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The optimal time to evacuate: A behavioral dynamic model on Louisiana resident data

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ABSTRACT

Understanding what affects the decision process leading to evacuation of a population at risk from the threat of a disaster is of upmost importance to successfully implement emergency planning policies. Literature on this is broad; however, the vast majority of behavioral models is limited to conventional structures, such as aggregate participation rate models or disaggregate multinomial logit models. This research introduces a dynamic discrete choice model that takes into account the threat's characteristics and the population's expectation of them. The proposed framework is estimated using Stated Preference (SP) evacuation data collected from Louisiana residents. The results indicate that the proposed dynamic discrete choice model outperforms sequential logit, excels in incorporating demographic information of respondents, a key input in policy evaluation, and yields significantly more accurate predictions of the decision and timing to evacuate.

1. Introduction

In the event of a threat, the potentially affected population goes through a cognitive process by which they estimate probabilities and consequences of the threat and their potential actions. In this sense, such population goes through four stages of reaction: collection, evaluation, decision, and implementation (Williams, 1964). In the first stage, the population collects information on the threat, mainly through disaster warning messages. Then, the information is evaluated, generally based on the perceived *personal* relevance (Perry et al., 1981). Finally, a decision is made and implemented within a selected timeframe. These stages also serve as the basis for more current behavioral theories and models, such as the Protective Action Decision Model, which divides the rational thinking into pre-decisional processes and core perceptions—threat, protective action, and stakeholder perceptions (Lindell & Perry, 2004; 2012). The transition through this complex cognitive process makes travel demand for evacuation different from ordinary travel behavior. In order to understand travel needs in threatening situations, it is necessary to gather knowledge on evacuation behavior. For this, research to comprehend evacuation must move beyond understanding the characteristics of those who evacuate and those who do not, towards an understanding of what factors are crucial in determining the forces behind evacuation travel demand (Dash & Gladwin, 2007; Lindell et al., 2005, Xu et al., 2016, Yamada et al., 2016).

Recent literature has also pointed out that the evacuation process is a dynamic process and that a temporal dimension should be accounted for when modeling evacuation during a disastrous event (Pel et al., 2011a). This will help identify when people evacuate, what type of information and which channel is the most appropriate to evacuate the population in a timely manner, and would eventually help decision makers to better organize resources and personnel over time.

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This research proposes behavioral methods based on discrete choice models to estimate the decision to evacuate over time. It adds to existing approaches by explicitly modeling the optimal time to evacuate as the results of a succession of decisions, where the respondents evaluate both present and expected future conditions.

The remaining of this paper is organized as follows. Section 2 provides a review of the literature surrounding behavior during evacuation, and dynamic modeling both in transportation and in related fields. Section 3 describes the methodological framework. Section 4 offers a simulated case study, where static and dynamic estimation of individual choices are compared. The dataset used for model estimation and related descriptive statistics are in Section 5. Model estimation results and model validation are presented in Section 6. Conclusions and future development from the analysis proposed are given in Section 7.

2. Literature review

2.1. Modeling behavior during evacuation

The literature related to disaster events and to model for emergency situations has grown substantially in recent years. In this Section we concentrate on papers that are mainly concerned with behavioral models during emergency situations. Published research (Dash & Gladwin, 2007), has found that factors such as age of the decision maker (Mileti et al., 1975; Gruntfest et al., 1978; Perry R. W., 1979), presence of kids or seniors in the household (Carter et al., 1983; Gladwin & Peacock, 1997), gender (Bolin et al., 1996; Fothergill, 1996; Bateman & Edwards, 2002), disability (Van Willigen, Edwards, Edwards, & Hessee, 2002), ethnicity (Drabek & Boggs, 1968; Perry & Greene, 1982; Perry & Mushkatel, 1986), and income (Schaffer & Cook, 1972; Sorensen et al., 1987; Bolin, 1986) all have an influence on evacuation outcomes. Additionally, previous experience (Hutton, 1976; Baker, 1979; Perry et al., 1982; Sorensen et al., 1987) and geographic location (Simpson & Riehl, 1981; Gladwin & Peacock, 1997) affect the evacuation decision-making process. Similarly, Charnkol and Tanaboriboon (2006) found that, as expected, permanent residents, larger families, people living further away from the seashore, people that haven't directly or indirectly experienced a disaster event, and people without disaster knowledge are less likely to have a faster response time (i.e., time required to physically travel to safer area) than their counterparts; the same results are found when other types of threats and disasters are evaluated.

However, the correlation between the cited factors and the decision to evacuate should not be completely generalized as they may change from study to study (and/or location by location). Baker (1991) highlighted the previous specifically for demographic variables. A recent statistical meta-analysis by Huang et al. (2015) shows the significance and consistency of these (and other) variables over 49 evacuation studies. Their findings are summarized in Table 1, where the correlation indicates the likelihood effect of the variable and the consistency indicates how often it is found to be significant or not throughout the sampled studies. The reader is referred to Carnegie and Deka (2010), Lindell and Prater (2007) and Murray-Tuite and Wolshon (2013) for a more comprehensive review of the array of factors that have been reported to influence evacuation decision.

The suggestion of incorporating time into evacuation modeling is found throughout the literature (Pel et al., 2011a). Identifying what will get people to evacuate in a timely manner would enable more robust traffic-clearing models during threats and disasters. A common practice in hurricane evacuation travel demand estimation is to estimate the total evacuation demand and departure time through simple relationships such as means, rates, and distributions rather than the more sophisticated mathematical relationships observed in urban transportation planning (Mei, 2002). These estimates are generally determined by applying an exogenous response curve stating the percentage of departures in each time interval (Pel et al., 2011b). Response curves have been extensively studied; however there is still a debate about the distribution it should follow: instantaneous departure (Chen & Zhang, 2004; Chiu et al., 2006), a uniform distribution (Liu et al., 2006; Yuan et al., 2006), a Poisson distribution (Cova & Johnson, 2002), a Weibull distribution (Lindell et al., 2002) or sigmoid curve (Kalafatas & Peeta, 2009; Xie et al., 2010), to mention a few. The drawback of the response curve approach is that there is no clear behavioral basis to justify the method (Pel et al., 2011a).

An area that requires much additional effort is the translation of the considerable amount of knowledge on evacuees' behavior during the time of crisis into reliable quantitative measures of the timing of evacuee mobilization (Southworth, 1991). Behavioral models based on discrete choice analysis have been suggested to study different types of choices during an emergency or evacuation: time to evacuate, path to safe zones, or mode choice (Sadri et al., 2014).

2.2. Dynamic discrete choice models

Dynamic models estimate decisions as a sequence of discrete choices where at each time period the decision maker chooses the utility-maximizing alternative. In his seminal work, Rust (1987) developed a regenerative optimal stopping model of bus engine replacement based on accumulated mileage, in which at each time period the decision-maker is faced with the decision of whether to replace the engine of a public transportation bus or to wait one more period, risking unexpected engine failure. The model allows for recurrent participation of the buses by resetting their mileage to zero after their engine is replaced––hence the term regenerative. Rust estimates the utility based on the expected cost of operation of each alternative, where expected accumulated mileage is given by a draw from an exponential distribution. Other influential

Table 1
Correlation with evacuation decision, consistency and significance of variables.

Variable	Correlation		Consistency	Significant	Non-significant
	Positive	Negative			
Risk area	+		High	X	
Mobile home	+		High	X	
Official warning	+		High	X	
Environmental cues	+		High	X	
Peers evacuating	+		High	X	
Business closing	+		High	X	
Expected storm intensity	+		High	X	
Expected nearby landfall	+		High	X	
Expected rapid onset		–	Low		X
Expected surge damage	+		High	X	
Expected flood damage	+		Moderate	X	
Expected wind damage	+		Moderate	X	
Expected personal casualties	+		Moderate	X	
Expected job disruption		–	Moderate		X
Expected service disruption	+		High	X	
Female gender	+		Moderate		X
Age		–	Moderate		X
White ethnicity	+		High		X
Black ethnicity		–	High		X
Hispanic ethnicity	+		High		X
Marital status		–	High		X
Household zize		–	High		X
Children at home	+		Moderate		X
Education	+		High		X
Income	+		High		X
Household ownership		–	Moderate	X	
Previous experience	+		Moderate		X
Coastal tenure		–	Moderate		X
"Unnecessary" evacuation	+		Moderate		X
Reliance on authorities	+		Low		X
Reliance on news media	+		Low		X
Reliance on peers	+		Low	X	
Concern about looting		–	High		X
Concern about property protection from storm		–	High		X
Concern about evac. expenses	+		High		X
Concern about traffic jams	+		High		X

papers from this line of research include Wolpin (1984) on fertility and child mortality, Miller (1984) on job matching and occupational choice, and Pakes (1986) on patent renewal.

