, would be highly motivated to use an alternative route when expected delays are observed on the intended route if advanced traveler information system information is available for alternate routes. The study found 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 limitation 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.

Research conducted by Wu et al. focused on household evacuation logistics in nine counties or parishes that conducted evacuations during Hurricanes Katrina and Rita (*56*). The study reported the choice of evacuation destination and route in different counties and presented the necessity of developing mathematically tractable models of household evacuation route choice. Murray-Tuite et al. reported that many evacuees base their routing decisions on the belief that the selected route would be shortest, is their usual or most familiar route during hurricane evacuation, or both (*19*). Recently, Sadri et al. developed a mixed logit model to understand the choice of routing strategies during hurricane evacuation by using data from Hurricane Ivan in 2004 (*57*). The model identified and explained several important factors that influence the routing behavior of evacuees among three significant alternatives: selecting the usual route, following the routes recommended by emergency officials, and possibly detouring or route switching.

This study presents a random-parameter multinomial logit model (i.e., a mixed logit model) to capture the underlying unobserved characteristics in the evacuation routing behavior of the evacuees from Miami Beach during a major hurricane in selecting one of the six major bridges or causeways available for them to evacuate. This study identifies the variables associated with bridge choice decision making and then provides some rational inferences about hurricane evacuation routing strategies of Miami Beach residents.

DATA

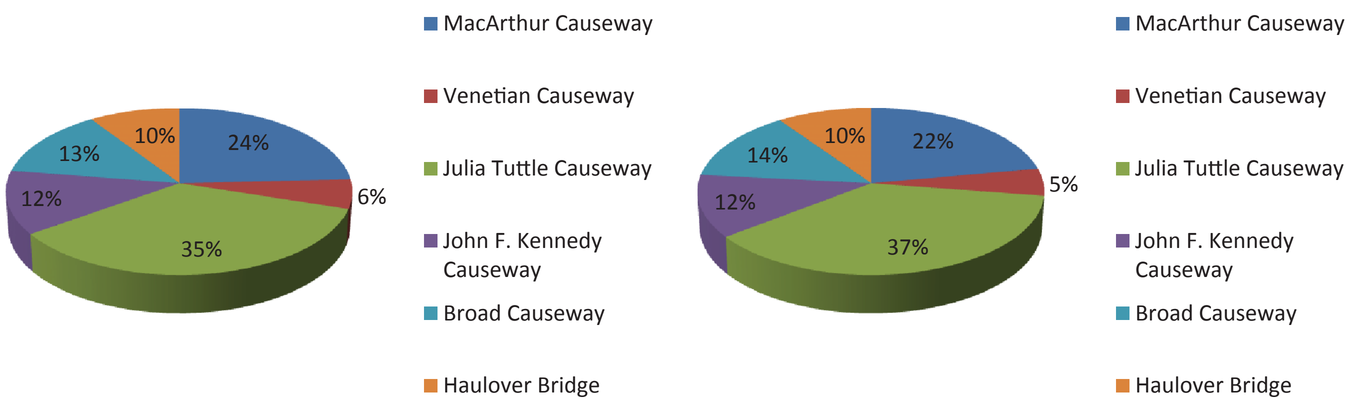
In this study, data were collected from a survey of randomly sampled Miami Beach residents (18 years and older), who participated voluntarily. The survey was funded by the National Science Foundation. Miami Beach has a specific geographic shape with approximately 90,000 residents who have to evacuate over one of the six causeways or bridges. Approximately 70% of the population from high-risk areas such as Miami Beach evacuated over a 10-h period during Hurricane Andrew (*58*). This area was also threatened by Hurricane Floyd later, in 1999. A total of 13,565 numbers were called for a telephone survey (later in 2012) and 61% of them were potential residences. In residences where a person was reached and asked to do the survey, approximately 54% agreed.

