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Taking the freeway: Inferring evacuee route selection from survey data

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ABSTRACT

Effective evacuation management plans can help reduce the negative impacts of disasters. Understanding evacuee travel behavior is critical for the design of evacuation plans. In this paper, we explore which factors contribute to evacuees selecting freeway vs. non-freeway evacuation routes. Freeways are of particular interest due to their ability to evacuate large volumes of traffic. This study used survey data collected for the Hampton Roads region of Virginia. Respondents were asked to provide their preferred route types in the event of a hypothetical Category 4 hurricane evacuation. A mixed (random parameters) logit model was proposed to determine factors that influence evacuees selecting between freeway and non-freeway route. The study found that several factors contribute to evacuees choosing a freeway over other routes. In the descending order of importance (i.e., marginal effects), these factors are: willingness to use the official recommended route, living in a single-family or duplex housing, expected travel time to reach the destination, being employed, and possessing prior evacuation experience. Conversely, a few factors had a negative effect on choosing a freeway. These factors are: willingness to evacuate two days prior to landfall and evacuating to a public shelter or a second home. The findings of this study can help emergency management and transportation agencies design effective traffic control plans to safely evacuate populations during a hurricane.

Introduction

Hurricanes are a major concern for coastal areas in the United States. The 2018 hurricane season emphasized the substantial role of evacuation in hurricane-prone areas. For example, a large number of people were stuck in gridlock over several hours on the North Carolina Interstate highways during Hurricane Florence (CBS News, 2018). Gridlock could lead to significant injuries and property damage if a storm makes landfall while drivers are still on the road (Lindell et al., 2005). Understanding evacuee travel behavior is critical to the design of effective traffic management plans. Within engineering models, evacuee travel behaviors typically include the evacuate/stay decision, destination choice, departure time, mode choice, and route choice. Evacuation route choice is the primary focus of this study. A better understanding of intended route choice behavior allows planners and policymakers to design more realistic evacuation plans. Route choice is also a critical input to simulation models used to test evacuation traffic management plans and traffic control strategies. Developing such models with more detailed human behavioral data will improve their value.

Simulation models are often based on aggregate assumptions of behavior. The most famous of these are the system optimum, which minimizes the collective travel time for all vehicles, and user equilibrium, in which each traveler minimizes his/her individual travel time (Wardrop, 1952). System optimum is generally considered an ideal, which cannot be currently obtained. User equilibrium is more practically obtained through repeated experience with the transportation network under similar conditions and travel information systems. Fang and Edara (2013) reported the sensitivity of evacuation performance estimates to evacuee route choice behavior. Because of the lack of repeated experience with evacuation traffic conditions, true equilibrium in unlikely to be obtained in reality. To better understand the conditions that may emerge from individual preferences, models of route selection developed from disaggregated data can identify factors influencing this choice.

Evacuation processes are complex and involve a series of related decisions. Homeowners must choose to evacuate or stay, they must decide when to go, how many cars to take, where to seek accommodations, a destination, and a route(s) that would help them reach their

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destination efficiently. State transportation agencies typically work to influence those decisions with communications and through planning efforts, such as designating evacuation routes. The intersections between homeowners and agency choices are important for life and livelihood. To better understand those choices, social scientists have developed a number of theoretical models of the related behavioral choices and their influences on action including the Protective Action Decision Making (Lindell and Perry, 2012), Warning Processing (Mileti and Sorensen, 1990), and Risk Interpretation and Action (Eiser et al., 2012). While this particular analysis was not developed with one theoretical model in mind, in building the survey on which this analysis was based, we controlled for or considered a broad range of survey items that influence evacuations decisions as represented in these models. For example, variations in information provided by official agencies and other sources, access to information, environmental cues, social cues, prior experiences, impediments such as limited income, demographic differences, and other factors.

Using the data described above, the objective of this study is to develop a household evacuation route choice model based on survey data collected from households in the Hampton Roads area of Virginia. The study area includes the nine cities of Chesapeake, Hampton, Newport News, Norfolk, Poquoson, Portsmouth, Richmond, Suffolk, and Virginia Beach. The survey collected socio-demographic information and evacuation-related characteristics related to route selection. A mixed logit (random parameter logit) model was then developed to identify the factors influencing the selection of freeways versus non-freeways.