Since these early papers, dynamic discrete choice models (DDCM) has been applied in many different scenarios, including labor economics, industrial organization, economic demography, health economics, development economics, political economy, and marketing. Keane & Wolpin (1997) studied the career choices of young men based on the reward of each occupation alternative (i.e., to study or to work) over the life cycle. Their model optimize such reward by taking into account the individual's evolution of education (and its related cost), income and skill-sets through a given age range. Similarly, Ge (2013) focused on the decision of whether to attend college, work or a combination of both of women with a high school degree. Furthermore, Heckman & Navarro (2007) evaluated associated earnings outcomes for different levels of education while considering anticipations about potential future outcomes associated with the various choices. For this, they provide a semiparametric non-regenerative formulation of dynamic discrete choice models of treatment times and the consequences of choice.

From an employment perspective, Rust & Phelan (1997) and Karlstrom et al. (2004) used dynamic discrete choice models to estimate retirement from the labor force based on time-dependent retirement benefits (e.g., pension and healthcare). On the other hand, Gurmu et al. (2008) estimate the participation on full-time employment of families that receive welfare through a dynamic probit model which incorporates residential location and time-varying variable, such as employment status. More broadly, Keane & Wolpin (2002a, 2002b) evaluated the impact of welfare benefits on economic and demographic behavior—employment status, household size and education to mention a few.

In market share analysis, Gönül (1998) assessed the effect of time-varying cost and preferences (purchase history) on the sales of different over-the-counter medicine brands. Whereas Hetrakul (2012) evaluated ticket cancellations and exchanges within railway service in response to varying trip schedule, cost, and refund/exchange policy.

Many other examples of the application of dynamic models exist in the literature. The reader is referred to Keane et al. (2011), Aguirregabiria & Mira (2010) and Keane & Wolpin (2009) for a comprehensive survey of the literature surrounding the different structures and applications of DDCM.

2.3. Dynamic discrete choice models in transportation

Despite the vast application of DDCM, its use within the field of transportation has been limited when compared to other fields. Gao et al. (2010) proposed a policy routing choice model with a cumulative prospect theory utility function (a non-expected utility framework) to measure choice under risk. Their model is adaptive since information is updated as the traveler traverses through a stochastic network (*en route*). Alternatively, Fosgerau et al. (2013) developed a dynamic route choice model where the path choice problem is formulated as a sequence of link choices. At each stage (i.e., node), the traveler chooses the link that maximizes the sum of instantaneous utility and the expected downstream utility. On the other hand, dynamic models have also been used to estimate car ownership and its related decisions (e.g., type of vehicle, tenure and usage), where variables such as income, fuel prices and cumulated mileage are treated as stochastic state variables—see de Lapparent & Cernicchiaro (2012), Cirillo et al. (2014), and Glerum et al. (2015).

In evacuation analysis, dynamic travel demand is usually modeled through repeated binary logit models where the share of people who decide to evacuate and depart presently, or postpone the decision to evacuate, are estimated at each time period. Fu & Wilmot (2004) developed a sequential binary logit model to estimate the decision to evacuate when threaten by a hurricane at several time intervals before landfall. For this, information from 320 households in Southwest Louisiana was collected following hurricane Andrew. In their model, travelling speed of the hurricane, time of day, and distance from the hurricane were treated as dynamic variables. They concluded that sequential binary logit is capable of estimating the decision of whether to evacuate or not. Later, Fu et al. (2006) improved the model by including hurricane wind speed and time-to-landfall data from hurricane Floyd in South Carolina and tested the calibrated model on the hurricane Andrew data. The predicted dynamic travel demand yielded similar results to the observed travel demand, indicating that there is potential in transferring weights to different location and hurricane scenarios. Similarly, Wilmot & Gudishala (2013) developed a sequential logit model based on newly collected hurricane data from a State Preference (SP) survey in Louisiana. Czajkowski (2011) presents an economic model where a cutoff point is sought between the decisions to evacuate or not based on the cost of each alternative. Czajkowski's uses cost and potential risk values estimated from previous research, collected data and probabilistic assumptions to determine the time period (and associated costs and risk) after which a household may decide to evacuate.

The current state-of-practice is to estimate the dynamic utility of evacuating (or not evacuating) using prevailing conditions. However, it is logical to assume that people not only consider current conditions, but are also capable of predicting future conditions and base their decision on this information as well (Pel et al. 2011a). For example, Wilmot & Gudishala (2013) developed a sequential nested logit that combines the decision of whether to evacuate or stay into time period nests. The nested model linked the utility of a lower nest to an upper nest, that is linking time period $i+1$ to i, by using the logsum of the utilities.

The purpose of this research is to contribute to the literature of DDCM by applying demand estimation during hurricane evacuation through a new approach, founded on Cirillo, Xu & Bastin's (2016) work on dynamic modeling of car ownership and Hetrakul's (2012) work on dynamic modeling of train user's ticket cancellation/exchange behavior. Here, the previous models will be adapted to develop a hurricane evacuation model using a dynamic discrete choice regression model capable of combining prevailing and expected hurricane conditions, resulting in a more robust estimation of the evacuation response and factors affecting it. The model is then applied using SP data collected from Louisiana residents.

3. Evacuation modeling framework

This section provides the theoretical background on the optimal stopping problem developed to study the behavior of evacuees in the midst of a threat, which for this study is a hurricane.

3.1. General evacuation decision problem

Consider a population set $S = \{1, \ldots, M\}$ and time periods t = 0, 1, . . .T. At each time period t, consumer i has two options:

1) to evacuate and obtain a terminal period payoff u_{it};
2) to postpone and obtain a one-period payoff c_{it}, which is a function of individual i's attributes and the current characteristics of the threat, i.e. $c(x_{it}, q_{it}; \theta_i \alpha_i)$. x_{it} is a vector of attributes for individual i at time t (e.g., gender, education, income, age) and q_{it} is the vector of characteristics of the threat (e.g., category, expected time to landfall, time of day). θ_i and α_i are parameters vectors for x_{it} and q_{it} respectively.

Using a bold font for random variables and normal font for their realizations, the payoff $\boldsymbol{b_{it}}$ (i.e., to evacuate at time t) is expressed as a random utility function:

$$\boldsymbol{b_{it}} = u(x_{it}, \boldsymbol{y_t}, \theta_{it}, \lambda_i, \epsilon_{\boldsymbol{it}}) \tag{1}$$

where

- $x_{it}, \theta_i \in \Re^Q$ are defined a above;

- $\boldsymbol{y_t} \in \Re^H$ is a random vector of dynamic attributes at time t, which represents the evolution of a threat over time. λ_i is a vector of parameters related to $\boldsymbol{y_t}$.
- $\varepsilon_{\boldsymbol{it}}$ is an individual-specific random term, whose components are independently and identically GEV distributed amongst individuals and periods. It is assumed that $\varepsilon_{\boldsymbol{it}}$ is independent from $\boldsymbol{y_t}$.

A one-step decision process is assumed, in which, at each time period t, the individual decides whether to evacuate or to postpone the evacuation until the optimal time period $\boldsymbol{\tau}$, time when the consumer decides to evacuate instead of postponing. The individual deciding to evacuate or postpone is the optimal stopping problem at time t:

$$D_t(\boldsymbol{b_{it}}, c_{it}) = \max_{\boldsymbol{\tau}} \left\{ \sum_{k=t}^{\boldsymbol{\tau}-1} \beta^{k-t} c_{it} + \beta^{\boldsymbol{\tau}-t} E_{\boldsymbol{y_\tau}}[\boldsymbol{b_{i\tau}} | y_t] \right\} \tag{2}$$

where

- β is a discount factor in [0,1);
- c_{it} is the payoff function of individual i's attributes and the characteristics of the threat when choosing to postpone the evacuation, as defined before.