The survey was primarily designed to discover Miami Beach residents' most likely plans in case of a major hurricane. The respondents were given a hypothetical scenario in which a major Category 4 hurricane was approaching South Florida from the east and was forecast to reach the study area early Thursday morning, 5 days from the day (Saturday) on which the survey was being conducted. Hypothetically, Miami–Dade County announced that people in all evacuation zones would have to evacuate by 10:00 a.m. Wednesday morning. Given this situation, the survey respondents were requested to provide their most likely evacuation plans. The data included household sociodemographic information and evacuation-related features such as evacuation decision, the time and day of evacuation, the destination, evacuation mode choice, previous hurricane experience, different activities to participate in, choice of major bridges to evacuate, and so forth.

Originally, the data included 301 bridge choice observations, which included one of the six options: MacArthur Causeway, Venetian Causeway, Julia Tuttle Causeway, John F. Kennedy Causeway, Broad Causeway, and Haulover Bridge. Figure 1 presents the geolocations of these respondents and the location of the bridges and causeways; the dots in Figure 1 were color-coded by bridge selection. Respondents provided the approximate location of their evacuation destinations and these locations were geocoded by using GPSVisualizer (*59*). Then a Python code was used to measure the approximate distance in miles from Google Maps required to travel from a given origin to the destination by using each of those crossings (*60*). Starting with an initial distribution of 301 respondents (Figure 2*a*), the number of observations was reduced to 248 (margin of error ±6.2%) after the missing data for some of the explanatory variables in the data set were accounted for (Figure 2*b*). Table 1 provides additional information on the mean, standard deviation, minimum, and maximum of the variables included in the model.

METHODOLOGY

To evacuate off-beach, Miami Beach residents need to use one of the six major causeways or bridges: MacArthur Causeway, Venetian Causeway, Julia Tuttle Causeway, John F. Kennedy Causeway, Broad Causeway, and Haulover Bridge. The locations of these crossings are presented in Figure 1. Thus, the evacuees only have six discrete choices in order to reach the preferred evacuation destination from their households. Such preferences can efficiently be modeled by using the analytical framework of logit models, that is,



(a) (b)

FIGURE 2 Bridge choice distribution for Miami Beach residents: (*a*) initial distribution (301 observations) and (*b*) final distribution (248 responses).

discrete outcome models (*61, 62*). In the derivation and application of a standard logit model, the underlying assumption is that the estimated parameters are fixed across all observations. However, parameter estimates will be inconsistent and the outcome probabilities would be erroneous if this assumption does not hold (*63*).

Under the foregoing circumstances, it is appropriate to apply a methodological framework that accounts for the possible variation (unobserved heterogeneity) of the influential variables affecting bridge choice strategy across different evacuees participating in the evacuation. Because of the variance present in the sociodemographic and evacuation-related attributes of different evacuees, it is unrealistic to assume that the effects of selected variables are the same across all observations. Previous research also demonstrated the effectiveness of mixed logit models, which can explicitly account for the variations across different observations of the effects that variables have on the choices of major bridges considered in this study (*64, 65*). A function determining the outcome of the bridge choice for evacuee n is considered:

$$\mathrm{BC}_{i,n} = \beta_i X_{i,n} + \varepsilon_{i,n} \tag{1}$$

where

$\mathrm{BC}_{i,n}$ = function determining bridge choice category i in I (i = 1, 2, 3, 4, 5, 6),
$X_{i,n}$ = vector of explanatory variables (see Table 1),
β_i = vector of estimable parameters, and
$\varepsilon_{i,n}$ = error term.

