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16. Abstract

Little attention has been given to estimating dynamic travel demand in transportation planning in the past. However, when factors influencing travel are changing significantly over time – such as with an approaching hurricane - dynamic demand and the resulting variation in traffic flow on the network become important. In this study, dynamic travel demand models for hurricane evacuation were developed with two methodologies: survival analysis and sequential choice model. Using survival analysis, the time before evacuation from a pending hurricane is modeled with those that do not evacuate considered as censored observations. A Cox proportional hazards regression model with time-dependent variables and a Piecewise Exponential model were estimated. In the sequential choice model, the decision to evacuate in the face of an oncoming hurricane is considered as a series of binary choices over time. A sequential logit model and a sequential complementary log-log model were developed. Each model is capable of predicting the probability of a household evacuating at each time period before hurricane landfall as a function of the household's socio-economic characteristics, the characteristics of the hurricane (such as distance to the storm), and policy decisions (such as the issuing of evacuation orders).

Three datasets were used in this study. They were data from southwest Louisiana collected following Hurricane Andrew, data from South Carolina collected following Hurricane Floyd, and stated preference survey data collected from the New Orleans area.

Based on the analysis, the sequential logit model was found to be the best alternative for modeling dynamic travel demand for hurricane evacuation. The sequential logit model produces predictions which are superior to those of the current evacuation participation rate models with response curves. Transfer of the sequential logit model estimated on the Floyd data to the Andrew data demonstrated that the sequential logit model is capable of estimating dynamic travel demand in a different environment than the one in which it was estimated with reasonable accuracy. However, more study is required on the transferability of models of this type, as well as the development of procedures that would allow the updating of transferred model parameters to better reflect local evacuation behavior.

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MODELING HURRICANE EVACUATION TRAFFIC: DEVELOPMENT OF A TIME-DEPENDENT HURRICANE EVACUATION DEMAND MODEL

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ABSTRACT

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IMPLEMENTATION STATEMENT

This research developed dynamic travel demand models for hurricane evacuation. The application of the models developed in this study will improve travel demand estimation for hurricane evacuation. The models can be used to estimate hurricane evacuation travel demand within discrete time intervals under different storm scenarios and evacuation policy variable–type and timing of evacuation orders. The models support the application of dynamic traffic assignment techniques, which represent the state-of-the-art transportation modeling since they provide a more accurate and realistic prediction of the traffic conditions as time changes.

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INTRODUCTION/BACKGROUND

Hurricanes are one of the major natural threats to the coastal regions of the United States. An effective measure to reduce the potential damage of hurricanes is to evacuate the population at risk from the threatened area. However, hurricane evacuation is a complicated activity since "it involves moving a large population that may grow or change, onto a highly congested and possibly damaged road network, towards destinations that are not easily determined." *[1]* As a result, a hurricane evacuation modeling system, which provides decision support capability to local officials and emergency response teams to effectively develop, test, and compare evacuation plans and management strategies, is very important. A major component of the modeling system is the modeling of the transportation system.

In general, transportation modeling for evacuation has followed similar procedures to that used in urban transportation planning. Historically, the traditional urban transportation planning method has been used to estimate traffic conditions for an average weekday or for a peak period. This approach has worked reasonably well for long-range transportation planning, especially when congestion in the system was not pronounced. However, with increasing levels of congestion that have developed in urban areas over time, the need to conduct air quality analysis, evaluate Transportation Demand Management (TDM) alternatives, and assess the impact of Intelligent Transportation Systems (ITS) has resulted in the demand for the ability to estimate traffic conditions in urban transportation planning on the network more accurately. One of the consequences of this need has been the development of time-of-day modeling procedures, which can produce a more accurate estimate of the traffic conditions. This has relevance to evacuation modeling as well since it is not only the total volume of traffic that uses a facility that is of interest, but the time at which it is used by individual vehicles, leading to peaking, congestion, and delays.

In time-of-day analysis used in urban transportation planning, a day is divided into different periods according to the levels of congestion normally experienced during the day. For example, a day could be divided into three periods: the morning peak period, afternoon peak period, and the rest of the day. Typically, people are more interested in the peak periods since the demands of these periods are usually used to determine the facility size. The time-of-day factor (TODF), the ratio of vehicle trips made in a peak period to those in some given base period (usually a day), is commonly used in urban transportation planning to estimate time-of-day volumes. TODFs are commonly derived either from household surveys or from traffic counts. TODFs are then factored into the four-step modeling procedures to produce estimates of traffic conditions for the periods in which they are estimated. TODFs can be applied in different places of the four-step procedures with different advantages and limitations *[2]*.

One of the most significant features of urban transportation planning, with respect to evacuation modeling, is that the forecast of traffic conditions is static. That is, traffic is forecasted for a period, such as a day or a peak period, and, within that period, traffic is assumed to flow uniformly. In reality, traffic conditions, especially during peak hours, change regularly, and people make route-changing decisions dynamically due to varying traffic conditions. The traditional static procedures do not give any information on the dynamics of the traffic. Moreover, Robles and Janson *[3]* demonstrated that dynamic traffic modeling yields much closer estimates of traffic conditions than traditional static procedures when applied to urban area networks during congested periods.

Another feature of static traffic assignment that does not suit the evacuation environment well is that in the assignment process, all links on the shortest path between an origin and destination are assumed to carry the traffic between those two points. In an urban environment where trip lengths are relatively short with respect to the time period considered (e.g. a day or a peak period), this assumption is acceptable because most trips that are made will occupy each link in the shortest path at some time during the time period. However, in evacuations, trips are long with long travel times due to congestion, meaning that the assumption that each trip will occupy each link in their shortest path can only be true if the time period in which the traffic is reported is longer than the longest trip. Thus, the reporting periods of evacuation traffic using static traffic assignment must be long, yet it is the traffic conditions in shorter time periods that are of interest. For example, peaking within the time period can cause congestion that would not be discerned with static assignment over longer periods, and knowing when vehicles occupy each link will help get the maximum use out of the network by ensuring that each link is used to its capacity each hour of the evacuation period. The maximum use of the network could conceivably be orchestrated by issuing evacuation orders among the different counties/parishes in such an order that the resulting evacuating traffic uses the network optimally without overloading some links in one of the short time period and underutilizing them in another.

In the past 20 years, one of the fastest growing research areas in travel demand modeling has been Dynamic Traffic Assignment (DTA) *[4-9]*. The advancement of some aspects of ITS, such as Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS), have generated the need to model travel behavior dynamically, as drivers respond to traveler information or traveler directives issued in response to current conditions *[10,11,12]*. DTA seeks to assign traffic continuously, or in very short time intervals, and then keeps track of the vehicles both temporally and spatially. This makes it possible to know, at every moment, or in short periods of time, which vehicle is traversing which link at what speed. This is fundamentally different from static assignment, as described earlier, which only tells that a certain vehicle will use certain links of a route with certain average speeds during the analysis period, which may be a day or several hours. Moreover, DTA can make the assignment responsive to varying road conditions, such as capacity changes due to incidents, road closures, or the reverse-laning of facilities at certain times during the evacuation process. As a result, DTA provides a more accurate and realistic prediction of the traffic conditions as time changes. Such dynamic modeling represents the future state-of-the-art transportation modeling since there exists little operational capability at the present time to solve the computational demands represented by large-scale networks *[8,9]* except for the work by Boyce et al. *[13]* and Robles and Janson *[3]*.

To perform dynamic modeling, the estimation of time-dependent origin-destination (O-D) demand is required. However, most researchers assume such time-dependent O-D tables are available a priori. Ziliaskopoulos and Peeta *[9]* pointed out in their recent review on DTA:

> "Probably, the single most challenging obstacle to overcome, before deploying DTA for planning applications, is that of estimating and predicting the time-dependent origin-destination demand… Surprisingly, the problem of estimating the temporal distribution of demand has been addressed by only a few studies."

Hurricane evacuation is a very different situation from that of day-to-day travel. It involves, as mentioned earlier, long travel times (usually more than several hours), high levels of extended congestion (more people traveling in the same period of time on limited evacuation routes), uncertainty of road conditions (wind, visibility, availability of facilities), and the possibility that destinations may need to be changed due to closed roads or roads that are overcrowded, just to name a few. In urban transportation planning, trips are more discretionary in nature and some trips can be postponed from one day to the next (e.g. shopping trips), while in a hurricane evacuation situation, relatively little discretion is allowed for when to make the trip. Evacuees are more willing to follow official directions as to which route to use and are less likely to choose the shortest path than the urban travelers who make regular trips. These differences all point to the fact that while travel is also being generated during evacuation, as it is in regular urban travel, the motivation for travel and the resulting travel behavior is considerably different in the two situations. The capability to accurately forecast dynamic traffic conditions in terms of speed, travel time, volume, level of congestion, and the overall evacuation time would greatly enhance the ability to effectively develop, test, and compare evacuation plans and management strategies. Dynamic assessment of travel conditions is important in modeling hurricane evacuation.

There are several computer packages to model evacuation. Some of the packages can be applied to hurricane evacuation. The majority of the packages were developed for nuclear power plant evacuation. Some provide limited information on traffic conditions, with their main purpose being to calculate evacuation time using static assignment. Others use dynamic assignment to different degrees, providing more accurate information about traffic conditions. However, all of the packages assume that an O-D table is available. For those that use dynamic assignment, a time-dependent O-D table is assumed to be given, or a response (loading) curve, which represents percentage of trips traveled in each time interval for the analysis period, has to be specified.

In conclusion, dynamic modeling of travel demand can more accurately and realistically forecast traffic conditions than traditional procedures. Its application in hurricane evacuation can be especially valuable to improve planning capability. At the present time, time-dependent O-D tables are assumed to be provided a priori for *DTA*. Therefore, the development of dynamic travel demand estimation for hurricane evacuation is needed as the first step in providing an improved modeling process for hurricane evacuation.

In the research reported in this dissertation, the position has been taken that the decision to evacuate and the decision to depart are, in fact, a joint decision. It is also suggested that this joint decision is an issue that is considered repeatedly prior to it being taken. That is, it is assumed that each household repeatedly reviews the conditions surrounding a storm as it develops, each time making the decision to not evacuate, until, if they decide to evacuate, a threshold is reached in their decision process and the decision is made. To model this process, the use of survival analysis models and sequential choice models are proposed.

OBJECTIVE

The objective of this research is to develop alternative dynamic travel demand models of hurricane evacuation travel and to compare the performance of these models with each other and with the state-of-the-practice models in current use. Specifically, the research is directed at addressing the following hypotheses:

- Dynamic travel demand models can be developed that reproduce hurricane evacuation travel more accurately than conventional methods that use evacuation participation rates and response curves.
- Dynamic travel demand models can be developed that are capable of reproducing hurricane evacuation travel at different locations and under different storm and policy conditions.

SCOPE

The research in this study explored different methodologies to develop dynamic demand models for hurricane evacuation. Two survival analysis method models (the Cox Proportional Hazards model and the Piecewise Exponential model) and two sequential choice models (sequential logit model and complementary log-log model) were used in the study. Household survey data from several hurricanes were utilized in the modeling effort, including two revealed preference surveys and one stated preference survey. The models developed in this study were compared with the traditional models. The transferability of the developed models was also tested.

LITERATURE REVIEW

In this section, a brief review of evacuation packages is first presented, followed by a review of several proposed modeling frameworks of hurricane evacuation. These reviews will serve to demonstrate that the state of practice in evacuation is shifting toward dynamic modeling, and the development of dynamic travel demand model is needed. The last part is a review on travel demand modeling methods for hurricane evacuation.

Evacuation Package Review

Early evacuation studies focused on determining clearance times during an emergency evacuation *[14]*. Recent studies require models with the capability of providing information on the dynamics of the traffic system. Jamei *[15]*, Southworth *[16]*, and Mei *[17]* have provided thorough reviews on the packages. The following is a brief review of important recent developments in evacuation software packages, emphasizing the dynamic capabilities of the packages and how travel demand is treated.

Evacuation packages can be grouped into two categories: those using static assignment and those using dynamic assignment procedures. DYNEV and ETIS belong to the static group while NETVAC, MASSVAC, and OREMS are in the dynamic group.

DYNEV was developed for the Federal Emergency Management Agency (FEMA) by KLD Associates *[18,19]* for nuclear plant evacuation simulation. It is the most widely reported network evacuation model *[16]*. As a macroscopic traffic simulation model, DYNEV performs static equilibrium traffic assignment. It requires traffic volume, entering each link as input. The output of the model gives detailed information about the operational performance of each link, including vehicle speed, traffic density, and volume. This information can help identify bottlenecks along the evacuation routes.

The Southeast United States Hurricane Evacuation Travel Demand Forecasting System was developed by PBS & J *[20]* for the states of Florida, Georgia, Alabama, North Carolina, and South Carolina. The system is a web-based hurricane evacuation travel demand forecasting model with GIS capabilities designed for emergency management officials to access the model on-line. It has subsequently been named the Evacuation Traffic Information System (ETIS) *[17]*. Input to the system includes category of hurricane, expected evacuation participation rate, tourist occupancy, and destination percentages for expected counties. Default values for participation rates, tourist occupancies, and destination percentages from each county are available in the model. The model uses a shortest-path algorithm to forecast traffic volumes on the major highways in the region. Output includes: expected levels of congestions by highway segment, tables of expected volumes of traffic crossing state lines by direction, and number of vehicles generated by each county traveling to specific inland locations. ETIS does not have the capability to model traffic dynamically.

NETVAC was perhaps the first evacuation package with dynamic assignment capability. Sheffi et al. *[21]* introduced NETVAC1 as a macro traffic simulation model developed for the evacuation of nuclear power plants. The model is capable of handling large networks with different control strategies within the network. Route choice in NETVAC is performed dynamically at each intersection. Based on the directionality of the exit links and the traffic conditions directly ahead, the probability of a driver choosing an outbound link, j, at an intersection at time, t, $P_j(t)$, is calculated based on these conditions. Time-varying O-D tables are required as input. For each link and each specified interval, the output gives queues, speeds, and other measures of level of service and flow pattern throughout the evacuation process.

Hobeika and Kim *[22]* introduced MASSVAC4.0 as an expanded and modified version of MASSVAC3.0 *[23]* with the addition of a user-equilibrium assignment algorithm (UE). For each simulation interval, say 15 minutes, a time-dependent O-D trip table is assigned using the UE algorithm. After comparing the assigned link volume against link dissipation rate, if the link volume does not exceed link capacity, the network is assumed to have served all the vehicles assigned; otherwise, the remaining volumes of the congested links are calculated and recorded. These volumes are added to the volumes assigned in the next simulation interval. Although O-D trip tables are assigned dynamically, the system does not keep track of vehicles, and they are assumed to occupy the entire path instantaneously. From this point of view, MASSVAC4.0 is not a true dynamic package.

The Oak Ridge Evacuation Modeling Systems (OREMS) Version 2.5 was developed by the Center for Transportation Analysis at the Oak Ridge National Laboratory *[24]*. As a macroscopic simulation model developed to simulate traffic flow during an emergency evacuation both from a man-made and natural calamity, it has perhaps the most advanced features and functions among all the packages. The analytical core of OREMS is a FORTRAN-based program ESIM (for Evacuation SIMulations). Depending on data availability, ESIM can perform three kinds of simulations. If intersection turning counts data are available, it performs a link-based simulation; if the user provides origin-destination data, it performs a path-based simulation; and if only origin demand and destination attraction factors are available, the model distributes the trips for O-D pairs and then performs a path-based simulation. ESIM assigns traffic using the user-equilibrium assignment procedure. The simulation model moves groups of vehicles on the links. If it is a path-based simulation, then the next link is determined by the path assigned to the vehicles. If it is a link-based simulation, then the downstream link is chosen according to the turning data. The effects of traffic control measures, such as signals, STOP, and YIELD signs, are simulated at every intersection.

OREMS can provide dynamic and graphical output about link speed, volume, congestion, etc. It can perform both static and dynamic assignment. However, it requires a loading curve for its O-D trip table.

From the above review, it can be concluded that the simulation packages have evolved from static assignment with simple capabilities of calculating network clearance time and giving limited information on link volume for potential bottlenecks to dynamic assignment that can perform dynamic traffic assignments, providing time-varying traffic information. However, to perform dynamic assignment, all models require a loading curve or time-dependent O-D tables. To date, no dynamic travel demand model has been developed. There appears to be a clear need to develop a dynamic travel demand model for hurricane evacuation.

Hurricane Evacuation Modeling Frameworks Review

Before the 1990s, most of the attention on transportation analysis of evacuations focused on man-made disasters, especially nuclear power plant evacuations, as evidenced from the development of many evacuation packages such as CLEAR *[25]*, NETVAC1 *[21]*, DYNEV *[19]*, MASSVAC *[23,26]*, etc. However, in more recent times, interest in modeling hurricane evacuation has increased. Lewis *[27]*, Barrett et al. *[1]*, and Franzese and Han *[28]* have proposed traffic modeling frameworks to model hurricane evacuation.

Lewis *[27]* defined evacuees as either residents living in surge-flooded areas in the coastal region or wind-vulnerable residents living in mobile homes or substandard housing in inland areas. Trips are generally home-based trips to shelters, hotels, or friends/relatives. Lewis pointed out the close parallel between the travel demand forecasting process for urban travel demand and that needed in evacuation forecasting: zonal delineation, zonal data development, network preparation, trip generation, distribution, and assignment. He suggested modeling hurricane evacuation trip generation by trip purpose (i.e., Red Cross/public shelters, hotel/motel, friends/relatives, or out-of-county destinations) and by evacuation zone for selected hurricane scenarios. Behavioral response curves were used to describe the slow, medium, and rapid response of evacuees leaving their homes. The entire procedure parallels that of the traditional transportation modeling procedure.

Barrett et al. *[1]* proposed a framework in which a dynamic traffic management model for hurricane evacuation can be used for long term and short term planning purposes as well as for real-time operational purposes. They proposed functional requirements for dynamic hurricane evacuation modeling. The system is set up to provide not only evacuation time, but also evacuation routes and departure times that drivers can be predicted to choose and maximize the system performance. The system also allows development of management strategies that optimize evacuation from either the user or the system perspective. Barrett et al.'s framework *[1]* is a dynamic modeling approach. It utilizes time-dependent travel demand. However, it is not clear how demand estimation will be modeled.

To reflect the dynamic nature of the demand and network conditions, Peeta and Mahmassani *[29]* proposed a Rolling Horizon (RH) approach. The underlying philosophy behind the RH approach is that events "far" in the future will not influence current events. For example, current vehicle assignment may be performed with only limited consideration of vehicle assignments that are "far" in the future, because by the time future trips are assigned current vehicles are already out of the system *[11]*. The RH approach assumes that deterministic information of dynamic traffic demand and network conditions is available only for a short period of time, and the model is implemented in every "roll period" *[30]*. The demand and network data are updated for each roll period. At each time period, the time horizon is rolled forward by a length equal to the roll period. The problem with this method is that if the updated information is not accurate, the result will be sub-optimal *[9]*.

Franzese and Han *[28]* developed a traffic modeling framework for hurricane evacuation called the Incident Management Decision Aid System (IMDAS). In their framework, hurricane evacuation analysis is conducted in several steps. The first step is the classification of the evacuation area into an Immediate Response Zone (IRZ), a Protective Action Zone (PAZ), and a Precautionary Zone (PZ) according to the risk each area faces. The next step determines the population at risk within the IRZ, which, with hurricanes, includes coastal communities and areas housing tourists and other transient populations. Step three uses behavioral analysis to estimate the number of people that will actually evacuate. Departing times, destinations, and vehicle occupancy are determined as part of this process.

The output of the first three steps is an O-D trip table. This O-D table, along with the transportation network, serves as input to the traffic model that is used to evaluate the effectiveness of evacuation. The traffic model can evaluate and compare different alternatives involving alternate routes, destinations, traffic control strategies, traffic management strategies, evacuee response rates, and evacuee departing times.

An evacuation departure time curve is used to represent the temporal travel demand distribution. The O-D trip table is factored according to the evacuation departure curve (slow, medium, or rapid response) to produce a time-varying travel demand. The central component of the system is a traffic simulation model developed at ORNL, which was reviewed earlier.

Travel Demand Modeling for Hurricane Evacuation

State-of-the-Practice in Urban Travel Demand Modeling

Urban travel demand modeling has evolved over the past forty years into an established procedure, which is usually referred to as the classical four-step approach *[31]*. Since the 1960's, urban travel demand modeling has followed the four-step procedure: trip generation, trip distribution, mode choice, and traffic assignment. As the first step in travel demand modeling, the traditional trip generation model estimates the number of trips originating or ending in each Traffic Analysis Zone (TAZ). The analysis can be performed at two levels, disaggregate or aggregate. At the disaggregate level, trip estimation is based on the characteristics of households, such as income, household size, number of workers, car ownership, and number of licensed drivers in the household; while, at the aggregate level, the characteristics of the TAZ are used.

In general, statistical analysis methods are used in trip generation modeling. The simplest method is to use zonal or household trip rates as estimated using either regression or cross-classification (sometimes also referred to as category analysis) *[32,33]*. In cross-classification analysis, several techniques might be used to classify travelers into a few homogeneous and distinct groups so that each has a characteristic trip rate. These techniques include: analysis of variance, factor and cluster analysis, contingency tables, and discriminant analysis *[31]*.

Recently, there have been some efforts to use Artificial Neural Networks (ANN) to model trip generation *[34-36]*. Anderson and Malave *[37]* developed a dynamic trip generation model for a medium sized urban community. It is a linear regression model aggregated at the zonal level. The variables used in the model include socioeconomic characteristics of the zones and the distance to the central business district. With data collected from 7:30 a.m. to 8:30 a.m., they developed two dynamic trip generation models, one for every five minute interval and one for every 15 minute interval. The model using the 15 minute time interval outperformed the one with the five minute time interval.

At either level of aggregation, planning agencies spend significant resources collecting zonal or household information (usually through household surveys). With this information, trip generation models are usually developed to produce 24-hour trip production and attraction estimates. There have been limited attempts to collect time-dependent trip generation data and to model trip generation in a time-dependent manner. It is therefore not surprising that the time-dependent trip generation model in hurricane evacuation modeling has received relatively little attention in the past as well.

Current Practice in Hurricane Evacuation Travel Demand Modeling

Current practice in hurricane evacuation travel demand modeling is to conduct the process of estimating travel demand in two steps: the estimation of total evacuation demand in the first step and the estimation of departure time in the second. Generally, these steps are conducted using simple relationships, such as means, rates, and distributions, rather than the more sophisticated mathematical relationships observed in urban transportation planning *[17]*. The most common method of estimating total evacuation demand is to use evacuation "participation rates" of geographic subdivisions of the area in which evacuation behavior is considered homogeneous. Participation rates are the proportion of households in an area that evacuate. Participation rates are assumed to vary among these geographic subdivisions (evacuation zones) depending on the severity of the storm and its flooding potential. Participation rates are established subjectively based on past behavior under different storm conditions.

Some researchers report the use of logistic regression to model hurricane evacuation demand *[17,38,39]*. Johnson and Zeigler *[40]* used logistic regression to model evacuation demand from areas surrounding the Three Mile Island nuclear power station following the nuclear accident there in 1979. Using data from *Three Mile Island Telephone Survey*, Johnson and Zeigler *[40]* selected eleven variables in their logistic regression analysis. The variables included: locational variables (including perceived distance and direction), stage-in-life-cycle variables (including age of household head, marital status, whether young children were present in the home and whether there was anyone pregnant in the home), educational status (years of school completed), and pre-accident attitude toward the nuclear plant at Three Mile Island (general attitude toward nuclear power, attitude toward the Three Mile Island plant, and perception of risk of an accident at the Three Mile Island facility). The dependent variable was the evacuation decision. The analysis found that the evacuation decision was directly influenced by all of the above variables.

The independent variables tested in the study by Irwin et al. *[38]* were: type of dwelling, gender, marital status, education, age, race, income, prior hurricane experience, and perception of being hurt if they did not evacuate. Income was not found to be influential in the evacuation decision probably because of the presence of other socio-economic variables such as education and race in this particular data set. It was found that the perception of risk, type of dwelling, gender, and age significantly influenced the probability of evacuation for Hurricane Andrew. A critique on the problems of the study is provided by Mei *[17]*.

A team from the Regional Development Service (RDS) and East Carolina University *[39]* used logistic regression analysis to model the probability that a household will evacuate using a sample of 940 households collected following Hurricane Bonnie *[39]*. Nine variables were tested in the model and all were significant. These variables were evacuation order, perceived risk of flood, whether the household had an evacuation plan or not, vehicle ownership, whether the respondent was working full-time, whether neighbors evacuated or not, the presence of pets, housing type (mobile home or not), and level of education.

Mei *[17]* used logistic regression to develop a trip generation model with Hurricane Andrew household survey data from southwest Louisiana. The dataset was relatively small (410 households). The dependent variable was the probability of a household evacuating. The independent variables, which were found significant, included housing type, whether the household received a mandatory evacuation order or not, age of the respondent, distance of the household from the closest body of water, and marital status. Variables tested but found to be insignificant included ownership of the residence, prior hurricane experience, race, education level, and household size.

Mei *[17]* also utilized ANN to develop trip generation models for hurricane evacuation with disaggregate data. Three kinds of ANN models were tested. They were a Bayesian-based probabilistic neural network (PNN) model, a learning vector quantizer (LVQ) model using an adaptation of the Kohonen Self Organizing Mapping approach, and a conventional feed-forward neural network model using back propagation in its estimation (BPNN). The backpropagation neural network model described the probability of a household evacuating while the other two models, being classification-type models, directly identified whether the household would evacuate or not. The Root-mean-squared-error (RMSE), the percent correctly predicted (PCP), and results from the Receiver Operating Characteristic (ROC) curve were used to compare models. In general, the study demonstrated that ANN models can be used to model evacuation travel demand estimation with similar accuracy to other methods of evacuation demand. The logistic regression and neural networks displayed similar predictive performance, but the logistic regression and the BPNN models were a little better than the PNN and LVQ models. The models performed well with the overall percent correctly predicted with rates ranging from 65 percent to 68 percent.

The models reviewed all produce trip generation estimates without considering when these trips will take place. That is, trip generation models that have been developed for hurricane evacuation in the past, as well as those that have been developed to model other travel behavior, have not tried to model the time at which the trips were generated. Instead, in hurricane evacuation modeling, a response curve has typically been used to predict the percentage of trips evacuating in each time interval during the analysis period. A response curve is the assumed departure time distribution of evacuees. It is also sometimes referred to as a loading or mobilization curve. The loading curve is usually portrayed as the cumulative percentage of evacuees evacuating by time period and, traditionally, has been assumed to take on a sigmoid or "S" shape. According to how readily the analyst expects the evacuees to respond to an order to evacuate, loading curves are typically classified as "quick", "medium", or "slow". The quicker the response, the steeper the curve. The choice of a loading curve is a subjective decision by the analyst.

Leik et al. *[41]* was among the first to study the cumulative percent of evacuees leaving home during each hourly period in the face of an oncoming hurricane. Leik et al.'s study, and other evacuation planning related studies in social science, showed that highway network loading starts at a low rate at the beginning and as time progresses the rate increases until it reaches its maximum rate of loading approximately halfway through the total loading period. The loading curve takes the form of a sigmoid or 'S' shape. Jamei *[15]* gave the following equation to describe the loading curve:

$$P(t) = 1/\{1 + \exp[-\alpha(t-\beta)]\}, \qquad (1)$$

where $P(t)$ is the cumulative percentage of total trips loading the network, α is a curve slope factor, β is the half loading time (the time at which half of the total volume is loaded on the network), and t is current time. Figure 1 gives three loading curves compiled by Earl J. Baker of Florida State University *[42]*, representing slow, medium, and rapid loading as obtained from past records of vehicle volumes observed during the evacuation from numerous hurricanes. The time when the evacuation order is issued is defined as 0 on the horizontal axis. Equation 1 is adopted by Radwan et al. *[26]* and Hobeika and Kim *[22]*. Lewis *[27]* and U.S. Corps of Engineers *[42]* also use similar curves as in Figure 1. The same sort of response has also been reported for flash flooding *[43]*.

Tweedie et al. *[44]* reported a loading curve that can be approximated by the Rayleigh probability distribution function given by:

$$F(t) = 1\text{-exp}(-t^2/1800), \qquad (2)$$

where $F(t)$ is the percentage of the population mobilized by time t, and t is the mobilization time in minutes.

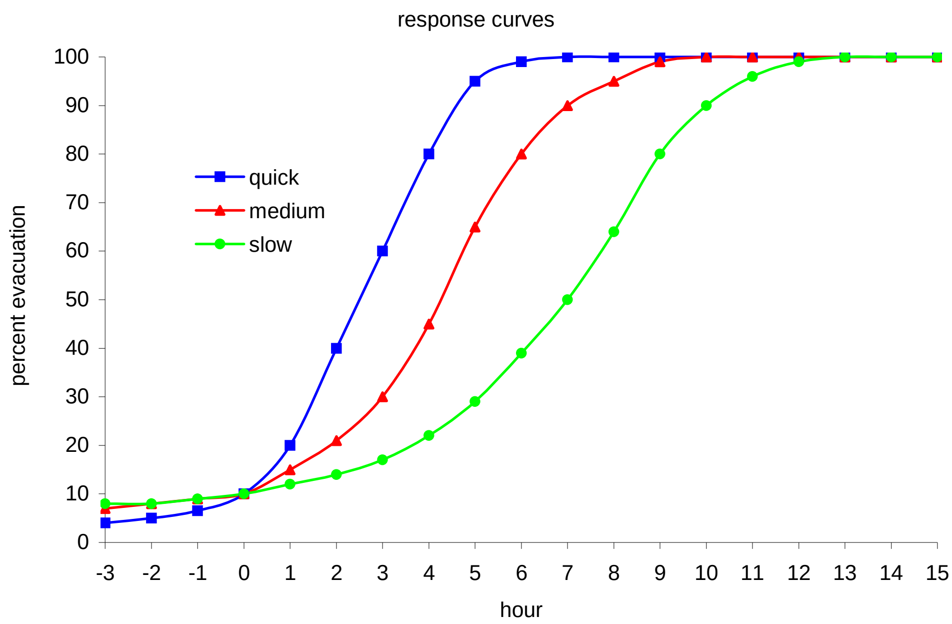


Figure 1
Three different loading curves *[42]*

DESCRIPTION OF DATA

Three datasets were used in this study. They came from surveys of different hurricanes at different geographic locations. Two were from revealed-choices and one was from stated-choices. The variety of data makes it possible to create models with different methodologies and test their transferability.

Southwest Louisiana Post-Andrew Household Survey Data

One dataset used in this study was collected in southwest Louisiana following the passage of Hurricane Andrew through that region in August 1992. The survey was conducted by the Louisiana Population Data Center at Louisiana State University (LSU) and sponsored by the Louisiana Office of Emergency Preparedness. The survey asked about 100 questions covering a variety of information of a household. Data collected included household socio-demographic information, type and location of residence, past hurricane experience, perceived assessment of risk from the hurricane, the ability to protect property, whether a hurricane evacuation order was received, the time of evacuation if the household evacuated, evacuation destination and how to get there, etc. Of the 651 households surveyed, 466 were living in an affected parish when Andrew struck. After deleting households with missing information on evacuation time, the final dataset contained data from 428 households of which 156 evacuated. The time of evacuation for each household was reported in terms of four time intervals per day (12 a.m. to 6 a.m., 6 a.m. to 12 p.m., 12 p.m. to 6 p.m., and 6 p.m. to 12 a.m.). Since evacuation lasted for three days, in this case, the total number of time intervals reported in this study was 12.

During initial data analysis, the information that was clearly not related to hurricane demand modeling, such as evacuation destination and how to get there, were deleted first. Next, AnswerTree, a statistical software package from SPSS that facilitates finding the best grouping strategy for categorical variables, was applied to find the best ways to group different levels of a categorical variable. Third, Gehan's generalized Wilcoxon test *[45]* was conducted for each of the variables to test the impact of each variable on evacuation. In Gehan's generalized Wilcoxon test, every observation in one group was compared with every observation in another group, a score was given to the result of every comparison. The total of all scores was an indication of the impact of the levels of the variable on evacuation. A statistical test is available to test the level of significance. Any variable that did not pass the test at a 20 percent level of significance was deleted from the dataset. The names of remaining variables were changed from the original coding names into ones that more appropriately reflect the nature of the variables. At this time, the data were split into two parts, 85 percent of the data was retained for model estimation and 15 percent for model validation. Fourth, the 85 percent estimation dataset was transformed so that each household would have multiple rows in the dataset. The number of rows for each household was the same as the time interval in which the household evacuated. The 15 percent validation dataset was transformed in the similar way, but each household had 12 rows, which was the total number of time intervals for the Andrew data. Fifth, data enhancement was conducted, which will be discussed later. Last, the values of distance from each household to the center of the storm were calculated using the longitude and latitude information of the storm and of the household. All the households from one city shared the same longitude and latitude, which represented the geometric center of the city. A variable representing time-of-day was also created. This variable distinguished between nighttime, morning, and afternoon. For the multiple rows for each household, information was the same for static variables but different for time-dependent (or dynamic) variables.

South Carolina Post-Floyd Household Survey Data

Another dataset used in this study was collected in South Carolina following the passage of Hurricane Floyd through that region in September 1999. The data were collected as part of a study sponsored by the Corps of Engineers and conducted by Dr. Earl J. Baker of Florida State University. The survey was stratified by county and by risk area. Approximately 600 telephone interviews were conducted in southern South Carolina, including the coastal counties of Beaufort, Jasper, and Colleton; approximately 600 telephone interviews were conducted in the northern region of South Carolina, including the coastal counties of Horry and Georgetown; and approximately 600 telephone interviews were conducted in the central coastal portion of South Carolina, including the coastal and adjacent counties in the Charleston region. After deleting households with missing information on evacuation status and time of evacuation if evacuated, the dataset contained data from 1,688 households of which about 60 percent evacuated. Data items in the dataset were similar to those of the Andrew data. Evacuation during Hurricane Floyd lasted from the 12th to the 17th of September 1999. The time of evacuation for each household was reported by each hour of the day. About 98.5 percent of evacuation occurred in the first four days. To reduce the number of time intervals in the model, each time interval was set to two hours and only the first four days were modeled. As a result, 48 time intervals were established for the Floyd data.

The Floyd data were much larger than the Andrew data. During data preparation, those variables that were obviously unrelated to evacuation demand modeling were deleted first. Most of the variables were retained without the process of applying the Gehan's generalized Wilcoxon test. The split between estimation and validations data was 75 percent and 25 percent. Then the datasets were transformed into multiple rows in the same manner as in the Andrew data. The only difference was that the total number of time intervals was 48 for Floyd instead of 12 for Andrew, and each time interval was two hours for Floyd instead of the six hours for Andrew. Data enhancement was conducted last. Values of distance were calculated and a time-of-day variable was created in a similar manner to the Andrew data. Variable names were changed from the original coding names into ones that more appropriately reflect the nature of the variables.

New Orleans Stated Preference Data

A stated preference (SP) survey of evacuation behavior was conducted in New Orleans as part of a pilot study entitled "Assessment and Remediation of Public Health Impacts due to Hurricanes and Major Flooding Events" in 2003. The SP survey was conducted by the Center for the Study of the Public Health Impacts of Hurricanes (CSPHIH), established at

LSU in 2002 through grant support provided by the Louisiana Board of Regents, Millennium Trust Health Excellence Fund. The survey involved 607 households who provided information about the social linkages they felt existed in their communities that they could rely on in times of crisis, such as during evacuation from a hurricane. In the SP portion of the survey, respondents were presented with different storm scenarios and asked, in each scenario, if they would evacuate and, if so, when they would evacuate. The storm scenarios were combinations of different storm and respondent conditions. The conditions and the range are shown in Table 1.

Table 1
Attributes and their values in the SP survey

Attribute	Level			
	0	1	2	3
Evacuation ordered	No	Precautionary	Recommended	Mandatory
Level of Storm Advisory	Watch	Warning		
Time to expected landfall	>2 days	1-2 days	12-24 hours	<12 hours
Distance from expected landfall	<10 miles	10-50 miles	50-100 miles	>100 miles
Expected intensification of storm	None	Slight	Medium	Considerable
Current Storm width	<50 miles	50-100 miles	100-200 miles	>200 miles
Direction of storm approach	Sector 1	Sector 2	Sector 3	Sector 4
Expected maximum winds	<100 mph	100-130 mph	130-150 mph	>150 mph
Expected rainfall	<5 inches	5-12 inches	12-20 inches	>20 inches
Expected storm surge	<5 ft.	5-10 ft.	10-15 ft.	>15 ft.