It is important to note that the expectation in (2) is taken with respect to the threat evolution $\boldsymbol{y_t}$. D_t remains a random function due to the terms ε_{it} present in the random utility functions. According to the previously described assumption about ε_{it}, b_{it} is Gumbel distributed with a scale factor equals to 1 and γ_{it} is the mode of the distribution of b_t. It is also stressed that if $\tau = t$, the right-hand term in (2) reduces to b_{it}. It is then easy to see the individual's decision can be transformed from (2) into:

$$D_t(b_{it}, c_{it}) = \max \left\{ \boldsymbol{b_{it}},\ c_{it} + \beta E_{\boldsymbol{y_{t+1}}} \left[D_{\boldsymbol{t}+1} \left(\boldsymbol{b_{i,t}}_{+1}, c_{i,t+1} \right) | y_t \right] \right\} \tag{3}$$

Eq. 3 indicates that the decision process consists of evacuating at time t or delaying it over one period, taking the payoff c_{it} plus the discounted future return. This is a standard optimal stopping problem, with a stopping set given by

$$\Gamma(y_t) = \{ b_{it} | b_{it} \geq W_{it} \} \tag{4}$$

where W_{it} is the reservation utility level for individual i and its defined as:

$$W_{it} = c_{it} + \beta E_{\boldsymbol{y_{t+1}}} \left[D_{\boldsymbol{t}+1} \left(\boldsymbol{b_{i,t}}_{+1}, c_{i,t+1} \right) | y_t \right] \tag{5}$$

Using (5), (3) can be simplified to:

$$D_{\boldsymbol{t}}(\boldsymbol{b_t}) = \boldsymbol{max}\{ b_{it}, W_{it} \} \tag{6}$$

It is assumed that the random terms ε_{it} take specific realizations when selecting an individual i, meaning that the individual i has access to all values of his/her utility function—the vectors ε_{it} are simply the unobserved factors. Simply put, individual i will choose to evacuate at time t only when $b_{it} > W_{it}$. If i is randomly drawn from the population, the analyst can compute the probability of postponing the evacuation until the next period as:

$$\begin{aligned} \pi_{it}(y_t) &\stackrel{\text{def}}{=} P_{it}[D_t(b_{it}) = W_{it} | y_t] \\ &= P_{it}[b_{it} \leq W_{it}] \\ &= F_v(W_{it}, y_t) = e^{-e^{-(W_{it} - \gamma_{it})}} \end{aligned} \tag{7}$$

Note the probability is taken with the set of random variables ε_{il}, for $l =$ t, t + 1, ..., i.e. the variables unobserved by the analyst but with known values for individual i.

3.2. Dynamic estimation process

The parameter estimation process is done by applying the maximum likelihood estimation method to:

$$\mathcal{L}(\theta, \lambda, \beta) = \prod_{i=1}^{M} \prod_{t=1}^{H} P_{it}[D_t(b_{it}) | \theta, \lambda, \beta] \tag{8}$$

where:

- θ is a vector of stationary preference parameters related to individual attributes x_{it}.
- λ is a vector of parameters related to the dynamic attributes of the threat, y_t.
- β is the discount factor, set to 1 for simplicity.

The probabilities of (8) are taken with respect to the distribution of the variable ε_{it}, as in (7), given the values of the parameters. H represents the number of time periods where observations were collected, which in this case is limited by the number of forecasts – therefore H is equal to four.

As explained before, the probability of π_{it} depends on W_{it}, which can be calculated as in (5). W_{it} is composed of two parts: the utility of the current threat attributes c_{it} and the expected utility in the next time period

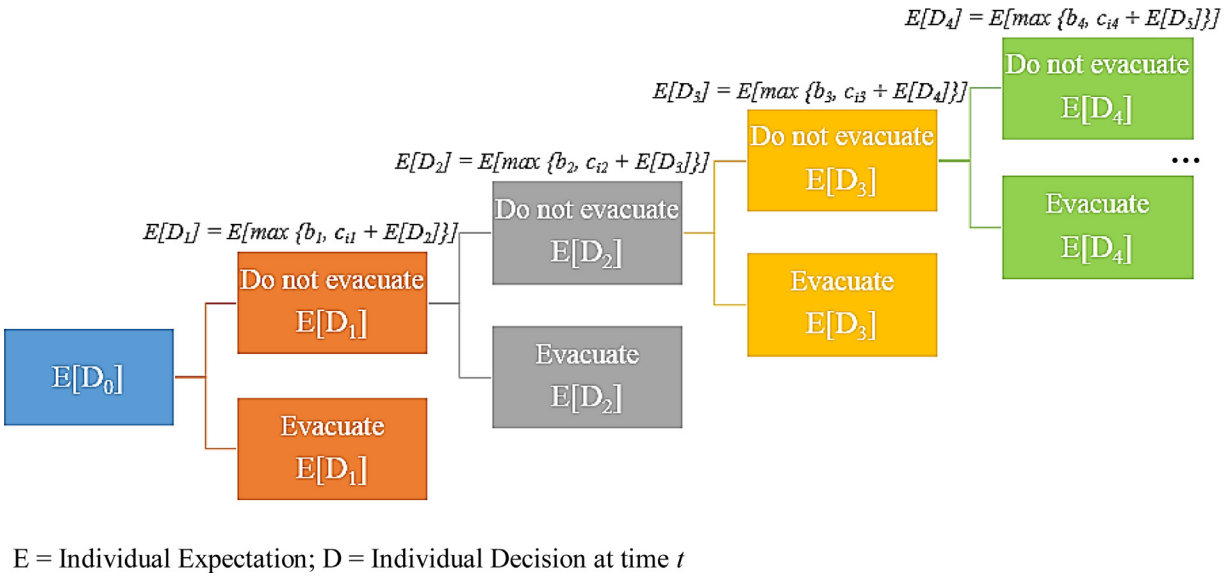

Fig. 1. Scenario tree.

$\beta E_{\boldsymbol{y_{t+1}}}[D_{\boldsymbol{t}+1}(\boldsymbol{b_{i,t+1}}, c_{i,t+1}|y_t]$. The key step during the estimation process is to identify how to calculate the expected utility. At each time period, the individual is assumed to be forward-looking (i.e., they have a perception about the future scenarios), which are characterized by the threat's attributes changing over time. This research uses a finite horizon scenario tree providing a reasonable behavioral rooting since individuals can only perceive future attributes for a limited number of time periods (see Shapiro et al., (2009), Hetrakul (2012) and Cirillo et al., (2014) for examples). Therefore, at time period t, the individual faces two alternatives, to evacuate or to postpone evacuation. The individual will continue the decision process into the period $t+1$ only if he/she had decided to postpone evacuation in time period t. Therefore, the decision process can be characterized by a scenario tree (see Fig. 1), which is the base for the expected utility calculation. The following steps describe the procedure to calculate π_{i1} based on the expectation $E_{\boldsymbol{y}_1}[D(\boldsymbol{b_{i1}}, c_{i1})|i]$, which will be indicated by $E[D_1]$ because all the expectations in the example are for individual i:

- Assumption: It is assumed that the individual has the expectation over a limited number of future periods. Given that we are dealing with threats with usually limited forecasts, here it is assumed that individuals can only predict one period ahead. Therefore, at time period $t=1$, the individual can anticipate the future characteristics of a threat (e.g., category and evacuation order) at time period $t=2$. Whereas $E[D_3]=0$ since the individual knows nothing of time period 3 when faced with the decision at time period 1, same for any time period beyond $t+1$.
- Evaluation of $E[D_2]$: To obtain the probability of π_{i1} it is necessary to estimate W_{i1} (using Eq. 5), which in hand depends on $E[D_2]$. At time 1, the individual has two alternatives for successive time 2, to evacuate or not to evacuate (see Fig. 1). The right side of the utility function $E[D_1]= E[\max\ \{b_1,\ c_1\ +\ \beta E[D_2]\}]$ represents the utility of the "do not evacuate" alternative. Based on the above assumption, $E[D_3]$ is zero when calculating $E[D_2]$ at time t= 1.
- These steps are then repeated to calculate π_{i2} with the assumption that respondent can anticipate the characteristics of the threat at time period 3 and $E[D_4]$ is zero, and so on for the rest of the estimations.

It should be clarified that while this research follows a concept similar to Czajkowski (2011), it does so in a different manner. As explained, Czajkowski's uses cost and potential risk values estimated from previous research, collected data and probabilistic assumptions to determine the time period (and associated costs and risk) after which a household may decide to evacuate. The present study does so through applied econometrics in which a dynamic discrete choice model is used to estimate the utility associated with the decision of whether to evacuate or not considering current and expected hurricane conditions and household-specific demographic information. Furthermore, our approach attempts to include predicted values from a household perspective.