TABLE 1 Descriptive Statistics of Explanatory Variables

Variable Description	Mean	SD	Minimum	Maximum
Variables That Vary Across Alternatives				
Distance via MacArthur Causeway (mi)	472.460	787.665	6	3,367
Distance via Venetian Causeway (mi)	471.258	787.714	5	3,365
Distance via Julia Tuttle Causeway (mi)	469.802	787.409	7	3,363
Distance via John F. Kennedy Causeway (mi)	469.319	786.648	5	3,361
Distance via Broad Causeway (mi)	468.972	785.999	4	3,360
Distance via Haulover Bridge (mi)	471.105	785.177	5	3,361
Variables That Do Not Vary Across Alternatives				
Evacuation specific variables				
Evacuation day (1 if evacuee is most likely to evacuate 1 day before landfall, 0 otherwise)	0.343	0.475	0	1
Evacuation day (1 if evacuee is most likely to evacuate 2 days before landfall, 0 otherwise)	0.359	0.480	0	1
Evacuation time (1 if evacuee is most likely to evacuate between 6:00 a.m. and 12:00 p.m., 0 otherwise)	0.456	0.498	0	1
Evacuation time (1 if evacuee is most likely to evacuate between 12:00 p.m. and 6:00 p.m., 0 otherwise)	0.423	0.494	0	1
Evacuation mode (1 if evacuee is most likely to evacuate by a car, 0 otherwise)	0.891	0.312	0	1
Evacuation destination (1 if evacuee is most likely to evacuate to a shelter or a hotel, 0 otherwise)	0.234	0.423	0	1
Evacuee specific variables				
Gender (1 if evacuee is female, 0 otherwise)	0.641	0.480	0	1
Race (1 if evacuee is white, 0 otherwise)	0.935	0.246	0	1
Number of years lived in South Florida	27.097	16.505	1	83
Evacuation experience (1 if evacuee evacuated previously for a hurricane, 0 otherwise)	0.649	0.477	0	1

NOTE: Number of observations = 248. SD = standard deviation.

Assuming $\varepsilon_{i,n}$ to be generalized extreme value distributed (*66*), the multinomial logit model results in $P_n(i)$, the probability of bridge choice type i (among all the types I) for evacuee n (*62*):

$$P_n(i)=\frac{\exp\left[\beta_i X_{i,n}\right]}{\sum_I \exp\left[\beta_i X_{I,n}\right]} \tag{2}$$

An important assumption in the multinomial logit approach is that the disturbance terms $\varepsilon_{i,n}$ are assumed to be independently and identically distributed from irrelevant alternatives. This assumption indicates that the relative probability of choosing an alternative remains unchanged if a choice option is removed from the choice set and erroneous specification could result when this assumption does not hold; that is, a subset of the alternatives shares the same unobserved effects. The consideration of a nested logit model (*66*) accounts for such an issue by nesting different alternatives to cancel out the shared unobserved effects in each nest (*62*). Although nested logit models can only handle issues related to independence of (from) irrelevant alternatives, the mixed logit model is preferred since it accounts for both the former assumption and unobserved heterogeneity across observations.

In order to account for the variations of parameters across different evacuees (variations in β), a mixing distribution is proposed for the bridge choice probabilities (*61*):

$$P_n(i)=\int \frac{\exp\left[\beta_i X_{i,n}\right]}{\sum_I \exp\left[\beta_i X_{I,n}\right]} f(\beta|\varphi)\,d\beta \tag{3}$$

where

$P_n(i)$ = probability of bridge choice type i (among all types I),
$f(\beta|\varphi)$ = density function of β, and
φ = vector of parameters of density function (mean and variance).

This β can now allow evacuee-specific variations of the effect of X on bridge choice probabilities and the density function $f(\beta|\varphi)$ 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 (*67*). Since the estimation of maximum likelihood of mixed logit models is computationally cumbersome, a simulation-based maximum likelihood method is preferred. Out of different simulation-based techniques, Halton draws provide more efficient distribution of draws for numerical integration than purely random draws (*68*). McFadden and Ruud (*69*), Stern (*70*), and others offer details about the simulation-based maximum likelihood methods. In this study, 200 Halton draws were considered since 200 Halton draws are usually sufficient for accurate parameter estimation (*68, 71*) and random parameters are assumed to be normally distributed. The probability of the outcome in the case of a mixed-logit model is replaced by the corresponding simulated probability obtained from repeated Halton draws.

MODEL ESTIMATION RESULTS

By following the modeling framework just discussed, a multinomial logit model with random parameters (i.e., a mixed logit model) is estimated in this study. To model evacuees' bridge choice decisions within a mixed logit framework, NLOGIT Version 4.0 was used (*72*). All the explanatory variables used in the model are generic variables that are common among the alternatives except the distance variable, which varies across different alternatives. A discussion of the model goodness-of-fit measures, estimated parameters, and marginal effects is presented in the subsequent sections.