The rest of the paper consists of five sections. The first explains the background and previous literature related to hurricane evacuation route choice. The second discusses the discrete choice methods utilized to develop the model. The third section describes the data used in this study. The fourth section presents the results of model estimation and validation. A summary of significant findings and conclusions are drawn in the final section.

Background

Evacuees select an initial route before beginning their evacuation trips. While en-route, they may continually re-evaluate their choice based on the traffic they are currently experiencing as well as traffic information from a variety of sources, such as mobile navigation applications, variable/dynamic/changeable message signs (VMS/DMS/CMS), and radio traffic reports. Since the data in this study comes from a behavioral intention survey, the focus of this literature review is on pre-trip route selection.

Evacuees often base their pre-trip route choice on their regular routes to their destinations (Lindell et al., 2018). Familiarity with the route, as well as believing that it will be the fastest or shortest, have been cited as reasons for choosing a particular route during Hurricanes Ivan, Katrina (Murray-Tuite et al., 2012), and Lili (Lindell et al., 2011). Freeways typically have higher design speeds and greater capacities than lower classifications of roadways, suggesting that many evacuees will select freeways when provided a choice. Dow and Cutter (2002) found that this inherent preference can lead to a severe imbalance of traffic where freeways are over-utilized, and other routes are underutilized. Chiu and Mirchandani (2008) also found a preference for freeways in a stated preference questionnaire.

However, some evacuees with prior evacuation experience anticipate severe congestion on their normal routes and may select other routes, expecting them to be less congested (Lindell et al., 2018). Lindell et al. (2001) study of five hurricane areas in Texas indicated that between 9 and 37 percent of potential evacuees intended to use unofficial evacuation routes. While the exact methodology for defining evacuation routes is not readily available in published literature, they tend to be high capacity roadways perpendicular to the hazard when possible (Lindell et al., 2018).

The designation of a route as an evacuation route by a transportation agency is not necessarily the governing reason for its use, and not all evacuees have information about the official routes (e.g., only 26 percent of Hurricane Bret evacuees received such information (Zhang et al., 2004). As discussed above, evacuees select their routes based on familiarity and belief that it will be the fastest, at least partially aligning with user equilibrium assumptions. In addition to these criteria, Prater et al. (2000) study found that 69 percent of their respondents (Hurricane Bret) thought their route was the most logical, 4 percent followed hurricane evacuation maps, 3 percent followed official recommendations, and 24 percent based their decisions on other reasons. Similarly, in a study of Hurricane Katrina and Rita evacuees, Wu et al. (2012) found that evacuees relied on the following sources from most to least: past experience, en-route traffic conditions, recommendations from news media, recommendations from local authorities, and written evacuation guidance. However, Carnegie and Deka (2010) found a much higher percentage (81) of survey respondents who were likely to self-evacuate would “very likely” follow route instructions.

These differing reasons for selecting routes, information provision, personal familiarity, and prior experience, suggest that individual route selection can be complex to predict. When modeling the major bridge Miami Beach residents intended to use for a hurricane evacuation with a random parameter (mixed) multinomial logit model, Sadri et al. (2015) found a mixture of evacuation characteristics, evacuee characteristics, and distance to the evacuation destination to be significant. Evacuees tended to prefer closer bridges. Race, gender, prior evacuation experience, type of accommodations, evacuation timing (number of days before landfall, and time of day), and transportation mode influenced bridge choice (Sadri et al., 2015). These authors also used Hurricane Ivan survey data and random parameters (mixed), multinomial logit models, to select among the routing strategies of familiar routes and recommended routes, where the familiar routes also included those usually used and thought to be the fastest (Sadri et al., 2014). Variables with mixed effects for at least one utility expression included the number of years of residence in the current home, accommodation type, channel (Lindell and Perry, 2012, 2004) of evacuation notice and the number of days before landfall that the evacuee departed. Variables with fixed effects included geographic home location, evacuation distance, income categories, number of children in the household, and age of the evacuee (Sadri et al., 2014). Our study tests related variables, to the extent that they are present in both the current and prior surveys.