The first attribute, evacuation ordered, referred to whether an evacuation order had been issued or not. In Louisiana, beside the possibility of no evacuation order being issued, there are three types of evacuation orders that can be issued. The first, a precautionary evacuation order, is also referred to as a voluntary evacuation order and is meant to convey that persons in the area can decide for themselves whether to evacuate or not. The second level is where evacuation is recommended, while the third level is where evacuation is mandatory and inhabitants are no longer expected to exercise their own discretion. Storm advisories are issued by the National Hurricane Center and pertain to geographic areas which are designated as “hurricane watch” areas when hurricane landfall is within 36 hours, and “hurricane warning” areas when the storm is within 24 hours of landfall. The other attributes in Table 1 are self-explanatory with the exception of the sectors, which describe the direction from which the storm is approaching. Sectors 1 through 4 refer to quadrants ranging from an approach due east of New Orleans for sector 1 to an approach from the southwest for sector 4. The survey was supposed to be an orthogonal fractional factorial design that accounted for main effect only. Therefore, no interactions were assumed to exist. Thirty-two scenarios were created using different combinations of the conditions shown in Table 1. Eight different respondent sets were created from the 32 scenarios with each scenario being used twice. Each respondent set had eight scenarios, and each respondent was asked to answer one respondent set.

During initial data preparation, households with missing data were deleted first. Among the eight respondent sets, the minimum number of remaining households was 63. To retain orthogonality in the SP design, the number of households in each respondent set must be the same, and, therefore, excess households were deleted randomly to establish 63 households in each respondent set. As a result, each respondent set had 63*8=504 valid answers. Then data from all the eight respondent sets were joined together, resulting in 504*8=4032 valid answers when all respondent sets were combined. The dataset was next split into two in the ratio 75 percent and 25 percent for model estimation and validation respectively. Each dataset was transformed to have multiple rows of data with each row representing a time interval, as described in the transformation of the Andrew data earlier. Last, two additional variables were added to the datasets. They were the flooding potential of the households and their housing types. The total number of time intervals for this data was seven, and the lengths of the time intervals were unequal. A detailed discussion of data preparation and analysis is presented in the model structure and estimation section.

Data Enhancement

The original Andrew and Floyd datasets only had static variables and lacked the dynamic information regarding the hurricane and policy decisions made by the authorities during the onset of the storm. Using supplemental information from a variety of sources, the data were enhanced by adding hurricane advisory information (time and location of hurricane watches and hurricane warnings), characteristics of the hurricane (the forward speed, intensity, and location of the storm), and the distance from the storm to each household at every time interval. Most of the information was obtained from the National Hurricane Center.

It is known that the timing and the type of an evacuation order play an important role in the evacuation decision *[46]*. However, for Hurricane Andrew, this critical information was not available from many of the local authorities from whom the data were collected. The only information that was available for these cases was whether a household perceived receiving an evacuation order, as reported in the survey. No time was associated with the answer to the question, and, as a result, the evacuation order was treated as a static variable in this dataset, although it would normally be an important time-dependent variable. However, the evacuation order information for Hurricane Floyd was complete and evacuation order was treated as a time-dependent variable. Table 2 shows a hypothetical example of the information that was added to the dataset for enhancement.

Table 2
Example hurricane information added to enhance the dataset

Date/Time	Longitude (W)	Latitude (N)	Wind Speed (mph)	Stage/Category	Evacuation Order
6:00	67	25.6	70	Tropical storm	No
12:00	68.3	25.8	90	Category 1	Recommended
18:00	69.7	25.7	100	Category 2	Mandatory

METHODOLOGY

Overview of Survival Analysis

Survival Analysis is a statistical procedure that analyzes time-to-event data. Thus, it is often used to model the time to events, such as the onset of a disease, remission of breast cancer (medicine), the lifetime of electronic devices (engineering), felon's time to parole (criminology), duration of first marriage (sociology), length of newspaper or magazine subscription (marketing), etc. *[45]*. Survival analysis is sometimes also referred to as duration analysis.

In survival analysis, censoring is an important concept. A censored observation is an observation for which the exact time to the event is unknown because the event is not observed during the period of observation. There are various kinds of censoring, including, left, right, and interval censoring. Right censoring is the most common. It occurs when the only information about the subject under observation is that the subject has not yet experienced the event at the time observation ceases. This occurs when a subject under observation withdraws from the experiment before the event occurs, or the experiment itself concludes before the subject experiences the event. Left censoring occurs when the subject under observation has already experienced the event before the subject is observed in the study. Interval censoring occurs when the subject under observation is only known to have experienced the event in a certain time interval, but the actual time of the event is unknown. If censoring occurs, only partial information about a subject's experience of the event under study is available. A unique feature of survival analysis is that it can use such incomplete information in the analysis.

When the event times of more than two subjects occur at the same time, or when two or more closed event times are grouped into the same intervals, it is a tie. Tied data are common and provisions are made to take account of such occurrences in the formulation of survival analysis models, as explained later.

Review of Survival Analysis in Transportation

Survival analysis began its application in the transportation field in the late 1980's. Initial studies focused on accident and safety issues and automobile ownership. Hensher and Mannering *[47]* provided a review of the use of survival analysis in transportation up to the early 1990's. Niemeier and Morita *[48]* studied the duration of trip-making activities by men and women. Bhat *[49,50]* studied factors affecting shopping activity duration during the trip returning home from work. Bhat *[50]* applied the approach by Han and Hausman *[51]* to estimate both the covariates' effects and the baseline hazard parameters simultaneously while taking the effects of unobservable heterogeneity into account. Yee and Niemeier *[52]* applied the Cox proportional hazards model to the Puget Sound Transportation Panel data to analyze durations of several non-work activities.

There have been several applications of survival analysis to study the dynamic effects of travel demand. Mannering and Hamed *[53]* studied the duration that travelers delay their departure from work to avoid congestion. Hamed and Mannering *[54]* studied home-stay duration between trip generation activities. Both studies applied the parametric Weibull model. Mannering et al. *[55]* also studied the home-stay duration problem with the Cox model. However, none of the studies used time-dependent covariates, and no published applications of survival analysis in developing a dynamic travel demand model for hurricane evacuation were found. A brief overview of the basic functions used in survival analysis is given next.

Basic Functions Used in Survival Analysis

There are three important functions used in survival analysis. They are the survival function *S(t)*, the hazard function *h(t)*, and cumulative hazard function *H(t)*. The survival function is the basic relationship employed in describing time-to-event phenomena. It is the probability of a case surviving beyond time *t*, as defined in the following expression:

$$S(t) = P(T > t)\,. \tag{3}$$

The survival function is a non-increasing function with a value of one when time is zero and zero when time is infinity. The graph of *S(t)* is called the survival curve. A steep survival curve represents low survival rate or short survival time; a gradual or flat curve represents a high survival rate or long survival time.

Another fundamental quantity is the hazard function. It is also known as the conditional failure rate in reliability, the force of mortality in demography, and the age-specific failure rate in epidemiology *[56]*. The hazard function is defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}\ . \tag{4}$$

An easy way to understand the meaning of *h(t)* is to recognize that *h(t)Δt* is the approximate probability of failure during a small time interval *Δt*, provided the individual has survived to time *t*. It can take any non-zero values. The relationships between *S(t)* and *h(t)* can be given as *[57]*:

$$h(t) = f(t) / S(t)\,, \tag{5}$$

where *f(t)* is the probability density function and can be calculated with $f(t) = -\frac{dS(t)}{dt}$. If so define:

$$H(t) = \int_0^t h(x)dx\,, \tag{6}$$

then:

$$S(t) = \exp[-\int_0^t h(x)dx] = \exp[-H(t)], \tag{7}$$

where *H(t)* is the cumulative hazard. The relationship can be easily discretized to accommodate the situation when time is not considered continuous. Figure 2 plots examples of the Weibull survival functions and the Weibull hazard functions. Note that unlike the survival function, which has a maximum value of one because it is defined as a probability, the value of hazard rate can take any positive number.

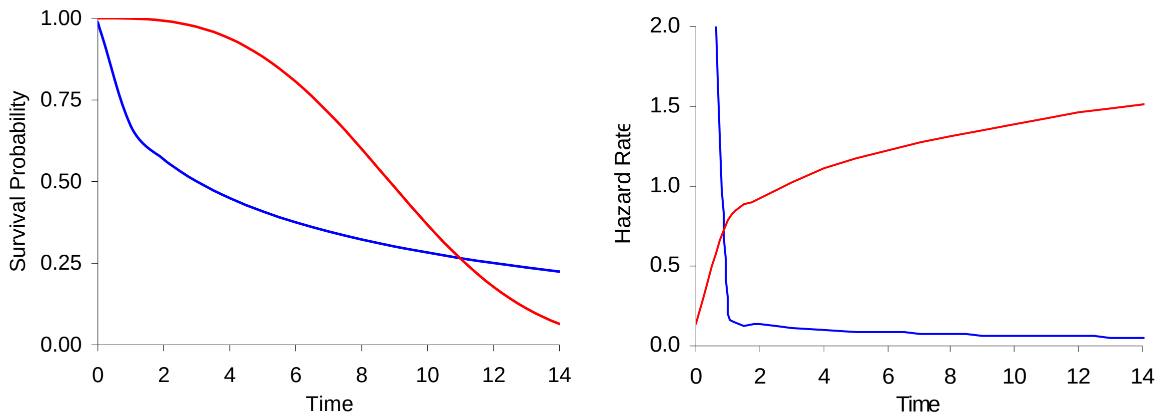


Figure 2
Weibull survival functions *S(t)* and Weibull hazard functions *h(t)*

Cox Proportional Hazards Regression Model
Survival analysis can be performed using non-parametric, semi-parametric, or parametric models. Non-parametric models use the Kaplan-Meier estimator *[58]* or life-table analysis of existing data to estimate the survival function. These models are oftentimes used to compare similar groups of time-to-event data to determine, for example, whether there is a difference among different treatments. However, nonparametric models cannot be used to estimate the effect of explanatory variables explicitly. They are applicable only to right censored data *[57]*.

There may be situations in which the survival time distribution has a known parametric form, for example, from previous studies. In this case the use of parametric models may be justified. Some of the important parametric models include exponential, Weibull, gamma, log normal, log logistic, etc., as described by Meeker and Escobar *[57]*. They also discuss the advantages of using parametric models.

If the survival distribution is unknown and it is desirable to analyze the impact of associated information (sometimes referred to as covariates, explanatory variables, or independent variables) on survival, then semi-parametric models are the form of models to use. This would be the situation in modeling travel demand for hurricane evacuation, where the interest is to know what variables influence the decision to evacuate or not evacuate and when evacuation will take place, if at all. Such variables may be socioeconomic, demographic, or psychological characteristics of the population, or they may be related to the characteristics of the hurricane or the characteristics of the location of the home of evacuees.

The most popular form of semi-parametric models is the Cox proportional hazards regression model *[59]*. There are two important reasons for the popularity of the Cox model. First, no particular probability distribution needs to be chosen to represent survival times. If the Cox model is used when the hazard function is from a known distribution, statistical efficiency will be lost with higher standard errors. However, it has been suggested that the loss of efficiency is not a serious issue *[60]*. Second, it is relatively easy to incorporate time-dependent covariates in the model *[61]*.

The basic Cox regression model without time-dependent covariates can be written as:

$$h(t \mid x_i) = h_o(t)\exp(\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}) = h_o(t)\exp(\sum_{j=1}^{p} \beta_j x_{ij}), \tag{8}$$

where $h_o(t)$ is the non-negative baseline hazard function of the underlying survival distribution when all the x variables have values of zero, β 's are regression coefficients, p is the number of covariates in the model, x_{ij} is the value of jth explanatory variable for subject i, and $h(t|x_i)$ is the hazard for subject i taking into account the influence of the covariates x_{ij}.

A key feature of the Cox model is that when all the covariates are fixed, the hazard rates of two individuals with distinct values of x are proportional, that is:

$$\frac{h_1(t \mid x_1)}{h_2(t \mid x_2)} = \frac{h_o(t)\exp(\sum_{j=1}^{p} \beta_j x_{1j})}{h_o(t)\exp(\sum_{j=1}^{p} \beta_j x_{2j})} = \exp\left[\sum_{j=1}^{p} \beta_j (x_{1j} - x_{2j})\right]. \tag{9}$$

Note that in equation 9 the baseline hazards are canceled out, and the hazard ratio of two subjects does not rely on the baseline hazards at all but depends entirely on the relative magnitude of their covariate values.

Partial Likelihood Function

Maximum Likelihood Estimation (MLE) is generally used in survival estimation. MLE produces estimators that are consistent, asymptotically efficient, and asymptotically normal *[62]*. Different types of censoring schemes have different likelihood functions. Klein and Moeschberger *[56]* give a complete description of functional forms for different types of censoring. The likelihood function for the proportional hazards model depends on the parameters' β s, the baseline hazard, and the survivorship functions. However, Cox *[59]* proposed a "partial likelihood function" that depends only on the unknown parameters' β s. The partial likelihood function $L(\beta)$ without ties is given by:

$$L(\beta) = \prod_{i=1}^{D} \frac{h_i(t_i)}{\sum_{k \in R(t_i)} h_k(t)} = \prod_{i=1}^{D} \frac{\exp(\sum_{j=1}^{p} \beta_j x_{ij})}{\sum_{k \in R(t_i)} \exp(\sum_{j=1}^{p} \beta_k x_{kj})}, \tag{10}$$

where $R(t_i)$ is the set for all subjects who have not yet experienced the event at time t_i yet, and D is the total number of event times.

Partial Likelihood Function for Tied Data

Equation 10 is only valid for data without ties. Consequently, equation 10 needs to be modified if tied data are present. There are several techniques to handle tied data, including the *Breslow, Efron, EXACT*, and *DISCRETE* methods *[61,63]*. The *Breslow* and *Efron* methods are approximations to the *EXACT* method. In general, *Efron*'s approximation is always superior to that of *Breslow*; the last two methods produce true partial likelihood estimates but need a substantial amount of computing time for large datasets with many ties. All four options give similar results when ties are few, and they give identical results when ties are not present.

Time-Dependent Covariates

So far, the covariates discussed are all fixed-time variables. That is, their values are fixed at the start of the study and do not change throughout the study. However, there are situations where the values of certain covariates are time-dependent. An example in hurricane evacuation would be the distance to the storm, which varies as the hurricane approaches. This dynamic variable is intuitively believed to play an important role in people's evacuation decision. The Cox model can be easily extended to include time-dependent covariates. All that needs to be done is to change the x_{ij} variable in equations 8 through 10 into $x_{ij}(t)$, although this involves a considerable increase in the computational effort.

Estimation of Baseline Hazard

Because of the structure of the Cox model, it is imperative to have a good estimate of the baseline hazard $h_o(t)$ in order to make any accurate predictions. It is easier to estimate the cumulative baseline hazard $H_o(t)$ first and then calculate the baseline hazard. The cumulative baseline hazard can be estimated with the *Breslow* estimator:

$$\hat{H}_o(t) = \sum_{t_i \le t} \frac{d_i}{\sum_{i \in R(t_i)} \exp(\sum_{j=1}^{p} \beta_j x_{ij})}, \tag{11}$$

where d_i is the number of events in the time interval t_i. After estimating the cumulative baseline hazard $\hat{H}_o(t)$, the baseline hazard $\hat{h}_o(t)$ can be easily calculated by taking the derivative of $\hat{H}_o(t)$. For this study, the hazards are assumed stable for each time interval. As a result, the baseline hazard $\hat{h}_o(t)$ for each time interval is calculated by simply taking the difference of the cumulative hazard $\hat{H}_o(t)$ between the previous time interval and the current time interval. A problem with this estimation of baseline hazard is that there is no statistical test for its goodness-of-fit.

Residuals

There are several useful residuals in the Cox model to aid the modeling. They are the martingale, the score, and the Schoenfeld residuals. Let $N_i(t)$ indicate whether the *i*th subject has experienced the event, and let $Y_i(t)$ indicate that subject i is under observation at a time just before time t. Then, the martingale residual $\hat{M}_i$ for subject i is defined as:

$$\hat{M}_i(t) = N_i(t) - \int_0^t Y_i(s)\exp(\sum_{j=1}^{p} \hat{\beta}_j x_{ij}) d\hat{H}_o(s) . \tag{12}$$

Normally people are more interested in the martingale residuals when time $t = \infty$. The score residual L_{ij} for the ith subject on the jth covariate is defined as:

$$L_{ij}(t) = \int_0^t [x_{ij}(s) - \bar{x}_j(s)] d\hat{M}_i(s) , \tag{13}$$

where $\bar{x}_j(t)$ is defined as:

$$\bar{x}_j(t) = \sum_{i=1}^{n} w_i x_{ij}(t), \quad \text{and } w_i \text{ is given by: } w_i = \frac{Y_i(t)\exp(\sum_{j=1}^{p} \beta_j x_{ij})}{\sum_{i=1}^{n} Y_i(t)\exp(\sum_{j=1}^{p} \beta_j x_{ij})} . \tag{14}$$

The Schoenfeld residual is defined for each event time k on the jth covariate as:

$$s_{kj} = \int_{t_{k-1}}^{t_k} \sum_i [x_{ij} - \bar{x}_j(\hat{\beta}, s)] \, d\hat{M}_i(s) . \tag{15}$$

Each one of the residuals plays an important role in examining some aspect of the model fit. The martingale residual can be used to test the functional form of the covariates; the score residual can be used to assess individual influence on the coefficients estimated and for robust variance estimation; and the Schoenfeld residual can be used to test for proportional hazards conditions.

The Proportional Hazards Assumption

An important assumption of the Cox model is proportional hazards. Equation 9 shows that for those fixed-time covariates, the hazards ratio for any two subjects is independent of time. This assumption applies to fixed-time covariates only.

The proportional hazards assumption can be tested with the scaled Schoenfeld residual and will be discussed later. If the proportional hazards assumption is violated, Therneau and Grambsch *[63]* summarize several remedies including stratification, partitioning the time axis, using time-dependent covariates, and using alternative models. In the case of stratification, a covariate with non-proportional effects can be incorporated into the model as a stratification factor instead of a regressor. This will eliminate non-proportionality, although the effect of the covariate can no longer be explicitly modeled. If the proportional hazards assumption holds for different periods of the study time, then, for each time period, the Cox model can be applied separately. A third alternative is to introduce an additional time-dependent covariate into the model so that the time-varying impact of a covariate can be accounted for by the new time-dependent covariate. The last alternative is to use a different model. For example, an additive hazards model may be more appropriate for the data.

The Piecewise Exponential Model

One characteristic of the Cox proportional hazards model is that the baseline hazard is conditioned out, and only the impact of the covariates are estimated by maximizing the partial likelihood. No functional form of the hazard has to be specified, making the Cox model very flexible. On the other extreme, the parametric models have to specify the functional form of the hazard function. However, when the hazard function is of interest, as in this study, it is usually estimated with the *Breslow* estimator (Equation 11). This estimate lacks the ability to test hypotheses about the shape of the hazard function. The Piecewise Exponential model is a model that is in between the two extremes. It has the flexibility of the Cox model and the ability to statistically test the hazard function.

It is well known that if the survival time is exponentially distributed, the hazard function is a constant. In the Piecewise Exponential model, time is divided into intervals. The hazard in each interval is assumed to be constant but can vary across intervals. Let I denote the total number of intervals, and $a_0, a_1, \ldots, a_{i-1}, a_i, \ldots, a_I$ as cutpoints of intervals, with $a_0 = 0$, and $a_I = \infty$. The hazard can be written as:

$$h(t) = h_i e^{x'\beta} \qquad \text{for} \qquad a_{i-1} \le t < a_i\,, \tag{16}$$

where h_i can be considered the baseline hazard, which is the hazard when all the covariates are zero, x and β are vectors of the covariates and corresponding parameters. Taking logarithms on both sides of the equation, it becomes:

$$\ln[h(t)] = \alpha_i + x'\beta\,, \tag{17}$$

where the intercept $\alpha_i = \ln(h_i)$, can vary from one interval to another. However, if a new intercept α, and an additional variable T, which is a categorical variable that represents the time intervals, are introduced, then:

$$\alpha_i = \alpha + (\alpha_i - \alpha) = \alpha + T_i \gamma_i\,,$$

as a result,

$$\ln[h(t)] = \alpha + T_i \gamma_i + x'\beta, \tag{18}$$

where T_i's are the dummy variables introduced for the categorical covariate T, and γ_i's are the corresponding parameters. Now the baseline hazard h_i can be expressed as:

$$h_i = e^{\alpha + T_i \gamma_i} \tag{19}$$

Overview of Sequential Choice Model

Review of Sequential Choice Model in Transportation

The application of logistic regression in transportation started in the mid 1960's, modeling binary choice of travel mode *[64-66]*. In the early 1970's, research focused on mode choice models with more than two alternatives using the multinomial logit model (MNL) and applications to other travel related choices, such as trip frequency, car ownership, and housing. Ben-Akiva and Lerman *[67]* provided a detailed review. Recently, the ordered logistic model has been used extensively in transportation-related studies *[68-72]*, although most of the applications used the proportional-odds-type model instead of the continuation-ratio model, as described shortly.

Amemiya *[73]* first described the sequential probit and logit models for ordered discrete alternatives. Kahn and Morimune *[74]* used a sequential logit model to explain the number of employment spells a worker experienced in 1966. Heckman and Willis *[75]* used a similar sequential concept to analyze sequential labor force participation by married women. They went further to explore the heterogeneity among women if the independent and identical distribution (IID) assumption of the disturbances was not present. Ben-Akiva and Lerman also gave a brief review of the application of the sequential model based on the method of random utility. They noted the applications of this model to represent a household's trip generation by Hendrickson and Sheffi *[76]* and Sheffi *[77]* to search for a residence by Hall *[78]* and to predict the frequency of tours instead of one-way trips by Daly and Zwam *[79]*. However, none of these models supported time-dependent covariates, which are essential for studying dynamic travel demand with this kind of model.

The applications of the sequential choice model in transportation focused on the outcome of choices made as a result of the sequential decision making and not on the temporal distribution of the sequential choice. For example, in the application of trip generation modeling, the number of trips made was the focus of the study. However, in our study of hurricane evacuation, the sequential model not only gives the probability of evacuation (travel demand) but also when that evacuation travel is generated. This enables the study of dynamics of hurricane evacuation travel demand, i.e., how people make evacuation choices as time progresses and their environment changes. The final product of this application is a dynamic travel demand model.

The Multinomial Logit Model

The Multinomial Logit Model (MNL) and its variations have been used extensively in transportation for the last several decades to model discrete choices. The terms logistic model and logit model can be used interchangeably. The MNL model is typically suitable for nominal choices (i.e., distinguished by name) as, for example, in the choice among travel modes, such as auto and transit. As implied by the name, the choices modeled are multiple (more than two), mutually exclusive, discrete choices. The MNL model can be derived by the random utility theory. It requires that the choices are independent of each other. The logit model is mathematically flexible and easy to use.

The Ordered Logit Model

The Independently Identically Distributed (IID) assumption of the error terms in the MNL model requires that modeled choices must be distinct or the Independence from Irrelevant Alternatives (IIA) property that results from violation of that assumption will distort the model's predictions. Alternatively, more complex models, such as nested logit or mixed logit, can be used to overcome this difficulty. However, when ordinal choices are modeled (i.e., choices in which order among the alternatives is significant), the order may impose some dependence among alternatives and models that are explicitly constructed to handle such ordered choices as necessary.

There are different models to choose from in the ordered logistic model depending on what outcomes are being compared. Agresti *[80]* describes the three most commonly used models: the adjacent-category model, the continuation-ratio model, and the proportional odds model. The adjacent-category model compares each outcome to the next larger outcome. The model is expressed in the logit form as:

$$\ln\left[\frac{P(Y=i)}{P(Y=i-1)}\right]=\alpha_i + x'\beta_i , \tag{20}$$

where $P(Y = i)$ is the probability of choosing alternative i, x is a (p x 1) vector of covariates, β_i is a (p x 1) vector of parameters, and α_i are scalar parameters, which are to be estimated. The continuation-ratio model compares each outcome to all higher outcomes (or, alternatively, to all lower outcomes). The logit is of the form:

$$\ln\left[\frac{P(Y=i)}{P(Y>i)}\right]=\alpha_i + x'\beta_i , \tag{21}$$

where $P(Y > i)$ is the probability of the decision maker choosing outcomes higher than i. The proportional odds model compares the probability of an equal or smaller outcome to the probability of a larger outcome. The logit is of the form:

$$\ln\left[\frac{P(Y\le i)}{P(Y>i)}\right]=\alpha_i + x'\beta_i , \tag{22}$$

where $P(Y \le i)$ is the probability of the decision maker choosing outcomes lower or equal to i. In all three models, if it is assumed that β_i does not change over i, then there is a common vector of slope parameter β but different constant terms, namely:

$$\text{logit} = \alpha_i + x'\beta \tag{23}$$

The proportional odds ordered logit model has been used in several transportation applications in the past *[55,71,72]*. It is presented in terms of a latent (unobserved) variable framework by Greene *[62]* as described later in this section.

The Random Utility Sequential Choice Paradigm
Ordered outcomes considered in the past display a subtle difference. In one case, ordered outcomes are described as a ranking without any linking or sequence of choices implied among the outcomes. Examples of this kind of ordering are choices among grades of gasoline (regular, super, and premium), choice of level of employment (part-time or full-time), whether to purchase cheap, medium-priced, or expensive theater tickets, number of days vacation to take, or size of home to buy. The other type of ordered outcome considered is where the choice of an outcome implies that all earlier outcomes in the ordering had to be considered first. This occurs, for example, when a family considers having another child, a household considers purchasing an additional vehicle, or an individual is choosing a university for graduate study. If trip generation is seen as a sequence of decisions of whether or not to make an additional trip, then trip generation is also an example of this specific type of ordered choice. Ordered choices of this type are more aptly termed sequential choice since higher categories of outcome can only be reached by proceeding through each lower category of outcome in a sequence of binary choices.

Sequential ordered choice occurs in dynamic travel demand modeling of evacuation. If time is discretized into time intervals, then, in time interval *I*, a household has the binary choice to evacuate or not evacuate, provided the decision to not evacuate was made in all earlier choices. If the choice in time interval *i* is not to evacuate, then the household faces the same binary choice in time interval i+1 and so on until either a decision to evacuate is made, or the end of the analysis period is reached with no decision to evacuate being made. Amemiya *[73]* described a model that can handle such sequential decisions based on random utility theory. Fahrmeir and Tutz *[81]* derive a similar model based on latent regression.

Amemiya's model can be illustrated using the random utility principle in the context of hurricane evacuation. Let $U^c{}_i$ denote the utility of a household to not evacuate in the time interval *i*, and let $U^s{}_i$ denote the utility of the household to evacuate in time interval *i*, where the superscripts *c* and *s* stand for "continue" and "stop". If in any time interval the utility to evacuate is greater than the utility to not evacuate, i.e.,$U_i^s \geq U_i^c$, then the household will evacuate in that time interval. Because the utilities are random variables, then $P(Y = i)$, the probability of the household evacuating in time interval *i* can be expressed as:

$$
\begin{aligned}
P(Y=i) &= \Pr[(U_1^c \geq U_1^s) \cap (U_2^c \geq U_2^s) \cap ...(U_{i-1}^c \geq U_{i-1}^s) \cap (U_i^s \geq U_i^c)] \\
&= P(1)_c P(2)_c \cdots P(i-1)_c P(i)_s \\
&= P(i)_s \prod_{j=1}^{i-1} P(j)_c \qquad (24) \\
&= P(i)_s \prod_{j=1}^{i-1} [1-P(j)_s],
\end{aligned}
$$

where $P(i)_s$ is the conditional 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 and $P(i)_c$ is the conditional probability that the utility of a household to not evacuate is greater than the utility of the household to evacuate in time interval *i*, provided that the household has not already evacuated. The derivation requires that $U_i^c - U_i^s$ are independent among time intervals. As a result, the probability to evacuate in any time interval *i* is the product of *i* independent conditional probabilities, the first of which are the conditional probabilities to not evacuate in time intervals 1 through *i*-1, and the last of which is the conditional probability to evacuate in time interval *i*. The derivation also recognizes that $P(i)_s + P(i)_c = 1$, i.e., the total conditional probability to evacuate and not to evacuate in each time interval is one.

Assume that each of the random utilities U_i^c and U_i^s is composed of a systematic component $x'\beta$, which represents the impact of explanatory variables, and a disturbance (also referred to as error term) ε, i.e., $U = x'\beta + \varepsilon$. Also, assume that the utility differences $U_i^c - U_i^s$ are independently logistic distributed (which is equivalent to assuming that U_i^c and U_i^s are *IID* Gumbel distributed) for each time interval, then the conditional probability $P(i)_{s/c}$ of a household evacuating in time interval *I*, provided it has not evacuated yet, can be expressed as a binary logit model *[67]*:

$$P(i)_{s/c} = \frac{e^{x'\beta}}{1 + e^{x'\beta}}, \qquad (25)$$

The standard MNL model assumes that the differences in the disturbances between alternatives are independent and identical logistic variants. However, in this sequential model, it is the marginal utilities, $U_i^c - U_i^s$ that are assumed to be independent and identical logistic variants because the alternatives are represented by successive choices over time. Sheffi *[77]* provides justification for the independency among the utility differences $U_i^c - U_i^s$, although the independency is derived by assuming the distributions of the utilities are multivariate normal. Based on the special structure of equation 24, this sequential model can be solved using the existing binary logit estimation. Each binary logit is treated as a separate observation. Ben-Akiva and Lerman *[67]* pointed out that this model is not based on the assumption of global utility maximization; the decision maker stops when the first local optimum is reached. It can be proved that the total probability to evacuate over all intervals does not exceed one.

The Latent Variable Sequential Choice Paradigm

The sequential choice model can also be derived from the latent variable framework, where it is assumed that the observable outcome variable *Y* is a categorized version of a latent continuous variable *U*. Let the latent variable $U_i = -x'\beta + \varepsilon_i$, where *i* represents the outcome categories (*i* =1, 2 …), ε_i is a random variable with distribution *F*, and *x* and β are vectors defined as before. Note that, if necessary, it can be assumed that β varies with *i* and becomes β_i, although it is not considered the case here. Let α_i denote the threshold parameter for the outcome category *i*. The response mechanism is specified by:

$$Y = i \quad given \quad Y \geq i \qquad if\ and\ only\ if \qquad U_i \leq \alpha_i . \tag{26}$$

Take hurricane evacuation as an example. If in time interval 1, the latent variable is smaller or equal to the threshold α_1, i.e., $U_1 \leq \alpha_1$, then the household evacuates in time interval 1, and $Y = 1$; if not, then $U_1 > \alpha_1$, the process continues into time interval 2. If $U_2 \leq \alpha_2$, then the household evacuates in time interval 2, and $Y = 2$; if not, then $U_2 > \alpha_2$, the process continues into time interval 3 and so on. Only the final resulting category is observable. As a result, the conditional probability of the household evacuating in time interval *i*, if the household has not yet evacuated, becomes:

$$\begin{aligned} P(Y = i \mid Y \geq i) &= P(U_i \leq \alpha_i) = P(-x'\beta + \varepsilon_i \leq \alpha_i) \\ &= P(\varepsilon_i \leq \alpha_i + x'\beta) = F(\alpha_i + x'\beta) \end{aligned} \tag{27}$$

where *i* represents the time interval in which a household evacuates. This conditional probability is also known as discrete-time hazard which represents the hazard of evacuation in time interval *i*. If the conditional probabilities are independent of each other, then the unconditional probability of the household evacuating in time interval *i* is given by:

$$P(Y = i) = P(Y = i \mid Y \geq i) \prod_{j=1}^{i-1} [1 - P(Y = j \mid Y \geq j)]. \tag{28}$$

It is obvious that equations 24 and 28 have the same model structure, although equation 24 is derived from the random utility method, and equation 28 is based on a latent variable concept.

If *F* is chosen as the standard logistic distribution $F(x) = 1 / (1 + e^{-x})$, the conditional probability becomes:

$$P(Y = i \mid Y \geq i) = \frac{e^{\alpha_i + x'\beta}}{1 + e^{\alpha_i + x'\beta}} . \tag{29}$$

This model is the equivalent to Agresti's continuation-ratio model (Equation 21) when β_i is assumed to be equal across the alternatives. This can be derived by:

$$\ln\left[\frac{P(Y = i \mid Y \geq i)}{P(Y > i \mid Y \geq i)}\right] = \ln\left[\frac{P(Y = i \mid Y \geq i)}{1 - P(Y = i \mid Y \geq i)}\right] = \ln\left(\frac{\dfrac{e^{\alpha_i + x'\beta}}{1 + e^{\alpha_i + x'\beta}}}{1 - \dfrac{e^{\alpha_i + x'\beta}}{1 + e^{\alpha_i + x'\beta}}}\right) = \alpha_i + x'\beta . \tag{30}$$

Equation 29 has the same model structure as equation 25. Both are conditional binary logit models. If *F* the is standard smallest extreme value (*SEV*) distributed, then $F(x) = 1 - \exp[-\exp(x)]$, and the model becomes:

$$P(Y = i \mid Y \geq i) = 1 - \exp[-\exp(\alpha_i + x'\beta)]. \quad (31)$$

Equation 31 can be transformed into the so-called complementary log-log model:

$$\log[-\log(P = i \mid P \geq i)] = \alpha_i + \beta' x. \quad (32)$$

The properties of this model will be discussed shortly.

Model Estimation

From equations 24 and 28, the probability of a household evacuating in time interval *i*, $P(Y = i)$ is the product of *i* independent binary choices, the first *i*-1 choices being not to evacuate and the *i*th to evacuate. Because of this special structure, this sequential model can be estimated using existing methods for binary choice models.

One intuitive method is to apply the continuation-ratio logistic model concept given in equation 21 to estimate the parameters of each individual binary choice model (the conditional probability). Then, the unconditional probability of evacuating in each time interval for every household can be calculated based on equations 24 or 28. To do this, the data must be arranged in the following way. For time interval 1, the outcomes of those who evacuate in this interval are coded as 1; all those who do not evacuate in the interval are coded as 0, and the parameters of a binary logistic model for time interval 1 are estimated. For time interval 2; data for those who evacuate in the previous time interval are excluded. The outcomes of those who evacuate in time interval 2 are coded as 1; all of those who do not evacuate in time interval 2 are coded as 0. Then the parameters of a binary logistic model for time interval 2 are estimated. This procedure is repeated for every time interval. However, there are several drawbacks to this method. First, multiple models have to be estimated, involving more data manipulation and modeling effort. Second, there is less data to estimate the parameters in the later intervals, resulting in less reliable estimation of the parameters. This is because as households evacuate in earlier intervals, there are fewer and fewer households remaining. Third, restrictions such as equal parameters for different time intervals, which might be a valid option, cannot be applied. As a result, the predictions beyond the scope of the observed time intervals cannot be obtained.

There is an alternative method to estimate this model that allows the consideration of all binary choices simultaneously and avoids the disadvantages just mentioned. Let $P_n(Y = i)$ denote the probability that household *n* evacuates in time interval *i*. The likelihood function is

$$L = \prod_{n=1}^{N} P_n(Y = i). \quad (33)$$

If equation 28 (or similarly equation 24) is substituted into this likelihood function, then:

$$L = \prod_{n=1}^{N} P_n(Y = i \mid Y \geq i) \prod_{j=1}^{i-1} [1 - P_n(Y = j \mid Y \geq j)]. \quad (34)$$

This likelihood requires the estimation of a binary model with a pooled dataset constructed in the following way. Each individual binary choice made at consecutive time intervals for the same household is treated as an independent observation. If a household evacuates in time interval *i*, that household will have *i* rows in the dataset, along with all the covariates of that household for each time interval respectively. The outcome variables for the first *i*-1 rows of each household will be coded as 0 for not evacuating. But the outcome variable for the *i*th row of the household will be coded as 1 for evacuating. For example, if a household evacuates in time interval 3, then there will be three rows of data with the outcome variable coded as 0 for the first 2 intervals and 1 for the third interval. After pooling the data, existing software can be used for binary choice models to estimate the parameter vector β and α_i. Such estimation implicitly assumes that the coefficients of the conditional probabilities are the same for all time intervals. Finally, the unconditional probability of evacuation at each time interval for each individual household will be calculated using equations 24 or 28. One extra benefit of this format is that time-dependent variables can be easily accommodated.