Goodness-of-Fit Measures

To distinguish between the estimated mixed logit (random-parameter logit) model and the standard logit (fixed-parameter logit) model, the estimation results of both of the models are reported in Table 2. In addition, a likelihood ratio test is run to test the overall statistical significance of the mixed logit model over the standard logit model. Here, the likelihood ratio (LR) is calculated with the following equation:

$$\mathrm{LR}=-2\left[\mathrm{LL}\left(\beta_{\text{fixed}}\right)-\mathrm{LL}\left(\beta_{\text{random}}\right)\right] \tag{4}$$

where $\mathrm{LL}(\beta_{\text{fixed}})$ is the log likelihood at convergence of the standard logit model (fixed) and $\mathrm{LL}(\beta_{\text{random}})$ is the log likelihood at convergence of the random-parameter logit model (mixed). 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 9.533 and the critical value of $\chi^2_{0.05,2}$ (5% level of significance or 95% level of confidence and degrees of freedom equal to 2) is 5.990 (Table 3). As a result, the null hypothesis of no random parameters (i.e., a fixed-parameter logit model) is rejected and the validity of the mixed logit model over the standard fixed-parameter logit model is established. To compare the goodness-of-fit measures for both of the models, the values of ρ^2 and adjusted ρ^2 are also reported in Table 3.

Parameter Estimates

As presented in Table 2, most of the variables included in the mixed logit model are statistically significant with plausible signs at the usual 5% or 10% levels of significance except four important evacuation-specific variables (time, day, destination, and previous experience). Despite relatively low *t*-statistics, these variables are included in the model by assuming that they influence the choice of a routing strategy and by following the discussion on criteria for omitting a variable by Ben-Akiva and Lerman (*73*). Two parameters in the model are treated as random (vary across the population) since their standard deviations are statistically significant for their assumed normal distribution, whereas the others are treated as fixed parameters (standard errors not significantly different from zero).

The constant terms are defined for the MacArthur Causeway and Venetian Causeway utility functions, which indicate, all else being equal, that the evacuees are more likely to take Venetian Causeway followed by MacArthur Causeway as compared with the other alternatives. Everything else being the same, Venetian Causeway is the most preferred bridge because it has the lowest annual average daily traffic (fewer than 15,000 vehicles) (*74*). This finding is similar to that for Hurricane Ivan, when evacuees took the route that they thought would be the least congested (*6*). The natural logarithm of distance from origin to the evacuation destination along different bridges is included in all utility functions of the model since this variable varies across different alternatives (*62*). The negative sign indicates that the likelihood of a bridge's being selected decreases with increasing distance. The natural logarithm of this distance is used in