3.3. Mixed dynamic model

In order to accommodate taste heterogeneity, or the variations in the coefficients that are related to observed attributes of the decision maker (Train, 2009), we integrate the choice probabilities in Eq. 8 over the density of the parameters assumed to be randomly distributed. The deriving likelihood function is:

$$\mathcal{L}(\theta, \lambda, \beta) = \int \prod_{i=1}^{M} \prod_{t=1}^{H} P_{it}[D_t(b_{it})|\theta, \lambda, \beta] f(\theta) d\theta \tag{9}$$

The probabilities are then approximated through simulations:

$$S\mathcal{L}\ (\theta, \lambda, \beta) = \frac{1}{R}\sum_{r=1}^{R}\prod_{i=1}^{M}\prod_{t=1}^{H} P_{itr}[D_{tr}(b_{itr})|\theta, \lambda, \beta] \tag{10}$$

where R is the number of random draws used for the Monte Carlo simulation. For this study 1000 random draws have been used for model estimation.

4. Experiments based on simulated data

The methodological approach proposed is validated with a series of Monte Carlo experiments; the objective being to evaluate the errors resulting from specifying a model as static when in fact the decision process is dynamic and vice versa. A synthetic sample of 1000 households' choices over four potential time periods has been simulated to validate the proposed dynamic discrete choice formulation. The hypothetical scenario is a hurricane in route to make landfall for which five forecasts are provided, $t \in \{1,\ldots, 5\}$. In order to comply with the one period look ahead assumption, choices are estimated for the first four periods. At each observation period, there are two alternatives in the choice set that mimic respectively the decision to evacuate or do not evacuate. It should be noted that this model is not regenerative, as any household that decides to evacuate is out of the sample.

Two types of variables were generated in the simulated dataset, static and dynamic. Static variables relate to household characteristics, specifically household's income, size, presence of kids, and previous experience with evacuation; whereas dynamic variables provide time-varying information of the threat, namely hurricane category, time to expected landfall, and whether they are at the last forecast. These variables were selected based on the information found in the literature review regarding the factors that influence evacuation decisions. With reference to the socio-demographic variables it should be said that these variables have been found to be significant predictors in *some* studies but the best scientific estimate is that they have negligible effects (Huang et al., 2015). The variables in the simulated dataset have been generated using the following criteria:

- Household income varies on 7 levels of variation: (1) Less than \$15,000; (2)=\$15,000 to \$24,999; (3) \$25,000 to \$39,999; (4) \$40,000 to \$79,999; (5) \$80,000 to \$119,000; (6) \$120,000 to \$149,000; and (7) Over \$150,000. It was assumed that 10% of the population had income level 1, 20% had level 2, 50% were uniformly distributed between levels 3 and 4, and the remaining 20% were uniformly distributed between levels 5 through 7.
- It was assumed that 70% of households have between 1 and 3 family members and that the remaining 30% have between 4 and 6.
- Assumption of presence of kids (i.e., under 17 years of age) were made based on the size of the household. Single-member households were assumed to have no kids. If the household were composed of 2 members, there was a 5% chance of one of them being a kid. Households with 3 or 4 members were given a 50% probability of having a kid, whereas families with 5 or more members were given an 80% probability of having at least one kid.
- It was assumed that 50% of households have had previous experience with evacuation (either directly or indirectly).
- For the first forecast, hurricane category was uniformly distributed in the range of 1–5 following the Saffir-Simpson scale. After this initial forecast, it was assumed that hurricanes could only increase or decrease (within the 1 to 5 scale limit) at most two categories between forecasts. For example, if in Forecast 2 the category is 2, then in Forecast 3 the category was uniformly distributed between 1 and 4.
- Time to expected landfall was uniformly distributed within each forecast following these ranges: (1) 67–77 hrs, (2) 44–52 hrs, (3) 21–27 hrs, (4) 10–14 hrs, and (5) 4–8 hrs away.
- The communication of the last forecast is a dummy variable with 0–1 values that takes the value of 1 if the period of observation is forecast 4 and 0 otherwise.

Respondents are supposed to choose between two alternatives: evacuate and not evacuate. Utility of evacuation of household i on time t can then be specified as:

$$U_{evac.it} = \beta_{income}HHinc + \beta_{size}HHsize + \beta_{kids}HHkids + \beta_{exp}HHexp + \beta_{category}HC + \beta_{time}TTEL + \beta_{Last\ FC}FC4 + \varepsilon_i \tag{9a}$$

where *HHinc* is household income, *HHsize* is household size, *HHkids* is the presence of at least one kid in the family, *HHexp* is the experience of the household with evacuation, *HC* is the hurricane category, *TTEL* is the time to expected landfall and *FC4* is the last forecast. The random term ε_i is iid extreme-value distributed at a given time period.

Three models were estimated using the simulated data and the specification defined above: (i) a model where decisions are generated following a logit distribution and estimated with a dynamic model, LogDyn; (ii) a model where decisions are generated following a dynamic distribution and estimated with a logit model, DynLog; and (iii) a model where both generation and estimation are done dynamically, DynDyn. In the logit model (DynLog), respondents are not considering the future threat evolution when making decisions at each time period. The model is simply formulated as a traditional MNL with two alternatives; utilities include both static and dynamic variables, for consistency with the dynamic model formulation. All models are coded in R language. Model coefficients in Table 2 are averaged over the one hundred models' estimates; we also report confidence interval (CI) and minimum and maximum values obtained across the simulated datasets generated.

Table 2
Estimation with simulated data.

Variable	True value	Model	Average	SD	CI 95%	Min	Max
Hurricane category	0.2	LogDyn	0.1465	0.0258	0.0051	0.0932	0.2119
		DynLog	0.2635	0.0287	0.0057	0.2004	0.3365
		DynDyn	0.1971	0.0275	0.0055	0.1305	0.2752
Time to expected landfall	−0.03	LogDyn	−0.0280	0.0021	0.0004	−0.0341	−0.0235
		DynLog	−0.0337	0.0022	0.0004	−0.0402	−0.0289
		DynDyn	−0.0302	0.0019	0.0004	−0.0352	−0.0264
Last forecast (FC4)	−3.3	LogDyn	−3.1601	0.3534	0.0701	−4.3564	−2.4143
		DynLog	−3.5930	0.1910	0.0379	−4.2687	−3.2495
		DynDyn	−3.2767	0.3395	0.0674	−4.1807	−2.5989
Previous experience	0.9	LogDyn	0.7650	0.1009	0.0200	0.5055	1.0276
		DynLog	1.0805	0.0971	0.0193	0.8290	1.3691
		DynDyn	0.9001	0.0959	0.0190	0.6623	1.1650
Household size	−0.3	LogDyn	−0.2829	0.0460	0.0091	−0.3959	−0.1744
		DynLog	−0.3139	0.0436	0.0086	−0.4223	−0.2226
		DynDyn	−0.2981	0.0388	0.0077	−0.3852	−0.1719
Presence of kids	0.3	LogDyn	0.2592	0.1456	0.0289	−0.0632	0.5928
		DynLog	0.3024	0.1385	0.0275	0.0272	0.6166
		DynDyn	0.2943	0.1247	0.0248	0.0124	0.5575
Household income	−0.15	LogDyn	−0.1550	0.0260	0.0052	−0.2291	−0.0887
		DynLog	−0.1402	0.0257	0.0051	−0.2039	−0.0841
		DynDyn	−0.1474	0.0242	0.0048	−0.2195	−0.0874
	RMSD	LogDyn	0.0780				
		DynLog	0.1324				
		DynDyn	0.0092				

Root Mean Square Deviation (RMSD) is adopted to validate which model better recovers the true values. RMSD aggregates individual differences between the true and predicted values into a single measure of predictive power. The bigger the RMSD, the poorer the model's ability to reproduce the true phenomenon. The RMSD is defined as

$$RMSD\left(\hat{\theta}\right) = \sqrt{E((\hat{\theta} - \theta)^2)} = \sqrt{\frac{\sum_{i=1}^{n} (\widehat{\theta_i} - \theta_i)^2}{n}} \tag{10a}$$

where $\hat{\theta}$ is the observed (true) value, θ is the modeled value at time i, and n is the number of parameters. Results of the estimations are presented in Table 2. The last part of the table reports the RMSD. Overall, models with dynamic estimation obtained lower RMSD, indicating lower bias in its coefficients, with DynDyn model yielding the lowest value of all (as expected).