Methods

In this study, we assume that an individual who has decided to evacuate can choose from a choice set of two routes –a freeway or a non-freeway (i.e., arterial/local roads). Logit models comprise of an analytical framework for modeling individual preferences towards alternatives. However, in the derivation and application of a standard logit model one assumes that the parameters or coefficients of variables are fixed across all individuals. When this assumption does not hold, parameter estimates will be inconsistent with reality, and the outcome probabilities would be erroneous (Washington et al., 2010). In such instances, a methodological approach that allows for the variation of parameters is more appropriate and can help capture the variance present in the sociodemographic and evacuation-related attributes of various evacuees. Previous research (Revelt and Train, 1998; McFadden and Train, 2000) has also demonstrated the effectiveness of such a methodological approach that can explicitly account for parameter variability.

The methodological framework for this study is illustrated in Fig. 1. In the first step, a household survey was conducted to collect data pertaining to route selection preferences of potential evacuees. The survey responses were processed by removing incomplete responses and using data encoding procedures to prepare socio-demographic and evacuation-specific data. The next step involved using the prepared data

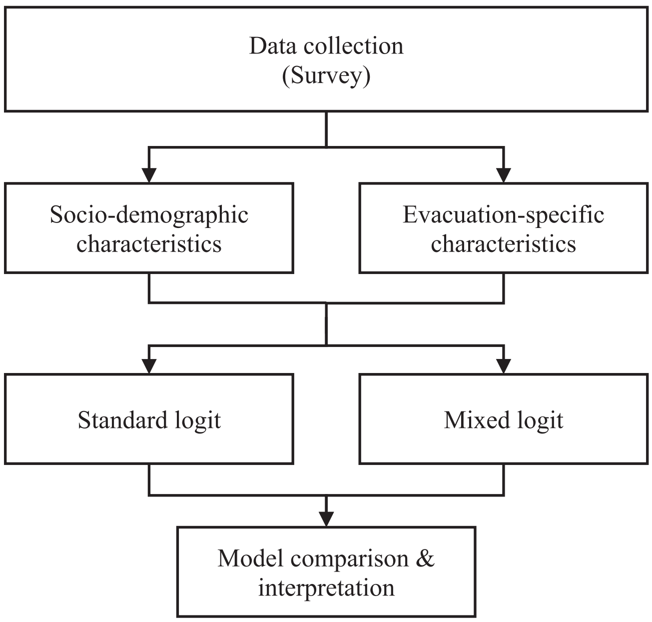

Fig. 1. Modeling Framework.

to estimate logit models for route choice. A backward stepwise method was used in the R statistical computing software to select variables. For variable selection, several goodness of fit measures were utilized including improvements to adjusted R-square, Akaike information criterion (AIC) and Bayesian information criterion (BIC) as well as the significance of each variable (Zhang, 2016). Two binary logit models were estimated using the selected variables; one is a standard logit (fixed-parameter logit) model, the other is a mixed logit (random parameter logit) model. The final step of the methodology involved model validation, interpretation, and comparison of the fixed and mixed logit model results.

The route choice function for evacuee n is presented in Equation 1 (Washington et al., 2010):

$$RS_{i,n} = \beta_i X_{i,n} + \varepsilon_{i,n} \tag{1}$$

where

$RS_{i,n}$ = route choice function determining the route type i.
$X_{i,n}$ = vector of explanatory variables (see Table 1).
β_i = vector of estimable parameters.
$\varepsilon_{i,n}$ = error term.

If $\varepsilon_{i,n}$ are assumed to be generalized extreme value distributed (Manski and McFadden, 1981), the binomial logit model results in $P_n(i)$, the probability of route choice type i among all the types I for evacuee n shown in Equation (2):

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

To consider the variations of parameters across different evacuees, a mixed logit model is used to compute the route choice probabilities (Train, 2009) as shown in Equation (3):

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

where

$P_n(i)$ = probability of route choice type i (among all types I).
$f(\beta|\varphi)$ = density function of β.

Table 1
Descriptive statistics for explanatory variables.

Variable Number	Variable Description	Mean	SD	Type	Range
Response variable					
1	Evacuation route type (if use freeway 1; if not 0)	0.636	0.482	Dichotomous	[0,1]
Socio-demographic characteristics					
2	Evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.288	0.453	Dichotomous	[0,1]
3	Employment status (if employed 1; otherwise 0)	0.559	0.497	Dichotomous	[0,1]
4	Dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	0.868	0.338	Dichotomous	[0,1]
Evacuation-specific characteristics					
5	Evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	0.082	0.275	Dichotomous	[0,1]
6	Evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	0.345	0.476	Dichotomous	[0,1]
7	Willingness to use recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	0.888	0.316	Dichotomous	[0,1]
8	When asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	0.203	0.403	Dichotomous	[0,1]
9	Willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.447	0.498	Dichotomous	[0,1]
10	Expected travel time to reach destination on a normal day (hours)	3.838	3.254	Continuous	[0.16,18]
11	Willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.318	0.466	Dichotomous	[0,1]
12	Evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0)	0.301	0.459	Dichotomous	[0,1]

Φ = vector of estimates of the density function (mean and variance).