TABLE 2 Estimation Results of Logit Models for Choice of Evacuation Bridge

Estimation Result	Random-Parameter Model Coefficient	Random-Parameter Model t-Stat.	Random-Parameter Model Marginal Effect	Fixed-Parameter Model Coefficient	Fixed-Parameter Model t-Stat.	Fixed-Parameter Model Marginal Effect
MacArthur Causeway						
Constant	2.107	2.55	na	1.690	2.52	na
Natural logarithm of distance (mi)	–6.169	–5.50	–3.534	–4.464	–5.89	–0.693
Indicator variable for evacuation mode (1 if evacuee is most likely to evacuate by a car, 0 otherwise)	–1.514	–2.41	–0.152	–1.204	–2.47	–0.187
Indicator variable for evacuation time (1 if evacuee is most likely to evacuate between noon and 6:00 p.m., 0 otherwise)	–0.616	–1.40	–0.029	–0.569	–1.65	–0.088
Indicator variable for evacuation destination (1 if evacuee is most likely to evacuate to a shelter or a hotel, 0 otherwise)	–0.528	–1.12	–0.013	–0.335	–0.83	–0.052
Venetian Causeway						
Constant	2.462	2.29	na	1.991	1.93	na
Natural logarithm of distance (mi)	–6.591	–5.89	–1.070	–4.826	–6.34	–0.210
Indicator variable for evacuation day (1 if evacuee is most likely to evacuate one day before landfall, 0 otherwise)	1.561	2.07	0.028	1.110	1.72	0.048
Indicator variable for previous evacuation experience (1 if evacuee evacuated previously for a hurricane, 0 otherwise)	–1.981	–2.72	–0.035	–1.557	–2.47	–0.068
Indicator variable for race (1 if evacuee is white, 0 otherwise)	–2.386	–2.07	–0.040	–1.641	–1.95	–0.071
(SD of the parameter estimate)	(1.611)	(1.83)	na	na	na	na
Julia Tuttle Causeway						
Natural logarithm of distance (mi)	–6.062	–5.51	–2.259	–4.462	–5.95	0.943
Indicator variable for race (1 if evacuee is white, 0 otherwise)	–0.285	–0.35	0.041	0.714	1.60	0.151
(SD of the parameter estimate)	(5.024)	(3.80)	na	na	na	na
John F. Kennedy Causeway						
Natural logarithm of distance (mi)	–6.318	–5.72	–2.478	–4.616	–6.18	–0.462
Indicator variable for evacuation time (1 if evacuee is most likely to evacuate between 6:00 a.m. and noon, 0 otherwise)	0.836	1.83	0.037	0.733	1.84	0.073
Broad Causeway						
Natural logarithm of distance (mi)	–6.320	–5.72	–2.428	–4.610	–6.17	–0.460
Number of years lived in South Florida	0.027	2.23	0.067	0.022	2.09	0.002
Indicator variable for evacuation time (1 if evacuee is most likely to evacuate between noon and 6:00 p.m., 0 otherwise)	–0.879	–1.77	–0.025	–0.656	–1.57	–0.065
Haulover Bridge						
Natural logarithm of distance (mi)	–6.096	–5.52	–1.991	–4.437	–5.91	–0.341
Indicator variable for gender (1 if evacuee is female, 0 otherwise)	1.249	2.15	0.062	0.875	1.77	0.067
Indicator variable for evacuation day (1 if evacuee is most likely to evacuate 2 days before landfall, 0 otherwise)	–0.731	–1.29	–0.012	–0.711	–1.34	–0.055
Indicator variable for evacuation mode (1 if evacuee is most likely to evacuate by a car, 0 otherwise)	–1.251	–1.68	–0.068	–0.776	–1.20	–0.060
Indicator variable for previous evacuation experience (1 if evacuee evacuated previously for a hurricane, 0 otherwise)	–0.713	–1.37	–0.024	–0.618	–1.36	–0.048

NOTE: *t*-stat. = *t*-statistic; na = not applicable.

TABLE 3 Goodness-of-Fit Measures for Random- and Fixed-Parameter Logit Models

Goodness-of-fit Measure	Random Parameters	Fixed Parameters
Number of parameters	24	22
Log likelihood at zero, LL(0)	–444.3563	–444.3563
Log likelihood at convergence, LL(β)	–339.3677	–344.1343
ρ^2	0.236	0.226
Adjusted ρ^2	0.182	0.176
LR test[2]	Random versus fixed parameters	
$LR = -2[LL(\beta_{fixed}) - LL(\beta_{random})]$	9.533	

[a]Degrees of freedom = 2; critical $\chi^2_{0.05,2}$ (0.95% level of confidence) = 5.990; number of observations = 248.

the model to achieve normality, and the use of linear distance indicates that an undefined increment of distance has the same linear effect in the choice probabilities, which is unrealistic. Estimation of different parameters for the six distances suggests that distance is not valued equally via the six bridges and distance on the Venetian Causeway is the most onerous ($\beta = -6.591$).