A concern that arises is the validity of the analysis of multiple records for each subject. Two issues are involved here. The first one is about the accuracy of the estimated variance of parameters. It is well known that if observations are from the same subject, in this case the same household, the estimated variance of parameters will be smaller than what it should be. As a result, the statistics for inference will be inflated. However, this should not be a problem in this case because the likelihood function factors into a distinct term for each subject. Nevertheless, when the data are for multiple events for each subject, this will be a problem *[82]*. The second issue is the potential correlation among the error terms. From equation 24, the assumption that the error term ε is independent among the alternatives (i.e., whether to evacuate or not) in any one time period is not difficult to justify as the alternatives are distinctly different. However, if the conditional binary logit model, P_s in equation 25, is not estimated on observations from each time period separately but on observations from all time intervals collectively, as is suggested here, then repeated observations of the same household will occur in the estimation dataset, and the potential exists for correlation among the error terms. The extent that characteristics of the household affect the decision to evacuate or not shows that the potential for correlation among observations of the same household exists. However, the greater impact on the evacuation decision is expected from characteristics of the storm, which change over time and are unrelated to households (e.g., proximity of the storm or wind speed).

Stated-Preference Data and Technique

Next, the stated preference technique, the advantages and disadvantages of stated choice vs. revealed choice data, and fractional factorial design will be briefly discussed. This review is primarily based on the book of Louviere et al. *[83]*.

Stated Preference Data

There are basically two kinds of data collected in a travel survey. The first kind is the traditional revealed preference (RP) data, where data are collected on what a respondent actually did. However, there are situations where RP data are not available or not appropriate for the purpose of this study. An alternative is stated preference (SP) data, where a respondent states what he/she would do under certain conditions. Examples of such situations are abundant. To study the impact of introducing a new product, such as a new light rail transit system, which has new attributes or features, people have to rely on SP data since RP data are simply not available. Sometimes variables in the RP data are highly collinear, making it difficult to identify the impact that these variables have on the behavior in question. In addition, RP data are sometimes difficult to obtain because the behavior under study relates to a rare event, such as a hurricane. Both RP and SP data are consistent with the random utility theory that is the basis of the discrete choice model.

A Comparison between RP and SP Data

RP data are generally restricted in helping to understand people's choices within the current scope of a product. However, SP data can extend our understanding beyond the existing scope into areas of interest but where no observed behavior is available. Louviere et al. *[83]* compared the features of the two types of data and they are listed in Table 3.

Table 3
Comparison between RP and SP data

RP data	SP data
Depicts the world as it is now	Describes hypothetical contexts and conditions
Possesses inherent relationships between variables	Controlled relationships between attributes
Can only observe on existing alternative	Can include multiple hypothetical choice alternatives
Embodies market and personal constraints on the decision maker	Cannot easily represent changes in market and personal constraints effectively
Has high reliability and face validity	Reliable when respondents understand questions and are committed to responding realistically to questions
Yields one observation per respondent per time	Yields multiple observations per respondent per time

To take advantage of both RP and SP data, RP and SP can be combined in the analysis. SP data can often provide more robust parameter estimates (and hence increase confidence in the parameter estimates) than RP-based models. On the other hand, RP data can provide more realistic estimates of market shares. To combine the RP and SP data, they have to be from the same respondents.

In the study of hurricane evacuation, the SP technique can play an important role because of the following characteristics of RP hurricane data:

1. Many of the variables describing hurricane evacuation are highly correlated. For example, the distance to the storm and the time when an evacuation order is issued or the forward speed of the storm and flooding potential are highly correlated variables.
2. Lack of variable variability. For example, in a particular hurricane, the category and forward speed of a storm may change little during the study period. Conclusions from a study on RP data from a category 3 hurricane cannot be applied to a category 4 or 5 hurricane with certainty.
3. Data is collected from only one hurricane at a time.
4. Hurricanes are relatively rare events and, therefore, make planning the collection of RP data difficult and the availability of the data uncertain.

The Design of an SP Survey

Unlike RP data, from which the variable levels are recorded as the way they are, SP data are generated by a systematic and planned experimental design process. In the experimental design, variables, their levels, and the combinations of variable levels (called profiles) are carefully designed to test the respondents' preferences or choices. Factorial designs are widely used in experimental design. In a factorial design, each level of each variable is combined with every level of all other variables. Such a design is a complete enumeration if all possible combinations of variable levels are achieved - hence the name complete factorial. A complete factorial design makes it possible to estimate all possible effects. In addition, all the effects of interest are independent (orthogonal). In other words, model parameters can be estimated independently of one another. However, the number of combinations in a complete factorial increases dramatically with the number of variables and the levels used. As a result, fractional factorial designs are introduced for large, complicated problems. A fractional factorial design includes only a subset of all possible combinations of variable levels, which is important to the study.

There are two kinds of effects: main effect and interaction effect. A main effect is the impact of different levels of a variable. An interaction between two or more variables occurs when the effect of a variable level depends on the levels of other variables. For linear models, Dawes and Corrigan *[84]* estimated that main effects typically account for 70 percent to 90 percent of explained variances; two-way interactions typically account for 5 percent to 15 percent of explained variances; and the rest of variances are explained by higher order interaction. In order to reduce the size of a design, a fractional factorial design selects a subset of the complete factorial so that certain effects of interest can be estimated efficiently. It is usually assumed that high order interactions do not exist. This might result in a loss of statistical information and, hence, biased and misleading model estimates.

MODEL STRUCTURE AND ESTIMATION

Survival Model Estimation with Southwest Louisiana (Andrew) Data

From the overview in the previous section, survival analysis seems to be a suitable tool to model dynamic travel demand for hurricane evacuation. As a hurricane approaches, a household repeatedly evaluates the risk and makes a decision whether to evacuate or not. If the decision to evacuate is considered the event under study, the conditions facing households in each time interval is considered the covariates in the procedure, and the survival function is considered the probability that a household has not evacuated, then survival analysis can be used to estimate the probability of a household evacuating in each time interval leading up to storm landfall. If a household does not eventually evacuate, it is considered a right censored observation. The impacts of explanatory variables can be accounted for using the Cox Proportional Hazards Model or Piecewise Exponential model with time-dependent variables. The baseline hazard for the Cox model can be estimated with the *Breslow* estimator.

A Cox model was first estimated. SPSS 10.0 was used in the early stage of modeling, especially during the stepwise forward selection of covariates and interactions among the static variables; however, S-Plus 6.1 was used as the major software package for survival analysis thereafter, especially for analyzing time-dependent covariates. *Efron*'s method was used in model estimation. Then a Piecewise Exponential model was estimated.

The Cox Proportional Hazards Model

The Basic Cox Models. Using the Andrew data, a stepwise forward selection process was conducted to find the covariates and their interactions in the Cox model. The six variables that had levels of significance greater than 5 percent in the Cox model are listed in Table 4.

Table 4
Covariates in the Cox survival model

Covariate	Definition
dist	A function of distance to the storm at time *t*.
orderper	1 if the household perceived receiving an evacuation order, 0 otherwise.
flood	1 if the residence is very likely to be flooded, 0 otherwise.
mobile	1 if a mobile home, 0 otherwise.
hurtrisk	1 if a serious risk of being hurt is perceived, 0 otherwise.
protect	1 if consider staying home enables to better protect property, 0 otherwise.

Among the selected covariates, *dist* is the only time-dependent variable. Distance is not expected to have a linear impact on evacuation because a change of 100 miles when a hurricane is 1,000 miles away will have a very different impact on a person's decision to evacuate or not than when the hurricane is only, say, 300 miles away. The natural logarithm of distance is used to represent that effect. However, once the distance of a hurricane to a household is within a minimum distance or reaches a certain threshold, d_{min}, it will be too dangerous to evacuate. At this stage, the change of distance should no longer have an impact on evacuation. From analysis of the data it was found that an appropriate value for d_{min} was 94 miles. As a result, following the transformed value of distance, *dist*(*t*), was chosen:

$$dist(t) = \begin{cases} 0 & \text{if } d(t) \le d_{min} + 1 \\ \ln[d(t) - d_{\min}] & \text{otherwise} \end{cases} . \quad (35)$$

For the data used in this study, other time-dependent variables such as *TOD* (a variable representing time-of-day, which will be formally defined later) and hurricane speed have the same values for every household for each time interval. As a result, their coefficients cannot be estimated because of the structure of the partial likelihood function. A detailed explanation is given later. This is the same for a hurricane watch, which was issued at the same time for all the households. While the hurricane warning did vary among the observations, the coefficient estimated for a hurricane warning was found to be negative, meaning people are less likely to evacuate if a hurricane warning is issued. Such a result is counter-intuitive, and it was, therefore, dropped from the model. No interactions among the covariates were found to be significant. Table 5 lists the estimated coefficients and the statistics of the two final models. Model 1 includes predictable variables only, and model 2 includes perceptions from households as well. The last row gives the likelihood ratio index for the two models.

Table 5
Summary results of the Cox survival models

Covariate	Model 1			Model 2		
	β	se(β)	*p-value*	β	se(β)	*p-value*
dist	-0.436	0.219	0.046	-0.768	0.239	0.001
orderper	0.537	0.207	0.010	0.467	0.219	0.003
flood	0.676	0.212	0.002	0.724	0.229	0.002
mobile	1.568	0.208	0.000	1.261	0.234	0.000
hurtrisk	-	-	-	0.861	0.229	0.000
protect	-	-	-	-0.895	0.219	0.000
LL(0)	-645.2			-575.9		
LL(β)	-608.6			-518.8		
-2[*LL*(0) - *LL*(β)]	73.2			114.2		
ρ^2	0.057			0.100		

There are multiple ways to measure the logit model goodness-of-fit (*GOF)*. The likelihood ratio test is the most widely used statistic for testing *GOF*. It is defined as -2[(*LL*(0)-*LL*(β)], where *LL*(0) is the likelihood value when no parameters were included in the model, and *LL*(β) is the likelihood value when all the explanatory variables are included in the mode. This statistic is Chi-square distributed; the degree of freedom is the number of explanatory variables in the model. The likelihood ratio test is used to test the null hypothesis that all the parameters estimated are zero. Ben-Akiva and Lerman *[67]* recommend also using the log likelihood ratio index ρ^2, which is defined as $[LL(0) - LL(\beta)] / LL(0)$. It is a *GOF* measure that estimates the proportion of the initial log likelihood explained by the model. ρ^2 is best suited in comparing different model specifications for the same dataset. This index is widely used in transportation.

The likelihood index tests were 73.2 and 114.2 with degree of freedom values equal to four and six for models 1 and 2, respectively. The *p-values* were 0.000, rejecting the null hypotheses that all the explanatory variables in each of the models were zero. From Table 5, all coefficients from model 1 have *p-values* significant at five percent level, while model 2 has a larger likelihood ratio index ρ^2 and better *p-values* across the board than model 1. The inclusion of two static covariates *hurtrisk* and *protect* in model 2 clearly improves the ρ^2. But these two variables are subjective and difficult to get in practical applications. Therefore, model 1 is the preferred model. In general, all the coefficients of covariates have the correct signs, and their values are reasonable. From Table 5, of the four covariates in the model, covariate *mobile* has the largest coefficient, implying that households living in mobile homes are nearly five times ($e^{1.568}$) more likely to evacuate than people not living in mobile homes. Covariate *flood* also plays a significant role. If a household lives in a location that is very likely to be flooded, then such a household is twice ($e^{0.676}$) as likely to evacuate as a household not in a flood area. The impact of the perceived evacuation order is similar in magnitude to that of *flood*. Ideally, covariate *orderper* should have been treated as a time-dependent variable; instead, it is treated as a static variable because no dynamic information was available for it. Past studies have shown that the coefficients of a covariate can vary greatly depending on whether the covariate is treated as a static or a time-dependent variable *[85]*. Covariate *dist* is the only time-dependent covariate in the model, and the negative coefficient means that the nearer the storm, the more likely a household would evacuate. From the dataset used for this model, the values of *dist* ranges from zero to severn and the hazards ratio between the two extremes of *dist* is 21 ($e^{0.436*7}$), making *dist* the most influential covariate in the model.

Using the residuals discussed in the methodology section, model 1 was further tested on the functional form, proportionality, heterogeneity, and existence of outlier *[86]*. The test results indicated that the functional forms for the continuous variables were correct; the proportional hazards assumption upheld; and there were no heterogeneity and outliers.

Baseline Hazards. As mentioned earlier, the cumulative baseline hazards can be estimated by the *Breslow* estimator (equation 11). The resulting cumulative baseline hazards, the baseline hazards, and baseline survival for each time interval are given in Table 6. Figure 3 plots of baseline survival and baseline hazards.

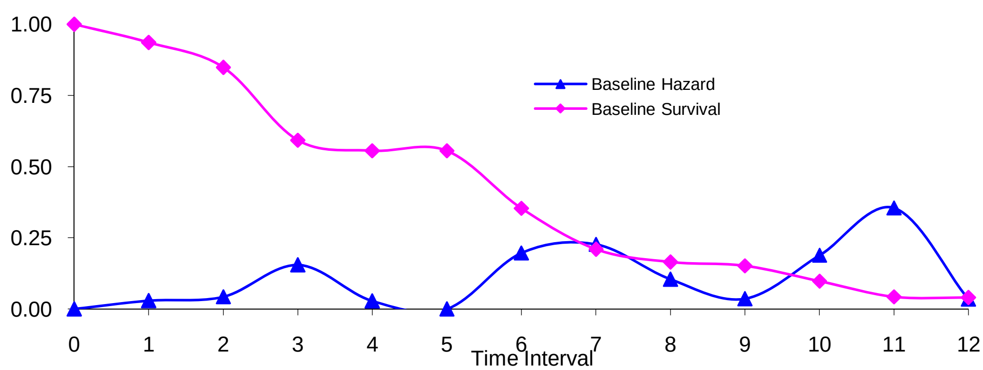


Figure 3
Baseline hazards and baseline survival of the Cox model

Table 6
Baseline hazards and baseline survival of the Cox model

Time	Cumulative Baseline	Baseline Hazard	Baseline Survival
1	0.029	0.029	0.936
2	0.071	0.043	0.848
3	0.227	0.155	0.593
4	0.255	0.028	0.556
5	0.255	0.000	0.556
6	0.452	0.197	0.354
7	0.679	0.227	0.210
8	0.783	0.104	0.165
9	0.818	0.036	0.152
10	1.008	0.189	0.098
11	1.363	0.355	0.043
12	1.398	0.035	0.040

Model Goodness-of-Fit. Because of the complexity of survival analysis, there is no simple measure of *GOF* as in linear regression analysis or other estimation procedures. In addition to the likelihood ratio index ρ^2, which is a good index for comparing models with different specifications, there are other methods to assess the *GOF* of survival analysis. *Cox-Snell* Residuals *[87]* can provide a graphic representation of the *GOF* of a Cox model. The Cox-Snell residuals r_i are defined as:

$$r_i = \hat{H}_{0i}(t_i)\exp[\sum_{j=1}^{p}\beta_j x_{ij}(t_i)], \qquad \text{i} = 1,...,\text{n}, \tag{36}$$

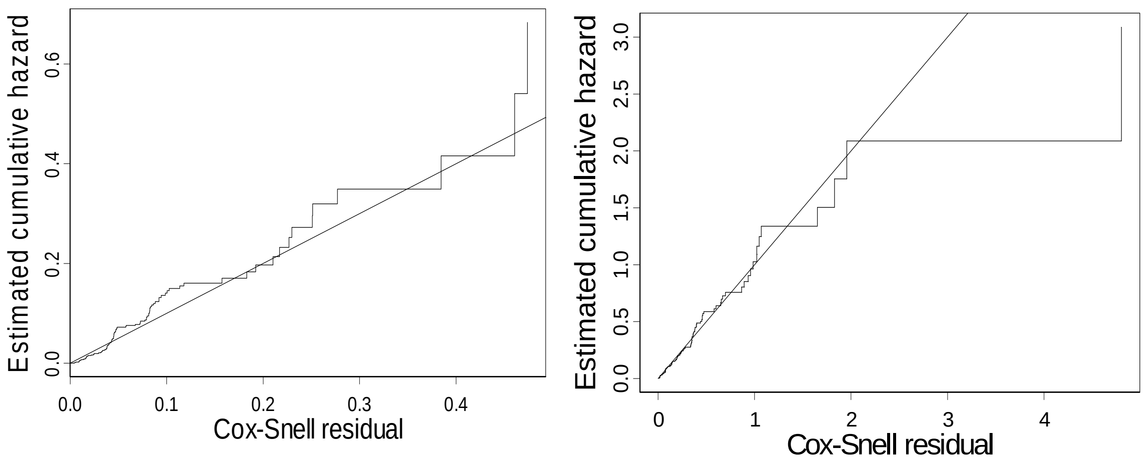
where r_i is the Cox-Snell residual for individual i who evacuated in time interval t_i with covariate values $x_{ij}(t_i)$; β_j is the coefficient estimated for the Cox model; and n is the number of subjects under observation. $\hat{H}_{0i}(t_i)$ is the *Breslow* estimator of the cumulative hazard defined by equation 11. If the Cox model is correct and the estimated coefficients are close to the true values of the coefficients, then r_i should behave approximately as a random sample from a unit exponential distribution *[56,88]*. To produce the graphic, first the *Cox-Snell* residuals (r_i) are calculated, and it is determined if the corresponding subject evacuated or not; next, the *Nelson-Aalen* estimate of the cumulative hazard of r_i is obtained with the data, then, the cumulative hazard against the *Cox-Snell* residuals is plotted. The resulting plot should follow the 45° straight line from the origin if the Cox model is appropriate.

The Nelson-Aalen estimator just mentioned is defined as *[56]*:

$$\hat{H}(t) = \sum_{t_i \le t} \frac{d_i}{Y_i}, \tag{37}$$

where d_i is the number of events in time interval i, and Y_i is the number of individuals at risk at time t_i.

Applying this test to the model estimated in this study, the results shown in Figure 4 were obtained. In the figure, one set of results was plotted against each observation and the other against each subject. Generally, the curve centers on the 45° line for most of the points except in the tail, where the number of observations is sparse, and the distances from the 45° line become larger. Overall, the model fit seems reasonable. However, Allison *[61]* mentions that this method of the *GOF* test is not sensitive to differences in model fit. He gives the *GOF* plots of two models, both of which are close to the 45° line. However, based on the likelihood ratio test, one model fits well, and the other model ought to be rejected.



(a) Per observation (b) Per subject

Figure 4
The Cox model GOF

Grønnesby and Borgan *[89]* proposed an overall *GOF* test for the Cox model. May and Hosmer *[90]* extended this test and showed that by adding group indicator variables to the model and testing the hypothesis that the coefficients of the new variables are zero via the score test; their method is algebraically identical to that of Grønnesby and Borgan. However, the May and Hosmer method not only simplifies the calculation of the test but also makes it possible to compare observed events and model predicted events within each group. The grouping is based on the risk score $r_i = \sum_{j=1}^{p} \beta_j x_{ij}$. All the observations are sorted by the risk score and grouped into G groups. Each group is assigned a number, and this group number becomes a new categorical variable. The new variable is added as an additional covariate to the existing model with group 1 as the reference group. If the coefficients of the new covariate are not zero by the score test or the likelihood ratio test, then the model fit is rejected. May and Hosmer *[90]* also suggest using a 2 by G table with the observed and predicted numbers of events for each group to summarize the model fit. A *z*-score can be formed by dividing the difference between the observed and expected number of events by the square root of the expected number of events. For large values of means in the cells, the *z*-score is, approximately, normally distributed.

When applying this test to model 1, all the observations were grouped into eight groups. With the first group as the reference group, seven indicator covariates were added to the model. The value of the resulting score test statistic was nine with seven degrees of freedom, resulting in a p-value of 0.353. Thus the score test could not reject the null hypothesis that the model fits at the five percent level of significance.

The two by eight table is presented in Table 7. The observed and expected numbers of evacuation, *z*-score tests and *p-values*, are listed for each of the eight groups. The *p-values* show no evidence of rejecting model fit for each of the groups.

Table 7
The Cox model GOF by group

Group	Observed	Expected	*z* score	*p-value*
1	2	1.73	0.21	0.83
2	2	1.97	0.02	0.98
3	10	9.23	0.25	0.80
4	4	7.05	-1.15	0.25
5	17	20.1	-0.7	0.48
6	16	15.1	0.21	0.84
7	24	19.5	1.02	0.31
8	41	41.2	-0.04	0.97

Arjas *[91]* suggested plotting the cumulative observed number of events versus the cumulative expected number of events for non-censored subjects, and Hosmer and Lemeshow *[92]* suggested plotting each of the G groups to assess model fit. If the Cox model is appropriate, then the points should be around the 45^o line from the origin. Figure 5 shows the plots for each of the eight groups. The dotted lines are the 45^o lines from the origin. For groups 1 and 2, the difference is large because there are only two observed cases for each group. The difference for group 4 is also large, since the number of observed cases is only four. For the rest of the groups, it seems that the points do follow the 45^o line. Figure 6 shows the plot that combines all eight groups together. The overall fit is good. As a result, it is reasonable to say that the model does fit well. From the above analysis, it can be conclude that the Cox model developed in this study (model 1 in Table 5) has a good overall *GOF*.

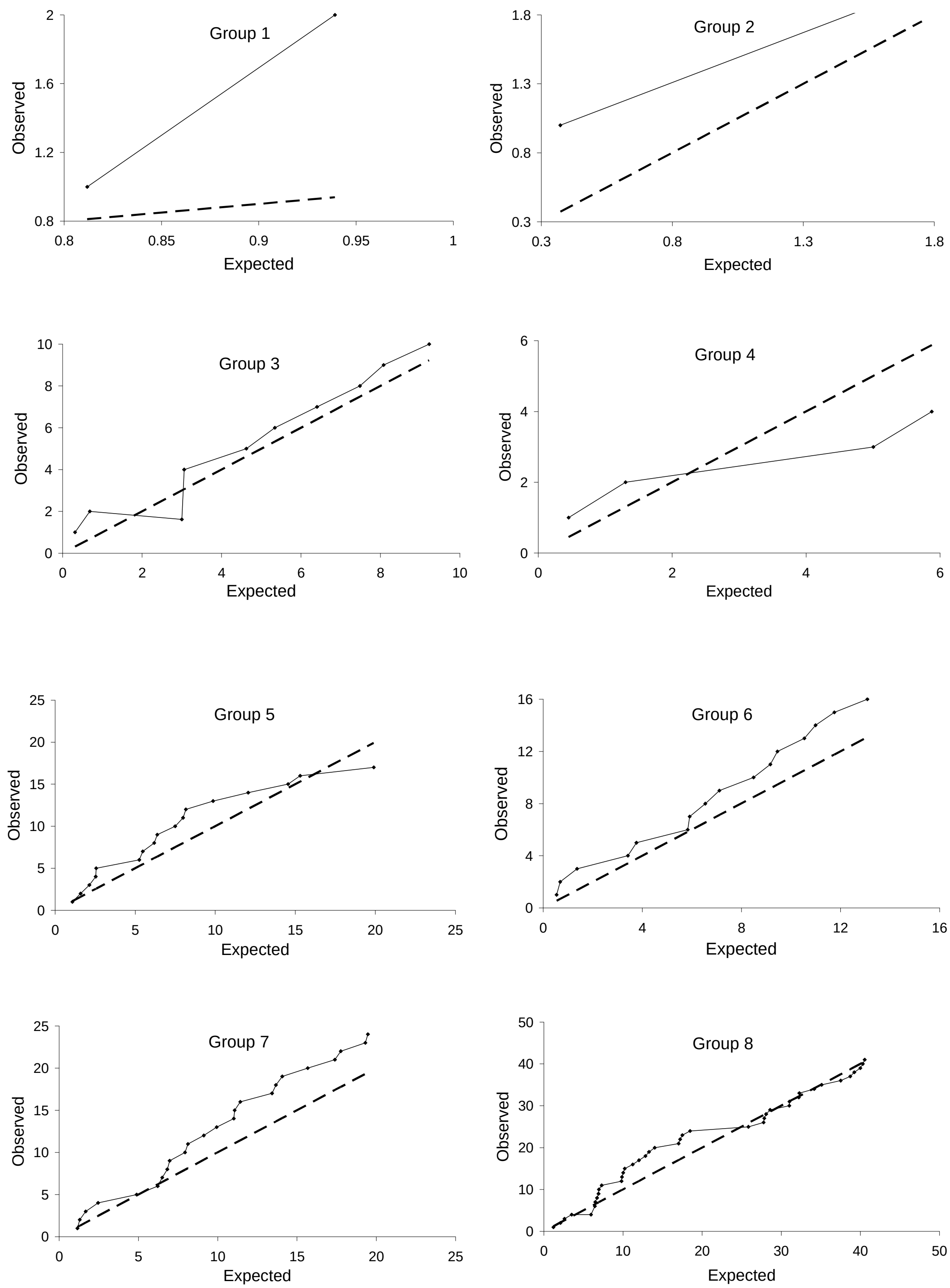


Figure 5
Expected vs. observed cumulative count for each group

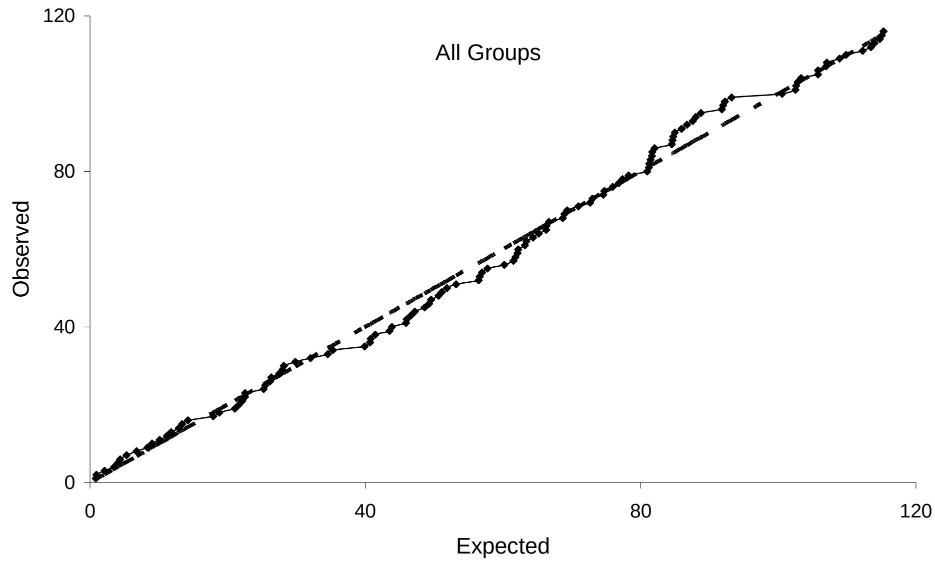


Figure 6
Expected vs. observed cumulative count for all groups of the Cox model

The Piecewise Exponential Model

In this section, the Andrew data was applied to estimate a Piecewise Exponential model. The parameter estimation of the Piecewise Exponential model was carried out using parametric regression models of survival analysis through the use of maximum likelihood *[61]*. Three models were tested with the Andrew data. In addition to the four variables used in the Cox model, the first model included the time interval as a covariate; the second model included time-of-day (TOD); and the third model included both. The first model is superior to the second one. Multiple collinearities occurred in the third model. As a result, the first model was selected. The summary model results are presented in Table 8.

Since an intercept was estimated in the model, the likelihood ratio test becomes -2[LL(C) - $LL(\beta)$] instead of -2[LL(0) - $LL(\beta)$], and the degrees of freedom becomes the number of explanatory variables minus one. *LL(C)* is the value of the likelihood function when only the alternative-specific constant (*ASC*) is included in the mode. The model had a likelihood ratio value of 320.8 with 15 degrees of freedom. The *p-value* was 0.000, rejecting the null hypothesis that all the explanatory variables except for the *ASC* were zero. Since there were 12 time intervals, 11 dummy variables were used. Time interval 12 is the reference variable. The high coefficient value for *interval(5)* causes the hazard for time interval 5 to be zero. This conforms to the fact that there was no evacuation in time interval 5 from the dataset. Overall this variable is very significant. This model has a very high likelihood ratio index value of 0.276, which indicates a very good model fit.

Table 8
Summary results of the Piecewise Exponential model

Covariate	Piecewise Exponential Model		
	β	se(β)	*p-value*
dist	-0.422	0.220	0.055
orderper	0.529	0.206	0.010
flood	0.676	0.211	0.001
mobile	1.469	0.207	0.000
intercept	-2.584	0.828	0.002
Interval(11 dummies)			
Interval(1)	-0.187	1.214	0.878
Interval(2)	0.200	1.130	0.860
Interval(3)	1.474	1	0.140
Interval(4)	-0.218	1.170	0.852
Interval(5)	-22.184	40788.530	1.000
Interval(6)	1.695	0.918	0.065
Interval(7)	1.843	0.880	0.036
Interval(8)	1.082	0.879	0.218
Interval(9)	0.031	0.950	0.974
Interval(10)	1.656	0.736	0.024
Interval(11)	2.217	0.635	0.001
LL(C)	-580.4		
LL(β)	-420		
-2[*LL*(C) - *LL*(β)]	320.8		
ρ^2	0.276		

The hazard for each time interval can be calculated with equation 19. First, the sum of the intercept and the coefficient of each time interval are calculated, and then the exponential of each sum is the corresponding hazard for that time interval. For example, the hazard for time interval one is $e^{(-2.5841-0.1870)} = 0.06260$. Table 9 lists hazard rates for each of the 12 time intervals.

Table 9
Hazard rates for 12 time intervals from the Piecewise Exponential model

Interval	1	2	3	4	5	6	7	8	9	10	11	12
Hazard	0.063	0.092	0.330	0.061	0.000	0.411	0.477	0.223	0.078	0.395	0.693	0.075

Sequential Model Estimation with Southwest Louisiana (Andrew) Data

In the sequential choice paradigm as discussed in the methodology section, a household faces a series of binary choices for each time interval as conditions of the hurricane change until the decision to evacuate is reached, or the hurricane makes landfall. The probability of evacuation in each time interval is the product of the conditional probability to evacuate in the current time interval and the conditional probabilities not to evacuate in all previous time intervals. The impact of explanatory variables can be accommodated in the conditional binary choice models. Next, the Andrew data are used to estimate two sequential choice models, one sequential logit model and one sequential complementary log-log model.

Model Estimation

A stepwise forward selection process was conducted to find the covariates and their interactions. The eight variables that had levels of significance greater than five percent are listed in Table 10.

Table 10
Covariates in the sequential model from the Andrew data

Covariate	Definition
dist	A function of distance to the storm at time t. Same as in survival analysis.
TOD	Time-of-day, 0 for night (reference), 1 for morning, and 2 for afternoon. Two dummy variables.
speed	Forward speed of the hurricane (miles/hour).
orderper	1 if the household perceived receiving an evacuation order, 0 otherwise.
flood	1 if the residence is believed very likely to be flooded, 0 otherwise.
mobile	1 if a mobile home, 0 otherwise.
hurtrisk	1 if a serious risk of being hurt is perceived, 0 otherwise.
protect	1 if consider staying home enables to better protect property, 0 otherwise.

Two more dynamic variables, *TOD* and *speed*, were selected in addition to the variables identified in the survival analysis (Table 4). For *TOD*, morning was from 6 a.m. to 12 p.m., afternoon was from 12 p.m. to 6 p.m., and night was from 6 p.m. to 6 a.m. *Speed* was the forward speed of the hurricane (in miles/hour) in the past time interval. No interactions among the covariates (both static and dynamic) were found to be significant. *TOD* and *speed* had the same values for every household in each time interval. As a result, their impacts could not be estimated in the Cox model because of the structure of the partial likelihood function. However, this is not a problem with the sequential models. Each covariate was treated as an alternate-specific variable because none of them vary across the two choices (to evacuate or not to evacuate) in a time interval. As a result, it is specified that the covariates only appear in the choice to evacuate, and the choice of not to evacuate is the reference choice without any variables and an alternative-specific constant.

The parameters for *hurtrisk* and *protect* were significant, and inclusion of these variables in the models clearly improved the model fit. But these two variables were subjective and difficult to estimate in practical applications, as discussed previously. Therefore, they were eliminated from the models.

One advantage of the logistic and complementary log-log models is that the time interval can be treated explicitly as a covariate. It can be included either as a continuous variable or a categorical variable. Both were tested in this study. When time was modeled as a continuous variable, a strong correlation existed between time intervals and *dist*. Between the two, *dist* was preferred. If time was modeled as a categorical variable and represented by a set of dummy variables, the net effect was to make the alternative-specific constants, α_i vary across alternatives. However, it was found that the parameters for time during night times (between 6 p.m. to 6 a.m.) were not significantly different from each other, and there were strong correlations among categories of time intervals and *TOD*. If a time interval was used instead of *TOD*, the model would get a better goodness-of-fit, and the difference between the observed and model predicted probabilities were smaller. However, *TOD* was considered a better covariate than time interval and was preferred in the model. The inclusion of *TOD* also served to make the alternative-specific constant, α'_i vary across some time intervals, although not for every time interval, for example when time was in the model as a covariate.

The models to be estimated were the conditional probability models with logistic and extreme minimal-value distributions, although the models used for predictions were the unconditional probability models. The slope parameters, β were assumed to be the same across time intervals. Table 11 gives the estimated parameters and the statistics of the two models. The *p-values* in the table are the probabilities of the Wald test for the parameters to be zero. The last row gives the likelihood ratio index for the two models.

Table 11
Summary results of the sequential models with the Andrew data

Covariate	Logit model			Complementary log-log model		
	β	se(β)	*p-value*	β	se(β)	*p-value*
intercept	-2.8238	0.9123	0.002	-2.9294	0.853	0.000
dist	-0.7995	0.1144	0.000	-0.7305	0.0997	0.000
TOD(1)	1.4512	0.3096	0.000	1.4142	0.3009	0.000
TOD(2)	2.0244	0.2811	0.000	1.9468	0.2698	0.000
speed	0.1463	0.0691	0.034	0.1326	0.066	0.045
orderper	0.5401	0.218	0.013	0.4842	0.2047	0.018
flood	0.7809	0.2276	0.001	0.6917	0.2123	0.001
mobile	1.6496	0.2293	0.000	1.502	0.2058	0.000
LL(C)	-580.4			-580.4		
LL(β)	-420.0			-421.0		
-2[*LL*(C) - *LL*(β)]	320.8			318.8		
ρ^2	0.276			0.275		

The likelihood ratio test had values of 320.8 and 318.8 with a degree of freedom of seven for the logit model and the complementary log-log model, respectively. The *p-values* were 0.000, rejecting the null hypotheses that the explanatory variables, except for the *ASC* estimated for each of the models, were zero. In general, all the coefficients of covariates for both models have the right signs, and their values are reasonable. They have *p-values* significant at five percent level. Each model has a high likelihood ratio index (0.276 for the logit model and 0.275 for the complementary log-log model), indicating good *GOF*. The coefficients from the two models are very close, with the largest percent difference being about eleven percent for the estimates of the coefficient of *flood*. Among all the covariates in the model, *TOD* has the largest absolute parameters. It has a major impact on when people evacuate. A more detailed discussion on this will be presented next. *Mobile* has the second largest coefficient, implying that households living in mobile homes are over five times ($e^{1.65}$=5.2) as likely to evacuate as people not living in mobile homes. *Flood* also plays a significant role. Households living in a flood-prone area are more than twice ($e^{0.78}$=2.2) as likely to evacuate as people not living in a flood-prone area. The impact of a perceived evacuation order is next to that of *flood*. For the same reason discussed in the subsection on the basic Cox models earlier, the covariate *orderper* was treated as a static variable in the model. Households that receive an evacuation order are 1.7 times ($e^{0.54}$=1.7) as likely to evacuate as people who do not receive an evacuation order. Covariate *dist* is a dynamic continuous variable in the model, and the negative coefficient means that the nearer the storm, the more likely a household will evacuate. From the dataset used for this model, the values of *dist* ranged from zero to seven and the odds ratio between the two extremes of *dist* was 270 ($e^{0.8*7}$=270.4), making *dist* the most influential covariate in the model. Compared to the survival models, an additional dynamic variable was included in this sequential model. This variable was the forward speed of the hurricane. The faster the forward speed, the more likely a household is to evacuate. Note that the discussion above applies to the conditional binary model not the unconditional sequential model.