The β can now allow evacuee-specific variations of the effects of X on route choice probabilities and the density function $f(\beta|\varphi)$ is used to determine β. The mixed (random parameter) logit probabilities are then obtained by a weighted average for different values of β across evacuees where some factors of the vector β may be fixed and some may be randomly distributed (Gkritza and Mannering, 2008). Simulation approaches are commonly used to estimate the maximum likelihood of mixed logit models. One of the simulation-based approaches considers Halton draws which provide a better distribution of draws for numerical integration than purely random draws (Bhat, 2003). McFadden and Ruud (1994) and Stern (1997) provide further details about the simulation-based maximum likelihood approaches. In this study, we considered 200 Halton draws, which are usually sufficient for accurate estimation under the assumption that parameters are normally distributed (Bhat, 2003).

Data

In this study, data were used from a household survey of the Hampton Roads region in Virginia conducted by the research team in May 2018. The Hampton Roads region has a population exceeding 1.6 million residents. The survey was distributed following the best practices from social science literature. Dillman (2007) recommends five elements for achieving high survey responses rates: respondent-friendly surveys, four contacts through first-class mail, stamped return envelopes, personalization of correspondence, and prepaid financial incentives (p. 150–153). Respondents were presented with a hypothetical scenario of a category 4 storm with wind speeds between 130 and 156 mph forcing a mandatory evacuation of the region and included questions related to evacuation, risk perception, past experience, hurricane planning, and demographics. The sample for the survey was purchased from Genesys, a branch of the Marketing Systems Group, which utilizes the U.S. Postal Service's address database system to select random addresses for research purposes. In selecting from that database the sample included zipcodes in coastal areas near Hampton Roads, Virginia. In order to be eligible to participate in the survey, respondents must be at least 18 years old. Completed surveys were returned by 415 households. The blue ovals in Fig. 2 show the approximate locations of the respondents.

The response rates for the general survey were AAPOR Response Rate 2 = 19%, AAPOR Cooperation Rate = 96%, AAPOR Refusal Rate 1 = 1%, AAPOR Contact Rate 1 = 20%. After checking the reliability of the survey responses, 22 observations were removed due to respondents choosing 'I don't know' for the route and another 28 observations were removed due to missing responses to one or more questions. Thus, data from 365 (of 415) observations were deemed to be valid for the analysis. Sixty-four percent of the households (232 out of 365) that responded to the survey said they would choose a freeway to evacuate while the remaining 36% (133 of 365) said they would use a non-freeway route. Sadri et al. (2015) showed that evacuees are more likely to use usual or familiar route during their evacuation. For evacuees traveling to destinations out of the region, they may prefer to use a freeway as they would in normal conditions for long trips. The stepwise selection process resulted in 11 explanatory variables. The variables include both household socio-demographic information and evacuation-related characteristics such as employment status, evacuation accommodation, expected travel time to the destination, the time and day of the evacuation, and previous evacuation experience. Table 1 shows the variables used in the final model specification and their descriptive statistics. Table 2 shows the correlations between variables. The correlation values in most cases were less than 0.2 (threshold commonly used for variable selection) (Mukaka, 2012). There was only one correlation value of −0.229 that slightly exceeded the 0.2 thresholds. In terms of the correlation between the dependent and independent variables, evacuation accommodation, expected travel time to reach destination on a normal day and dwelling type had the highest correlation to the dependent variable of route choice.