5. Dataset description

Hurricane Katrina came in contact with the city of New Orleans in 2005. Later on September 1, 2008, Hurricane Gustav made landfall near Cocodrie, Louisiana as a Category 2 hurricane. Gustav originated as a tropical storm southeast of Port-au-Prince, Haiti, on August 25, 2008 and developed into a hurricane on August 26. These two experiences combined with the closeness between events, highlighted the need of a practical and more reliable framework for evacuation behavior analysis.

On 2010, the Public Policy Research at Louisiana State University conducted a survey that collected information on the evacuation behavior of resident of New Orleans. The survey had two main parts: 1) a Revealed Preference (RP) section that gathered information of the respondent's evacuation decision during the threat of hurricane Gustav (not discussed in this study), and 2) a Stated Preference (SP) section that registered the respondent's evacuation behavior based on hypothetical hurricane scenarios. The survey used the RP data and adapted it to collect dynamic information and enhance the realism of each scenario by presenting it in audio-visual form on a DVD. A total of nine hypothetical storms were developed based on past hurricanes characteristics; retrieved history contained information on the path of a hurricane and other characteristics, such as storm category, storm location, and time of landfall (Gudishala, 2011). In the stated preference survey, each generated storm was described in terms of the following time-dependent variables: hurricane category (HC), evacuation order (EO), time of day, in a 24 h clock (TOD), time to expected landfall (TTEL), and day of the week (DOW) (Monday is one), see Table 3. The population was divided into 3 sample groups and each household was presented with 3 hypothetical storms randomly chosen from the nine developed by the analysts. Each storm contained 4 forecasts; at each forecast the respondent made the decision of whether to evacuate or not. The response sheet asked for input on day and time of evacuation, mode of evacuation, type of destination (e.g., house, motel, shelter, etc.), location of destination, and route. The reader is referenced to Wilmot & Gudishala (2013) for a more detailed explanation of the survey design and data collection process.

A total of 310 households responded to the survey, including 22 households that were part of the pilot survey. This study only considered information gathered from the main survey––288 households, which translate into 864 potential observations. However, not all data points could be used. A data cleaning process was undertaken to eliminate incoherent

Table 3
Hypothetical storms presented to interviewed households.

Storm	Characteristics	Forecast1	Forecast2	Forecast3	Forecast4
1	HC1	4	4	4	3
	EO1	None	Voluntary	Mandatory	Mandatory
	TOD1	10.25	6.25	0.25	14.25
	TTEL1	70	50	32	18
	DOW1	3	4	5	5
2	HC2	5	4	3	2
	EO2	Voluntary	Mandatory	Mandatory	Voluntary
	TOD2	12.50	14.50	16.00	1.00
	TTEL2	72	45	19	8
	DOW2	1	2	3	4
3	HC3	3	4	3	3
	EO3	None	Voluntary	Mandatory	Mandatory
	TOD3	6.50	6.50	8.50	15.50
	TTEL3	68	44	18	11
	DOW3	6	7	1	1
4	HC4	5	3	2	2
	EO4	None	Voluntary	Voluntary	Voluntary
	TOD4	12.50	13.50	12.50	1.50
	TTEL4	69	44	21	8
	DOW4	3	4	5	6
5	HC5	3	5	2	1
	EO5	None	Voluntary	None	None
	TOD5	9.50	12.50	11.50	23.50
	TTEL5	76	49	26	14
	DOW5	2	3	4	4
6	HC6	5	3	2	1
	EO6	None	Voluntary	Voluntary	Voluntary
	TOD6	9.50	15.50	16.50	3.50
	TTEL6	75	45	20	9
	DOW6	3	4	5	6
7	HC7	1	3	2	2
	EO7	None	Voluntary	Mandatory	Mandatory
	TOD7	11.50	9.50	9.50	0.50
	TTEL7	74	52	28	13
	DOW7	5	6	7	1
8	HC8	4	3	3	3
	EO8	None	Voluntary	Mandatory	Mandatory
	TOD8	12.50	9.50	8.50	20.50
	TTEL8	67	46	23	11
	DOW8	7	1	2	2
9	HC9	5	3	2	1
	EO9	None	Voluntary	Voluntary	Voluntary
	TOD9	6.50	10.50	6.50	22.50
	TTEL9	75	47	27	11
	DOW9	6	7	1	1

answers, such as evacuating before the first forecast. After cleaning the data, 281 households remained––yielding to 250 observations for sample group 1, 253 for sample group 2, and 260 on sample group 3, and a total of 763 observations.

5.1. Socio-demographic characteristics

This subsection describes the sampled population based on the gathered information; all descriptive statistics presented here are based on weighted data. The surveyed households are distributed across 10 neighborhoods, all of them highly vulnerable to extreme weather events given their low altitude and proximity to the coast. The sampled households present demographic distributions parallel to Louisiana's 2010 National Census data in many of the different characteristics, indicating that a random sample was successfully collected. For instance, 64.5% of the sample was white, 20% African-American, and 6% other – 9.5% did not respond – whereas the census data yields 63.9%, 32.8%, and 3.3% for the same races live in other type of housing.

An analysis of the household size shows that the majority of households (61%) have at most 2 members, while 16% have 3 members, 14% have 4, and the remaining 9% have 5 or more members. This distribution results in a sample's average household size is 2.44 members.

The majority of households (75%) have 1 or 2 vehicles, whereas 14% has 3 or more vehicles. The remainder of the households does not own any vehicle. The average number of vehicles owned per household is 1.65. Over 40% of households with an income below $15,000 do not own a vehicle. Surprisingly, around 10% of high income households do not own a vehicle.

Table 4
Household location and income distribution within each location.

Parish name	% of HH	Parish household income distribution						
		Less than $15k	$15k-$24.9k	$25k-$39.9k	$40k-$79.9k	$80k-$119.9k	$120k-150k	More than $150k
Jefferson	33.1%	5.5%	23.2%	17.8%	26.6%	16.3%	4.7%	5.9%
St. Tammany	18.5%	20.7%	7.4%	6.2%	39.1%	13.6%	3.3%	9.7%
Orleans	15.0%	16.8%	13.9%	8.7%	43.1%	8.4%	4.0%	5.1%
Terrebonne	13.4%	36.6%	10.6%	13.7%	10.5%	14.9%	8.6%	5.2%
Tangipahoa	6.9%	8.0%	10.7%	19.9%	28.7%	14.3%	11.0%	7.4%
Lafourche	5.0%	0.0%	24.4%	15.0%	21.1%	31.2%	4.1%	4.1%
St. John the Baptist	3.9%	12.5%	55.3%	11.9%	20.2%	0.0%	0.0%	0.0%
St. Charles	2.6%	0.0%	7.9%	7.9%	45.9%	15.3%	15.3%	7.8%
St. Bernard	0.8%	0.0%	23.8%	0.0%	0.0%	76.2%	0.0%	0.0%
Plaquemines	0.7%	0.0%	0.0%	0.0%	27.4%	46.0%	26.6%	0.0%
Overall		14.10%	17.10%	13.00%	29.10%	15.10%	5.50%	6.10%

Table 5
Evacuation decision distribution.

Evacuation decision	% of observations	% of evacuees
After forecast 1	18.3%	32.2%
After forecast 2	26.3%	46.2%
After forecast 3	11.5%	20.2%
After forecast 4	0.8%	1.4%
Do not evacuate	43.1%	–
Total	100%	100%

One could speculate that this might be because those households are well located and therefore do not need a vehicle. As for education, approximately 37% of households achieved at most a high school degree. In contrast, 38% of households have at least one member with a bachelor degree or higher. The rest of the household attend some college or obtained an associate degree. Table 4 shows the income characteristics of the households across the parishes. As can be seen, a third of them are located in the Jefferson parish, followed by St. Tammany, Orleans and Terrebonne. Saint Bernard and Plaquemines are the parishes with the fewest households, accounting for only 1.5% of the sample combined. Furthermore, around 31% of the households earn less than US$25,000, meaning that a significant percentage could be considered as low income. Approximately 68% of households in St. John the Baptist and 47% in Terrebone are low income. In contrast, 12% of households could be considered as high income (HIHH) as they earn US$120,000 or more, with Plaquemines and St. Charles having the highest percentage of high income households, 27% and 23% respectively. Furthermore, the data shows that income has little effect on the type of house residents live in. The majority (85%) of the sampled population live in a permanent house, with 8% living in an apartment/condo and only 5% live in a mobile home, the rest live in other type of housing.