The Sequential Logit Model *GOF*

In addition to the log likelihood ratio and log likelihood ratio index tests, the Hosmer-Lemeshow test *[93,94]* provides a convenient way to assess a binary logit model *GOF* and is available on most popular statistical software. The Hosmer-Lemeshow test organizes subjects into *g* groups based on the values of the estimated probabilities *[95]*. For example, if *g* =10, there will be 10 groups and the grouping cutpoints are based on percentiles. There will be two rows for every group, one for outcome=1 and one for outcome=0. The Hosmer-Lemeshow statistic $\hat{C}$ is obtained by calculating the Pearson Chi-square statistic from the g by two table of observed and model estimated expected frequencies and is given by:

$$\hat{C} = \sum_{k=1}^{g} \frac{(o_k - n_k \overline{\pi}_k)^2}{n_k \overline{\pi}_k (1-\overline{\pi}_k)}, \tag{38}$$

where n_k is the total number of subjects in the *k*th group, o_k is the number of choices that are *Y*=1 in the *k*th group, $\overline{\pi}_k$ is the average estimated probability in the *k*th group, and $\hat{C}$ is chi-square distributed with *g*-2 degrees of freedom. A large $\hat{C}$ will result in a small *p-value*, meaning an inferior *GOF*. Usually, if the *p-value* is smaller than 0.05, the null hypothesis, the model fits the data well, will be rejected. The appropriateness of the *p-value* depends on the assumption of m-asymptotics, which means the estimated expected frequencies in each cell have to be large when the total number of samples becomes large. A rule-of-thumb is that the frequency is no smaller than five. Furthermore the number of groups *g* should not be smaller than six.

The contingency table for the binary logistic model from SPSS output for the Hosmer and Lemeshow test had the number of groups *g*=10. The Hosmer and Lemeshow statistic was 7.309 with eight degrees of freedom. The *p-value* was 0.504. This indicates that the null hypothesis, the model fits well, should not be rejected.

However, the expected frequencies in several groups were below five (another was on the border line). Regrouping is needed so that each group would have sufficient large frequencies and the number of groups should be at least six. Low frequency groups were combined, and other groups were kept intact. The new contingency table is given in Table

12. The Hosmer and Lemeshow statistic was 4.439 with five degrees of freedom. The *p-value* was 0.488. As a result, the null hypothesis, the model fits well, is not rejected.

Table 12
Contingency table for *g*=7 with the Andrew data

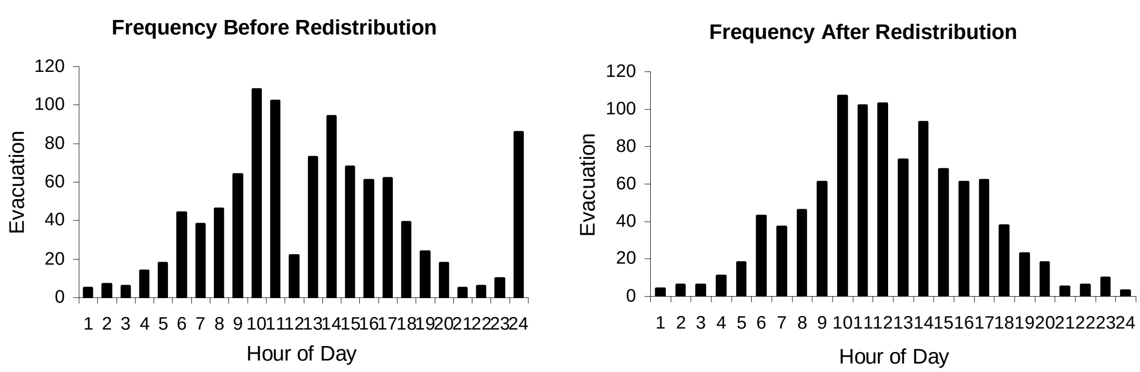
Group	Evacuate=0		Evacuate=1		Total
	Observed	Expected	Observed	Expected	
1	1381	1380	7	7.9	1388
2	333	333	5	4.9	338
3	334	331	4	6.7	338
4	329	329	10	9.9	339
5	326	325	13	14.3	339
6	309	317	30	22.3	339
7	262	259	47	50.1	309

Sequential Model Estimation with South Carolina (Floyd) Data

In this subsection, the sequential logit and complementary log-log models were estimated with the Floyd data from South Carolina.

Preliminary Data Analysis

The data were first reviewed to check for any errors or inconsistencies that may be present in the data. One serious flaw that was discovered in the data was that a large number of evacuations were recorded for the 24th hour (midnight) and only a few for the 12th hour (mid-day noon). Figure 7(a) shows the frequency distribution of evacuation by time of day. The excess evacuations at the 24th hour were identified by observing the reported evacuations in the 23rd and 1st hours. The abnormality is obvious. It was probably caused by the wording in the questionnaire that described a.m. as “morning/or midnight until noon” and p.m. as “afternoon/evening or noon until midnight.” Households were randomly selected from the 24th hour and moved to the 12th hour until the proportion between the two was consistent with the observations in the hours surrounding them. Figure 7(b) shows the frequency after the redistribution.



(a) (b)

Figure 7
Floyd Evacuation frequency distribution by hour of day

Model Estimation
A stepwise forward selection process was conducted to find the covariates and their interactions in the models. Finally, six covariates were selected, as listed in Table 13. Variables *hurtrisk* and *protect* were not included in the model.

Table 13
List of covariates in the sequential model with the Floyd data

Covariate	Definition
gammadist	Transformation of distance, with gamma distribution.
TOD	Time-of-day. 0 for night (reference), 1 for early morning, 2 for midday, and 3 for late afternoon. Three dummy variables.
speed	Speed of the hurricane (miles/hour).
dynaorder	Dynamic evacuation order. 1 for voluntary, 2 for mandatory, and 0 for none. Two dummy variables.
flood	1 if the residence is in category 3 risk zone or above, 0 otherwise.
mobile	1 if the residence is a mobile home, 0 otherwise.

The definitions of the covariates are not exactly the same as those in the Andrew data. Time-of-day (*TOD*) is defined as a categorical variable with four levels: early morning (6 a.m. to 9 a.m.), mid-day (10 a.m. to 3 p.m.), late afternoon (4 p.m. to 7 p.m.), and night (8 p.m. to 5 a.m.). The definition of *flood* is no longer the perceived risk of flooding, but rather a more objective measure defined by risk zones from the planning authority (in South Carolina risk zones are classified into four categories: risk zones one through four, with increasing risk of flooding as the category increased from one through four). A unique feature of this dataset is that evacuation order can be treated as a time-dependent variable. At time interval 28, a voluntary evacuation order was issued to all the households in the survey; at time interval 31, a mandatory evacuation order was issued. Another difference lies in the treatment of distance. When modeling Andrew, a logarithm form of distance was used. Past experience and preliminary analysis show that the functional form for distance should not be linear. It is reasonable to believe that when the hurricane is far away, its impact on evacuation is very small, i.e., few people will evacuate; if the hurricane is too close, people will not evacuate because it will be too dangerous. However, those impacts are not symmetric, as the values of distance change. The impact when distance is far away changes gradually; when that impact reaches a peak, it will decrease faster. It is believed that the shape of the gamma distribution density function represents such behavior well. Therefore, distance was transformed with a gamma distribution density function in this application. The new variable was named *gammadist*. The gamma distribution density function is:

$$f(x,\alpha,\beta)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-\frac{x}{\beta}}, \quad (39)$$

where x is the value at which one wants to evaluate the distribution, $\alpha>0$ is the shape parameter, $\beta>0$ is the scale parameter, and $\Gamma(x)$ is the gamma function. When $\alpha>1$ the gamma density distribution is asymmetric, with longer tails to the right. Figure 8 plots *gammadist* for different shape and scale parameters with x = distance/100.

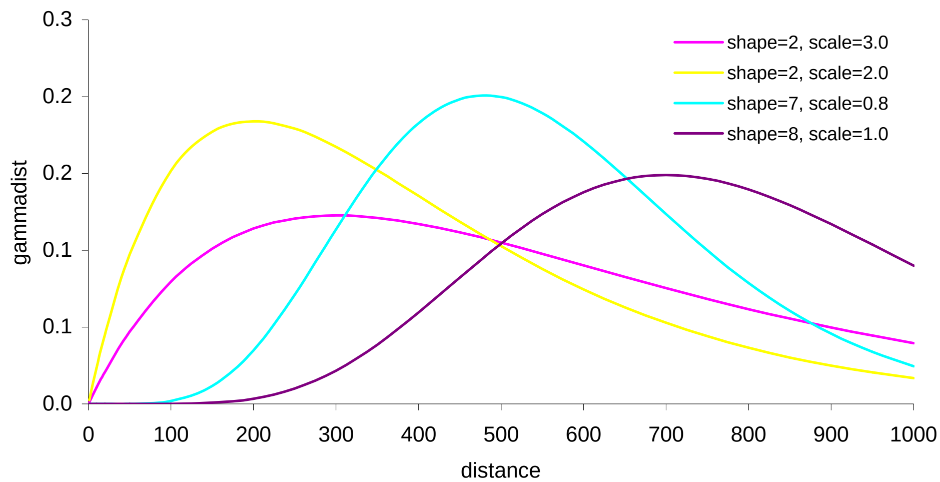


Figure 8
***gammadist* with different parameters**

This transformation gives different weights for different values of distance. If the frequency distribution of evacuation by distance for the Floyd data is plotted, the peak lies between 400 and 500 miles (see the transferability study subsection later for detailed discussion). Intuitively, this information provides some guidance for choosing the parameters. A wide variety of parameter combinations were tested in the modeling effort. The models' Hosmer and Lemeshow *GOF* tests were used to eliminate the models with the parameter combinations that result in rejecting the null hypothesis that the binary logit models fit the data well. However, a good Hosmer and Lemeshow *GOF* test only indicates that a good binary logit model is fitted. The overall performance of the sequential model, i.e., the model prediction vs. observation, as well as the balance of covariates that go into the model, should also be considered when selecting parameters for the transformation. Table 14 presents some summary information.

Table 14
Sequential model *GOF* for parameter combinations

No.	Gamma distribution Parameters		Hosmer and Lemeshow *GOF* Test			Sequential Logit Model *GOF*		
	Shape	Scale	χ^2	df	Significance	ρ^2	% Error	RMSE
1	2	3	14.832	8	0.062	-	-	-
2	3	2	5.106	8	0.746	-	-	-
3	6	1	6.144	8	0.631	-	-	-
4	5	1	6.973	8	0.540	0.198	-2.00%	2.68
5	7	0.7	7.481	8	0.486	0.197	-3.30%	2.79
6	8	0.6	8.641	8	0.373	0.197	-2.00%	2.79
7	9	0.5	9.995	8	0.265	0.198	-2.00%	2.75

The first part of the table (columns 2 and 3) gives the shape and scale parameters of the gamma distribution. The second part of the table (columns 4 through 6) gives the Hosmer and Lemeshow *GOF* test, including: the Chi-square statistic, degrees of freedom, and level of significance. The third part of the table (columns 7 through 9) gives the sequential model *GOF*, including: likelihood ratio index, percent error, and RMSE of total prediction versus observation. For combination 1, the Hosmer and Lemeshow Chi-square statistic was 14.832 with eight degrees of freedom, which equaled a low level of significance of 6.2 percent. This indicated that the estimated binary logit model did not fit well. Combinations 2 and 3 did have good Hosmer and Lemeshow *GOF* tests, indicating good fit between the binary logit model and the data. However, in the model estimated with combination 2, wind speed (covariate *speed*), which is a very important preferred variable to be included in the model, was not significant; in the model estimated with combination 3, *gammadist,* which is another very important preferred variable to be included in the model, was not significant. As a result, combinations 1 through 3 had to be eliminated. Combinations 4 through 7 all had good Hosmer and Lemeshow *GOF* test statistics. Moreover, each of the models estimated with the corresponding parameter combinations from 4 through 7 included important variables, such as wind speed and distance, although the parameter of wind speed in combination 4 was on the borderline with a level of significance at 0.061, a value that can still be tolerated. Other than that, the *GOF* tests of the sequential model were reasonably good and very similar among combinations 4 through 7. Based on the above analysis, for combinations 4 through 7, all the estimated binary logit models had good Hosmer and Lemeshow *GOF* test statistics; all the sequential model *GOF* tests were good; and all the models included the variables that are believed to be important for hurricane evacuation study. The transformations with parameter combinations 4 through 7 are plotted in Figure 9. As can be seen, they tend to have a very similar mode but only differ in variance slightly.

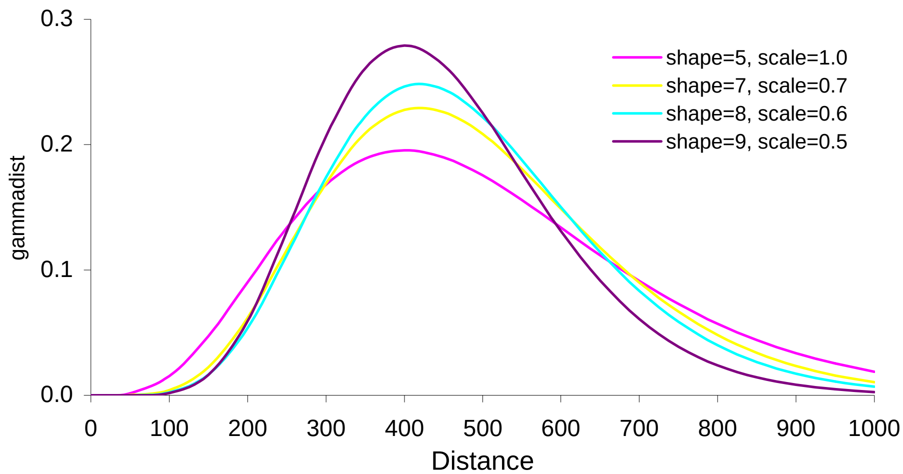


Figure 9
Searching for appropriate parameters for *gammadist*

Figure 10 plots the predicted evacuations from models for parameter combinations 4 through 7 with the validation data. The figure shows that the model predictions are almost identical.

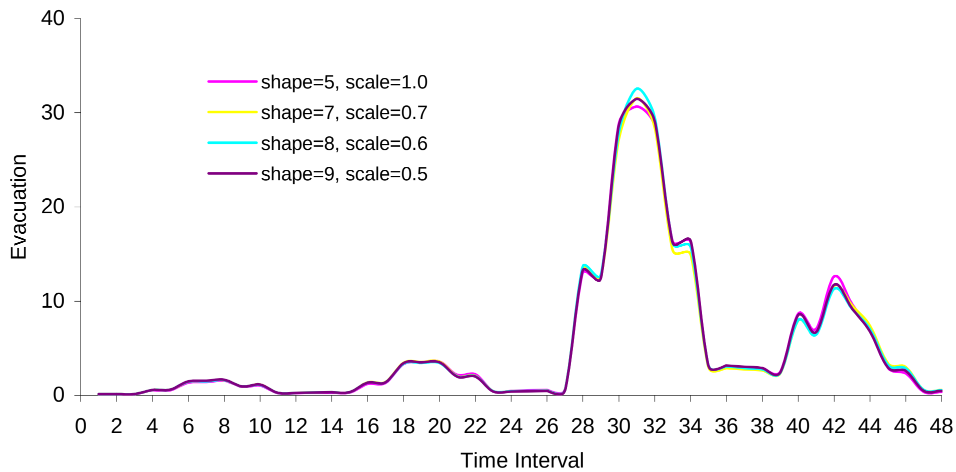


Figure 10
Model predictions for different gamma parameters

Figure 11 presents a comparison of the coefficients from the models with the above parameter combinations. The coefficients are very stable for all the covariates except for those of *gammadist* and, of course, the intercepts (i.e., the constants). This shows that the rest of the model is relatively unaffected by the alternative gamma distributions of distance tested, and, therefore, any one of the alternatives would be acceptable with regard to the impact of the other covariates on the outcome.

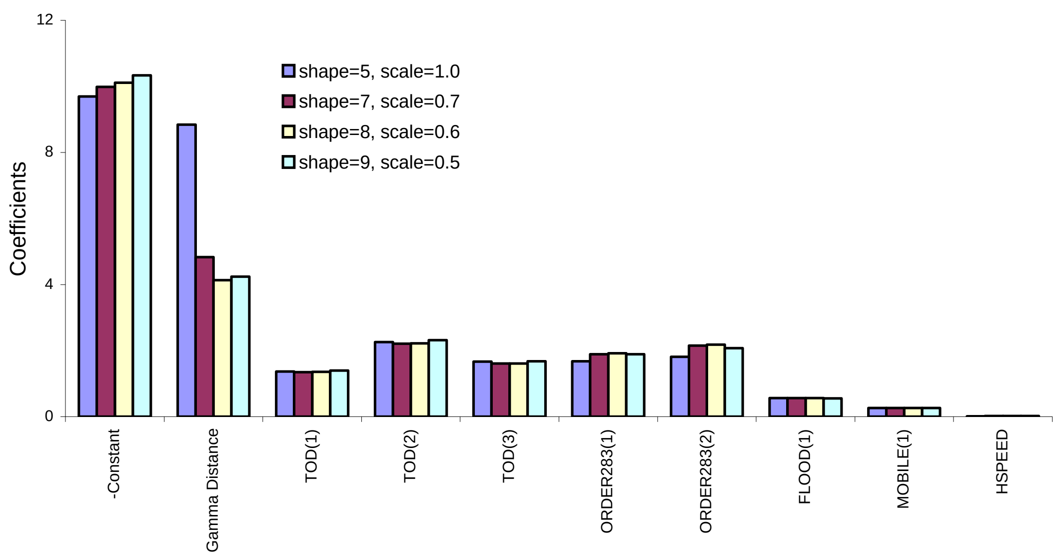


Figure 11
Comparing coefficients among the models with the Floyd data

The *RMSEs* of the models are very close, with values ranging from 2.68 to 2.79. Based on all the above analyses, it is decided to use combination 6, which has shape=8 and scale=0.6. Table 15 gives the model summary results for both logistic and complementary models.

Table 15
Summary results of the two sequential models with the Floyd data

Covariate	Logit			Complementary Log-Log		
	β	se(β)	*p-value*	β	se(β)	*p-value*
intercept	-10.108	0.891	0.000	-9.962	0.871	0.000
gammadistance	4.139	1.012	0.000	4.077	0.989	0.000
TOD(1)	1.353	0.171	0.000	1.336	0.169	0.000
TOD(2)	2.221	0.143	0.000	2.181	0.140	0.000
TOD(3)	1.610	0.156	0.000	1.588	0.153	0.000
dyanorder(1)	1.917	0.193	0.000	1.903	0.189	0.000
dyanorder(2)	2.181	0.213	0.000	2.148	0.209	0.000
flood	0.558	0.078	0.000	0.538	0.075	0.000
mobile	0.263	0.132	0.047	0.249	0.128	0.051
speed	0.017	0.006	0.006	0.017	0.006	0.007
LL(C)	-3871			-3871		
LL(β)	-3110			-3110		
-2[*LL*(C) - *LL*(β)]	1522			1522		
ρ^2	0.197			0.197		

In general, all the coefficients of covariates have the right signs, and their values are reasonable. The likelihood ratio index is almost 0.2, indicating good model fit. The coefficients of this model for *TOD* and *flood* are close to those from the sequential model based on the Andrew data (Table 11). The values of the three dummy variables for *TOD* indicate the smallest amount of evacuation at night, an increase in the morning, the highest at mid-day, and then a decrease in the afternoon again, but still higher than in the morning. *TOD* has the second largest absolute parameters after *gammadistance*. The large parameter for *gammadistance* is due to the fact that the values of *gammadistance* are much smaller than the original values of distance without the transformation or with the logarithm transformation. The parameters for the dynamic variable *dynaorder* are also much larger than their static counterpart from the Andrew model. This change has been confirmed by other research *[85]*. However, the impact of *mobile* is much smaller than those found from the sequential Andrew model. Note that the sequential Andrew model selected the forward speed of the hurricane as a covariate, while this model selected hurricane speed instead.

Goodness-of-Fit

Both models had likelihood ratio test values of 1522, with nine degrees of freedom. The p-values are 0.000, rejecting the null hypotheses that all the explanatory variables except for the *ASC*s were zero. The binary logit model has a log likelihood ratio index $\rho^2=0.197$. The contingency table for the binary logit model can also be calculated from the standard software package output for the Hosmer and Lemeshow test where the number of groups is g=10. The Hosmer and Lemeshow statistic is 8.641 with eight degrees of freedom. The *p-value* is 0.373. This shows that the null hypothesis, the binary logit model fits, should not be rejected. If the first three groups are aggregated so that each cell will have evacuation frequencies equal to at least five, as is normally done, the Chi-square is 2.251 with six degrees of freedom and the *p-value* is 0.895, which indicates that the same conclusion about the model *GOF* should be reached, as was done earlier, but with greater confidence. The contingency table without regrouping is given in Table 16.

Table 16
Contingency table for *g*=10 with the Floyd data

Group	Not Evacuated		Evacuated		Total
	Observed	Expected	Observed	Expected	
1	4877	4875	0	2	4877
2	4876	4873	1	4	4877
3	4864	4868	9	5	4873
4	4870	4872	11	9	4881
5	4830	4829	12	13	4842
6	4852	4856	25	21	4877
7	4846	4844	35	37	4881
8	4808	4804	68	72	4876
9	4698	4694	176	180	4874
10	4497	4502	412	407	4909

Sequential Model Estimation with Stated-Preference (New Orleans) Data

Preliminary Analysis and Preparation of Stated Preference Data

Based on the experimental design discussed in the description of the data section, eight respondent sets were created, each of which had eight profiles. Each respondent was presented with all the profiles in one set and was asked whether he or she would evacuate; if the answer was yes, then the respondent was asked to choose one of the following times in which he or she would evacuate:

1. 0-2 hours,
2. 2-4 hours,
3. 4-6 hours,
4. 6-12 hours,
5. 12-24 hours,
6. 1-2 days, and
7. More than 2 days.

Since a respondent was presented with multiple scenarios, it was a concern that they may have had difficulty in responding to the different variable level combinations (profiles or scenarios) in a meaningful way. To test whether respondents were sensitive to the different profiles, the responses from all the 32 profiles were studied. To present the analysis clearly, eight profiles were randomly selected from the 32 profiles and their responses were plotted by the stated time interval of evacuation, as shown in Figure 12.

Each colored line represents the stated evacuation distribution by time for each profile. Clearly, people did respond to different profiles differently as evidenced by the spread of the evacuation response in the diagram. However, it seemed that all the curves had similar trends. Evacuations were the highest in time interval 1, then decreased during time intervals 2 through 4, reached another peak in time interval 5, and lastly, decreased again. If the data were presented somewhat differently, the trends became more obvious. Figure 13 plots the stated evacuation for each time interval by profile for all 32 profiles, and Table 17 summarizes the percent evacuation distribution by time interval.

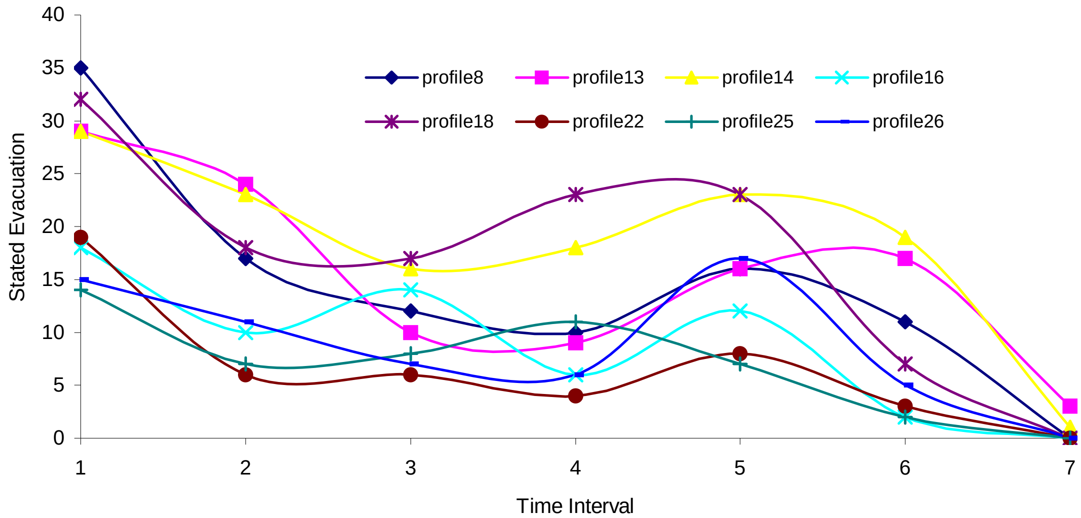


Figure 12
Stated evacuation distribution by time interval

It could be found that: 1). People were more likely to choose to evacuate in time interval 1, which was to evacuate almost immediately. The evacuation percentage in time interval 1 was 29.5 percent. 2). The next most popular time in which to evacuate were time intervals 2 and 5, which was from 2 to 4 hours and from 12 to 24 hours. Since the survey was conducted during the day, this may reflect the preference of people to evacuate during daylight rather than at night. 3). People were least likely to choose to evacuate in time interval 7, which was more than two days later. This seems intuitively correct because if someone has decided to evacuate, it is rare that the decision would relate to an intended evacuation more than two days later. If evacuation would only be necessary in two or more days, a respondent is more likely to defer the decision, knowing that more information is likely to be available at a later date.

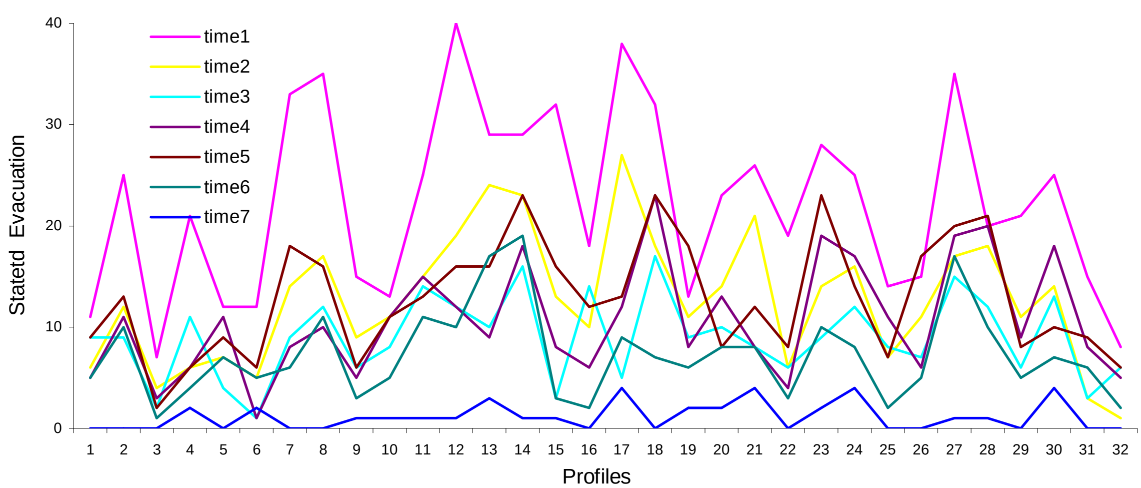


Figure 13
Stated evacuation distribution by profile

Table 17
Stated evacuation percentage by time interval

Time Interval	1	2	3	4	5	6	7
% Evacuation	29.5%	16.7%	11.8%	14.0%	16.9%	9.6%	1.5%

The choice of model time interval is dictated by people's stated choices of evacuation, which are the seven time intervals discussed above. Note that non-equal time intervals are present here. During data preparation, every effort had been made to maintain orthogonality. A respondent was deleted if there were any missing or invalid answers. The number of valid respondents of each respondent set was selected to be the minimum number of valid respondents among the eight sets, which was 63. As a result, the number of total valid respondents was 504, resulting in a total of 4032 valid choices. Each of the valid choices had a row of data in the dataset. Each row was then expanded into multiple rows. The number of expansion was determined by the time interval in which the respondent chose to evacuate. Each expanded row had its own variable levels corresponding to the time interval. For example, if a respondent chose to evacuate in time interval 5, then this correspondent had five rows of data in the dataset. Row one had the variable levels for time interval 1 for that respondent. Usually, those variable levels were the same for all the rows for the same correspondent except for dynamic variables, which had different values for different time intervals. For this study, the only dynamic variable that could reasonably be inferred for different time intervals was the *time to expected landfall* (which was named *landfall*). All other variables were treated as static variables, although, by nature, they are dynamic variables.

The way *landfall* for each time interval was calculated was constrained by the structure of the questions presented to the respondent and the answers from the respondent. There were four levels for the variable, *time to expected landfall*: less than 12 hours, between 12 and 24 hours, between 1 and 2 days, and more than 2 days. Presented with one of the levels, along with combinations of other variable levels, a respondent chose if he or she would evacuate. If evacuation was chosen, he or she would choose one of the seven time intervals for evacuation. Based on such information, the dynamic *landfall* values, up until the stated evacuation time interval, can be calculated with approximation. Table 18 shows the first step to calculate the dynamic values for *landfall.*

An example would help to explain the process. Suppose the values of *landfall* for a respondent with ID=1 is calculated whose stated choice is not to evacuate. Then the values for time intervals 1 through 7 need to be calculated. If the respondent's stated choice is to evacuate, no matter what interval he or she chose, the calculation would be included in this extreme case that calculates values for all time intervals. The respondent was presented with a profile that had an initial landfall shown in the column titled Initial Landfall. The next two columns give estimated values of the range of dynamic *landfall* for each time interval. Then the following column approximates the ranges into more general categories. For the four levels of initial landfall values, Table 19 yields six levels of values for the dynamic variable *landfall*. It is obvious that the estimates of landfall were only approximations. Sometimes subjective judgment was involved.

Table 18
First step to calculate dynamic landfall with the SP data

ID	Interval	Initial Landfall	Dynamic Landfall			Initial Landfall	Dynamic Landfall		
		Hour	Hour	Hour	Approximation	Hour	Hour	Hour	Approximation
1	1	<12	(<12)-(0-2)	<10-12	0.5 day	24-48	(24-48)-(0-2)	24-46	1-2 day
1	2	<12	(<12)-(2-4)	<8-10	0.5 day	24-48	(24-48)-(2-4)	22-44	1-2 day
1	3	<12	(<12)-(4-5)	<7-8	hours	24-48	(24-48)-(4-6)	20-42	1-2 day
1	4	<12	(<12)-(6-12)	<6	hours	24-48	(24-48)-(6-12)	18-36	1-2 day
1	5	<12	(<12)-(12-24)	0	0	24-48	(24-48)-(12-24)	24-Dec	.5-1 day
1	6	<12	(<12)-(24-48)	0	0	24-48	(24-48)-(24-48)	0	0
1	7	<12	(<12)-(48+)	0	0	24-48	(24-48)-(48+)	0	0
1	1	12-24	(12-24)-(0-2)	12-22	0.5-1 day	48+	(48+)-(0-2)	46-48	2 days
1	2	12-24	(12-24)-(2-4)	10-20	0.5-1 day	48+	(48+)-(2-4)	44-46	2 days
1	3	12-24	(12-24)-(4-6)	8-18	0.5-1 day	48+	(48+)-(4-6)	42-44	2 days
1	4	12-24	(12-24)-(6-12)	6-12	0.5 day	48+	(48+)-(6-12)	36-42	1-2 day
1	5	12-24	(12-24)-(12-24)	0	0	48+	(48+)-(12-24)	24-36	1-2 day
1	6	12-24	(12-24)-(24-48)	0	0	48+	(48+)-(24-48)	0-24	1-2 day
1	7	12-24	(12-24)-(48+)	0	0	48+	(48+)-(48+)	0	0

Table 19
Calculated categories for dynamic variable landfall with the SP data

Landfall	2 days or more	1-2 day	0.5-1 day	Half A Day	Several Hours	Immediately
Coding	0	1	2	3	4	5

In the models estimated previously, *mobile* and *flood* were two important covariates in the models. However, for this SP data, there were very few (actually 11) respondents who lived in mobile homes. Therefore, *mobile* was not included in the covariate list. The information about covariate *flood* came from two sources. One fourth of the respondents were asked if their homes were previously flooded or not, while the rest of the respondents were asked if their homes were flood-prone. To make use of such information, the two were combined into a single composite variable, *compflood*.

The preliminary data analysis discovered some serious flaws in the design and are listed below:

1. The variable levels of *expected rainfall* and *expected maximum wind speed* were identical for every profile.
2. A complete range of variable levels of *expected rainfall* and *expected maximum winds* did not appear in the profiles. Only three levels (instead of four) appeared in the design.
3. The frequencies of variable levels for *expected storm surge* and *direction of storm approach* were not identical.

Problem 1 resulted in an inability to distinguish the effects between *expected rainfall* and *expected maximum wind speed*. Problem 2 resulted in the inability to estimate the effect of the missing level. Problem 3 destroyed the orthogonality among variable effects. As a result, some compromise had to be made for model analysis. Because of problems 1 and 2, a new combined variable, *wind&rainfall*, was created and defined in Table 20.

Table 20
Definition of the new variable *wind&rainfall*

New Compound Variate	Original Variables	
wind&rainfall	Expected Maximum Wind	Expected Rainfall
0	Less than 100 mph	Less than 5 inches
1	100-130 mph	5-12 inches
-	130-150 mph	12-20 inches
3	More than 150 mph	More than 20 inches

Stated Preference Model Estimation

Estimating a satisfactory model from this SP data was a challenge. Because of the correlations among many variables, the use of factors needed to be balanced. After testing for numerous model specifications, a final model was selected. Six variables were found to be significant at the five percent level. Among the original 10 variables from Table 1, one of the variables that was not significant was level of storm advisory, which includes hurricane watch and warning. This confirms the findings of other studies of hurricane evacuation *[46]* where storm advisories were not found to be significantly influential in evacuation behavior because hurricane advisories usually cover too broad an area. Direction of storm approach was also found to have no significant in the model. This was a variable that was specially included for New Orleans because of its unique geographical location (it is surrounded by water from three directions). However, it appears as if the respondents were not aware of any significant difference to their personal safety depending on the direction the storm approached from. The width, or size, of the storm was also not found to be significant. This is not entirely unexpected since the size of the storm merely indicates that more people would be affected, but individuals are not affected by the size of the storm other than the increased potential for flooding that large storms produce. For the variable "expected intensification of storm" it was found that only the coefficient for the medium level of intensification was significant. Such a result is counter-intuitive because common sense indicates that the higher the expected intensification, the more people are likely to evacuate. Because of this irregularity, this variable was not included in the model. It was found that only the highest level of expected storm surge (more than 15 feet) had a significant impact on evacuation. As a result, this variable was regrouped into two levels. There was a regrouping for the categories for the dynamic variable *landfall*. Instead of having six categories, as in Table 19, *landfall* was finally regrouped into four categories. The definitions and levels of the variables retained in the model are listed in Table 21.

Table 21
Variables in the model with the SP data

Variable	Definition
compflood	A composite dummy variable. 1 if home is flood prone, 0 otherwise.
order	Evacuation order. 0 if no order, 1 if precautionary, 2 if voluntary, and 3 if mandatory.
landfall	Expected time to landfall. Dynamic variable. 0 if more than 1 day, 1 if 0.5-1 day, 2 if half a day, 3 if within several hours.
distance	Distance from expected landfall. 0 if more than 100 miles, 1 if 50-100 miles, 2 if 10-50 miles, and 3 if less than 10 miles.
wind&rainfall	Defined in Table 20.
surge	Expected storm surge. 1 if more than 15 feet, 0 otherwise.

Note that the meaning of distance in this SP dataset is different from the two RP datasets. In the SP dataset, it was defined as the distance of the household from the expected location of landfall. It was a static variable. However, in the Andrew and Floyd datasets, it was defined as the distance of the household from the center of the storm. This latter distance was a dynamic variable. Dummy coding was used for all the variables because they were all categorical variables.

The models estimated were the conditional probability models (the binary logistic and complementary log-log models), although the models used for prediction were the unconditional probability models. In model estimation, level 0 was the reference category. The slope parameters, β, were assumed to be the same across all time intervals. Table 22 gives the estimated parameters and the statistics of the two models with the 75 percent estimation data. The *p-values* in the table were the probabilities of the Wald test for the parameters to be zero. The last row gives the likelihood ratio index for the two models.

Table 22
Summary results of the models with the SP data

Covariate	Logistic			Complementary log-log		
	β	se(β)	p-value	β	se(β)	*p-value*
(Intercept)	-3.85	0.098	0	-3.8	0.093	0.000
compflood	0.256	0.047	0	0.236	0.044	0.000
order1	0.512	0.072	0	0.483	0.068	0.000
order2	0.620	0.071	0.000	0.583	0.066	0.000
order3	0.955	0.070	0.000	0.881	0.065	0.000
landfallcat1	0.211	0.064	0.001	0.190	0.058	0.001
landfallcat2	0.374	0.068	0.000	0.343	0.062	0.000
landfallcat3	-0.114	0.060	0.056	-0.104	0.056	0.063
distance1	0.159	0.067	0.017	0.150	0.062	0.016
distance2	0.178	0.069	0.010	0.154	0.064	0.016
distance3	0.239	0.067	0.000	0.216	0.063	0.001
wind&rainfall1	0.626	0.076	0.000	0.598	0.073	0.000
wind&rainfall3	1.296	0.066	0.000	1.216	0.063	0.000
surge	0.227	0.051	0.000	0.209	0.047	0.000
LL(C)	6904.3			6904.3		
LL(β)	6475.7			6477.2		
ρ^2	0.062			0.062		

Goodness-of-Fit

The binary logit model has a log likelihood ratio index ρ^2=0.062. The contingency table for the Hosmer-Lemeshow test is given in Table 23. The Hosmer-Lemeshow statistic is 18.197 with eight degrees of freedom. The level of significance is 0.02, which rejects the null hypothesis that our estimated model fits the data well. Another important *GOF* test is to compare the sequential model predicted evacuation using the validation data with the actual observation, which will be discussed in the analysis and discussion section.