Results and discussion

5.1. Fixed logit model

Past studies have used logit model to identify factors for route preference during an evacuation. Sadri et al. (2014) and Sadri et al. (2015) developed mixed logit (random parameter) model to reflect the heterogeneity of preference of evacuees. In this study, we used mixed logit model and compared it to a fixed logit model. Validation was performed using bootstrapping (Kohavi, 1995). Giancristofaro and Salmaso (2007) describe validation process to have three steps – exclude a sub-sample of observations, develop a model using remaining samples, and then test the model on the initially excluded sub-sample. Efron and Tibshirani (1997) and Steyerberg et al. (2004) showed that bootstrap is a

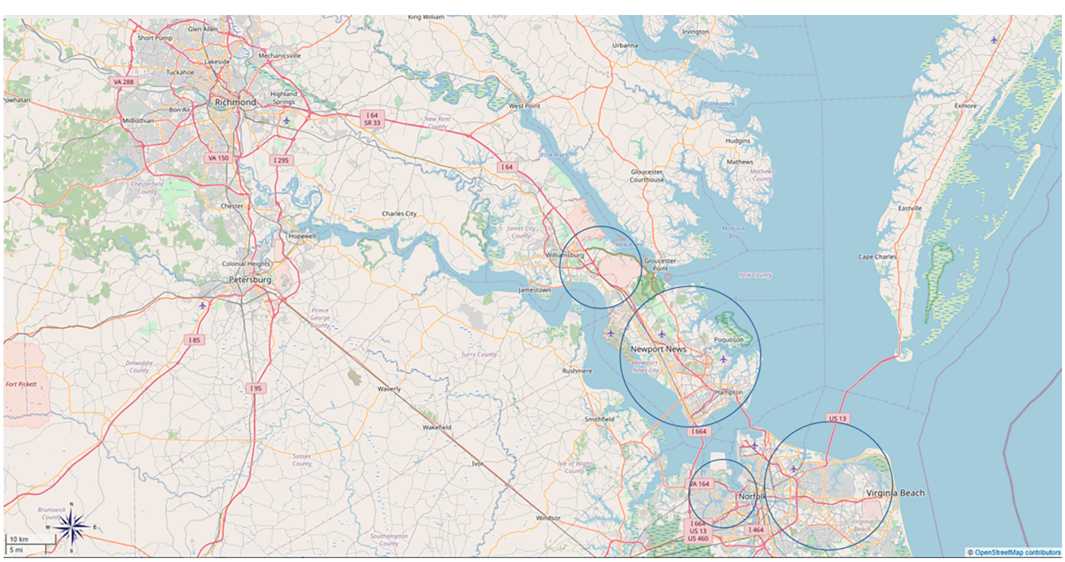

Fig. 2. Household surveys from the Hampton Roads region of Virginia (Source: © OpenStreetMap contributors licensed as CC-BY-SA, http://www.openstreetmap.org/copyright).

Table 2
Correlation matrix.

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1		0.13	0.16	0.18	−0.23	−0.01	0.16	0.09	0.04	0.19	0.10	0.14
2	0.13		−0.09	−0.01	−0.06	0.11	0.07	0.01	0.01	0.01	−0.01	−0.10
3	0.16	−0.01		0.14	−0.06	0.03	0.05	0.02	−0.01	0.07	−0.02	0.14
4	0.18	−0.01	0.14		−0.12	−0.01	0.02	−0.05	0.07	0.04	0.04	0.04
5	−0.22	−0.06	−0.06	−0.12		−0.05	0.01	−0.05	0.05	−0.14	−0.03	−0.04
6	−0.01	0.11	0.03	−0.01	−0.05		−0.02	0.14	−0.07	0.18	−0.01	0.13
7	0.16	0.07	0.05	0.02	0.01	−0.02		−0.17	−0.12	0.02	0.08	0.10
8	0.10	0.01	0.02	−0.05	−0.05	0.14	−0.17		−0.04	0.06	−0.01	−0.01
9	0.04	0.01	−0.01	0.07	0.05	−0.07	−0.12	−0.04		−0.11	0.01	−0.07
10	0.19	0.01	0.07	0.04	−0.14	0.18	0.02	0.06	−0.11		−0.07	0.09
11	0.10	−0.01	−0.02	0.04	−0.03	−0.01	0.08	−0.01	0.01	−0.08		0.04
12	0.14	−0.10	0.14	0.04	−0.04	0.13	0.10	−0.01	−0.07	0.09	0.04	

more efficient internal validation process compared to data-splitting, repeated data-splitting, jack-knife method, in terms of stable variance and low bias.

Table 3 shows the results of the fixed logit model and validation using the bootstrap method. The results of Table 3 show that all the explanatory variables were significant at the 10% level of significance. Also, the bootstrap results (of variable significance) were consistent with those in the estimated model, thus validating the model.