5.2. Stated preference socio-economic demographic

This subsection provides information regarding the evacuation behavior of the respondents, based on the 763 observations (each storm is considered an independent observation).

Table 5 shows the distribution of the households' evacuation decision, that is whether they evacuated or not, and if so, at what point in time. Households decided not to evacuate in 43% of the hypothetical scenarios, a low percentage given that 84% of the households are located in a flood zone. Also, there is a clear unwillingness to wait until the last moment to evacuate, as indicated by the low percentage of households (0.8%) that would evacuate after Forecast 4, and as is usually the case in coastal cities.

The evacuation behavior is related to the hurricane scenario presented to the household. For example, Storms 7 and 9 have the lowest percentage of evacuees, which might be explained by the low hurricane category in the case of Storm 7 and by the lack of a mandatory evacuation order in Storm 9. It should be noted that Storm 7 follows the actual characteristics of Hurricane Gustav. Furthermore, approximately 66% of the households that were presented with Storm 7 evacuated – resembling the 74% evacuation rate of the total sampled population during Gustav. Interestingly, 74% of those who did not evacuated during Gustav would not evacuate under the presented scenarios, whereas 32% of those who did evacuate would not evacuate now.

Generally, and when possible, sampled households prefer to evacuate sooner rather than later. Now, the decision of how much time to wait after a forecast depends, amongst many factors, on the time of that forecast. For instance, over 60% of households that would evacuate after the first forecast do so 16 hours or more after the forecast, see Fig. 2. However, this percentage halves on Forecast 2 and drops to almost zero on Forecast 3, indicating that the longer a household waits for future forecasts the faster they tend to evacuate after it – which is an expected behavior. Overall, 23.2% of households that

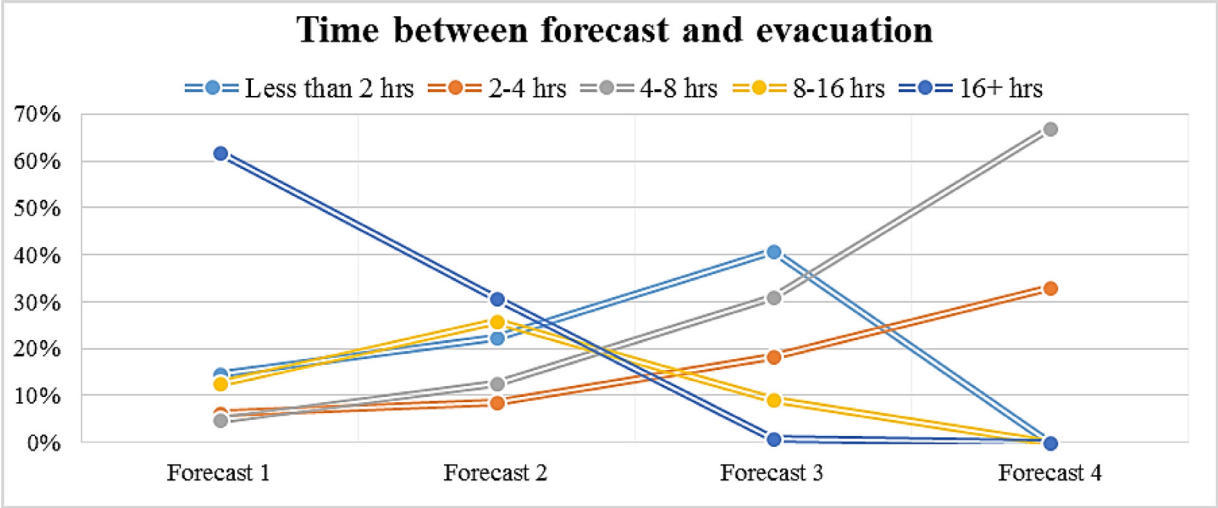

Fig. 2. Distribution of time between forecast and evacuation.

decided to evacuate do so within the first two hours, 10.1% between two and four hours, 14.6% between four and eight hours, 17.9% between 8 and 16 hours, and 34.2% would wait at least 16 hours to evacuate.

Data also show that there is a positive relationship between income level and the decision to wait longer to evacuate; the same results are obtained if education level is analyzed. It is also evident that regardless of income the majority of households that evacuate do so after the first two forecasts (comprising approximately 79% of the evacuees). No reliable information can be inferred from households that would evacuate after Forecast 4 because of its low percentage.

Around 94% of those who evacuate would do it by private vehicle, 5% would get a ride with someone else and 1% would use the bus. Those who evacuate with the assistance of another (i.e., take a ride) tend to wait more frequently until Forecasts 3 to do so. One reason for this might be that they would like to avoid the distress of moving from their location to the departure point so they wait to confirm whether it is necessary or not to evacuate.

6. Threat evolution and model estimation with real data

In this Section, we describe how dynamic variables were selected and modeled. An important aspect to take into account is that the dynamic nature of a variable does not guarantee that the variable is independently dynamic (i.e., their change is not correlated with other variables). Of the information available in the SP datasets, time of day and day of the week are continuous variables that progress linearly as time passes by; and evacuation order is a subjective decision made by officials based on the storm's forecasted intensity at landfall, forward movement speed and distance (Yi et al., 2017). This research takes into account that the time to expected landfall does not necessarily progresses linearly with time; however, to ensure compatibility across datasets, it is assumed that it changes linearly over time. In this manner, hurricane category can be viewed as the only one that truly behaves independently (and unsystematically).

From a modeling perspective, $\boldsymbol{y_t}$ represents the evolution of the threat's attribute over time (see Eq. 1), a key element in the estimation of expected utility. Since the future appears uncertain to the individual affected, this (expectation of) evolution needs to be represented in some sort. Here, it is proposed to estimate expectation from the respondent's perspective instead of using market (equilibrium) values, as it is commonly used in the literature (Keane & Wolpin, 1997; Rust, 1987). In this sense, this research experiments with two different threat evolution assessment methodologies:

1. Perfect Knowledge (PK): Respondents have perfect knowledge of the future value of the dynamic variable. For example, if we consider hurricane category as the dynamic variable, at time t respondent i knows the category of the hurricane at time $t+1$.
2. Stochastic Growth (SG): The hurricane category follows a stochastic growth model where dynamic variable changes according to a random walk with a drift. The respondents' expectation of the evolution of the hurricane is then simulated from that distribution.

6.1. Perfect knowledge

This approach is a theoretically ideal situation where knowledge is readily accessible, allowing households (and individuals) to make more educated decision. With approximately 75% of households in the US having access to internet (United States Census Bureau, 2014), accessibility to historic and real-time information is higher than ever. Therefore, it is sound to assume that, within reason, they can successfully estimate future trends and/or behaviors of threats. With this in mind, the

Table 6
Hurricanes that traversed through Louisiana between 1950 and 2010.

Name	Date	Name	Date
IDA	Nov. 10, 2009	JUAN	Oct. 27–31, 1985
IKE	Sept. 13, 2008	ELENA	Sept. 2, 1985
GUSTAV	Aug. 31, 2008	DANNY	Aug. 16, 1985
HUMBERTO	Sept. 13, 2007	BOB	July 11, 1979
RITA	Sept. 24, 2005	CARMEN	Sept. 7–8, 1974
KATRINA	Aug. 29, 2005	EDITH	Sept. 16, 1971
LILI	Oct. 3, 2002	CAMILLE	Aug. 17–18, 1969
GEORGES	Sept. 27–28, 1998	BETSY	Sept. 9–10, 1965
DANNY	July 18, 1997	HILDA	Oct. 2–3, 1964
OPAL	Oct. 4, 1995	CARLA	Sept. 10–12, 1961
ANDREW	Aug. 26, 1992	ETHEL	Sept. 15, 1960
GILBERT	Sept. 15–19, 1988	AUDREY	June 27, 1957
FLORENCE	Sept. 9, 1988	FLOSSY	Sept. 24, 1956
BONNIE	June 26, 1986		