The proposed model is also capable of explaining the effects of several evacuation-specific indicator variables (evacuation day, time, destination, and mode) on a specific bridge choice strategy. The indicator variables for evacuation day were defined for Venetian Causeway and Haulover Bridge utility functions. Evacuees who are most likely to evacuate one day before the hurricane landfall will prefer Venetian Causeway over any of the other bridges ($\beta = 1.561$) because people evacuating close to landfall may consider the other bridges overcongested whereas Venetian Causeway usually experiences the least amount of traffic with less than 15,000 AADT (*74*). However, evacuees who would like to evacuate 2 days before landfall are less likely to take Haulover Bridge as compared with the other alternatives. As far as evacuation time is concerned, John F. Kennedy Causeway is preferred by the evacuees who are most likely to evacuate in the morning (between 6:00 a.m. and noon) than any other bridge ($\beta = 0.836$). However, people evacuating in the afternoon (between noon and 6:00 p.m.) are less likely to take Broad Causeway ($\beta = -0.879$) followed by MacArthur Causeway ($\beta = -0.616$).

Miami Beach residents, who are most likely to evacuate to a hotel or a public shelter, are less likely to take MacArthur Causeway than any other bridge ($\beta = -0.528$). Sadri et al. found the evacuation destination to be a determining factor for a given routing strategy of evacuees who evacuated during Hurricane Ivan (*6*). An indicator variable for evacuation mode (evacuees most likely taking a car) was defined for both MacArthur Causeway and Haulover Bridge utility functions. With a negative sign, the estimated parameter suggests that evacuees taking a car to evacuate will be less likely to take MacArthur Causeway ($\beta = -1.514$) followed by the preference of taking the Haulover Bridge ($\beta = -1.251$). Previous evacuation experience plays an important role in different evacuation-related decisions. For example, Hasan et al. used evacuation experience as an indicator variable to study the question of whether or not to evacuate (*18*), whereas Sadri et al. used it to study the evacuation mode choice decision of Miami Beach residents (*39*). In this study, the indicator variable for previous evacuation experience was defined both for Venetian Causeway ($\beta = -1.981$) and for Haulover Bridge ($\beta = -0.713$). The negative parameters indicate that people having previous experience will be more likely to avoid these two bridges, that is, be less likely to take them.

The positive parameter on the gender indicator variable suggests that women are more likely to take the Haulover Bridge than any of the other five bridges. The variable representing number of years lived in South Florida is defined for the Broad Causeway utility function and the positive parameter indicates that the likelihood of taking the Broad Causeway increases with the number of years an evacuee has lived in South Florida. Sadri et al. found that the more an evacuee gains in traffic experience over time in a given location, the more confident she or he becomes in terms of route selection (*6*). Turning to the two random parameters estimated in the model, a race indicator variable was defined for both the Venetian Causeway and Julia Tuttle Causeway utility functions. With a mean of –2.386 and standard deviation of 1.611, the parameter estimates for the white indicator variable imply that 93% of the evacuees who are white have a lower probability of taking the Venetian Causeway to evacuate while the remaining 7% have a higher probability. However, 52% of the evacuees who are white have a lower probability of taking the Julia Tuttle Causeway while the remaining 48% have a higher probability (mean = –0.285 and standard deviation = 5.024). Both of the random parameters in the model were assumed to be normally distributed and standard deviations of the parameter estimates were statistically significant. Since the majority of Miami Beach residents are white by race (87.4%), this is an important finding that captures the unobserved heterogeneity across different evacuees (*7*).

Marginal Effects

Although the model explains the combined effects of the explanatory variables, marginal effects of the corresponding variables are also reported in order to determine the importance of individual parameters (see Table 2). Marginal effects are more appropriate in order to demonstrate indicator or dummy variables that can be computed as the difference in the estimated probabilities with the indicator variable changing from zero to 1, whereas all other variables are equal to their means (*62*). In this study, the average marginal effect across all observations is reported since each observation in the data has its own marginal effect. From the average marginal effect, for female evacuees the probability of taking the Haulover Bridge increases by 0.062 as compared with that of the male evacuees. For the indicator variable for evacuation mode (evacuees taking a car to evacuate), the average marginal effect suggests that the probability of taking the MacArthur Causeway decreases by 0.152. In addition, the average marginal effect implies that each additional year spent in South Florida increases the probability of taking the Broad Causeway by 0.067.