5.2. Mixed logit model

A mixed logit model with random parameters was also estimated in this study. Table 4 shows that most of the variables included in the random-parameter model are statistically significant (at 10% level of significance) with plausible signs. Only two variables were not significant at the 10% significance level; willingness to use multiple personal vehicles (p-value of 0.11) and willingness to evacuate early when expecting delay (p-value of 0.11). Nevertheless, these two variables were kept in the model due to their potential influence on evacuee's preference to choose a freeway (as evidenced by their positive coefficient signs). The parameters of departure hour produced statistically significant standard deviations for their assumed (normal) distributions. All other variables have fixed parameters. The positive value of a parameter means that evacuees are more likely to choose a freeway than a non-freeway.

5.3. Model validation

The performance of the fixed and mixed logit models was compared. A likelihood ratio (LR) was computed using the difference between the log-likelihood values of the mixed logit model and fixed logit model as shown in Equation (4) (Sadri et al., 2015):

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

where $\mathrm{LL}(\beta_{random})$ is the log-likelihood at convergence of the mixed logit (random-parameter) and $\mathrm{LL}(\beta_{fixed})$ is the log-likelihood at convergence of the standard logit (fixed-parameter) model. LR is χ^2-distributed with degrees of freedom equal to the difference in the number of parameters in both the models. The value of LR is 4.996 and the critical value of $\chi^2_{0.05,1}$ (5% significance level and degrees of freedom equal to 1) is 3.841. As a result, the null hypothesis of no random parameters can be rejected (Sadri et al., 2015). The goodness-of-fit measure, McFadden's pseudo R square (ρ^2), for both models are reported in Table 5. The ρ^2 value ranges between 0 and 1, with a value close to 1 indicating the best fit. Domencich and McFadden (1975) described that the ρ^2 values between 0.2 and 0.4 are considered to be an excellent fit for logit models. The ρ^2value for the mixed logit model (0.17) was slightly better than the ρ^2value of 0.159 for the fixed logit model.

The estimated models were also validated using the likelihood ratio test as implemented in Sadri et al. (Sadri et al., 2014). The dataset was split into two equal samples. After splitting the data, two separate models were analyzed with the same specification using these two samples. The likelihood ratio test statistic is shown in Equation (5).

$$\mathrm{LR} = -2[LL(\beta_{Full}) - LL(\beta_{sample1}) - LL(\beta_{sample2})] \tag{5}$$

where $LL(\beta_{Full})$ is the log-likelihood at the convergence of the model estimated using the full data and $LL(\beta_{sample1})$ is the log-likelihood at the convergence of the model estimated using sample 1, which is equal to −93.702, $LL(\beta_{sample2})$ is the log-likelihood at convergence of the model estimated using sample 2, which is equal to −97.358. According to Equation (5), the LR value is 15.417 and the degrees of freedom are equal to 13. Since $\chi^2_{0.05,13}$ is equal to 22.362, this test fails to reject the null hypothesis that the parameters across different samples are equal. As a result, this test validates the model specification applied in this study.

5.4. Model interpretation

The results of the two logit models are shown in Table 6. The parameter for the evacuation experience indicator variable has a positive sign. From the average marginal effect, for evacuees who have prior evacuation experience, the probability of selecting freeways increased (3.6% for the mixed model, 9.6% for the fixed model). These individuals may have experienced congestion during their prior evacuation and anticipate that freeways will provide faster travel times in their next evacuation.

Being employed also increased the chance of someone choosing a freeway for evacuation (5.5% for the mixed logit model, 10.1% for the fixed model). Under normal conditions too, Chang and Sohn (2015) reported that commuters are more likely to use freeways when traveling to work. Thus, familiarity using freeways could be a contributor to their use during evacuation. The dwelling type variable demonstrated that individuals living in a single-family home, duplex, or townhome had a higher preference (14.2% for the mixed logit model, 16.7% for the fixed logit model) towards freeways. The negative parameter for accommodation type shows that those who want to evacuate to a shelter or a second home prefer to use non-freeways rather than freeways. The marginal effect only shows a slightly decreased preference (2.0%) for the mixed logit model and a 8.4% decrease for the fixed logit model. Shelters may be located fairly close to the evacuee's home, making freeway use less practical. Another variable with a negative parameter was the lead time for an evacuation. If an evacuee were to depart two days in advance of landfall, their probability of using non-freeway routes over freeways increases by 3.4% for mixed logit model (9.4% for the fixed logit model) compared to individuals leaving earlier or later. Potentially, those leaving closer to landfall perceive freeways as providing a faster travel time, needed to arrive safely at their destination before hurricane hazards arrive.