Table 23
Contingency table for *g*=10 with the SP data

Group	Not Evacuate		Evacuated		Total
	Observed	Expected	Observed	Expected	
1	1858	1851	53	60	1911
2	1810	1817	99	92	1909
3	1905	1906	131	130	2036
4	1762	1721	104	145	1866
5	1848	1859	197	186	2045
6	1752	1771	228	209	1980
7	1684	1693	271	262	1955
8	1548	1558	328	318	1876
9	1581	1584	404	401	1985
10	1218	1207	419	430	1637

ANALYSIS AND DISCUSSION

In this section, a series of analyses of the models estimated in the previous section were conducted. First, each model was discussed separately, analyzing the model predictions versus observations, covariate effects, and issues that were specific to different types of models. Then, comparisons among the methodologies were made to find the best method to model dynamic hurricane evacuation travel demand.

The Cox Survival Analysis Model with Southwest Louisiana (Andrew) Data

Model Prediction

Perhaps the most important criterion in assessing a model is to study the model prediction with real data. This is usually conducted by comparing the observed and model predicted evacuation for each time interval on a separate dataset in which evacuation decisions are known. This process is also referred to as model validation. The aggregation technique in this study was complete enumeration of all households. Fifteen percent of the data were retained for this purpose. However, after eliminating the observations with missing covariates values, there were only 57 subjects in the dataset with 20 evacuations, making the total number of observations 684 (i.e., information from 57 respondents over 12 time periods). As a result, there were too few cases to compare for each time interval. To solve this problem the model predictions from the 15 percent sample were scaled up to match the number in the 100 percent sample and compared, in each time interval, with the observed evacuation for all subjects. The factor used to scale up the model predictions from the 15 percent sample was the ratio of the number of subjects in the 100 percent sample over the number of subjects in the 15 percent dataset. After eliminating those households with missing information for the covariates used in the model, the 100% sample had 350 households, out of which 124 were evacuees.

The application of the Cox model to the Andrew data involved calculating the hazard rate with equation 8 for each subject in the dataset, utilizing the baseline hazard from Table 6, the coefficients estimated from the Cox model (model 1 in table 5), and the covariate values from the 15 percent dataset. Following this, the individual hazard function was integrated to calculate the cumulative hazard; then the survival functions of each individual were calculated using equation 7. The probability of evacuation for each subject in each time interval of six hours was then calculated from the difference in the survival rates of adjacent time intervals. Finally, the probabilities were added up by time interval and compared to the observed number of evacuations for each time interval. Table 24 gives the final results.

Table 24
Observed vs. the Cox model predicted evacuation with Andrew validation data

Time Interval	1	2	3	4	5	6	7	8	9	10	11	12	Total
Observed	3	5	11	2	0	19	20	6	3	17	33	5	124
Predicted	2.6	3.9	14.0	2.5	0.0	18.1	19.6	8.9	3.3	18.6	35.1	4.8	131.3

The *RMSE* and percent *RMSE* of the observed vs. predicted evacuations are 1.5 and 19.7 percent respectively. Figure 14 plots the relationship between the observed and the model predicted evacuation for each time interval. It seems that the model prediction is very close to the actual observation.

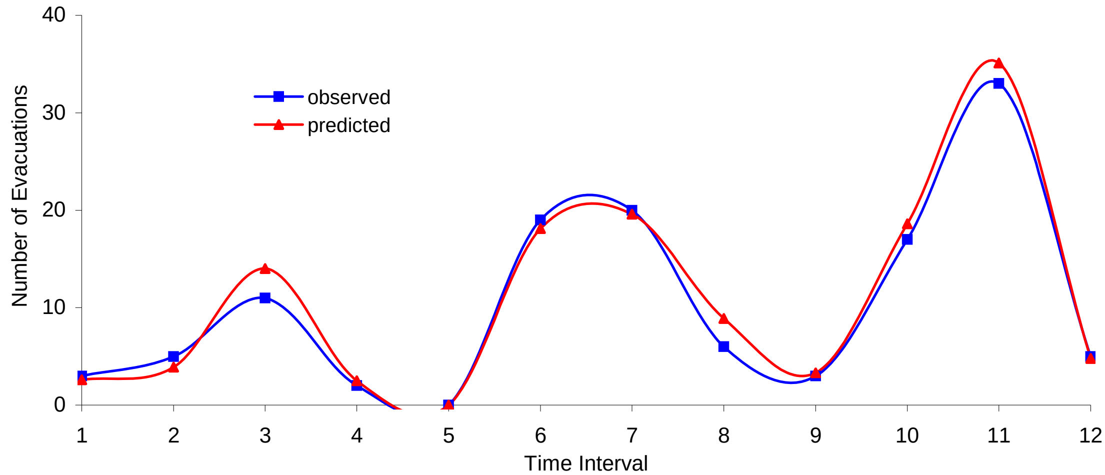


Figure 14
Observed vs. the Cox model predicted evacuation with Andrew validation data

The Impact of Time-of-Day
Figure 14 gives the number of evacuations for each time interval of six hours for three days. Obviously, there are patterns to uncover from it. The graph shows that people are least likely to evacuate during nighttime (time intervals 1, 4, 5, 8, 9, and 12), there are more evacuations in the morning (time intervals 2, 6, and 10), and people are most likely to evacuate in the afternoon (time intervals 3, 7, and 11). However, it is not possible to incorporate a time-of-day or a day-night variable explicitly in the Cox model. This can be explained by an example. Suppose a time-of-day dummy variable *TOD* is introduced with 1 for daytime and 0 for nighttime. *TOD* is a categorical time-dependent covariate. To simplify the example, it is further assumed that *TOD* is the only covariate in the model, and no ties are present. If the corresponding coefficient for *TOD* is β_{TOD}, the partial likelihood function in equation 10 could be written as *[61]*:

$$\prod_{i=1}^{D} \frac{e^{\beta_{TOD} TOD_i(t_i)}}{e^{\beta_{TOD} TOD_i(t_i)} + \sum_{j \in R(t_i)} e^{\beta_{TOD} TOD_j(t_i)}} = \prod_{i=1}^{D} \frac{e^{\beta_{TOD} TOD_i(t_i)}}{e^{\beta_{TOD} TOD_i(t_i)}(n_i+1)} = \prod_{i=1}^{D} \frac{1}{n_i+1}, \qquad (40)$$

where i is the household that evacuates in time interval t_i, and n_i is the number of households that are still in the risk set $R(t_i)$ at time t_i in addition to household i. The derivation uses the relationship that $TOD_i(t_i)=TOD_j(t_i)$; the time of day for a particular time interval is the same for all individuals. The coefficient β_{TOD} cancels out in the partial likelihood function, and, therefore, the time-of-day effect could not be estimated in the model. For the same reason, the impact of some storm specific characteristics such as intensity, speed, category, and in some situations even evacuation order, cannot be estimated explicitly by the Cox model if they are common to all respondents.

Joint Impact of Covariates

To assess the model performance, the joint covariate impacts were analyzed in this subsection. Eight scenarios representing different covariate combinations were considered, and the model predictions for different scenarios were discussed. First, a high-risk household was defined as a household that lives in a mobile home (*mobile*=1) and is considered very likely to be flooded (*flood*=1) during a hurricane, and a low-risk household was defined as a household that does not live in a mobile home (*mobile*=0) and is not very likely to be flooded (*flood*=0). A distant storm is defined as dist=7, which is about 1200 miles from the household; a close storm is dist=0, which is within 100 miles of the household. Table 25 gives the definitions of the eight scenarios. The numbers in the parenthesis are the relative hazards of the respective scenarios. The relative hazard is the part of the hazard function excluding the baseline hazard (Equation 8). It can be calculated using $\exp(\sum \beta_j x_{ij})$ with appropriate values of the coefficients and covariates. Keep in mind that the product of the hazard and the time interval is the probability of a household to evacuate in that time interval provided the household has not evacuated yet. With the same baseline hazard, the relative hazard represents the relative propensity to evacuation for the time interval.

Table 25
Eight scenarios and their relative hazards analyzed with the Cox model

Type of household	No evacuation order issued		Evacuation order issued	
	Storm distant	Storm close	Storm distant	Storm close
Low-risk household	1 (0.047)	2 (1.000)	3 (0.081)	4 (1.711)
High-risk household	5 (0.446)	6 (9.431)	7 (0.763)	8 (16.140)

Scenario 1, the reference scenario, is a low-risk household that does not receive an evacuation order (*orderper*=0), and the hurricane is far away (*dist=7*; about 1200 miles). The resulting relative hazard is 0.047. Scenario 2 is the same low-risk household, as in scenario 1, but the hurricane landfall is imminent (*dist*=0; less than 100 miles). Its resulting relative hazard is 1, and the relative hazards ratio is 21. Thus, the hazard of evacuation is about 22 times as high in scenario 2 as in scenario 1 because of the change of distance. Similarly, comparisons between scenarios 3 and 4, 5 and 6, and 7 and 8 reveal the impact of storm distance (distant and close) on the relative hazards of both low-risk and high-risk households with and without an evacuation order, resulting in ratios of about 21, which indicates that facing a close storm, households are 21 times more likely to evacuate than when facing a distant storm. Comparisons between scenarios 5 and 1, 6 and 2, 7 and 3, and 8 and 4 reveal the impact of household risk type on the relative hazards of facing distant or close storms, with and without an evacuation order, resulting in relative hazard ratios of about nine, indicating that high-risk households are nine times more likely to evacuate than low-risk households. Comparisons between scenarios 3 and 1, 4 and 2, 7 and 5, and 8 and 6 reveal the impact of an evacuation order on the relative hazards of both high-risk and low-risk households facing distant and close storms, resulting in relative hazard ratios of about 1.7, which indicates that households receiving an evacuation order are 1.7 times more likely to evacuate than households of same risk-level not receiving an evacuation order. Many other comparisons can also reveal useful insights on different covariate impacts that are not covered by the above comparisons. A final comparison was made between the two extremes, which are scenarios 1 and 8. Scenario 8 is the worst-case scenario, which is a high-risk household facing a close storm and receiving an evacuation order, as compared to a low-risk household facing a distant storm and not receiving an evacuation order. The ratio of relative hazards is 343, indicating that the household in scenario 8 is more than 300 times morelikely to evacuate than a household in scenario 1. The 3-dimensional diagram in Figure 15 presents the relative hazards for each of the eight scenarios.

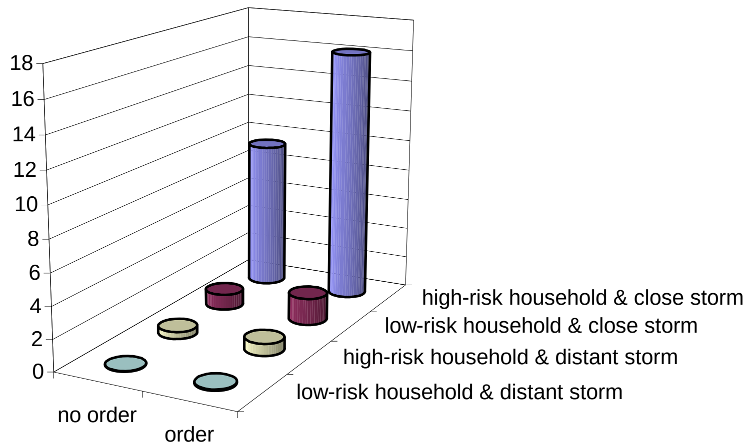


Figure 15
Relative hazards for eight scenarios with the Cox model

From the above analysis, it seems that the Cox survival model can provide predictions of the different impacts of the covariates on the models that are intuitively correct.

The Impact of Baseline Hazard

The baseline hazard becomes an important aspect of the Cox model when people are not only interested in studying the impacts of covariates, but they want to predict evacuation under different conditions. There are procedures that permit the estimation of the baseline hazard and the coefficients of covariates simultaneously from a single likelihood function *[50,51]*. However, most studies use the Cox model to estimate the model coefficients and, if necessary, estimate the baseline hazard, usually with the method mentioned in the methodology section. One important feature of the Cox model is the separation of the baseline hazard and the coefficients, i.e., the Cox model is a relative model and the coefficients can be estimated without the knowledge of the baseline hazard.

In the Cox model estimation, the model likelihood ratio index ρ^2 was only 0.06, a value that does not indicate a good model fit by common experience. However, the model did provide very good predictions with *RMSE* and percent *RMSE* values of 1.5 and 19.7 percent respectively. This might be attributed to the way the baseline hazard was calculated in this study. In equation 11, the baseline cumulative hazard is calculated using the *Breslow* estimator, utilizing not only the estimated coefficients and the covariates values but the number of events d_i in each time interval. The consequence of this is that errors incurred in the estimation of the Cox model might be partly compensated for in the calculation of the baseline hazard. The estimation errors referred to could include the omission and mis-specification of covariates, mis-specification of functional forms, and errors in the estimation of the coefficients. However, there is no statistical test available to measure the *GOF* of the baseline hazard estimated with the *Breslow* estimator.

In practice, the baseline hazard may be difficult to predict. In addition, it will be more difficult to make predictions for time intervals beyond those that are covered by the existing data. More study is needed to find the ways to estimate the baseline hazard for conditions beyond those encountered in the estimation data.

The Sequential Model with Southwest Louisiana (Andrew) Data

Model Prediction

The sequential logit model *GOF* measures how the binary logit model fits the transformed dataset. However, the real model of interest in is the sequential model that is derived from the series of binary models and is used to estimate dynamic travel demand. The model validation is conducted next. The aggregation technique used in this study was complete enumeration of all households. Fifteen percent of the Andrew data were retained for this purpose. However, for the same reason explained earlier in this section, for each time interval, the observed evacuation for all the subjects was compared with the factored model predicted evacuation based on the 15 percent data. The probability of evacuation for each household in each time interval was first calculated. Then the probabilities were added up by time interval and compared to the observed number of evacuations for each time interval. Table 26 gives the observed and model predicted evacuations for all time intervals. Figure 16 plots the data in Table 26.

Table 26
Observed vs. sequential logit model predicted with the Andrew validation data

Interval	1	2	3	4	5	6	7	8	9	10	11	12	Total
Observed	3	5	11	2	0	19	20	6	3	17	33	5	124
Predicted	1.5	9.9	14.5	2.4	2.9	14.7	24.9	4	3.7	15.6	28.7	5.6	128.5

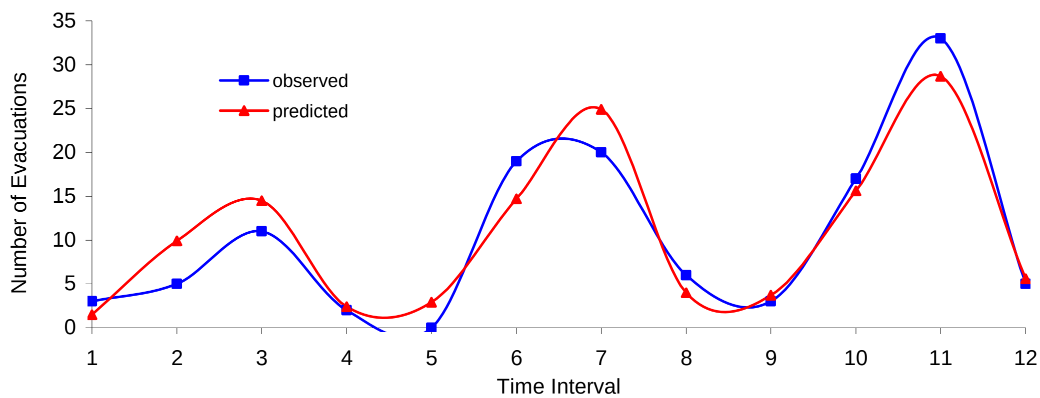


Figure 16
Observed vs. sequential logit model predicted evacuation with Andrew validation data

The model clearly reproduces the observed evacuation pattern. The total predicted evacuations over all time intervals are 128.5. This prediction is very close to the observed value of 124. The relative error is only 3.63 percent. If evaluated at the time interval level, the *RMSE* is 3.09, and the percent *RMSE* is 37.10 percent. The percent *RMSE* does not include the errors from time interval 5 because the observed value is zero. Therefore, the real percent *RMSE* is somewhat higher. Some intervals have very high relative errors, especially for intervals 1 and 2, with nearly 100 percent and 50 percent relative errors because the observed number of evacuations in those intervals is small. The rest of the intervals have relative errors between 10 percent and 35 percent. The maximum absolute error is smaller than five for every time interval.

The Impact of *TOD*

Figure 16 gives the probability of evacuation for each time interval of six hours for three days. Obviously, evacuation varies with time-of-day. To study its impact, the probabilities of evacuation for both a low-risk and a high-risk household with an evacuation order from two models were calculated. One model included *TOD* as a covariate, and the other did not. Table 27 gives the values used in the calculation for distance and forward speed of the hurricane for each time interval. These values were actual values taken from a household in the Andrew data. Figure 17 presents the results.

Table 27
Values of distance and forward speed in analyzing covariate impacts

Time Interval	1	2	3	4	5	6	7	8	9	10	11	12
Distance (mile)	1182	1096	1004	911	815	713	607	500	398	305	218	146
Speed (mph)	12.0	12.5	13.0	13.5	14.0	14.5	15.0	16.0	17.0	18.0	19.0	20.0

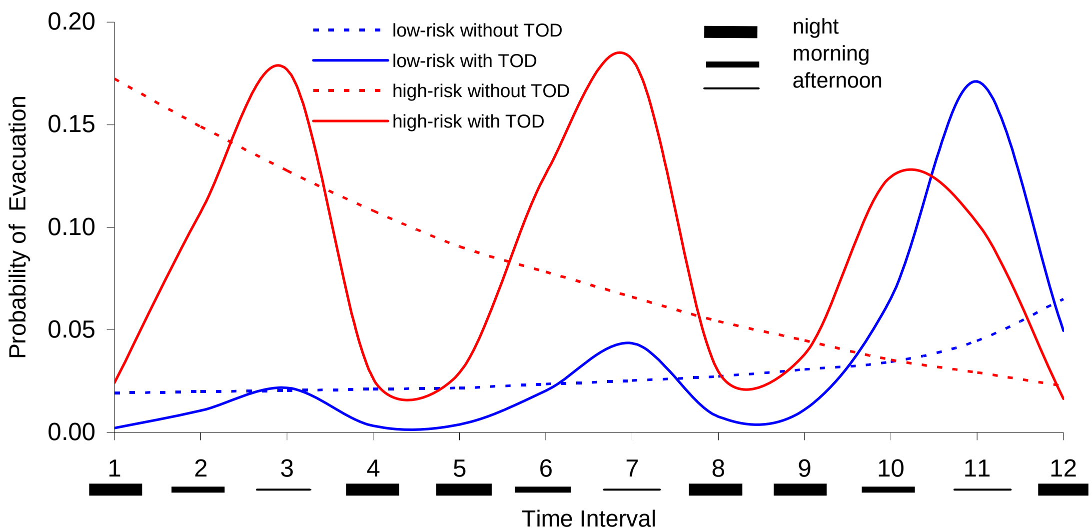


Figure 17
Impact of *TOD* using sequential logit model from Andrew

On the bottom of the figure, the time intervals are marked by different line types to denote night, morning, and afternoon. The thick dark line (e.g., during time intervals 1 and 4) depicts the time between 6.00 p.m. and 6.00 a.m., the medium thickness line depicts the period between 6.00 a.m. and 12.00 p.m., and the thin line depicts the period between 12.00 p.m. and 6.00 p.m. The graph shows that people are least likely to evacuate at night, that the number of evacuations tends to increase in the morning, and people are most likely to evacuate in the afternoon. Considering the high-risk and low-risk households with an evacuation order, the plots without *TOD* only show a general trend of how the evacuation probabilities change as the hurricane approaches. The low-risk household has an increasing trend, and the high-risk household has a decreasing trend. This suggests that the high-risk households who have been issued an evacuation order tend to evacuate early, and the low-risk households who were issued an evacuation order tend to evacuate late. However, the plots with *TOD* display the significant impact of time-of-day. They show low evacuation probability at nighttime, higher probability in the morning, and highest probability in the afternoon. The response curve with time-of-day impact is very different from the typical quick, medium, and slow response curves currently used to estimate the time of evacuation, which do not show time-of-day variation.

Joint Covariate Impacts

In this section of the analysis on joint covariate impacts, an approach that is somewhat different from the analysis for the Cox model was taken. Instead of comparing the relative hazards of different scenarios, as was done earlier, the actual evacuation probabilities for each time interval were calculated. Four scenarios were considered, as listed in Table 28. Scenario 1 is a low-risk household who does not receive an evacuation order (*orderper*=0). Scenario 2 is the same low-risk household as scenario 1, but the household receives an evacuation order (*orderper*=1). Scenarios 3 and 4 are a high-risk household without and with an evacuation order, respectively.

Table 28
Four scenarios analyzed with the Andrew sequential logit model

Types of household	No evacuation order issued	Evacuation order issued
Low-risk household	1	2
High-risk household	3	4

Based on the information from Tables 27 and 28, the sequential logit model estimated from the Andrew data (model 1 in Table 11) was applied to calculate the probabilities of evacuation for every scenario in each time interval. The results are plotted in Figure 18.

The diagram clearly shows that the probability of evacuation is much smaller for low-risk households than for high-risk households (scenarios 1 and 2 vs. scenarios 3 and 4), particularly when the storm is still far away. Low-risk households evacuate essentially only on the last day. High-risk households evacuate much earlier, with an evacuation order further accelerating the evacuation process. In fact, it appears that high-risk households that receive an evacuation order may evacuate so early that relatively few of them remain to evacuate on the last day. This is exactly the opposite of the three other scenarios shown in Figure 18, particularly the low-risk households (scenarios 1 and 2), where the greatest proportion of evacuees wait until the last day to evacuate. High-risk households tend to live near water or low-lying areas and, therefore, probably have longer evacuation distances. As a result, they are the first ones to evacuate once an evacuation order is received. Without an evacuation order, the same household would tend to wait and see how the situation evolves.

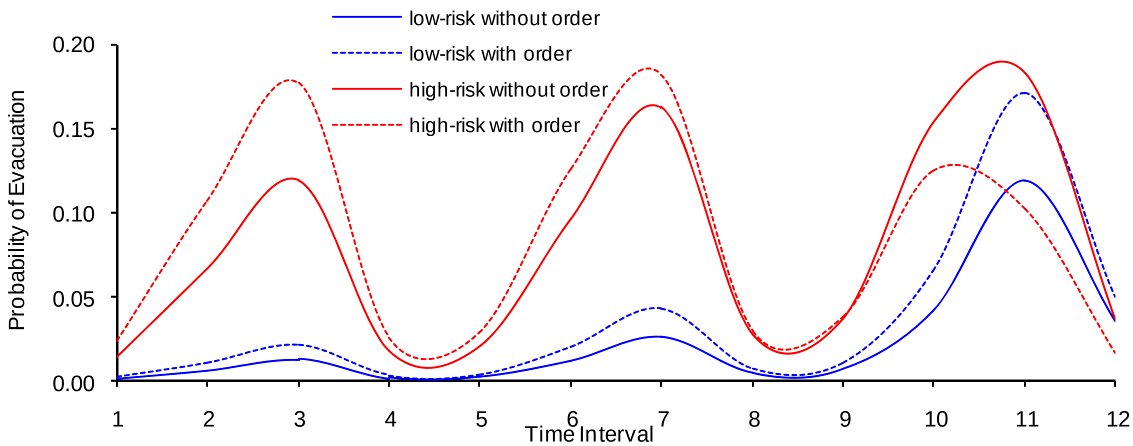


Figure 18
Probability of evacuation for four scenarios with the Andrew sequential logit model

The sum of probabilities for all the time intervals for each household is the probability of that household to evacuate during a hurricane. The difference between the sum of probabilities for the high-risk household with and without an evacuation order (98.0 percent and 92.1 percent) is smaller than that for the low-risk household (31.7 percent and 23.7 percent). This suggests that the impact of an evacuation order is more significant for low-risk households than for the high-risk households. The high-risk households tend to evacuate with or without evacuation orders under the same conditions.

The Sequential Model with South Carolina (Floyd) Data

In this subsection, the sequential logit model estimated from the Floyd data was discussed in detail. The model predictions and observations from the validation dataset were first studied at both aggregate and zonal levels. Then, the impacts of time-of-day, evacuation order, distance, wind speed, and forward speed, as well as the risk levels of households, were analyzed. The discussions serve to demonstrate that the sequential logit model, estimated with a different but richer dataset from a different storm than Hurricane Andrew, can be used to study a variety of covariate impacts and policy conditions. The analysis indicated the broad capability and the robustness of the sequential logit model. The model produced plausible predictions although the results were difficult to verify in many cases.

Overall Model Prediction

As mentioned earlier, the original Floyd dataset was divided into model estimation and validation parts with a 75 percent -25 percent split, respectively. The sequential logit model estimated on the 75 percent subset (Table 15) was applied to the 25 percent subset. Table 29 presents the results of the model predictions and observations for each of the 48 time intervals. It was a four-day evacuation and each time interval was two hours. Figure 19 plots the model validation results based on the information in Table 29.

Table 29
Observations vs. sequential logit model predictions with the Floyd data

Time	Observed	Predicted	Time	Observed	Predicted	Time	Observed	Predicted	Time	Observed	Predicted
1	0	0.14	13	0	0.30	25	0	0.48	37	1	2.90
2	0	0.14	14	1	0.34	26	0	0.51	38	2	2.77
3	0	0.14	15	2	0.34	27	2	0.53	39	4	2.36
4	1	0.58	16	1	1.35	28	4	13.70	40	12	7.99
5	0	0.61	17	2	1.39	29	12	12.77	41	14	6.44
6	1	1.45	18	0	3.38	30	29	27.97	42	15	11.32
7	1	1.51	19	2	3.45	31	35	32.57	43	10	9.18
8	3	1.61	20	3	3.47	32	25	29.43	44	6	7.04
9	1	0.93	21	2	1.99	33	26	16.13	45	3	3.27
10	0	1.13	22	1	2.02	34	11	15.76	46	3	2.90
11	0	0.27	23	0	0.43	35	6	3.14	47	1	0.56
12	0	0.27	24	1	0.44	36	2	3.08	48	1	0.56

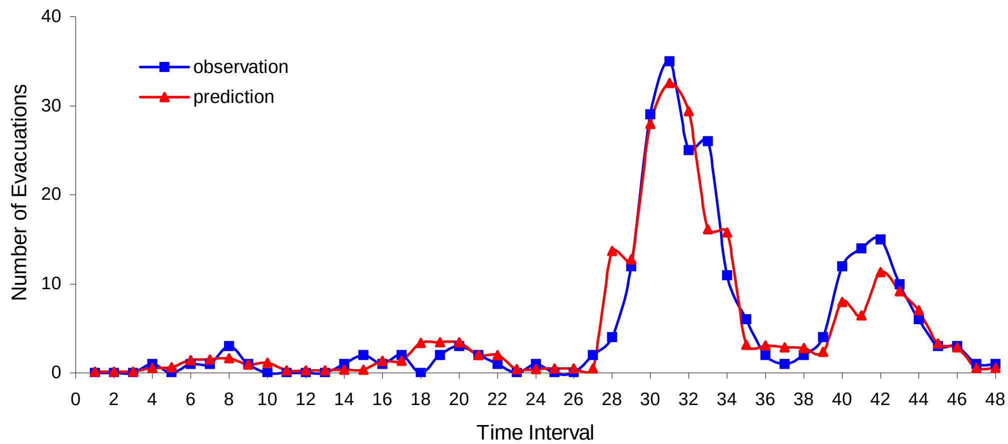


Figure 19
Observed vs. sequential logit model predicted evacuations using Floyd validation data

Note that evacuation patterns in the figure are quite different from those with the Andrew data (Figure 14). The Andrew data were from a three-day evacuation with time intervals of six hours and three *TOD* categories, and evacuation increased from day one through day three. Figure 19 presents a four-day evacuation with time intervals of two hours and four *TOD* categories, and evacuation peaked on the third day. The sequential logit model has the ability to accommodate such differences.

The total observed and model predicted evacuations are almost identical. The observed total evacuation is 246, while the model predicted 241, with a relative error of –2.0 percent and a *RMSE* of 2.79. The model overestimates evacuation for the first three days with values of 1.8 (25.7 percent), 3.9 (26.0 percent), and 4.1 (2.7 percent), respectively and underestimates evacuation for the fourth day, with 14.7 evacuations (-20.5%). The model predicts the third day extremely well when most evacuations took place. One noticeable difference is at time interval 28, (third day, 6 and 7 a.m.) where the model overestimates evacuation by about 10. The overestimation is due to the fact that a voluntary evacuation order was issued at this time interval, and the model predicts an immediate increase of evacuation, while in reality, people probably needed some time to digest the information and to prepare for the evacuation. This is confirmed by the very accurate prediction for the next time interval, which is interval 29, when the model predicts 12.8 evacuations compared to the observed value of 12. The irregularities between intervals 33 and 35 and intervals 40 and 42 were caused by two factors. The first factor was the change of *TOD* in those two periods, and the second factor was the weight the gamma distribution transformation put on the values of distance in those two periods. Intervals 33 and 34 were in the afternoon, while interval 35 was at night. There was a decrease of the utility to evacuate because of the change of *TOD* from afternoon to night. Furthermore, the distance in interval 34 had a slightly higher weight than in interval 33 but was almost the same as in interval 35 by the transformation. Therefore, the utility to evacuate in interval 34 was almost the same as in interval 33 but much higher than in interval 35. As a result, the predicted number of evacuations in interval 33 was almost the same as in interval 34 (16.13 versus 15.76) and much higher than in interval 35 (15.76 versus 3.14). A similar explanation applies to the irregularity between intervals 40 and 42. In general, the model reproduces the observed evacuation satisfactorily.

Zonal Model Prediction

Another very important test of the model is to not only compare the model predictions against the total number of evacuations but also at more disaggregate levels, such as the number of evacuations from individual hurricane evacuation zones. The Andrew dataset has too few observations for this purpose. However, the Floyd dataset was much larger and provided an opportunity to do so. Three relatively large zones were created based on the available geographic information of the households. Figure 20 shows the geographic locations of the zones and the actual track of Hurricane Floyd.

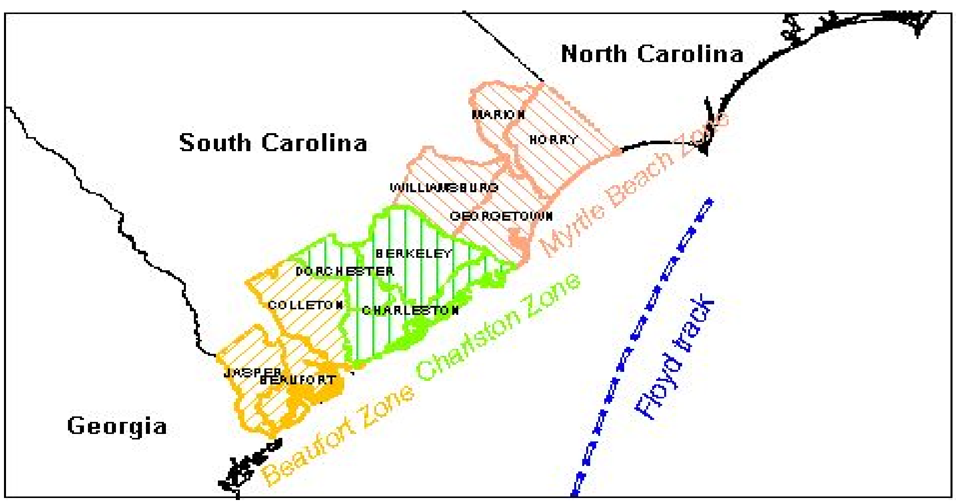


Figure 20
Three zones and Floyd's track

Zone one is Beaufort, in the southern region of South Carolina, including the coastal counties of Beaufort, Jasper, and Colleton; zone two is Charleston, which includes the counties of

Charleston, Dorchester, and Berkeley; and zone three is Myrtle Beach, in the northern region of South Carolina, including the counties of Horry, Georgetown, Williamsburg, and Marion. This zonal configuration, which grouped areas with different characteristics, such as coastal and non-coastal areas, into the same zone, was the result of lacking more appropriate geographic information in the dataset. Figure 21 presents the observed and model predicted evacuations for each zone with the 25 percent validation data.

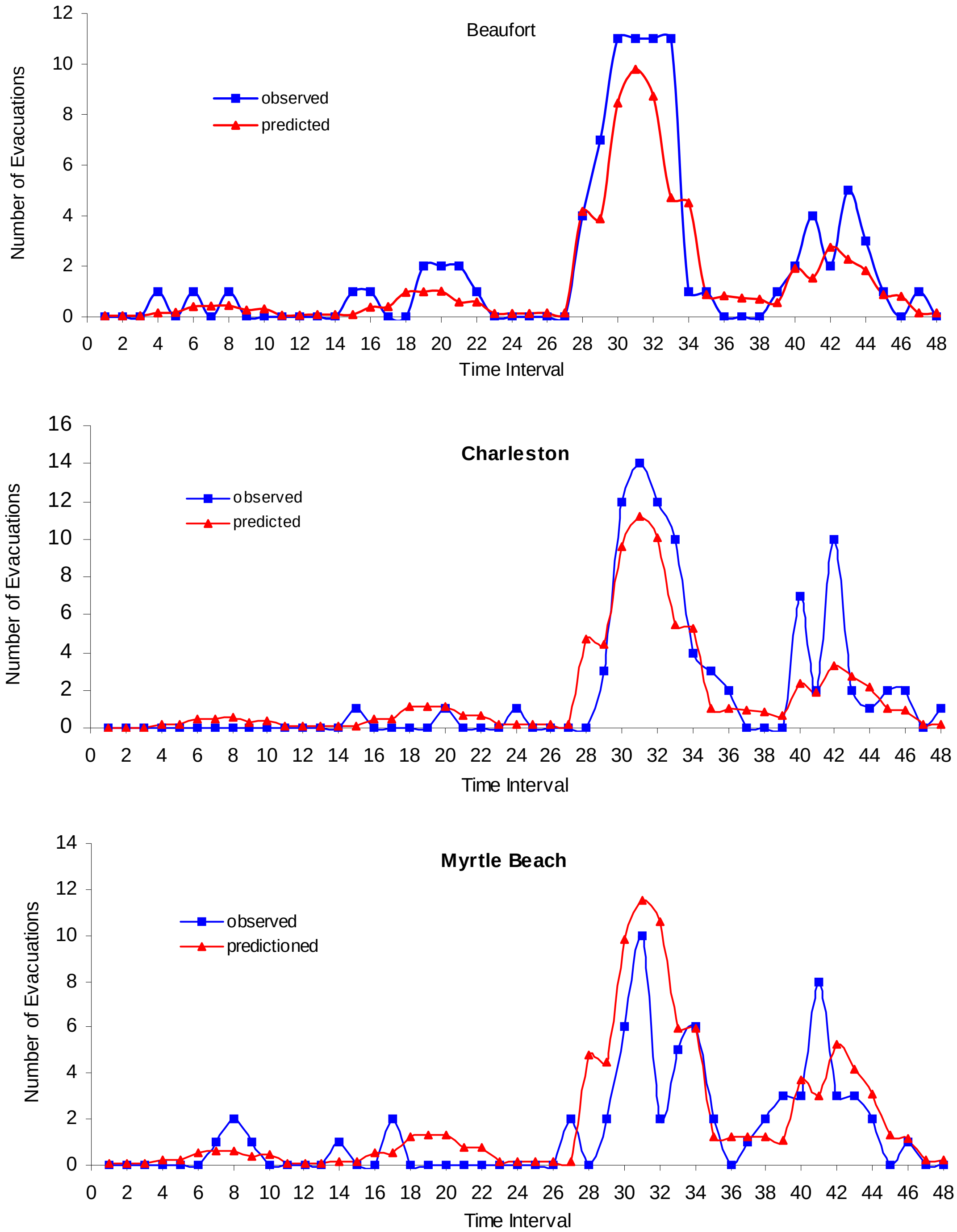


Figure 21
Observed vs. sequential model predicted zonal evacuations using Floyd validation data

The zonal level predictions in Figure 21 do not fit the observations as well as the overall prediction in Figure 19. For Beaufort and Charleston, the model under-predicts evacuation, with relative errors of 21.9 percent and 11.6 percent. For Myrtle Beach, the model over-predicts by 35.6 percent. However, in general the predictions do capture the daily variations and the time-of-day impacts. Table 30 presents the total observed and model predicted results for the three zones.