CONCLUSIONS

From the foregoing discussion and the proposed model, it is possible to make meaningful inferences about the off-beach evacuation routing strategy of Miami Beach residents during a major hurricane. Introducing random parameters helps to account for the heterogeneous responses of the evacuees in selecting a major bridge while evacuating to a safe destination. The proposed model would help practitioners to predict different fractions of people in selecting a major bridge or causeway and to determine the expected level of congestion.

Although only a few studies capture hurricane evacuation routing behavior from the evacuees' point of view, this study presents a mixed logit model to capture the underlying determining factors that influence the evacuation routing behavior of the evacuees from Miami Beach during a major hurricane. The model was developed by using data obtained from a survey that included a hypothetical Category 4 (major) hurricane scenario to reveal the most likely evacuation plans of Miami Beach residents, who need to use one of the six major crossings (MacArthur Causeway, Venetian Causeway, Julia Tuttle Causeway, John F. Kennedy Causeway, Broad Causeway, and Haulover Bridge) in reaching an off-beach destination. Once a household decides to evacuate and selects the evacuation destination, the following step is to select a routing strategy that they think would help them to reach the destination in the minimum possible time. A detailed understanding of this routing behavior is thus required, and a logical interpretation of the routing strategies would help emergency officials and planners to set up efficient evacuation policies and take appropriate control measures.

All of the explanatory variables included in the final model specification have plausible signs and provide useful implications. The combined effects of significant variables including evacuees' sociodemographic attributes (race, gender, etc.), evacuation-related attributes (time and day of evacuation, evacuation mode, and destination), and distance to travel would predict the routing behavior of evacuees in a better way as revealed from this empirical analysis. The random parameters (normally distributed) suggest that their effect varies across the observations and the random-parameter model shows a better fit than its fixed-parameter counterpart. The findings from this study provide some key insights regarding the bridge choice behavior of Miami Beach residents:

- The greater the distance that the evacuees need to travel by using a bridge, the less likely it is that the evacuees will take that bridge.
- Although the majority of Miami Beach residents are white (87.4%), the evacuees' being white results in a lower probability to take the Venetian Causeway (93%) and Julia Tuttle Causeway (52%) as compared with the other crossings.
- All else being equal, the evacuees are more likely to take Venetian Causeway followed by MacArthur Causeway as compared with the other bridges.
- Evacuees will prefer Venetian Causeway if evacuating 1 day before landfall and are less likely take Haulover Bridge if evacuating 2 days before landfall.
- John F. Kennedy Causeway is preferred by the evacuees who are most likely to evacuate in the morning, and afternoon evacuees are less likely to take Broad Causeway and MacArthur Causeway.
- MacArthur Causeway is less preferred by those evacuating to a hotel or public shelter.
- MacArthur Causeway and Haulover Bridge are less preferred by those evacuating by car.
- Female evacuees prefer the Haulover Bridge, and evacuees having previous evacuation experience are less likely to take Venetian Causeway or Haulover Bridge.

The proposed econometric model for evacuation routing behavior of Miami Beach residents would help different stakeholders to sort out more efficient evacuation plans by predicting different fractions of people taking each of the six bridges. Since bridges are the main sources of bottlenecks, it would be possible to determine the level of congestion with the help of this model. Different control measures, such as contraflow and bridge closure, could be employed during a hurricane threat as needed. This model may also be useful in evacuation simulation studies. The model can be used as an important input in terms of bridge choice to determine the evacuation clearance time by building more credible simulation techniques. However, future studies should focus on getting detailed path information of evacuees to develop more robust route choice models for evacuation.

ACKNOWLEDGMENTS

The authors are grateful to the National Science Foundation for grants to support the research presented here. The survey was conducted by Hugh Gladwin of Florida International University. The authors also acknowledge Fred Mannering of Purdue University for his valuable feedback on estimating the mixed logit model.

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The authors are solely responsible for the findings presented in this study.

The Task Force on Emergency Evacuations peer-reviewed this paper.