Table 3
Estimation and validation results for standard logit model of evacuation route choice.

Explanatory variables	Fixed parameter model			Bootstrap results	
	β	P-value	Marginal effect	Bias	P-value
Constant	2.588	0.000		0.141	0.000
Indicator variables for evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.731	0.010	0.096	0.036	0.014
Indicator variables for employment status (if employed 1; otherwise 0)	0.543	0.028	0.101	0.011	0.039
Indicator variables for dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	0.899	0.011	0.167	0.046	0.022
Indicator variables for evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	−1.529	0.001	−0.084	−0.084	0.012
Indicator variables for the evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	−0.506	0.059	−0.094	−0.021	0.073
Indicator variables for willingness to use the recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	1.153	0.003	0.215	0.062	0.006
Indicator variables when asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	0.888	0.009	0.065	0.055	0.011
Indicator variable for willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.451	0.075	0.064	0.025	0.087
Expected travel time to reach destination on a normal day (hour)	0.139	0.002	0.026	0.008	0.002
Indicator variable for willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.486	0.070	0.057	0.019	0.094
Indicator variable for evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0)	0.561	0.049	0.044	0.028	0.085

Table 4
Estimation results of mixed logit model for evacuation route choice.

Explanatory variables	Random parameter model		
	β	P-value	Marginal effect
Constant	3.096	0.000	
Indicator variables for evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.858	0.008	0.036
Indicator variables for employment status (if employed 1; otherwise 0)	0.698	0.016	0.055
Indicator variables for dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	1.078	0.009	0.142
Indicator variables for evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	−1.944	0.001	−0.020
Indicator variables for the evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	−0.648	0.042	−0.034
Indicator variables for willingness to use the recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	1.360	0.002	0.181
Indicator variables when asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	1.109	0.006	0.029
Indicator variable for willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.463	0.114	0.031
Expected travel time to reach destination on a normal day (hour)	0.167	0.001	0.087
Indicator variable for willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.502	0.111	0.023
Indicator variable for evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0) (Standard deviation of the parameter estimate)	1.771 (3.217)	0.104 (0.073)	0.001

Table 5
Goodness-of-fit measures for the random and fixed parameter logit models.

Goodness-of-fit Measures	Random parameter model	Fixed parameter model
Number of parameters	13	12
Log likelihood at zero, LL (0)	−252.998	−252.998
Log-likelihood at convergence, LL (β)	−198.768	−201.266
ρ^2	0.170	0.159
LR$test^2$	Random versus fixed parameters	
LR $= -2[\mathrm{LL}(\beta_{random}) - LL(\beta_{fixed})]$	4.996	
Number of observations	365	

Two interesting trends were observed with respect to the response to evacuation recommendations from emergency officials. Those individuals willing to use the recommended route exhibited a higher probability, of 18.1% for mixed logit model and 21.5% for fixed logit model, to use freeways. On the other hand, freeways were also preferred by individuals who would not comply with the recommended departure times. The marginal effect was higher (2.9% for the mixed logit model, 6.5% for the fixed logit model) for choosing a freeway for these individuals compared to those who believed they would comply with the recommended evacuation time. Those respondents who said they would use multiple personal vehicles to evacuate also expressed higher preference (3.1% for the mixed logit model, 6.4% for the fixed logit model) for choosing a freeway. Expected travel time to reach the destination on a normal day was positively associated with a preference for freeways.

Table 6
Comparison of random parameter model and fixed parameter model.