Table 30
Observed vs. predicted evacuations for three zones

Zone	Observed	Predicted	% Error	RMSE
Beaufort	88	68.8	-21.9%	1.46
Charleston	90	79.6	-11.6%	1.76
Myrtle Beach	68	92.2	35.6%	1.93
Total	246	241.0	-2.0%	2.79

The Impact of *TOD*

In this subsection, the importance of including *TOD* in the model in studying hurricane evacuation is demonstrated but from a different perspective. The impact of the models with and without *TOD* was discussed in terms of model predictions and observations using the 25 percent validation data. Two models were compared. The first one was the sequential logit model estimated from the 75 percent dataset identified in Table 15, which included *TOD* as a covariate; the second one was the sequential logit model estimated from the same 75 percent dataset excluding *TOD* as a covariate. Table 31 presents the summary results of the two models.

Table 31
Summary results of the sequential models with and without *TOD* using 75% Floyd data

Covariate	Sequential Logit Model with *TOD*			Sequential Logit Model without *TOD*		
	β	se(β)	*p-value*	β	se(β)	*p-value*
intercept	-10.108	0.891	0.000	-8.562	0.857	0.000
gammadistance	4.139	1.012	0.000	1.804	0.873	0.041
TOD(1)	1.353	0.171	0.000	-	-	-
TOD(2)	2.221	0.143	0.000	-	-	-
TOD(3)	1.610	0.156	0.000	-	-	-
dyanorder(1)	1.917	0.193	0.000	2.628	0.156	0.000
dyanorder(2)	2.181	0.213	0.000	2.662	0.194	0.000
flood	0.558	0.078	0.000	0.577	0.076	0.000
mobile	0.263	0.132	0.047	0.292	0.130	0.025
speed	0.017	0.006	0.006	0.016	0.006	0.009
LL(C)	-3871			-3871		
LL(β)	-3110			-3297		
ρ^2	0.197			0.148		

Without *TOD*, the likelihood ratio index reduced significantly from 0.197 to 0.148, indicating that the model excluding *TOD* is inferior to the one including *TOD*. The coefficients are very close for the two models except for those of distance and the alternative-specific constants. Figure 22 plots the observed and model predicted evacuations from the 25 percent Floyd validation dataset.

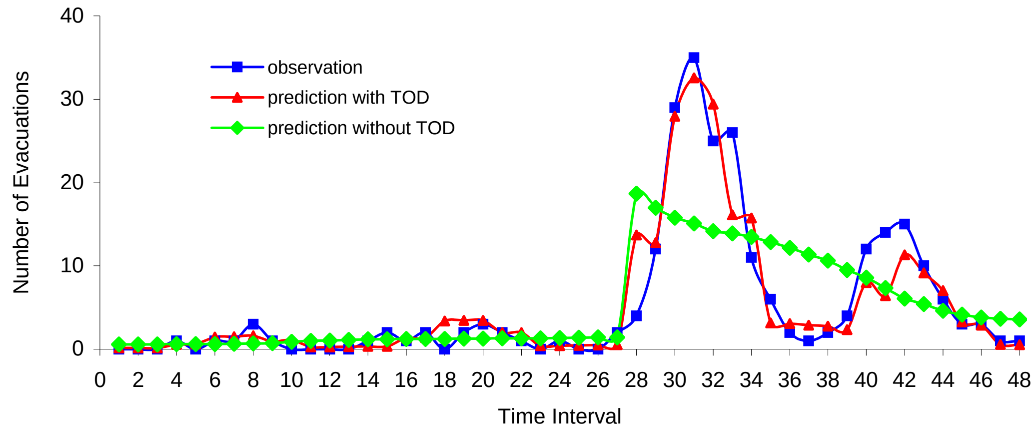


Figure 22
Predictions from sequential logit models with and without TOD with the Floyd data

From Figure 22, the model including *TOD* produces a very accurate prediction of evacuation. However, the model excluding *TOD* gives a very erroneous prediction for each time interval, although the total number of predicted evacuations are very close to the number of observed evacuations (the model including *TOD* predicts 241, the model excluding *TOD* predicts 240, and the observed evacuations are 246). The model without *TOD* predicts a slow and steady increase in the number of evacuations, until interval 28, when a voluntary evacuation order was issued and there is a huge increase in the number of evacuations. Then, the model predicts a decrease of evacuation at a steady but more rapid rate. The model without *TOD* shows no time-of-day variations in evacuation, and the *RMSE* for this model is 5.85. In contrast, the model with *TOD* accurately reproduced the observed evacuation pattern. It has a *RMSE* value of 2.79, which is a reduction of 52.4 percent in *RMSE*.

The analysis demonstrated that when *TOD* is excluded, the sequential logit model's prediction on the total percentage of evacuations, which is equivalent to the participation rate used in current practice, is accurate. However, evacuation predictions for each time interval are erroneous. Oppositely, the inclusion of *TOD* not only increases the *GOF* and the explanatory power of the model, but it also enables the model to give an accurate prediction of evacuations for each time interval as well as total evacuation.

The Impact of Evacuation Orders

This subsection discusses the impact of evacuation orders. The study demonstrated that the sequential logit model with evacuation order as a dynamic variable not only enhances the model performance, but it also meets the need of local officials for policy analysis in terms of the type and timing of evacuation orders.

Three studies were conducted to explore the impact of the type and timing of evacuation orders. The first studied the impact of a voluntary and a mandatory evacuation order issued at the same time of day and the combination of them in the same day; the second studied the impact of voluntary evacuation orders issued at the same time but on different days; and the last studied the impact of voluntary evacuation orders at different times of the day.

Table 32 gives the values of distance used in the analysis. They are actual values of distance from a household in the Floyd data. The values of hurricane wind speed were assumed to be 120 miles per hour, which is the speed of a category 3 hurricane. The evacuation probabilities were calculated for a high-risk household.

Table 32
Values of distance from a household in the Floyd data

Time Interval	Distance (mile)	Time Interval	Distance (mile)	Time Interval	Distance (mile)	Time Interval	Distance (mile)
1	1129	13	878	25	625	37	344
2	1106	14	859	26	602	38	329
3	1084	15	839	27	584	39	285
4	1070	16	812	28	565	40	273
5	1056	17	786	29	555	41	250
6	1044	18	761	30	535	42	222
7	1011	19	742	31	515	43	194
8	981	20	733	32	495	44	161
9	954	21	701	33	461	45	133
10	940	22	692	34	431	46	107
11	921	23	667	35	416	47	93
12	898	24	653	36	373	48	91

Figure 23 plots the predicted evacuation probabilities with a voluntary evacuation order issued at time interval 28 (6 to 7 a.m. of the third day), a mandatory evacuation order issued at time interval 28, and with combined voluntary and mandatory evacuation orders issued at time intervals 28 and 31 (12 p.m. to 1 p.m.), respectively, which was the case for the Floyd data. A curve without evacuation order is also plotted as a reference. Table 33 gives the total probability of evacuation for each condition.

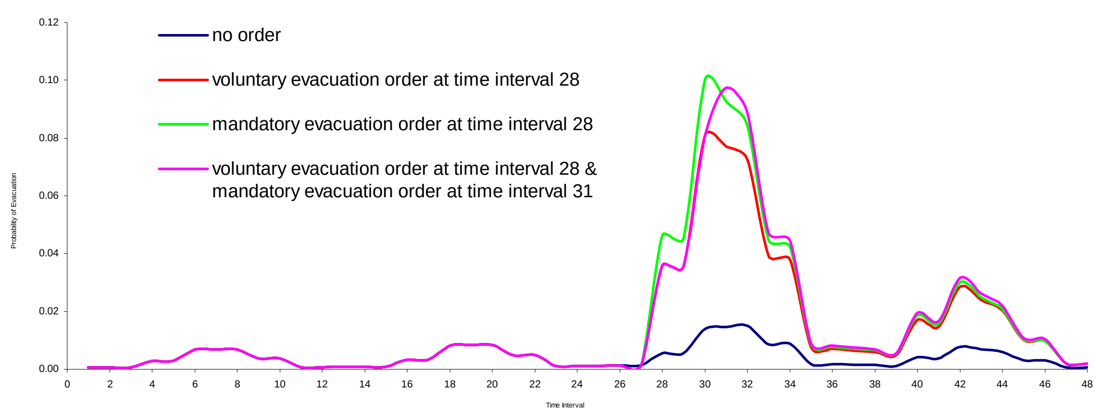


Figure 23
Impact of evacuation order type with the Floyd sequential logit model

Table 33
Total evacuation probability for different types of evacuation orders

Order	No Order	Voluntary at 28	Mandatory at 28	Voluntary at 28 and Mandatory at 31
Probability	20.3%	62.7%	71.2%	69.7%

All of the curves are the same before any evacuation orders were issued at interval 28 and are presented by one color. The evacuation orders increase the total probability of evacuation significantly from 20.3 percent to 60 percent -70 percent, depending on the type and timing of the orders. There are only moderate differences among the total probabilities of evacuation for voluntary and mandatory evacuation orders that are issued at time interval 28. The mandatory evacuation order has a larger coefficient (2.181 from Table 15) than that of the voluntary (1.917 from Table 15), hence a larger impact on evacuation. However, there is no significant difference between the probabilities of a mandatory order at time interval 28 and that of a voluntary order at time interval 28 followed by a mandatory order at time interval 31. In terms of the shapes, there is no significant difference among the curves for the following day, except for the day the evacuation orders were issued. Two conclusions can be observed from the above analysis:

1. It is the issuance of an evacuation order that has the primary impact, not the type of order (voluntary or mandatory), although the latter does have a somewhat stronger impact; and
2. A mandatory order following a voluntary order has a very limited impact.

Figure 24 plots the predicted evacuation probabilities with voluntary evacuation orders issued at time intervals 5, 17, 29, and 41, which are the late morning times (between 8 and 9 a.m.) for each of the four days prior to landfall. A curve without evacuation order is also plotted as a reference. Table 34 gives the total probability of evacuation for each condition.

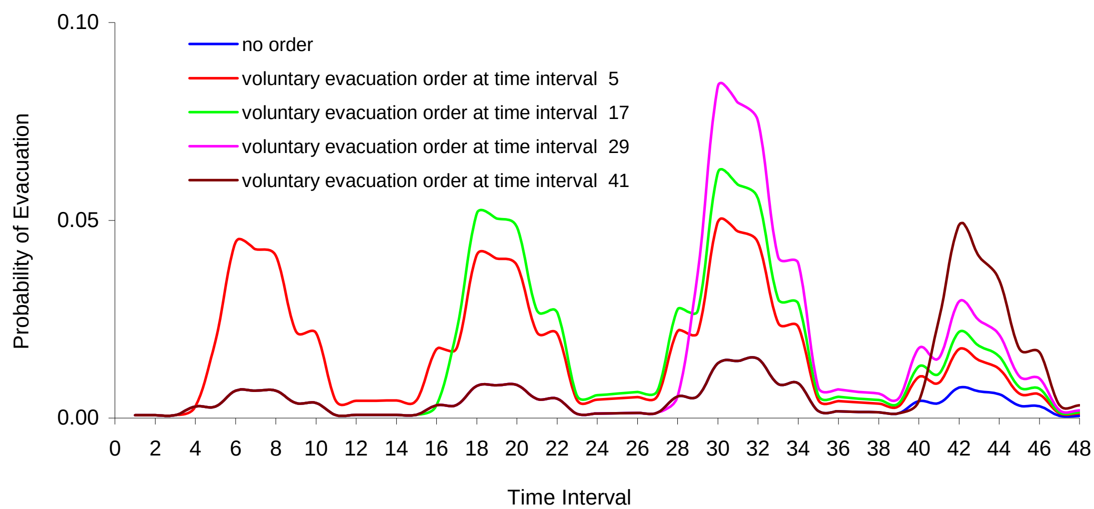


Figure 24
Impact of voluntary evacuation orders at same time of each day

Table 34
Total evacuation probabilities for voluntary orders at same time of each day

Order	No Order	Voluntary at 5	Voluntary at 17	Voluntary at 29	Voluntary at 41
Probability	20.3%	77.2%	71.5%	61.4%	36.2%

If no evacuation order is issued, the total probability of evacuation is low (20.3 percent). An evacuation order increases the probability significantly (between 36.2 percent and 77.2 percent). The earlier an order is issued, the higher the number of people who will evacuate. Issuing the order early (for example, at time interval 5) produces a more even distribution of evacuees. This would allow the traffic to be handled more easily. However, calling an evacuation order too early also increases the risk of unnecessary evacuation, a situation local officials are very reluctant to do. On the other hand, issuing the order too late (for example, at time interval 41), when the officials have more accurate and stronger evidence of a possible hurricane strike, would produce the smallest evacuation period (putting more people at risk) and load most of the evacuees onto the network in the last day. The total probabilities of evacuation for the other two scenarios are in between the two extremes discussed above. Note that the scenario issuing the order at time interval 29 produces a heavy concentration of evacuation on the third day, a situation that may cause potential traffic problems.

Figure 25 plots the predicted evacuation probabilities with a voluntary evacuation order issued at time intervals 13, 17, 19, and 22, which are between zero midnight or 12 a.m. and one a.m., 8 and 9 a.m., 12 and 1 p.m., and 6 and 7 p.m., respectively, on the second day for a high-risk household. A curve without evacuation order is also plotted as a reference. Table 35 gives the total probability of evacuation for each condition.

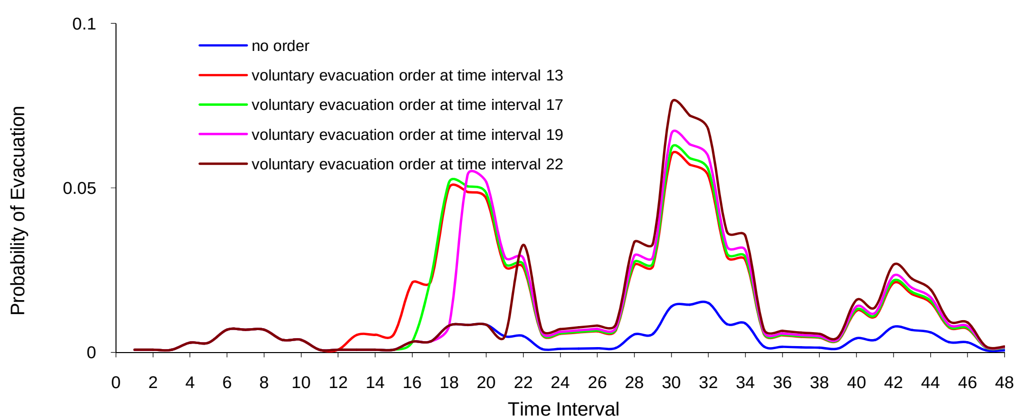


Figure 25
Impact of voluntary evacuation orders at different times of the day

Table 35
Total evacuation probability for voluntary orders at different times of the day

Order	No Order	Voluntary at 13	Voluntary at 17	Voluntary at 19	Voluntary at 22
Probability	20.3%	72.4%	71.5%	69.4%	65.2%

The total probabilities of evacuation do not vary significantly when a voluntary evacuation order is issued at different times of the day, although the trend is that the earlier the order, the larger the total probabilities. Although not shown here, the total evacuation probabilities do vary somewhat for the day when the orders are issued, even though the differences are small for the later days (days 3 and 4). However, the trend is that the later the order, the larger the probabilities for later days (days 3 and 4). An order at midnight (time interval 13) does not produce an increase in the probability of evacuation immediately; the impact does not materialize until the night is over. The same is true for the order in late afternoon. It appears that the impact of an order is offset by the arrival of nighttime as evacuees postpone their evacuation for early the next morning.

The above analysis showed the important role of the evacuation order in modeling hurricane evacuation. Compared with the current practice of using response curves to distribute evacuation trips, which mainly involves the evacuation after the issuance of an evacuation order, the sequential logit model has the ability to study the impact of evacuation orders.

The Impact of Distance

The distance from the storm to the household is determined by the hurricane track and the location of the household. Thus, different hurricane tracks would result in different evacuation patterns. To evaluate the evacuees' responses to distance from the storm, the results of three hypothetical hurricane tracks were compared: close, medium, and far, with and without a voluntary evacuation order. The medium scenario used the same distance information from Table 32. The values of distance for close and far scenarios were obtained by subtracting and adding 200 miles from the value of distance of the medium scenario for each time interval. If the value of distance was smaller than zero in the calculation, it was set to zero. The evacuation probabilities were calculated for a high-risk household. For the case with a voluntary evacuation order, it was assumed that the order was issued at time interval 28. The wind speed of the hurricane was assumed to be constant for all time intervals at 120 miles per hour.

One problem of the sequential logit model was revealed when the distance data were investigated in detail. It was found that for the close scenario, distance was smaller than 50 miles from time interval 41 onwards. It is believed that there exists a limit of distance, under which the probability to evacuate should approach zero because when a hurricane is that close, a household may face a more serious threat of being caught on the highway during the most intense portion of the storm. However, the sequential model still gives a non-zero probability even when the distance is zero. To correct this, the model was forced to generate zero probability of evacuation when the distance was within the threshold. For this analysis, it is assumed that the threshold was 50 miles. Figure 26 plots the evacuation probabilities before and after the correction for the close scenario. The two evacuations were identical until time interval 41, when the distance was within the limit. After that time interval, the probabilities were forced to be zero.

Another problem of the model can be revealed when a case where the distance is very far away is considered. No matter how far the hurricane is from a household, the sequential model always gives a non-zero probability of evacuation, which is obviously unrealistic. For example, if 1,000 miles were added to the values of distance in the medium scenario, the model still gives an estimate of total probability of 6.4 percent for a low-risk household. Such a result is not reasonable because, in reality, at such a distance the hurricane is not a threat to the household at all, and the probability of evacuation should be zero. Therefore, this model should not be used when the hurricane is so far away that it does not present a threat to the household at all. Thus, the model seems to behave appropriately within a window of approximately 1,200 miles at one extreme and, say, 50-100 miles at the other.

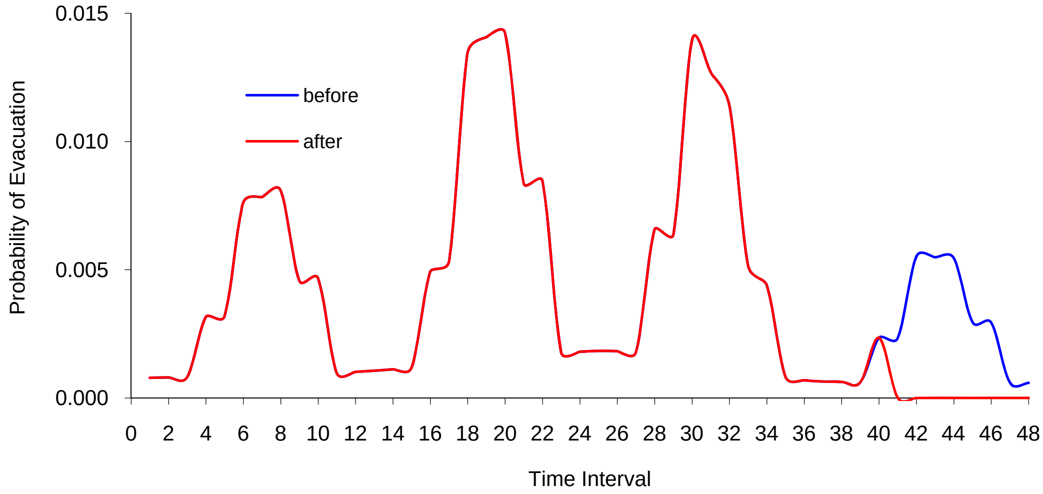


Figure 26
Before and after correction for the close scenario

The corrected evacuation probabilities of the close scenario, along with those of the medium and far scenarios without evacuation orders, are plotted in Figure 27. Table 36 presents the probabilities of evacuation for each day for each scenario.

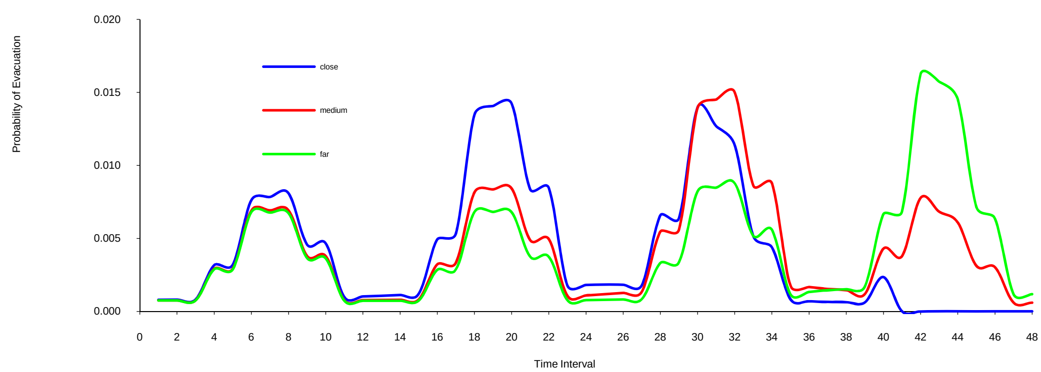


Figure 27
Impact of distance without evacuation order

The total evacuation probabilities are nearly the same. However, the evacuation patterns are quite different except for the first day, when the hurricanes are still far for all the scenarios. For the far scenario, evacuation probabilities increase day by day as the hurricane approaches, with the last day having the largest probability of evacuation; for the medium scenario, evacuation probability peaks on the third day, with the other three days having almost the same probabilities; and for the close scenario, the second day has the highest probability of evacuation, a slight drop on the third day, and almost zero probability on the fourth day. The closer the hurricane is, the earlier the household is likely to evacuate. This trend is intensified in the close scenario. As a result, the evacuation for the close scenario is a three-day evacuation instead of a four-day evacuation as for the medium and far scenarios.

Table 36
Evacuation probability for distance scenarios by day without evacuation orders

Day	Close	Medium	Far
1	4.4%	3.8%	3.7%
2	7.6%	4.6%	3.7%
3	6.7%	7.9%	4.8%
4	0.4%	4.0%	8.1%
Total	19.1%	20.3%	20.3%

The above pattern will change, however, when a voluntary evacuation order is issued in time interval 28. The results are plotted in Figure 28, with another close scenario without an evacuation order as a reference. Table 37 presents the total evacuation probabilities for each condition.

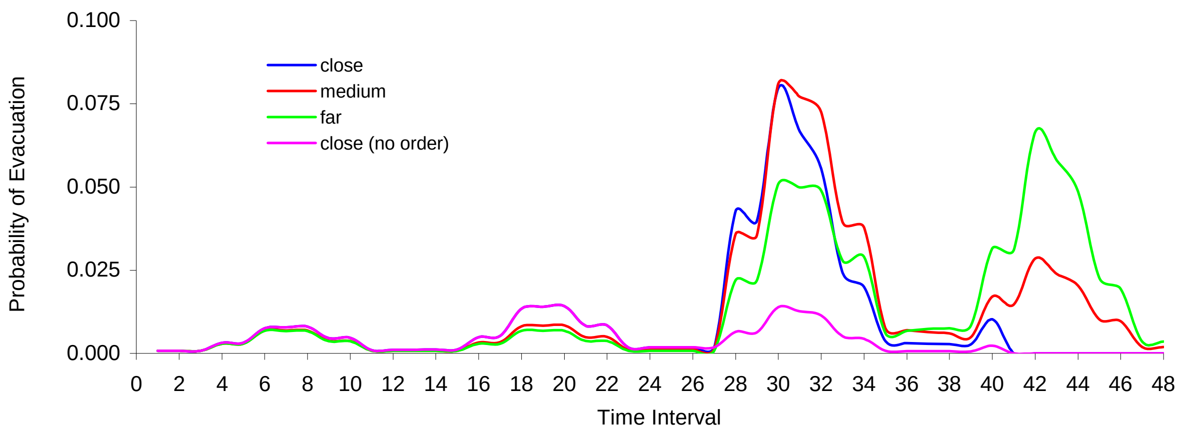


Figure 28
Impact of distance with voluntary order at 28

Table 37
Total evacuation probability for the impact of distance with evacuation order

Distance	Close (No Order)	Close	Medium	Far
Probability	19.1%	47.9%	62.7%	64.9%

The evacuation patterns are the same as the cases without an evacuation order until time interval 28, when a voluntary order is issued. Compared to the close scenario without an evacuation order, the probabilities of evacuation increase markedly for each of the conditions. For the close and medium scenarios, the majority of evacuations occur on the third day, as compared to the previous cases where evacuations are more evenly distributed among the days. However, for the far scenario, the evacuation pattern remains the same. The probabilities of evacuation increases daily, with the last day being the highest.

In the above analysis, the impacts of distance with and without evacuation orders were explored. The sequential logit model has the ability to predict evacuation behavior under different scenarios of change in distance along with other compounding influences, such as evacuation orders. On the contrary, the traditional two-step procedure of combining participation rate model with response curves does not have such capability.

The Impact of Hurricane Wind Speed

In order to evaluate the model's capability of estimating the impact of hurricane wind speed, three scenarios involving a category-2, a category-3, and a category-4 hurricane were analyzed. The scenarios were all analyzed against the backdrop of a high-risk household with a voluntary evacuation order issued at time interval 28. Values of distance were taken from Table 32. Each scenario has constant speed for the 48 time intervals. The values of speed for each scenario are the maximum speed in each of the three categories, i.e., 110, 130, and 155 miles per hour. Figure 29 plots the evacuation probabilities for each scenario. Table 38 gives the total evacuation probability for each condition.

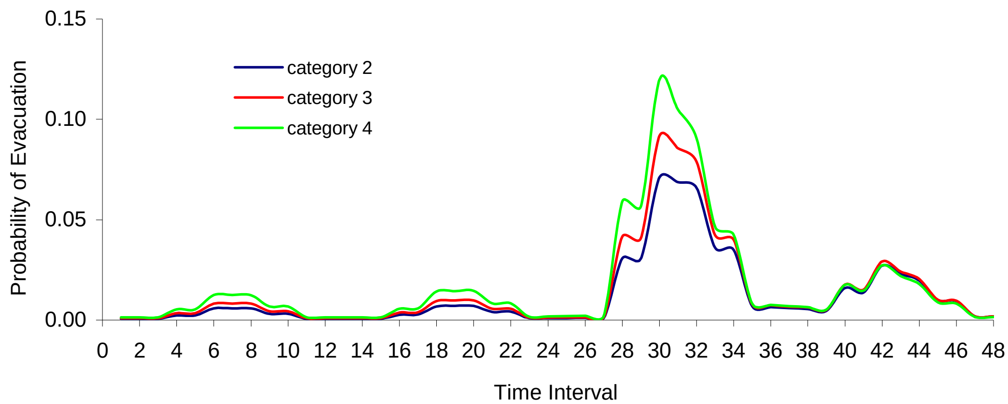


Figure 29
Impact of wind speed on evacuation behavior

Table 38
Total evacuation probability with different hurricane speed

Hurricane Speed	110	130	155
Total Probability	56.5%	68.9%	83.0%

In the figure, the evacuation probabilities increase with hurricane speed increases as the hurricane approaches. The higher the speed, the larger the probability to evacuate. For all scenarios, the evacuation probabilities increased sharply at time interval 28 because a voluntary evacuation order is issued at that time. Overall, the third day exhibits the highest probability for all three hurricanes. This is due to the combined impact of the evacuation order, the value of distance and the speed.

The current practice of the two-step procedure in hurricane modeling does not have the capability to predict the impact of hurricane speed on evacuation. Instead, it relies on the subject assessment of the analyst.

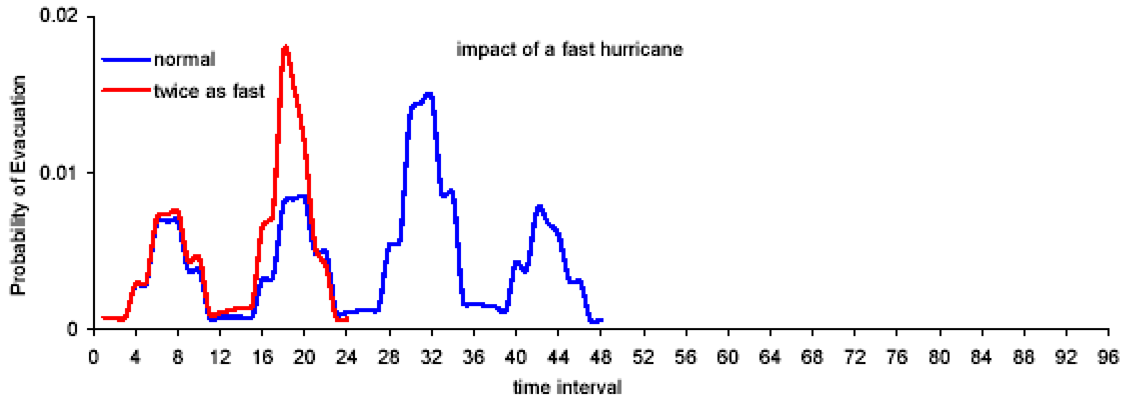
The Impact of Hurricane Forward Speed
Although the forward speed of a hurricane is not explicitly a covariate in the sequential logit model from the Floyd data, its impact can be analyzed by rearranging the temporal distribution of the same hurricane track. If the distance values were taken from Table 32 as our normal scenario, there are 48 time intervals in the normal scenario. However, if the scale of the time intervals is changed, new scenarios with different forward speeds of the hurricane can be generated. Scenario 2 is generated by assuming that the hurricane moves twice as fast as the hurricane in the normal scenario. As a result, the number of time intervals is reduced from 48 to 24. In scenario 3 it was assumed the hurricane moves at half the forward speed of the normal scenario, and the resulting number of time intervals is increased from 48 to 96. In scenario 4 it is assumed that the hurricane moves at the same pace as the normal scenario in the first two day but at half the speed in the last two days as in the normal scenario, and the resulting number of time intervals is increased from 48 to 72. The evacuation probabilities were calculated for a high-risk household with a constant hurricane wind speed of 120 miles per hour. Figures 30(a)-(c) plot the evacuation probabilities of each scenario with the normal scenario shown in each diagram for comparison purposes. Table 39 presents the total probability of evacuation for each scenario.

Table 39
Total evacuation probability at different forward speed

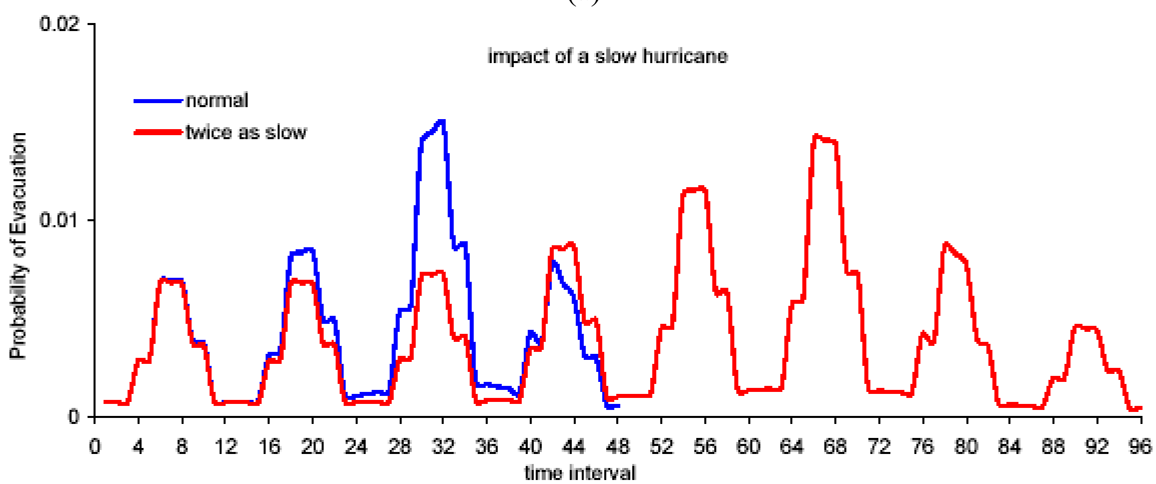
Scenario	Normal	Twice as fast	Twice as slow	Twice as slow in last 2 days
Probability	20.3%	11.5%	37.0%	31.2%

The normal scenario was the hurricane with the same pace as those studied so far. This involved 48 time intervals, in which the model predicted a total evacuation probability of 20.3 percent over four days of evacuation. If the hurricane moves twice as fast as in scenario 2, the hurricane makes landfall in two days instead of four (Figure 30(a)). The model predicts that on the first day, the evacuation patterns would be almost identical for the two scenarios. However, the evacuation pattern changes significantly on the second day. The probability of evacuation is much higher on the second day for the fast scenario, as would be expected. Nonetheless, the total evacuation probability for the fast scenario is a little more than half of that of the normal scenario, thereby suggesting that, all else being equal, the forward speed of the hurricane has a significant impact on the number of persons evacuating. It is difficult to verify whether this is a reasonable prediction or not since the impact of individual characteristics of hurricanes has not been quantified in the past.

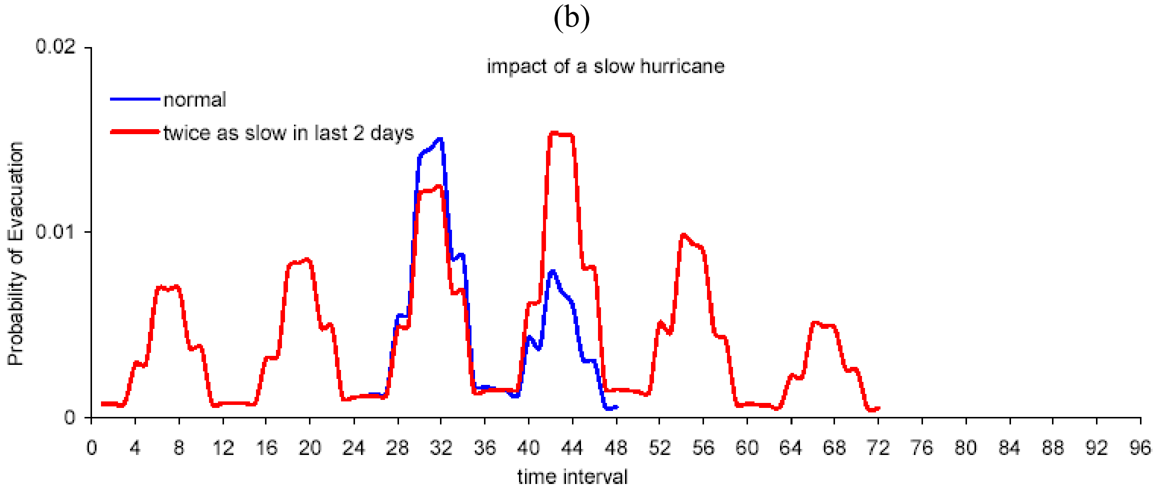
If the hurricane moves twice as slow as the normal case (Scenario 3), hurricane landfall occurs in eight days instead of four. In this case, the model predicts evacuation behavior, as shown in Figure 30(b). The peak evacuation day is delayed from the 3rd day to the 6th day. The probabilities of evacuation are spread more evenly across the eight days than in the normal case, which is expected. The total probability of evacuation is almost doubled, jumping from 20.3 percent to 37.0 percent. Again, it is difficult to assess if such a prediction is reasonable or not, although it is clearly possible.



(a)



(b)



(c)

Figure 30
Impact of hurricane forward speed

For the last scenario (Scenario 4), where the hurricane is assumed to move at the same pace as in the normal scenario for the first two days and then slow down to half the speed after that, the model predictions are shown in Figure 30(c). Scenarios 3 and 4 have identical evacuation patterns for the first two days, which is as expected, but the peak evacuation day is delayed from the 3rd to the 4th day in scenario 4. Total evacuation probability after the first two days is doubled, from 11.9 percent to 22.9 percent between scenarios 3 and 4. These responses seem plausible, although there is no way to verify the magnitude of the estimates.

The above analysis demonstrated the flexibility of the sequential logit model. Hurricane forward speed, though not explicitly a covariate in the model, can still be accommodated in the model analysis by rearranging the temporal distribution of the hurricane track.