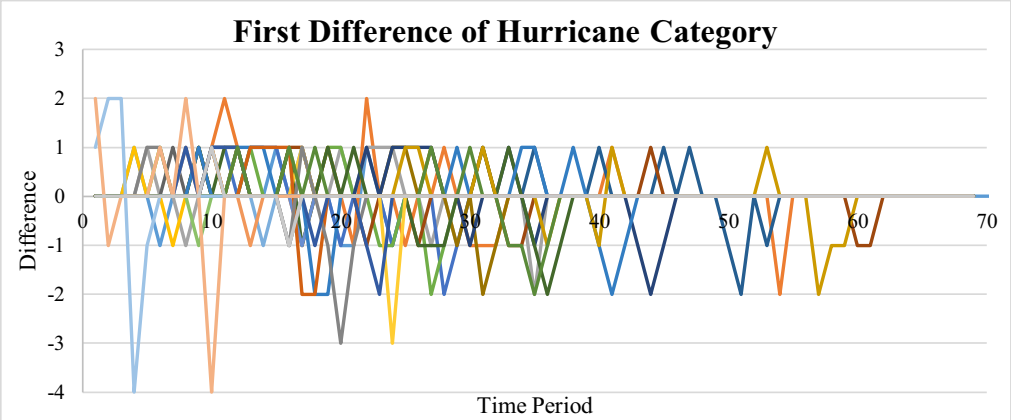

Fig. 3. First difference of hurricane category data.

dynamic model was estimated assuming a "perfect knowledge" approach for estimating the expected utility of respondents (i.e., expectations and future scenarios are an exact match).

Recall that at any forecast i our proposed model uses the household's expectation of how a threat may change over one period of time $(i+1)$. So, in order to estimate the evacuation share for Forecast 4, we needed to have information for one more period. Therefore, a new forecast scenario (Forecast 5) was developed using a static approach for the estimation of the final expected utility with a 6 hours difference from FC4. In here, it is assumed that respondent believed that the hurricane category and evacuation order would not change between Forecasts 4 and 5.

6.2. Stochastic growth

As a way to mathematically model threat evolution, this study proposes an assessment methodology where past observations can be used to predict future conditions. The first step to do so is obtaining data of past hurricanes. This study uses the dataset "Best Track Data" known as Atlantic HURDAT2 collected by the National Hurricane Center (NHC). The NHC conducts an analysis of all storms in its area of responsibility to determine the official assessment of the cyclone's history. Additionally, they perform ongoing retrospective investigation of any tropical cyclone brought to their attention, and update the historical record to reflect any changes found through their analysis. The end product is a rich dataset that provides detailed information for every six hours interval on location, speed and landfall, to mention a few, of all storms that traversed the Atlantic region between the years 1851 and 2014 (Landsea et al., 2015). For this study, all events prior to 1950 and those which did not reach a hurricane level within the area of study (i.e., Louisiana), following the Saffir–Simpson scale, were filtered out. At the end, 27 storms remained (see Table 6) yielding a total of 1065 data points.

With the objective to understand the random evolution of a hurricane, the first difference is taken in relation to each hurricane's category. The result resembles a pure noise (i.i.d. variations), demonstrating a stochastic behavior which could be characterized as a random walk (a sequence of random steps), see Fig. 3.

Autoregressive models are a suitable approach to describe time-varying processes based on a linear relation to past values and an error term. This method has been used in the past for different purposes. For instance, Melnikov (2013) evaluated

the impact of technological change on the dynamics of consumer demand based on the consumer's expectations of future product quality and consumers, while illustrating various ways of implementing random walks.

Several autoregressive models are available, however this study proposes the use of an Auto Regressive model of type 1, AR(1) model, which depends only on one previous value, with a drift:

$$r_t = \alpha r_{t-1} + \gamma + \varepsilon_t \tag{11}$$

where

- α is the dependence factor.
- γ is the drift.
- ε_t is a normally distributed error term with mean zero and variance σ^2.

Using Louisiana's historical hurricane data to estimate the coefficients in Eq. 11, it is found that the dependence factor (α) is equal to 0.931926, the drift (γ) is equal to 0.072533, and the standard deviation (σ) of the error term is 0.533634. The dynamic logit model can now be estimated using these values as input.

To compute the choice probability P, the dynamic model compares the reservation utility W and the mode of μ, the maximum of the alternative's utility (in this case only one, to evacuate). These two quantities depend on the predictors used in the model, which this study assumes to follow an AR(1) model. Therefore different realizations for these predictors will produce different values of W and μ. The procedure implemented here calculates the expected value of W and μ through simulation. The simulation generates B realizations of the AR(1) series of the predictors and compute the corresponding W and μ values. Then, the mean is taken of these simulated W and μ to compute the variable that will enter the utility of postponing the evacuation decision.

6.3. Results using real data

In this Section we present the estimation results for the optimal time to evacuate problem obtained by applying the dynamic model to the Louisiana resident data. In Table 6 we compare four model formulations: 1) a dynamic discrete choice model that assumes perfect knowledge; 2) a dynamic discrete choice model with dynamic variable on a random drift; 3) a sequential logit model; 4) a sequential logit model with the same independent variables used in the dynamic specification.

The sequential logit model is specified as in Fu and Wilmot (2004), who collected the Louisiana data and first modeled the time to evacuate using discrete choice models. The suggested method allows the use of all observations (i.e., binary choices) simultaneously, therefore reducing computational efforts and avoiding small data sample size for later time intervals. Their proposed model is as follows:

$$L = \prod_{n-1}^{N} P_n(i) = \prod_{n-1}^{N} P_n(i)_{s/c} \prod_{j=1}^{i-1} \left[1 - P_n(j)_{s/c}\right] \tag{12}$$

where $P_n(i)$ denotes the probability that household n evacuates in time interval i, N is the total number of households and $P_n(\bullet)_{s/c}$ is the probability that the utility of a household to evacuate is greater than the utility of the household to not evacuate in time interval i, provided that the household has not already evacuated. The reader is referred to the source paper for in depth explanation of the methodology.

Results from models' estimation are reported in Table 7. The coefficient estimates indicate that as hurricane category and evacuation order increase, so does the willingness to evacuate and that if the household waits until the last forecast, they are less likely to evacuate—matching previous evacuation behavior in the region. It is worth to note that the data showed that around 98% of Gustav's evacuees did so by at least 24 hrs before landfall, highlighting household's willingness to evacuate early. One can assume that the latter is due to the fact that households may prefer to avoid congestion and the risk of experiencing the hurricane out in the open. However, if the hurricane is too far away, this would lower the probability of evacuating. Additionally, having past experience with evacuation (i.e., if the household evacuated during Hurricane Gustav) has a significant positive effect on the decision to evacuate. In general, all model estimates have significant coefficients with expected signs. Finally, based on the results from the dynamic model, it is clear that households are less willing to evacuate during the evening and that household size and income have negative effect on evacuation, whereas the presence of kids has a positive influence on the decision to evacuate. None of the socio-demographic characteristics was found to be significant in the static approach as it can be seen from the fifth column in Table 7.

In order to compare the Dynamic Logit with PK and the Sequential logit we apply the non-nested hypothesis test proposed by Horowitz (1982) that calculates the Significance Level (SL) as follows.

$$SL = \Phi\left[-\left(-2\left(\rho_H^2 \cdot LL(0)_H - \rho_L^2 \cdot LL(0)_L\right) + (K_H - K_L)\right)^{\frac{1}{2}}\right]$$

where:

ρ_H^2 is the adjusted likelihood ratio index for the model with the lower value,
ρ_L^2 is the adjusted likelihood ratio index for the model with the higher value,
K_H and K_L are the numbers of parameters in models H and L, respectively, and

Table 7
Model estimation results.