Explanatory variables	Random parameter model (Mixed logit)			Fixed parameter model (Fixed logit)		
	β	P-value	Marginal effect	β	P-value	Marginal effect
Constant	3.096	0.000		2.588	0.000	
Indicator variables for evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.858	0.008	0.036	0.731	0.010	0.096
Indicator variables for employment status (if employed 1; otherwise 0)	0.698	0.016	0.055	0.543	0.028	0.101
Indicator variables for dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	1.078	0.009	0.142	0.899	0.011	0.167
Indicator variables for evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	−1.944	0.001	−0.020	−1.529	0.001	−0.084
Indicator variables for the evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	−0.648	0.042	−0.034	−0.506	0.059	−0.094
Indicator variables for willingness to use the recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	1.360	0.002	0.181	1.153	0.003	0.215
Indicator variables when asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	1.109	0.006	0.029	0.888	0.009	0.065
Indicator variable for willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.463	0.114	0.031	0.451	0.075	0.064
Expected travel time to reach destination on a normal day (hour)	0.167	0.001	0.087	0.139	0.002	0.026
Indicator variable for willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.502	0.111	0.023	0.486	0.070	0.057
Indicator variable for evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0) (Standard deviation of the parameter estimate)	1.771 (3.217)	0.104 (0.073)	0.001	0.561	0.049	0.044

Respondents showed a higher probability (8.7% for the mixed logit model, 2.6% for the fixed logit model) of choosing freeways for every 1% increase in travel time. Potentially, longer normal travel times indicate a farther destination, for which freeways may be more direct than other routes. When asked if the route preference would depend on early departure due to expected congestion, there was a higher preference (2.3% for the mixed logit model, 5.7% for the fixed logit model) to choose a freeway to evacuate among those that said they would depart early to avoid reaching their destination at the same time as hurricane landfall. The hour of departure variable was modeled using a random parameter. For the fixed logit model, for evacuees willing to leave between 12 am and 6 am, the probability to use freeways increased by 4.4%. For the mixed logit model, with a mean of 1.771 and a standard deviation of 3.217 (assuming a normal distribution of the parameter), it indicates that 17% of the evacuees who departed from their homes between midnight and dawn (6:00 a.m.) results in a lower probability of using freeways, whereas the remaining 83% have a higher probability of using freeways.

Thus, in summary, several factors contribute to evacuees choosing a freeway over other routes. In the descending order of marginal effects, these factors are: willingness to use the official recommended route, living in a single-family or duplex housing, expected travel time to reach the destination, being employed, and possessing prior evacuation experience. Conversely, a few factors had a negative effect on choosing a freeway. These factors are: willingness to evacuate two days prior to landfall and evacuating to a public shelter or a second home.

6. Conclusion

Freeway facilities carry large amounts of vehicular traffic in urban areas. They play a critical role in regional evacuations. In this study, factors influencing individual preferences for choosing a freeway were investigated. There are some practical implications of the study findings. Knowledge of factors having a positive effect on freeway route selection can help agencies better optimize the evacuation process. If freeways are expected to be underutilized during an evacuation, an agency might target one or more of the above factors to motivate individuals to use freeways. For example, an agency can recommend the use of freeways to evacuees who plan to leave two days before landfall reinforcing their innate preference. Capacity enhancing strategies such as contraflow lanes and use of hard shoulders could also be implemented for this time period for high demand areas. On the other hand, if freeways are expected to be overutilized, the agency can design countermeasures based on the same factors to encourage the use of local roads and arterials (i.e. non-freeways). Countermeasures such as traffic signal coordination in the outbound direction can be implemented on arterial streets and have public informed about the improvements. Conversely, ramp closures can be strategically determined to improve the utilization of local streets and reduce overcrowding of freeways. Finally, the factors that contribute to evacuees choosing a freeway found in this study could be used as contextual variables when modeling the performance of evacuation strategies using normative performance measurement models. This study can be expanded in a few ways in the future. Survey could be expanded to provide more insight into route choice. For example, questions related to perceived level of safety of an evacuation route, travel costs (e.g. tolls) of using a route, availability of services along an evacuation route, use of ride sharing, and decision making during a staged evacuation would provide new insights. While this study simplified the choice set (freeway vs. non-freeway), use of combination of freeway and non-freeway routes during an evacuation (e.g. 70% freeway, 30% local roads) could also be investigated.

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Author contributions

The authors confirm contribution to the paper as follows: study conception and design: D. Chang, P. Edara, P. Murray-Tuite; data conceptualization, measurement, and collection: J.Trainor; analysis and interpretation of results: D. Chang, P.Edara, P. Murray-Tuite; draft manuscript preparation: D.Chang; manuscript revision: D.Chang, P. Edara, P.Murray-Tuite, J.Trainor, K.Triantis. All authors reviewed the results and approved the final version of the manuscript.

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