The Impact of Household Risk Levels

Unlike the participation rate and response cure method currently used to predict hurricane evacuation, the sequential logit model is a disaggregate model that takes the characteristics of the households into consideration. The model utilizes, in addition to the dynamic information of the storm, the housing type and location of each individual household as important factors to assess the probability of the household to evacuate in each time interval. In this subsection, it will be demonstrated that the sequential logit model correctly describes the evacuation behavior among households of different risk levels.

Table 40 presents four scenarios that were used in the analysis. Scenario 1 is a low-risk household without any evacuation order; scenario 2 is the same low-risk household who receives a voluntary evacuation order at time interval 30, which is from 10 to 11 a.m. on the third day; scenario 3 is a high-risk household without any evacuation order; and scenario 4 is the same high-risk household who receives a voluntary evacuation order at time interval 30.

Table 40
Four scenarios analyzed with the Floyd sequential logit model

Household Risk Level	No evacuation order	Voluntary order at time interval 30
Low-Risk Household	1	2
High-Risk Household	3	4

In addition to the information from Table 40, hurricane wind speed is assumed to be constant at 120 mph, which is the speed of a category 3 hurricane. The values of distance for each of the 48 time intervals are the same as in Table 32. Based on the above information, the sequential logit model estimated with the 75 percent Floyd dataset was applied to calculate the probabilities for every scenario in each time interval. The results are plotted in Figure 31. The total evacuation probabilities for the scenarios are presented in Table 41.

Table 41
Total evacuation probabilities by household risk level

Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Probability	9.5%	33.7%	20.3%	60.0%

Before time interval 30, when a voluntary evacuation order is issued, scenarios 1 and 2, and scenarios 3 and 4 have identical evacuation patterns. As a result, the blue line for scenario 1 is under the red line for scenario 2, and the green line for scenario 3 is under the pink line. During this period, the high-risk households have higher evacuation probability than low-risk households. At time interval 30, the issuing of a voluntary evacuation order increases the probability of evacuation markedly for both low-risk and high-risk households, increasing the evacuation rate almost five times. For the same evacuation order, the high-risk and low-risk households respond differently (scenario 1 versus 2, and scenario 3 versus 4). The impact seems to be higher among high-risk households than low-risk households. Such behavior is consistent with our understanding of hurricane evacuation since high-risk households are generally more responsive to evacuation orders than low-risk households.

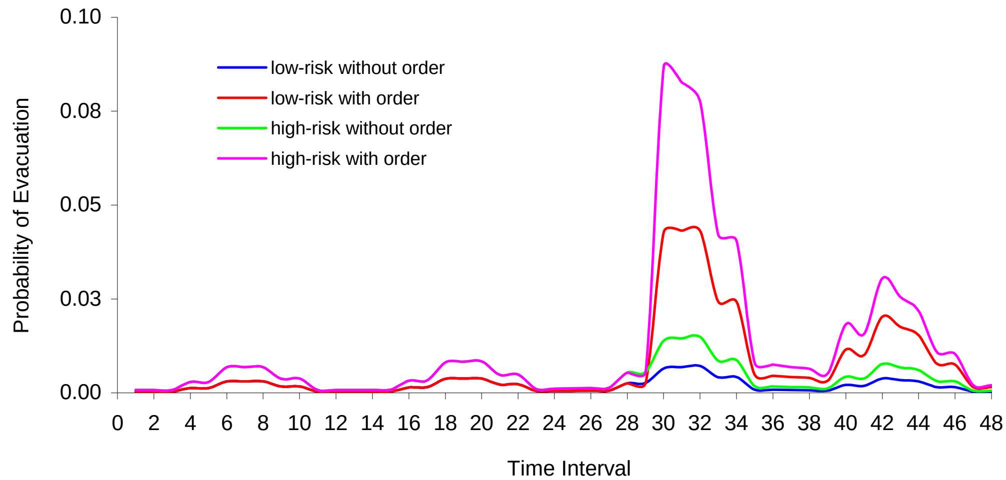


Figure 31
Impact of household risk level with the Floyd sequential logit model

The sum of probabilities for all the time intervals for each household is the probability of that household to evacuate during a hurricane. The difference between the sum of probabilities for the high-risk household with and without an evacuation order (60.0 percent and 20.3 percent) is larger than that for the low-risk household (33.7 percent and 9.5 percent). This indicates that the impact of evacuation order is more significant for high-risk households than for low-risk households. This conclusion is different from the analysis of the Cox model and the sequential logit model estimated from the Andrew data, which conclude that evacuation order has the same evacuation impact on low-risk and high-risk households for the Cox model and a smaller impact on high-risk households than on low-risk households for the sequential logit model estimated from the Andrew data.

The reason for the different conclusions from the three models lies in the different model structure and different forms in which the variable evacuation order appeared in the models. In the Cox model, the discussion involved only the relative hazards without referencing to baseline hazards, hence the analysis was crude at best; in the Andrew model, evacuation order was presented as a static variable; while in the Floyd model, evacuation order was treated as a dynamic variable, as it ought to be. It seems that the sequential logit model structure is more appropriate than that of the Cox model, and the dynamic portrayal of an evacuation order produces a much more realistic result.

The analysis above demonstrated that the sequential logit model can distinguish the household characteristics and correctly predict the evacuation behavior based on the distinction; the model performance improves when evacuation order is treated as a dynamic variable as it should be.

The Sequential Model with Stated-Choice Data

Model Prediction

The model used here is the sequential logit model estimated with the New Orleans's SP data. The original dataset was also divided into model estimation and validation parts with a 75-25 percent split respectively. There were seven unequal time intervals in the data. Table 42 presents the results of the model predictions and stated values based on the 25 percent validation data. Figure 32 plots the model validation results based on Table 42. The horizontal axis is the median of the values in column 2 of the Table.

Table 42
Predicted and stated evacuations with the SP data

Time Interval	Time (Hour)	Predicted	Stated
1	0-2	125.4	181
2	2-4	104.0	94
3	4-6	81.2	60
4	6-12	74.8	68
5	12-24	58.5	103
6	24-48	46.5	49
7	>48	38.6	9
Total Evacuation		529	564

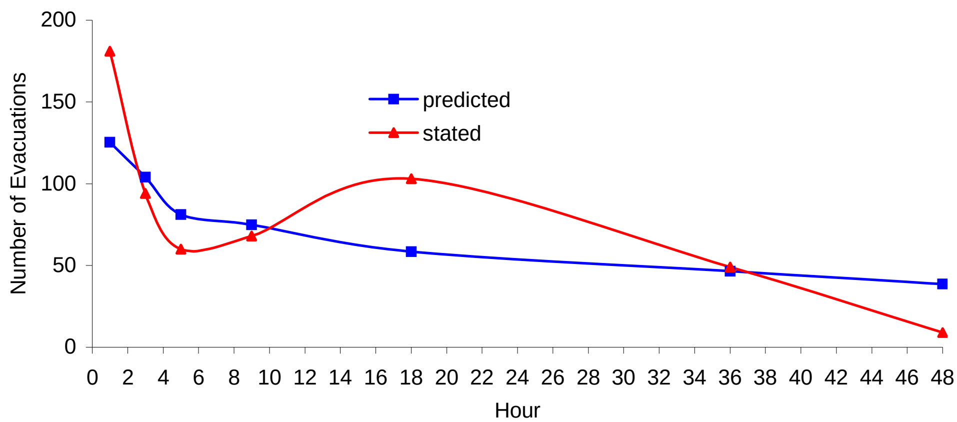


Figure 32
Model predicted vs. stated evacuation with the SP data

The model predicted total a evacuation of 529, and the total stated evacuation was 564, resulting in a low relative error of only 6.6 percent. However, the model does not reproduce the stated evacuation for most time intervals accurately. In contrast to the performances of the sequential models from the Andrew and Floyd data which accurately reproduced the observed evacuation patterns, this sequential logit mode estimated from the New Orleans data is inferior. It is believed that the following are the possible reasons the sequential logit model does not accurately predict the evacuation for the New Orleans SP data:

1. Lack of accuracy in estimating the variable *landfall*, which represents the estimated time that the hurricane will make landfall. *Landfall* is a dynamic variable in the model. Its role is similar to that of *distance* in the other models estimated in this study. However, from Table 18, the values for *landfall* are, at best, approximations. Many involve subjective judgment in their composition. In some instances, the values of *landfall* do not vary from time interval to time interval. Moreover, it is unreasonable to expect that evacuation can be predicted to within two-hourly intervals, as for intervals 1, 2, and 3, when the values of *landfall* are so roughly estimated.
2. Compared to the Floyd model, which has four dynamic variables among the six covariates, the variable *landfall* is the only dynamic variable in this model. As a result, the model explains far less variation in the data as characterized by the low log likelihood ratio index ρ^2, which is only 0.062 in the model estimated on the New Orleans stated preference data (Table 22).
3. Lack of validity of applying the sequential decision model. From the way the survey was performed, it is obvious that a respondent made up his/her mind concerning if to evacuate and, if so, when to evacuate at the very beginning. This does not conform to the sequential decision paradigm, which assumes that a decision maker makes the evacuation decision progressively based on the varying conditions of the environment. The validity of applying a sequential decision model to this SP survey is questionable.
4. Most importantly, there are serious flaws in the survey data as discussed earlier. From Figure 32, it can be seen that most respondents chose to evacuate in time interval 1 (between 0 and 2 hours), evacuation dropped for time intervals 2 (between 2 to 4 hours), 3 (between 4 to 6 hours), and 4 (between 6 to 12 hours), peaked again in time interval 5 (between 12 to 24 hours), and then gradually decreased to nearly zero during time intervals 6 to 7. For most profiles (scenarios) in the New Orleans stated preference survey, there was plenty of time between the first time interval and hurricane landfall for evacuation even as the hurricane threat intensified during these time periods. According to the sequential decision paradigm, the probabilities of evacuation should increase from time interval 1 since time-of-day impact was not considered. However, for most of the profiles, time interval 1 had the highest evacuation.
5. Another flaw of the survey is revealed if the evacuation responses by profiles that had the same variable level for the variable expected *landfall* is plotted. Table 43 presents responses from the eight profiles of the 75 percent estimation data that had the initial expected time-to-landfall time within 12 hours. Figure 33 plots the total stated evacuation.

Table 43
Responses of the profiles with initial time-to-landfall less than 12 hours

Interval	Hour	Profile 4	Profile 8	Profile 12	Profile16	Profile 20	Profile 24	Profile 28	Profile 32	Total
1	0-2	11	25	25	9	13	14	13	7	117
2	2-4	4	8	11	7	9	12	12	1	64
3	4-6	9	9	9	8	7	7	9	4	62
4	6-12	4	7	8	4	8	13	16	3	63
5	12-24	5	13	9	7	8	10	13	3	68
6	24-48	3	7	6	1	6	7	7	2	39
7	>48	2	0	1	0	2	3	0	0	8

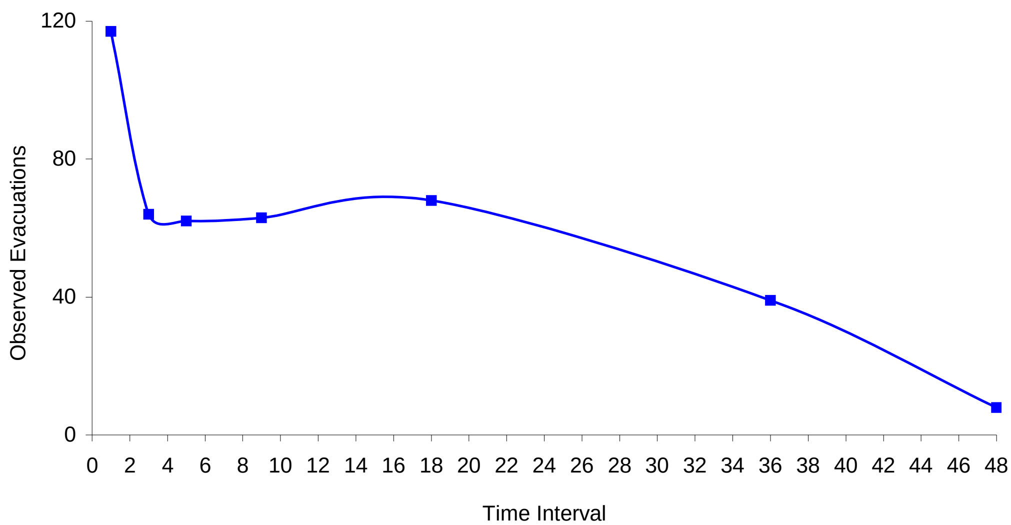


Figure 33
Stated evacuation for profiles with initial time-to-landfall less than 12 hours

Since the initial time-to-landfall was less than 12 hours, for time interval 4, which was between hours 6-12, the hurricane was 0 to 6 hours away, which means the hurricane was either about to land or would do so in a few hours. For time intervals 5 through 7, which were more than 12 hours away, the hurricane must have already landed. However, 27.3 percent of the evacuations occurred from time intervals 5 through 7. Between time intervals 4 through 7, 42.3 percent of the evacuations occurred. This observation showed that many of the respondents could not logically respond to the questions and give meaningful answers.

6. Lack of time-of-day information. Another serious flaw of this SP survey is the lack of time-of-day information. From our previous analysis, it is obvious that time-of-day plays a very significant role in hurricane evacuation. In reality, a respondent's evacuation decision will be very different depending on the time-of-day to which it applies.

Some Words on SP Data

As discussed in the section on stated-preference data and technique, it is believed that there are great potential applications of the SP technique in hurricane evacuation. Some modeling effort was made with the SP data from the New Orleans area in this study, but a good model could not be produced with the SP data. However, this in no way implies that the methodologies of this study are not applicable to SP data. The failure is due to some serious underlying design flaws and problems in the data.

Model Comparison

In this part of the analysis, the two survival analysis models, the Cox model and the Piecewise Exponential model, were first compared. It was then followed by comparison between the two sequential models: the sequential logit and the sequential complementary log-log model. Finally, a comparison between the two modeling methodologies was presented, and the best model was recommended.

Survival Models: The Cox Model vs. Piecewise Exponential Model
In order to evaluate the Cox model and the Piecewise Exponential model several comparisons were made between the two survival analysis models, including the model coefficients, *GOF*, baseline hazards, and model predictions vs. observations. The summaries of the two models are presented in Table 44. Figure 34 plots the model coefficients.

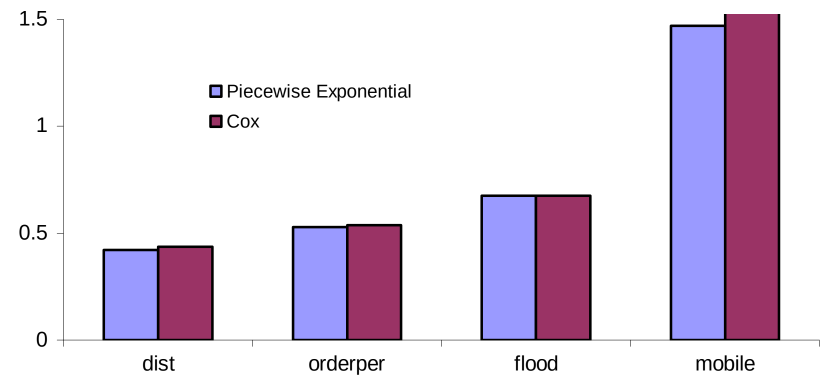


Figure 34
Comparison of the coefficients of the two survival analysis models

Table 44
Summary results of the two survival analysis models

Covariate	Piecewise Exponential Model			The Cox Model		
	β	se(β)	*p-value*	β	se(β)	*p-value*
dist	-0.422	0.220	0.055	-0.436	0.219	0.046
orderper	0.529	0.206	0.010	0.537	0.207	0.010
flood	0.676	0.211	0.001	0.676	0.212	0.002
mobile	1.469	0.207	0.000	1.502	0.208	0.000
LL(C)	-580.4			-645.2		
LL(β)	-420			-608.7		
ρ^2	0.276			0.057		

The coefficients of the two models are very close, as are the variances and the levels of significance of the coefficients. However, the likelihood ratio indexes are quite different. The Cox model has a low value of 0.057, while the Piecewise Exponential model has a high value of 0.276. This is because the Cox model conditioned out the baseline hazards from its partial likelihood function, while the Piecewise Exponential model estimates the baseline hazards from within the model. The baseline hazards from the Piecewise Exponential model explain part of the variations in the data, hence increasing the likelihood ratio index. In contrast, the estimation of the baseline hazards has to be made separately for the Cox model, through the *Breslow* estimator in equation 11. Table 45 presents the baseline hazards of the two models, and Figure 35 shows them graphically.

Table 45
Baseline hazards of the Cox and Piecewise Exponential models

Interval	1	2	3	4	5	6	7	8	9	10	11	12
Piecewise Exponential	0.063	0.092	0.330	0.061	0.000	0.411	0.477	0.223	0.078	0.395	0.693	0.075
The Cox Model	0.067	0.098	0.358	0.064	0.000	0.454	0.523	0.239	0.083	0.436	0.817	0.082

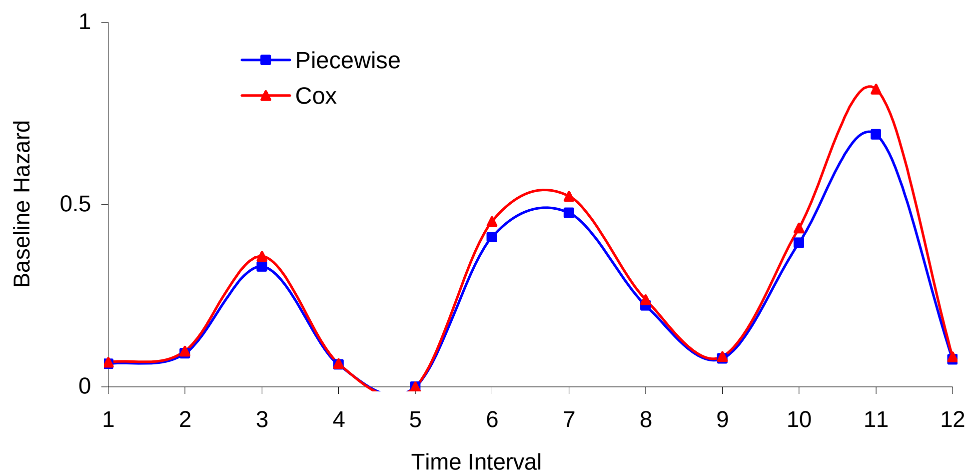


Figure 35
Comparison of the two baseline hazards

The baseline hazards are very close. Since the Piecewise Exponential model estimates the baseline hazards endogenously, their level of significance can be tested. However, there is no goodness-of-fit measure for the baseline hazards estimated through the *Breslow* estimator.

The observed and predicted evacuations from the Cox model in Table 24, along with the predictions from the Piecewise Exponential model, are listed in Table 46, and Figure 36 presents them graphically. The Piecewise Exponential model predictions were calculated with the model coefficients (estimated using the Andrew estimation data) listed in table eight, along with the Andrew validation data. The two models produced very similar predictions, and the predictions were very close to the observations. The *RMSE* and percent *RMSE* were 1.50 and 19.7 percent for the Cox model and 1.33 and 18.9 percent for the Piecewise Exponential model, respectively. Both the Cox model and the Piecewise Exponential model can accommodate time-dependent variables, and both have been observed to reproduce the observed evacuation accurately in this study. The Cox model is one of the most widely used methods in survival analysis. As a result, there are many tools to facilitate its application, including tests of proportionality, functional form, and heterogeneity, etc. On the other hand, applying and testing the Cox model is a cumbersome process. In addition, the partial likelihood function makes it impossible to estimate dynamic variables such as *TOD*, which have the same value for each household in each time interval but nevertheless plays an important role in hurricane evacuation. Moreover, the estimation of baseline hazards has to be done exogenously, giving no statistical test to measure the goodness-of-fit. In contrast, the Piecewise Exponential model is simple to apply. It can estimate the baseline hazards endogenously with measures of goodness-of-fit. Theoretically, it can accommodate such variables as *TOD,* although in reality the existence of collinearity may complicate the problem. In addition, since the time interval is included in the Piecewise Exponential model as a categorical variable (hence introducing I-1 dummy variables, where I is the number of time intervals) to produce the estimate of the baseline hazard, it is no longer practical to use the Piecewise Exponential model when the number of time intervals becomes large.

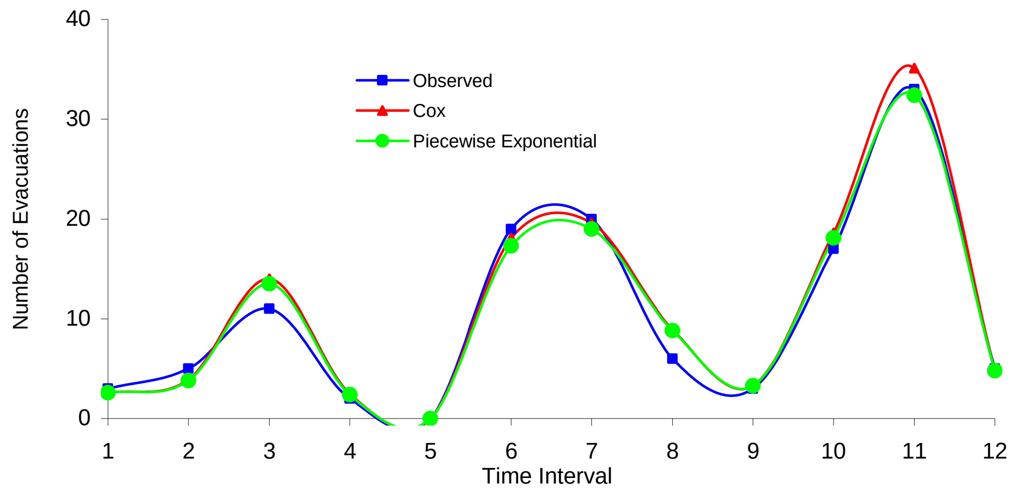


Figure 36
Observed vs. model predicted evacuations for the two survival models

Table 46
Model predicted and observed evacuations for the two survival models

Interval	1	2	3	4	5	6	7	8	9	10	11	12	Total
Observed	3	5	11	2	0	19	20	6	3	17	33	5	124
The Cox Model	2.6	3.9	14.0	2.5	0	18.1	19.6	8.9	3.3	18.6	35.1	4.8	131.3
Piecewise Exponential	2.6	3.8	13.5	2.4	0.0	17.3	19.0	8.8	3.3	18.1	32.4	4.8	126.2

Sequential Models: Logit vs. Complementary Log-Log Mode

It has been demonstrated earlier that the logit model and the complementary log-log model are closely related to each other. They can be derived using the same latent variable paradigm with different assumptions about the distribution of the random variable. The former assumes logistic distribution and the latter extreme minimal-value distribution. These two distributions are very similar. The two sequential models estimated with the Floyd data were first compared, followed by a comparison of the model predictions. The summary results of the two models in Table 15 are copied below and renamed as Table 47. From the table, the two models are almost identical with similar coefficients, variances, and levels of significance. The likelihood ratio indexes are the same. Figure 37 plots the absolute values of their coefficients. The logit model has consistently slightly larger coefficients in magnitude, which is usually the case except for the intercepts *[61]*.

Table 47
Summary results of the two sequential models with the Floyd data

Covariate	Logistic			Complementary Log-Log		
	β	se(β)	*p-value*	β	se(β)	*p-value*
intercept	-10.108	0.891	0.000	-9.962	0.871	0.000
gammadistance	4.139	1.012	0.000	4.077	0.989	0.000
TOD(1)	1.353	0.171	0.000	1.336	0.169	0.000
TOD(2)	2.221	0.143	0.000	2.181	0.140	0.000
TOD(3)	1.610	0.156	0.000	1.588	0.153	0.000
dyanorder(1)	1.917	0.193	0.000	1.903	0.189	0.000
dyanorder(2)	2.181	0.213	0.000	2.148	0.209	0.000
flood	0.558	0.078	0.000	0.538	0.075	0.000
mobile	0.263	0.132	0.047	0.249	0.128	0.051
speed	0.017	0.006	0.006	0.017	0.006	0.007
LL(C)	-3871			-3871		
LL(β)	-3110			-3110		
ρ^2	0.197			0.197		

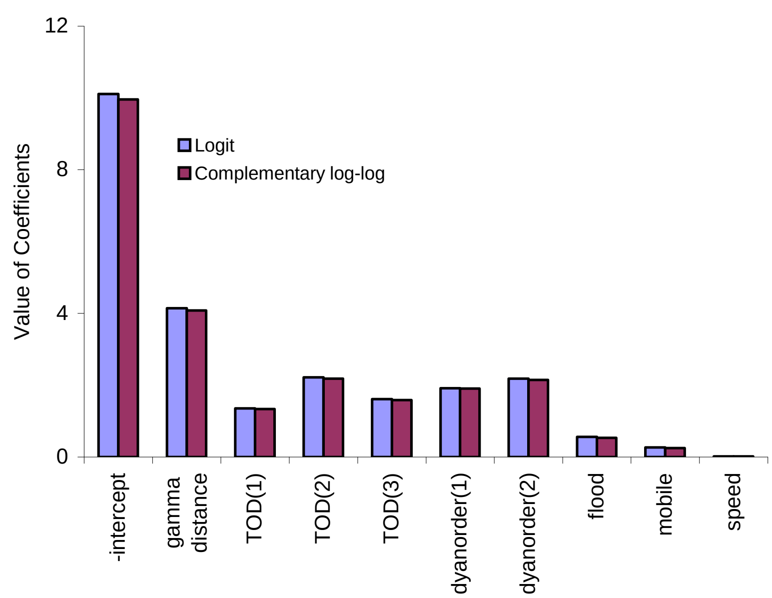


Figure 37
Coefficients of the two sequential models with the Floyd data

Since the two models are almost identical, predictions from the two models are expected to be close too. Figure 38 plots the observed evacuations and predictions from the two models using the 25 percent Floyd validation data. The two predictions are so close that the red line, the sequential logit model prediction, is almost totally covered by the green line, the sequential complementary log-log model prediction. This is the reason that only the sequential logit model from the Floyd data was used in the discussion earlier.

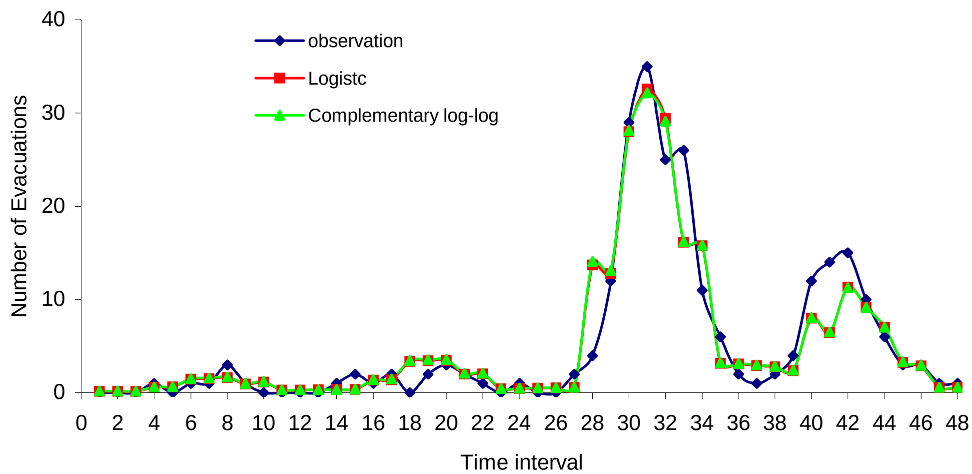


Figure 38
Model predictions from the two sequential models with the Floyd data

Model Comparison between the Survival Models and the Sequential Models
Based on the analysis of the sequential models and the survival models so far, the following advantages of the sequential model over the survival model were found:

1. The sequential model can accommodate all dynamic variables, including such variables as distance, time-of-day, and evacuation order. The Cox model cannot accommodate certain dynamic variables, which have the same values for every household for each time interval, such as time-of-day and evacuation order, if the order is issued to everyone at the same time. The Piecewise Exponential model theoretically can accommodate all dynamic variables, but the existence of collinearity makes it difficult, if not impossible, from our experience. As the number of time intervals becomes larger, the application of the Piecewise Exponential model becomes more impractical.
2. The sequential choice model is simple to use. The major task involves estimating a binary choice model, while the Cox model involves a series of cumbersome procedures.
3. The sequential model has a sound behavioral basis because it is based on the random utility theory, while the survival analysis models are pure statistical procedures.

Therefore, it is believed that the sequential model is superior to the survival analysis models. Because the logit model is well known in the transportation community and there are generally more statistical packages that support the logit model, the sequential logit model seems to be the best method to study dynamic travel demand for hurricane evacuation.

Variables in the Model

It is important for the models developed in this study to capture the underlying relationships between the dependent variable, the probability of evacuation for each time interval, and the independent variables. This subsection serves to show that our models, especially the sequential models, include the major variables that have been proven to play important roles in studying hurricane evacuation.

After studying 26 hurricane evacuations, Baker *[46]* identified the five most important variables in hurricane evacuation, as listed in Table 48. The variables used in this study are also listed in the table for comparison.

Table 48
Variable comparisons

Baker's Variables	Variables in This Study
Risk level (hazardousness) of the area	Flood
Action by public authorities	Evacuation order
Housing	Mobile
Prior perception of personal risk	Hurtrisk, protect
Storm-specific threat factors	Distance, wind speed, time of day

While the names of the variables between the two groups are different, it is clear that the variables used in this study are the cores identified by Baker. The variables representing prior perception of personal risk were found significant in the models but were excluded because data for such personal perceptions are difficult to get. The last variable, the storm-specific threat factors mentioned by Baker, are represented by distance from the storm, hurricane speed, and time-of-day in this study.

In addition to the variables listed in the table, our study of the Andrew and Floyd data demonstrated the important role of time-of-day in hurricane evacuation. For example, the Floyd data showed that people are least likely to evacuate at night, more likely to evacuate in the morning and in the afternoon, and most likely to evacuate in mid-day. Concerning the impact of time-of-day, Baker *[46]* stated: "Time of day has not proven to be a significant deterrent to whether people evacuate, however. It does appear that given a choice, many people would prefer to leave during the day, but many very successful evacuations have been conducted late at night…." For the Andrew and Floyd data, it might be that evacuation orders were issued such that many people had the choice of not evacuating at night. The time-of-day variable, *TOD* in our model, was estimated under such circumstances. More study is needed to model the second situation Baker mentioned.

Model Transferability and Post-Processing

Model Transferability

So far, the best model from this study is the sequential logit model based on the Floyd data. Among all the modeling methodologies, the sequential model includes the most important dynamic variables and produces the most powerful model to study the impact of a variety of covariates. The model not only reproduces evacuation behavior based on validation data, but it also produces reasonable predictions under different conditions. However, these results are based on data from one hurricane. If a model developed from one hurricane can be applied to different situations in terms of hurricane characteristics and geographic locations, then this model is transferable. A model that is transferable probably captures the fundamental relationships between the dependent variable and the independent variables; hence, it will have broader applications. McFadden *[96]* discusses multinomial logit model transferability when structure changes in tastes are present. He points out three kinds of shifts in the model. They are shifts in the alternative-specific constants (*ASC*s), in the scale of the other parameters, and in the relative values of these parameters. Since the ASCs represent the average of error terms in utility, their changes are most responsible for non-transferability. The second change, which is the shift in scale, reflects the change of variance of error terms caused by the differences in choice population. Usually, the relative values of parameters are more robust; hence, their changes are least important in terms of model transferability. As a result, McFadden suggests the following hierarchy for adjustment when transferring a model:

1. No adjustment when no data is available.
2. Adjusting ASCs only if the share of choosing an alternative is available.
3. Adjusting both ASCs and the scales of other parameters when more than one data points are available.
4. Estimate a new model when adequate new data are available using Bayesian methods to incorporate previous information.

The Andrew data were used to test the transferability of the sequential logit model estimated from the Floyd data. Since the two datasets were not completely compatible, some modifications were necessary and are described below:

1. The Floyd data was a four-day evacuation and had 48 time intervals with each time interval being two hours long; the Andrew data was a three-day evacuation and originally had 12 time intervals with each time interval being six hours long. To utilize the Floyd model, the information for Andrew had to be interpolated into two-hour intervals. The modified Andrew data subsequently had 36 time intervals.
2. The *TOD* for the Floyd model had four categories: morning, midday, afternoon, and night; the *TOD* for the Andrew model had three categories: morning, afternoon, and night. To make them compatible, the Floyd dataset was aggregated into three categories, the same as Andrew.
3. The Floyd data had information about evacuation time accurate to every two hours, and the Andrew data every 6 hours. To compare model prediction and observation, the model prediction had to be aggregated from every two hours to every six hours.
4. The Andrew data did not have complete evacuation information for all the parishes, which is required by the Floyd model. Out of the 21 parishes the survey covered, only 11 parishes had the required information. As a result, the households without the required evacuation information were excluded from the transferability study and 135 households remained.

After making the necessary modifications, a new sequential logit model based on the modified Floyd data was estimated. The model summary is listed in Table 49. In this model, *speed* (i.e., wind speed) is no longer significant at 15 percent level although it does have the correct sign. To be consistent, it is retained in the model. The binary logit model's Hosmer and Lemeshow *GOF* statistic is 4.065 with eight degrees of freedom. The *p-value* is 0.851. This shows that the null hypothesis that the binary logit model fits the data well cannot be rejected. The contingency table is given in Table 50. The first group ought to be combined with the second one because it has too few observations. However, the regrouping would reduce the Hosmer and Lemeshow statistic and make it harder to reject the null hypothesis that the binary logit model fits the data well. Therefore, it was left unchanged.

Table 49
Modified Floyd sequential logit model for transferability

Covariate	Logit Model		
	β	se(β)	*p-value*
intercept	-8.540	0.790	0.000
gammadistance	5.247	0.956	0.000
TOD(1)	1.543	0.136	0.000
TOD(2)	1.721	0.113	0.000
dyanorder(1)	1.681	0.187	0.000
dyanorder(2)	1.998	0.194	0.000
flood	0.555	0.077	0.000
mobile	0.267	0.131	0.043
speed	0.008	0.006	0.154
LL(C)	-7742.2		
LL(β)	-6304.5		
ρ^2	0.1857		

Table 50
Contingency table for the modified Floyd model

Group	Not Evacuated		Evacuated		Total
	Observed	Expected	Observed	Expected	
1	4874	4874	3	2.9	4877
2	4875	4876	5	4.2	4880
3	4866	4867	7	6.2	4873
4	4843	4845	12	10.1	4855
5	4869	4865	11	15.5	4880
6	4841	4842	22	21.3	4863
7	4844	4844	32	32.2	4876
8	4784	4782	80	81.8	4864
9	4679	4695	200	183.8	4879
10	4543	4529	377	391.5	4920

In this analysis of sequential logit model transferability, the knowledge of the total number of evacuations in the Andrew data was used to adjust the ASC in the model to ensure that the predicted probability of evacuation equals the observed number. This is conducted by observing the following equation:

$$\sum_{n=1}^{N}\sum_{i=1}^{T}P_{n,i}=\sum_{n=1}^{N}\sum_{i=1}^{T}\frac{e^{\alpha'+\beta x_{n,i}}}{1+e^{\alpha'+\beta x_{n,i}}}\prod_{j=1}^{i-1}(1-\frac{1}{1+e^{\alpha'+\beta x_{n,j}}})=\sum_{n=1}^{N}\sum_{i=1}^{T}\frac{e^{\alpha'+\beta x_{n,i}}}{\prod_{j=1}^{i}1+e^{\alpha'+\beta x_{n,j}}}=E, \qquad (41)$$

where E is the total number of observed evacuations, $P_{n,i}$ is the probability of evacuation for household n in time interval i from the model, N is the total number of households, T is the total number of time intervals, β s are the model parameters previously estimated, and α is the new ASC which is identified in an iterative solution process.

For this study, the updated *ASC* was found to be –8.180, an increase from the original value of –8.540. Table 51 lists the model predictions for each of the 36 time intervals. The same information is plotted in Figure 39.