Variable name	Mixed dynamic logit with PK	Dynamic logit with PK	Dynamic logit with AR(1)	Sequential logit	Seq. logit (Dyn. adaptation)
Hurricane category (mean)	0.2817	0.2256***	0.2020***	0.4776***	0.5790***
	(6.80)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Hurricane category (s.d.)	0.2957				
	(2.76)				
Evacuation order				0.4730***	
				(< 0.01)	
TOD4 (6PM-12AM) (mean)	-4.1620	-1.0564 (0.105)	-1.2288*		-0.969
			(0.082)		
	(1.10)				(0.205)
TOD4 (6PM-12AM) (s.d.)	4.5148				
	(1.18)				
Time to expected landfall	-0.0315	−0.0294***	−0.0277***	−0.0150**	-0.0330***
	(27.48)	(< 0.01)	(< 0.01)	(0.02)	(< 0.01)
Last forecast (FC4) (mean)	-6.7015	−3.3004***	−3.1979***	−2.8623***	-2.9444***
	(0.89)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Last forecast (FC4) (s.d.)	5.0349				
	(0.89)				
Evacuation experience Gustav (mean)	2.9815	0.8890***	0.8751***	1.5740***	1.5520***
	(6.14)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Evacuation experience Gustav (s.d.)	3.816				
	(8.37)				
Household size	-0.5533	−0.2733***	−0.2813***		0.0006
	(4.19)	(< 0.01)	(< 0.01)		(0.96)
Number of kids (Less than 17yrs old)	0.6788	0.2907***	0.3020***		0.0071
	(3.76)	(< 0.01)	(< 0.01)		(0.91)
Household income	-0.1719	−0.1561***	−0.1505***		-0.0286
	(2.58)	(< 0.01)	(< 0.01)		(0.44)
Constant				-3.6673*** (< 0.01)	-2.5797***
					(< 0.01)
Number of observations:	763	763		2155	2155
L(0):			-1918.44	-1086.63	-1086.63
LL:	-958.80	-968.51	−970.20	-909.04	-913.83
Adjusted R^2:	0.494	0.491		0.158	0.149

***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level

Φ is the standard normal cumulative distribution function.

The two models have the same number of coefficients estimated therefore the SL reduces to:

$$SL = \Phi\left[-(-2(0.491 \cdot -1918.44 - 0.158 \cdot -1086.63))^{\frac{1}{2}}\right] = \Phi[-39.20] \gg 0.001$$

which implies that the dynamic model is superior to the static model. However, the two dynamic model approaches (Perfect Knowledge and Stochastic Growth) yield strikingly similar results.

The dynamic model proposed has also been extended to accommodate taste heterogeneity; results are reported in the first column of Table 7. The mixed type dynamic model is specified with four random parameters, which are hurricane category, time of day, last forecast, and evacuation experience. They are all assumed to be normally distributed; as from a behavioral stand point there is no reason to constrain these coefficients to a random variable that can assume just one sign. The resulting model has a slightly better fit than the dynamic model with fixed coefficients. It can be noted that the all the coefficients keep the same sign obtained with fixed coefficient models. We calculate that although the Hurricane Category mean is positive, the coefficient is negative for 17% of the population. This might be due to the fact that under extreme weather conditions and due to the worsening of the hurricane, the respondents felt that evacuate was not a safe option. TOD4 that has negative mean is positive for 18% of the population; this confirms that people prefer to evacuate during the day; but a small percentage of them still prefer to evacuate later due probably to other constraints not registered in the present survey. Gustav Evacuation Experience, again positive for the majority of the individuals is negative for 22% of the population. Having experienced a hurricane in the past is a good motivation to evacuate; those with negative coefficients probably feel that their place is safe given the past experience. The variable Last Forecast becomes not significant.

In order to further validate the proposed approach, we re-estimated the model on eighty percent of the sample available and we applied the model on the remaining observations. Fig. 4 compares the observed evacuation decisions versus the estimated ones on the out-of sample. All the dynamic models reproduce well the observed choices. In particular, the dynamic PK mode and the dynamic AR(1) model have the same prediction results; the mixed dynamic model is in general worse than the former two except for evacuation on Time Period 3. The sequential logit models have low prediction power; they underestimate the number of people who are not evacuating and overestimate the number of evacuees, especially on

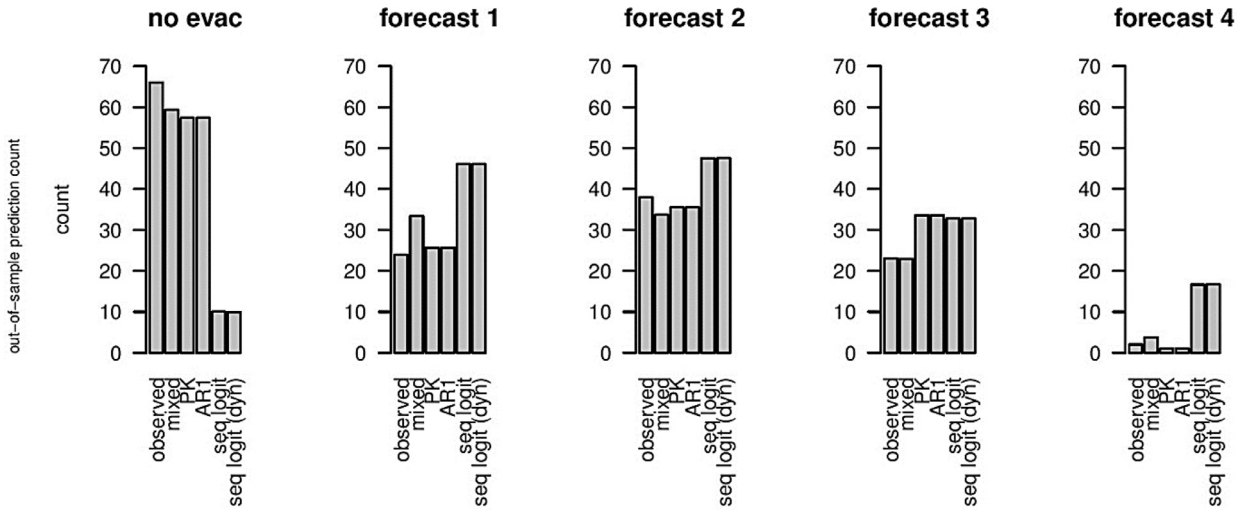

Fig. 4. Out of sample model validation.

Time Period 4. From both estimation and validation results, we can conclude that for this dataset the dynamic models have a better fit, and produce more realistic predictions over time.

7. Conclusion and future steps

Modeling approaches within evacuation behavior analysis generally do not account for the dynamic of decisions over time and do not incorporate dynamic variables. This paper has successfully estimated a dynamic behavioral model based on the optimal stopping time to evacuate that accounts for both stochastic variables and respondent's expectations during a hurricane emergency. Dynamic Discrete Choice Models (DDCM) have been (scarcely) used in the past within the field of transportation, and to the best of the author's knowledge, this is the first time such model is presented from an evacuation perspective. The proposed modeling framework has also been compared to existing discrete choice methods, namely Sequential Logit. We have demonstrated that simpler approaches yield to significant lower fit, significantly underestimate the probability of not evacuating and fail in incorporating demographic information. In this sense, it is evident that DDCM are more beneficial and insightful, and can serve as a tool for evaluating measures that could improve the efficiency of evacuations and emergency planning.

In general, the results found in this research follow tendencies in sign, but not in significance when compared to Baker's and Huang et al.'s findings. Hurricane category is the only variable that concurs in both sign and significance; whereas income differs in both. However, it should be noted that "despite the large hurricane evacuation database, each new study adds understanding" (Baker, 1991, pg. 309), and therefore results should be evaluated on a study by study basis.

This is just the first step in the development of a robust model that allows the consideration of stochastic variables into behavioral choices. In this specific case, further research is needed to better represent the evolution of the threat's attributes over time, a key element in the estimation of expected utility. Also, more attention should be devoted to the role of information during evacuation and on the decision to evacuate; models with more realistic assumptions about decision makers' information access and processing would yield to more robust representation of the evacuation process. This research experiments with two representations of hurricane evolution, however more and alternative approaches should be tested to improve estimation accuracy and to give general recommendations. Additionally, future research could include other formulations of random walks and consequently for the calculation of the future expected utilities. It would also be interesting to extend the dynamic model to include departure time, mode of evacuation and destination to further improve the analysis of policies regarding shelters location, demand management and distribution of resources. Future research could also look at developing comprehensive and robust learning mechanisms, such as a Bayesian approach, to determine expectations and evolution of believes over time. Comprehensive datasets are also needed to analyze socioeconomic factors that affect evacuation behavior, and most importantly that provide detailed and more variable observations over several time periods for the dynamic analysis. This will allow better understanding of the many different (dynamic) factors that influence the evacuation decisions.

Finally, our current dataset contains only four forecasts with significant time gaps between the first ones, and they do not fully align with official timing of watches/advisories and warning. For instance, the National Hurricane Center provides: 1) watches issued 48 hours in advance of the anticipated onset of tropical-storm-force winds and 2) warnings issued 36 hours in advance of the anticipated onset of tropical-storm-force winds. This is a potential limitation that should be further explored in future research.

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