Table 51
Model prediction for transferability

Time	ASC Adjustment		Time	ASC Adjustment		Time	ASC Adjustment	
	Before	After		Before	After		Before	After
1	0.08	0.20	13	0.11	0.16	25	1.14	1.33
2	0.08	0.12	14	0.11	0.16	26	1.19	1.40
3	0.09	0.13	15	0.11	0.16	27	1.20	1.42
4	0.43	0.63	16	0.54	0.79	28	5.15	5.94
5	0.45	0.66	17	2.34	3.29	29	5.00	5.74
6	0.47	0.69	18	2.43	3.39	30	4.21	4.72
7	0.59	0.87	19	3.06	4.19	31	4.06	4.44
8	0.59	0.87	20	3.30	4.46	32	3.30	3.53
9	0.60	0.88	21	3.60	4.78	33	3.05	3.61
10	0.11	0.16	22	0.85	0.99	34	0.47	0.56
11	0.11	0.16	23	0.95	1.10	35	0.47	0.55
12	0.11	0.16	24	1.05	1.22	36	0.46	0.55

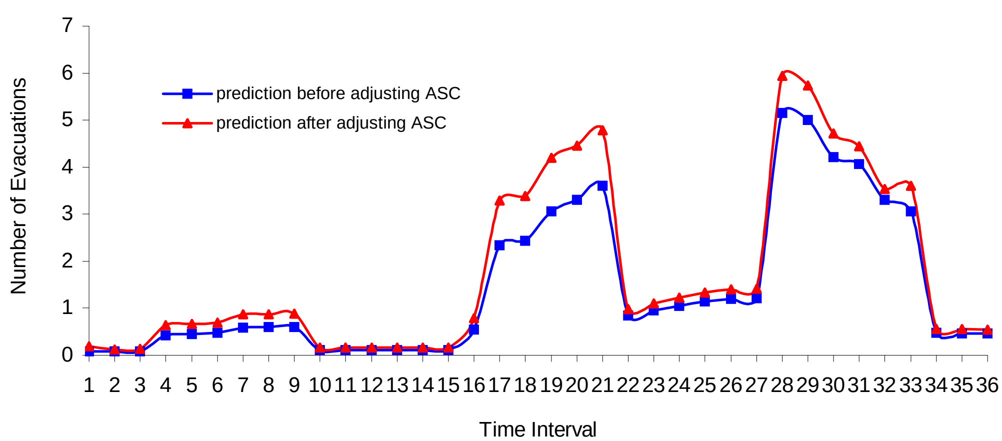


Figure 39
Model predictions before and after adjusting ASC

As seen from Figure 39, the impact of increasing the *ASC* is to increase the evacuation probabilities for each of the time intervals, as expected. To compare the model predictions with the observations, the length of time interval needs to be aggregated from two hours to six hours. Table 52 lists the observed and the model predicted evacuations after such aggregation before and after adjusting the *ASC*. The same information is plotted in Figure 40.

Table 52
Model prediction vs. observation for transferability

Time Interval	Observation	Prediction	
		Before Adjustment	After Adjustment
1	0	0.25	0.45
2	2	1.35	1.99
3	8	1.78	2.62
4	2	0.33	0.48
5	0	0.33	0.48
6	4	5.31	7.47
7	17	9.96	13.44
8	3	2.85	3.31
9	1	3.53	4.14
10	6	14.36	16.4
11	20	10.41	11.58
12	1	1.40	1.66
Total	64	51.86	64.02

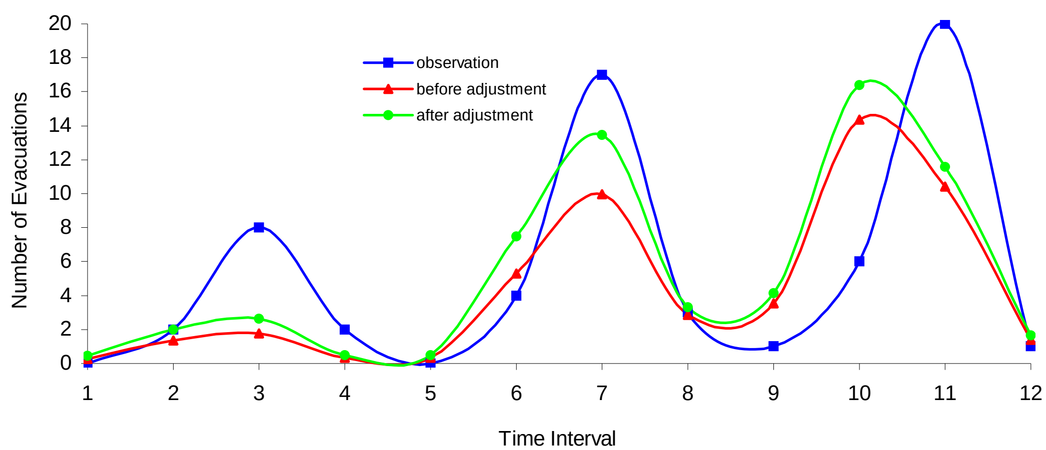
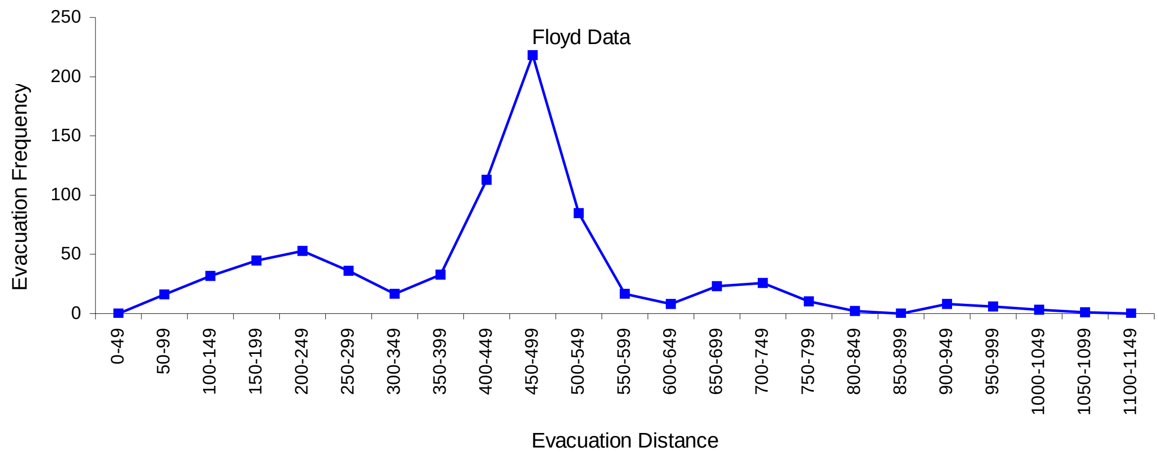


Figure 40
Observations and model predictions for transferability

In general, the model without adjustment reproduced the three-day evacuation pattern with time-of-day impact. The model predicted a total evacuation of 52 vs. the observed 64, which underestimated the total evacuation by 19.0 percent. For each of the three days, the model underestimated evacuation. After adjusting the *ASC*, the model produced the same total number of predicted evacuations as the observed. The *RMSE* reduced from 5.12 to 4.96. In terms of the sum of evacuations for each day, the modified model improved the prediction for day, one although it still was underestimated. It did very well for day two but not so well for day three. For the third day, the model reproduced the evacuation pattern relatively well, but the timing of the evacuations was offset by one time interval. More specifically, the model's predictions were one time interval before the observation. One possible reason for such a difference might be due to the weight assigned to distance. This can be shown in Figure 41, which plots the observed evacuation frequency distribution by distance for both the Andrew and Floyd data. The plot for Andrew is the 100 percent Andrew data, while the plot for Floyd is the 75 percent random sample for model estimation.



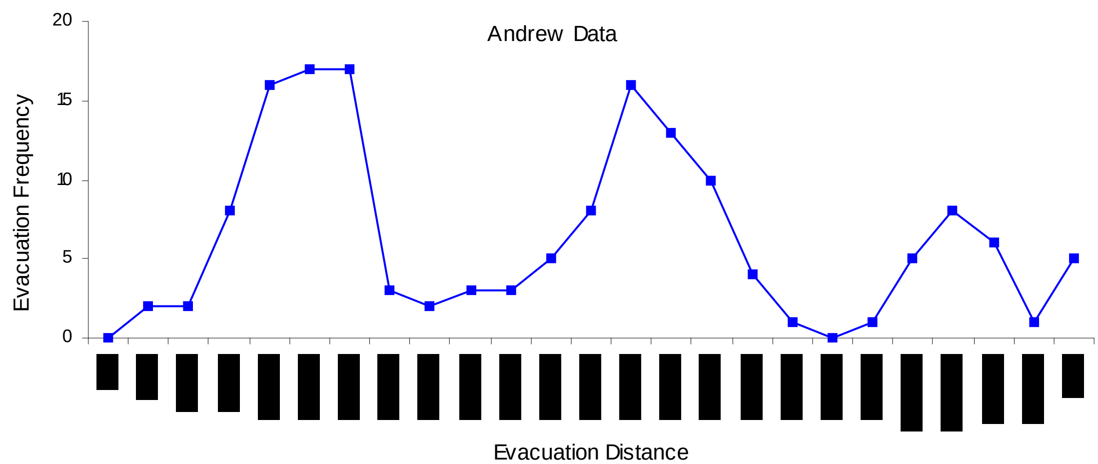


Figure 41
Observed evacuation frequency distribution by distance

From the figure, the Floyd data shows that there are four modes in the distribution. However, the second mode is significantly larger than the rest. This mode peaks when the distance is around 450 to 500 miles. The model is estimated with the weight of distance being the largest for this distance range (see Figure 9 for shape=8 and scale=0.6). On the other hand, the Andrew data shows that there are three modes; the first being the largest, and the second slightly lower. For the distance around 450-500 miles, the evacuation frequency is among the lowest. This is because it was nighttime for that distance range and evacuation tends to be the lowest at night. Having applied the same gamma distribution parameters from the Floyd data to the Andrew data, it seems that the distances in the neighborhood of 300 miles were not given correct weights. When distance was close to but larger than 300 miles, it was over-weighted; when distance was close to but smaller than 300 miles, it was under-weighted. The distance around 650-700 miles and 1000 miles was also under-weighted. As a result, the model under-predicts for the first two days, over-predicts at the beginning of the third day, and under-predicts the latter part of the third day. Therefore, to better transfer the model, further study of the treatment of distance is needed.

The fact that the two datasets were not completely compatible with each other and had to be modified for transferability study may also play a role in reducing the accuracy of model transferability. Instead of transferring the more accurate model estimated from the original Floyd data, a new model based on the modified Floyd data was estimated and applied to the Andrew data. In the new model, *TOD* only had three categories, which is contrary to four in the model estimated from the original Floyd data. Reducing the number of categories of *TOD* might hinder the model's capability to make accurate predictions. However, it seems that the impact of the weight of distance is more prominent.

To modify both the *ASC* and parameter scale is a more complicated issue. The non-linearity of equation 41 makes it difficult. Usually when applying multinomial logit models in transportation, for example in a mode choice model, some aggregate shares of mode choice are readily available. Such information can be used to update *ASC*s and/or even a scale factor for the rest of the parameters. However, for hurricane evacuation demand modeling, such information is difficult to find. As a matter of fact, the information used to adjust the *ASC*, which is the total number of evacuations, is part of what is expected of the model. Therefore, such an adjustment may not even be possible. The dilemma is that it is well known that the model's transferability will be improved if updated with some readily available local information, but at the current stage it is not even clear what such information is. This issue warrants further study.

Model Post-Processing

The model estimated through the maximum likelihood function is the binary logit model, not the sequential logit model itself. As a result, the model estimation process does not guarantee that the total value of model predicted evacuation for all time intervals for all households equals the total observed evacuation. For example, the sequential model with the Andrew data predicted a total evacuation of 128.5, while the total observed evacuation was 124 (Table 26); for the Floyd data, the model predicted a total evacuation of 241 and the observed evacuation was 246, which can be calculated from Table 29. The same procedure described by equation 41 should be used to correct this difference. Such a post-processing procedure not only ensures a valid estimation of the binary logit model but also keeps the sequential part of the model balanced with the total prediction and observation.

The Dynamic Models Developed in This Study vs. Models in Current Practice

In this subsection, the dynamic models developed in this study were compared with the models that are currently used in hurricane evacuation modeling. The purpose of the comparison is to demonstrate that the current practice cannot adequately satisfy the demand of producing dynamic evacuation predictions, while the dynamic models developed in this study can meet the challenge. Current practice in hurricane evacuation travel demand modeling is a two-step process that uses response curves to incorporate the dynamic aspect to the static assessment of evacuation demand from the participation rate models. Two comparisons were conducted. The first comparison was between the model predicted evacuation rates from our sequential logit model and those from the PBS & J model *[20]*. The data used were the Andrew data. The second comparison was between the commonly used response curves and the observed evacuation curves from the Floyd data.

Comparing the Evacuation Rates

Generally, participation rate models use simple relationships, such as means, rates, and distributions. Mei *[17]* applied the PBS & J model *[20]* to the Andrew data and gave a comparison of model predicted and observed evacuation rates for 12 parishes. The PBS & J model was a participation rate model. In this section, this information was used to compare the predictions from the sequential logit model with the Andrew data. Note that the Andrew sequential logit model is not our best model. Table 53 presents such comparison. The overall predicted evacuation rates in the table were weighted means of the predictions across the 12 parishes. However, the observed overall evacuation rates were calculated with all households, which were 410 for the PBS & J model and 350 for the sequential logit model. This difference is due to the fact that some households had missing information that was needed by the sequential logit model. As a result, the observed overall evacuation rates were different between the two models. Therefore, the percent error, which was defined as "(estimated value - observed value)/observed value" expressed in percentage, is the appropriate criterion for comparison.

Table 53
Comparing the sequential logit model and PBS & J model

Parish	PBS & J Model			Sequential Logit Model		
	Predicted	Observed	% Error	Predicted	Observed	% Error
Cameron	100.0%	100.0%	0.0%	52.4%	100.0%	-47.6%
Calcasieu	65.8%	30.1%	118.0%	25.6%	24.3%	5.3%
Jefferson Davis	37.2%	14.3%	160.0%	21.5%	14.3%	50.3%
Vermillion	66.5%	75.0%	-11.3%	34.9%	77.8%	-55.1%
Acadia	54.3%	34.6%	56.9%	28.4%	30.4%	-6.6%
Lafayette	14.8%	22.6%	-34.5%	28.9%	20.5%	41.0%
Iberia	98.6%	57.9%	70.0%	39.6%	54.5%	-27.3%
Iberville	44.7%	40.0%	12.0%	38.8%	33.3%	16.5%
St. Martin	43.6%	73.3%	-40.5%	31.4%	44.4%	-29.3%
Terrebonne	100.0%	42.9%	133.0%	51.9%	37.1%	39.9%
St. Mary	100.0%	90.3%	11.0%	48.8%	91.7%	-46.8%
Assumption	87.7%	40.0%	119.0%	36.7%	25.0%	46.8%
Overall Evacuation Rate	54.0%	42.5%	27.0%	34.3%	35.4%	3.1%

In terms of overall evacuation, the model predicted and observed evacuation rates were 54.0 percent and 42.5 percent, respectively, for the PBS & J model, compared to 34.3 percent and

35.4 percent for the sequential model, respectively. The PBS & J model had an overall percent error of 27.0 percent, which was much larger than 3.1 percent from the sequential logit model. At parish levels, the absolute value of maximum percent errors was 160.0 percent for the PBS & J model and only 55.0 percent for the sequential logit model. The *RMSE* was 29.6 percent for the PBS & J model and only 23.9 percent for the sequential logit model. It seems that the sequential logit model outperformed the PBS & J model in terms of predicting evacuation rates.

Comparing the Response Curves

A response curve is the assumed departure time distribution of evacuees, usually expressed as the cumulative percentage of evacuees evacuating by time period, and traditionally has been assumed to take on a sigmoid shape. According to how the analyst expects the evacuees to respond to an evacuation order, response curves are typically classified as "quick," "medium," or "slow." However, our study revealed a quite different shape of the response curve. In order to make a comparison, the response curves from Figure 1 and the observed and the sequential logit model predicted response curves from the 25 percent Floyd validation dataset were incorporated into Figure 42.

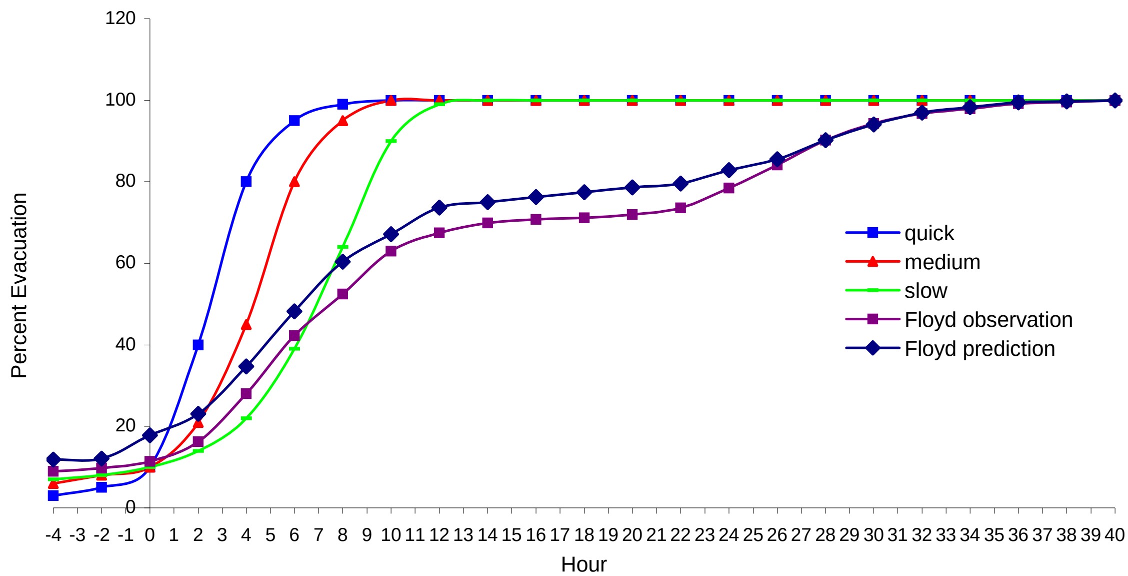


Figure 42
Floyd evacuation curve and typically used response curves

The 0 hour is time interval 28 in the Floyd model, between 6 a.m. and 7 a.m., when a voluntary evacuation order was issued. At the 6th hour, between 12 p.m. and 1 p.m., a mandatory evacuation order was issued. The assumed response curves are flat at the two ends and steep in the middle, indicating only one peak evacuation. However, the Floyd evacuation curve has two steep sections, indicating more than one peak evacuation. This reflects multi-day evacuation and time-of-day impact. None of the typically assumed response curves come close to resembling the shape of the actual Floyd evacuation curve.

However, the sequential logit model closely reproduced the observed response curve. Some disadvantages of the current response curve method can be drawn:

1. The current response curve method usually covers a shorter period of evacuation, for example, less than a day after an evacuation order is issued. However, actual evacuation may take several days, both before and after an evacuation is issued, as is the case for Hurricanes Andrew and Floyd.
2. The current response curve method takes the time when an evacuation order is issued as the reference point (zero hour), i.e., the values of time axis is relative. It cannot facilitate to study if an evacuation order should be issued; if yes, what type and when to issue. Neither can it distinguish the impact of a voluntary and a mandatory evacuation order, or a combination of both.
3. Because the values of the time axis are relative to the time that the evacuation order is issued, it is impossible for the typically assumed curves to reflect the time-of-day variation, as is seen for the Floyd response curve.
4. The response curve method is a completely separate step that bears no connection with the participation rate model.
5. The selection of the response curve is subjective, reflecting the perception of the analyst only. There is no mechanism to quantitatively analyze the impact of the hurricane characteristics, such as hurricane speed, storm track, etc. It is also an aggregate model that does not reflect the evacuation behavior of a household facing the threat of an incoming hurricane.

However, nearly all the above problems associated with the response curve method can be resolved with the methodologies discussed in this study, especially the sequential choice method. This is demonstrated throughout the analysis in this section.

Application of the Sequential Choice Model to Other Hazards

In this research, the sequential choice model was applied to study dynamic hurricane evacuation demand. Is the sequential choice model applicable to other hazard situations, such as nuclear power plant accidents, chemical spills, or even terrorist attack? To answer the question, the sequential choice paradigm used in this study needs to be revisited. The sequential choice considered in this study is based on the assumption that

1. individual household constantly reassess an approaching threat, thereby, incorporating sequential assessment as a basic characteristic of the approach;
2. conditions change over time; and,
3. people have enough time to assess the risk dynamically and make evacuation decisions accordingly.

Take the threat of a hurricane as an example. Storm advisories are issued by the National Hurricane Center showing areas that are at risk within the next 24-36 hours. Local media also provide information on the pending storm and the threat it poses. As a result, people are constantly being kept up to date with information on the hazard and how it is changing over time. For instance, the path of the hurricane may move closer to where the household lives, or it may take a different track and move away from the household; the storm may intensify, or the risk of storm surge and subsequent flooding may arise. Such dynamic information of the hurricane is readily available, helping people to assess the risk dynamically and making evacuation decisions according to the assessment of the risk. A hazard like this is an ideal candidate to apply the sequential choice model. On the other hand, in the case of a nuclear power plant accident, little warning may be provided; and the hazard may be so immense that the sequential assessment of the hazard, in which the decision to evacuate or not is made in each step of the sequence, is no longer applicable. However, if the authority has a reliable warning of an impending accident before the event, and the public is well informed of the development of the event such that people can assess the risk from the accident dynamically, then it is a sequential decision process, and the sequential choice model can be applied.

From the above analysis, whether or not the sequential choice model can be applied to a hazard depends on the specifics of the threat. If all the three conditions are met, then the sequential choice model can be applied.

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

Conclusions

The objective of this study was to address two hypotheses. The first hypothesis was that dynamic travel demand models could be developed that reproduce hurricane evacuation travel more accurately than conventional methods using evacuation participation rates and response curves. The second hypothesis was that such models could be transferred to different locations with different storm and policy conditions. Based on the study conducted in this research, the two hypotheses have been validated and the following conclusions can be drawn:

1. It is possible to produce dynamic travel demand models for hurricane evacuation that are more accurate than conventional models that use participation rates and response curves to estimate dynamic evacuation demand.

   The sequential logit model and the participation rate model from PBS & J were compared on the Andrew data. In terms of overall evacuation rates, the sequential logit model prediction had a percent error of 3.1 percent, contrasting the 27.0 percent for the PBS & J model. When compared at parish level, the sequential logit model had the maximum absolute percent error of 55.0 percent, while the PBS & J model had 160.0 percent; the sequential logit model had a *RMSE* of 23.9 percent, while the PBS & J model 29.6 percent. Clearly the sequential logit model outperformed the PBS & J model in terms of predicting evacuation rates.

   The comparisons of the response curves with the observed curve identified many problems associated with the response curve method. For example, the response curve method only covers a relatively short period of time after an evacuation order is issued, and the curves are flat at both ends and steep in the middle, indicating one peak evacuation in the middle of the evacuation. If the risk from the hurricane is high and evacuation order is issued late, a quick response curve is assumed. On the other hand, if the risk is low and evacuation order is issued early, then a slow response curve is assumed. However, the actual response curves observed from both the Floyd and Andrew data show much longer evacuation duration than those of the three typically assumed response curves. In addition, there were also several steep parts in the curve, indicating more than one peak evacuation. The conventional response curve method might be applicable to study storms in the past, but the rapid increase of coastal population versus relatively unchanged evacuation routes over the past decades *[97]* might make the conventional curve method obsolete. Hurricane Floyd was a good example. It was a large storm and caused the largest exodus in evacuation history with intensive congestion and extended delays. Other problems with the response curve method include being unable to assess the impact of the type and timing of evacuation orders, the subjective selection of a response curve, complete separation from the participation rate model, and the model's inability to include the impact of time-of-day, a variable that has been proven to have a strong impact on evacuation behavior. On the other hand, all the above problems can be resolved with the sequential logit model. This was demonstrated throughout the analysis.

Both survival analysis and sequential choice methods can model the behavior of dynamic hurricane evacuation travel demand, although the sequential models are superior to the survival analysis models because it can include dynamic variables that significantly improve the performance of the model. The two survival models lack the capacity to include the time-of-day variable in the models. The Cox model sometimes cannot include the variable evacuation order if the order is issued at the same time to all households. On the other hand, the sequential models have this capability. The inclusion of the time-of-day variable *TOD* in the sequential logit model increased the model likelihood index ratio from 0.148 to 0.197, decreased the *RMSE* from 5.85 to 2.79, resulting in a reduction of 52.4 percent in *RMSE*. Because of the popularity of the logit model, the sequential logit model is recommended over the complementary log-log model, although the two models have very similar estimated coefficients and produce almost identical predictions.

2. The sequential logit model developed in this study has demonstrated that it can reproduce the evacuation behavior observed in different locations and under different storm conditions with reasonable accuracy, i.e., the sequential logit model appears transferable. The model estimated with Hurricane Floyd data in South Carolina was applied to Hurricane Andrew data in southwest Louisiana. It reproduced the evacuation pattern with a *RMSE* of 4.53, although further study of the treatment of distance is needed. This is because the evacuation distributions by distance were different between Hurricanes Andrew and Floyd, but the same gamma distribution parameters were applied to both, causing certain values of distance being over weighted and others under weighted. The model was also applied to a set of hypothetical storm conditions to which the model estimated plausible results. For example, in the case of the Floyd data, a voluntary evacuation order was issued at time interval 28 followed by a mandatory evacuation order at time interval 31. The model estimation of the probability of evacuation for a high-risk household was 69.7 percent. However, the model predicted a probability of evacuation of only 20.3 percent if no evacuation orders were issued, 62.7 percent if a voluntary evacuation order was issued at time interval 28, and 71.2 percent if a mandatory evacuation order was issued alone at time interval 28. These results indicated that an evacuation order greatly increases the probability of evacuation; the impact of a mandatory evacuation order is only marginally larger than that of a voluntary evacuation order; and the impact of issuing a mandatory evacuation order is approximately the same as the impact of issuing a voluntary evacuation order first followed by a mandatory evacuation order. Another example was the impact of hurricane wind speed. Three different hypothetical values of speed were assumed for Hurricane Floyd, 110, 130, and 155 miles per hour, which are the maximum speeds of category 2, 3, and 4 hurricanes, respectively. A voluntary evacuation order was assumed to be issued at time interval 28.

The model predicted evacuation probabilities of 56.5 percent, 68.9 percent, and 83.0 percent respectively for a high-risk household, indicating that as the hurricane speed increases, the probability of evacuation increases accordingly. Other hypothetical storm conditions discussed in the analysis included different distance values resulting from different hurricane tracks, different forward speed, and different household risk levels.

3. The sequential logit model developed in this study uses readily available and/or easy-to-get variables in the model, which are also the major variables proven to be important in hurricane evacuation. For example, the characteristics of a household are represented only by its housing type (mobile home or not) and the propensity of the home location to flooding. The rest of the variables were either the characteristics of the hurricane, which can be obtained from public sources, such as the National Hurricane Center, *FEMA*, *NOAA*, or similar agencies; or they were variables describing evacuation policy, which are at the discretion of emergency officials. The comparison between the variables used in this study with those that were identified important by Baker *[46]* shows that the models in this study capture the major independent variables.

   The sequential logit model is easy to use. Only a binary logit model needs to be estimated, and the rest of the calculation can be easily conducted in a spreadsheet. The sequential logit model itself does not need to assume that the binary logit models for each time interval are the same. However, such an assumption greatly reduces the model estimation effort and improves the model applicability.

Directions for Future Research

During the course of this study, an increased understanding on modeling dynamic travel demand for hurricane evacuation was gained, and opportunities for further research were also identified. They are discussed below.

Treatment of Distance

The treatment of distance to the storm and its impact on evacuation behavior warrants further study. Throughout the study, the variable distance played a very important role in modeling hurricane evacuation. A logarithmic transformation was used to represent the impact of distance when modeling the Andrew data. However, for the Floyd data, a gamma distribution was used to represent the impact of distance. The impact of the logarithmic transformation is to give more weight to the distance when the hurricane is close and less weight when the hurricane is distant. However, the impact of the gamma distribution is to give more weight to distance in the middle. The weight increases gradually as the value of distance decreases when the hurricane approaches; after reaching the peak, the weight begins to decrease. In this study, distance was given the highest weight when its value was between 400 and 500 miles. It is believed the latter is a better alternative because it better represents the evacuation distribution of distance.

In addition, there seems to exist an interaction between distance and time-of-day that this study could not explore for lack of more extensive data. This was revealed from the analysis of the model transferability from Floyd to Andrew. It was suggested that the parameter selection of the gamma distribution might be different because certain values of distance that normally are associated with the maximum evacuation may fall into certain time-of-day that results either accentuates or attenuates evacuation more than the impact of distance and time-of-day on their own. Interaction between distance and other variables, such as the risk of flooding or the issuing of different evacuation orders, may also exist. Data in which these variables varied would be necessary to estimate the interaction effects.

Another issue for future research that is related to distance is determining whether "distance" is better described in terms of time to landfall (i.e., how many hours before the storm crosses the coastline) rather than the literal distance (i.e., how many miles away) as used in this study. The model estimated from the Andrew data in this study found both distance and forward speed of the storm to be significant variables, suggesting that a variable that combined them would be significant as well. However, treating them separately or combined would produce different results. This is because when they are considered separately they are considered additive terms in the utility function, and only distance is transformed with a non-linear transformation. It is likely that "time to landfall" would also need to be transformed in a similar manner to distance, although the transformation may be different. Further investigation of this aspect of the model formulation is needed.

Model transferability

Only limited transferability analysis was conducted in this study although the initial analysis showed encouraging results. More data that cover a wide range of geographic areas and hurricane categories are needed to better explore this subject. Updating *ASC*s and/or the scale of the parameters based on the aggregate shares of the population or sub-populations are something that is readily achievable in a regular multinomial logit model. However, in a sequential logit model, a binary logit model is estimated to best-fit conditions in all time intervals, and aggregate shares change for each interval. Typically, these aggregate shares are not readily available like they are in a regular multinomial logit model. For example, in a regular multinomial logit mode choice model, the alternative specific constants of a transferred model can be updated by merely knowing the aggregate modal share in the area to which the model is being transferred. On the other hand, transferring a dynamic sequential logit model to a new area would require share information (the proportion of households evacuating) for each time interval, and this is not readily available data unless a special survey is conducted. Even if such information were available, the procedure by which the parameters are updated still has to be developed.

The Impact of Time Interval Length

The impact that the length of the time interval has on the accuracy of dynamic demand estimation is unknown. Intuitively, the shorter the time interval, the more accurate the estimate. However, this will also mean there are more stringent data requirements, and the computational effort will be greater. On the other hand, if the time interval is too long, the dynamic aspect of the modeling will be lost. The optimal length of interval is likely to be a tradeoff between the accuracy of the study, the cost and availability of more detailed data, and the purpose of the study (long term, short term, or real time operation). Moreover, the impact of unequal time intervals also needs to be explored.

Model Performance at Evacuation Zone Level

In this study, the model was tested at parish level. However, ideally, the model should be able to predict the number of evacuations satisfactorily at the level of evacuation zone, which is typically much smaller than county level. Further study is needed to explore how the model performs at evacuation zone level.

Testing for State Dependency

One assumption that was made in the derivation of the sequential choice model was that the utility differences among different time intervals were independent, i.e., there is no state dependency among time intervals. This assumption needs to be satisfied to apply the sequential choice model. It is believed that this assumption can be tested by first estimating a new model, excluding one or more time intervals, and then testing for the hypothesis that the logit model parameters are the same between the new model and the original model. If independent, the hypothesis should not be rejected. The validity of this idea needs to be proved with further statistical derivation.

Detailed Categorization of Flood

In the use of the Floyd data in this study, households living in an evacuation zone that would be flooded with a category 3 storm or above were coded as households who were at risk of flooding. That is, the covariate *flood* was coded 1 if the household lived in a category 3 flood zone or above and 0 otherwise. However, intuitively, a more detailed categorization of households by a variety of factors (e.g., storm category, storm path, and storm surge potential) would seem appropriate. A more detailed definition of flooding potential and its impact on the accuracy of modeling evacuation behavior needs to be explored.

Search for Other Variables

There are other variables that may impact a household's decision to evacuate or not and were not included in this study because they did not appear within the data used. An example of such a variable is the evacuation behavior of a neighbor or the appeals of relatives and friends. Other examples include the manner in which evacuation orders are communicated, the content of the message, identification of those areas that will be affected by storm surge, and the impact that owning pets has on evacuation behavior. New covariates are to be explored and added in the model, provided such data are available.

Using SP Technique and Combining SP and RP Data

When studying hurricane evacuation, RP data are only available after an area has been hit by a storm. This limits the opportunity to collect RP data. Added to this is the fact that in an RP survey, some variables that would normally play a major role in an evacuation decision may not vary much within the storm being observed. As a result, the impact of such variables cannot be estimated in the model. On the other hand, an SP survey can be designed to investigate the impact of any variable, and it can be conducted at any time. In addition, a small sample of SP data could be useful in model transfer, providing information to update the model parameters through Bayesian updating procedures. It would seem that the potential to combine SP and RP data provides the greatest opportunity to develop and improve dynamic travel demand models for hurricane evacuation if the advantages of both approaches can be used.

Developing Dynamic O-D Table for Hurricane Evacuation

In hurricane evacuation, people's destination choice behavior is different from that of daily travel. The traditional gravity-type trip distribution model may not be applicable. Plus, the travel times between O-D pairs will not be constant but will vary from time interval to time interval. As a result, how to transform the dynamic travel demand into a dynamic O-D table is the natural challenge that follows.

Including Capacity Restraints to Dynamic Travel Demand

The models developed in this study have been estimated as if travel demand is insensitive to travel supply. That is, no explicit account has been taken of the capacity of the transportation network when estimating demand. This is a problem inherent in the basic four-step procedure developed for urban transportation planning, unless an iterative process is instituted to allow a balance to be established between supply and demand. However, such an iterative application of the travel demand and trip assignment process is seldom applied in urban transportation, primarily because demand is usually accommodated within the analysis periods commonly used in urban transportation planning. This is not the case in hurricane evacuation where evacuation demand may well exceed the capacity of evacuation routes for extensive periods of time, causing long delays that can inhibit demand as persons considering evacuating are discouraged by road conditions. Unfortunately, network conditions were not included in our model since data on the impact that road conditions have on travel demand were not available. Thus, even though the dynamic demand models developed in this study were calibrated on evacuation trips that were actually made, further development is required to make this evacuation demand process sensitive to the level of congestion on the evacuation routes. More study is needed to link demand with supply, and perhaps this can be achieved by adding an iterative feedback loop from a dynamic traffic assignment procedure to the demand estimation process or by adding a variable reflecting level of road congestions within the demand model formulation.

Predicting for the Maximum Evacuation

The model predicted evacuation probability as the sum of the expected values of each household, not the maximum values. In transportation planning it is sometimes appropriate to account for the maximum, or near maximum, value as the basis for decision making. An example is the use of the 30^{th} highest hourly volume as the design volume for a highway. In hurricane evacuation where people's lives are at risk, it may also be appropriate to plan for the worst case scenario, i.e., to plan for the situation where the model produces the maximum evacuation traffic instead of the mean. When calculating the conditional probability using the binary logit model, a standard error is available for the prediction. This makes it possible to calculate the confidence band with certain level of confidence. Hence, the demand that can be expected to be exceeded only a certain percentage of the time could be estimated. However, the actual probability of evacuation for a household in each time interval is the unconditional probabilities calculated with the sequential logit model, which uses the conditional binary logit models repeatedly. As a result, finding the maximum probability of evacuation with certain level of confidence is a more complicated problem. Further study is needed to address this problem.

ACRONYMS, ABBREVIATIONS, & SYMBOLS

Andrew	Hurricane Andrew, 1992
ANN	Artificial Neural Network
ATIS	Advanced Traveler Information Systems
ATMS	Advanced Traffic Management Systems
C Log-Log	Complementary Log-Log
DTA	Dynamic Traffic Assignment
FEMA	The Federal Emergency Management Agency
Floyd	Hurricane Floyd, 1999
IIA	Independent From Irrelevant Alternatives
IID	Identically Independently Distributed
IRZ	Immediate Response Zone
ITS	Intelligent Transportation Systems
GOF	Goodness-of-fit
LSU	Louisiana State University
MLE	Maximum Likelihood Estimation
MNL	Multinomial Logit Model
NOAA	National Oceanic and Atmospheric Administration
O-D	Origin-Destination
PAZ	Protective Action Zone
PZ	Precautionary Zone
RH	Rolling Horizon
RMSE	Root-Mean-Square-Error
RP	Revealed Preference
SP	Stated Preference
TAZ	Traffic Analysis Zone
TDM	Transportation Demand Management
TOD	Time-of-Day
TODF	Time-of-Day Factor

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