Evacuation Behavior during No-Notice Emergency Events

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THESIS

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SUMMARY

The study presented in this thesis focuses on creating a disaggregate evacuation demand model for analyzing evacuation behavior in the case of no-notice emergency events. The proposed framework is designed to be compatible with the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model for the Chicago Metropolitan Area. The study develops series of statistical and machine learning models designed specifically for each part of the evacuation decision-making process. Incorporation into an activity-based model allows for pinpointing persons and resources' location in the network, which is of most importance in the case of no-notice emergency events due to the dispersity of family members in the transportation network (which may result in additional trips to pick up family members). The models developed in this study are based on a stated preference survey that was conducted in 2012 from residents of Chicago metropolitan area.

The proposed evacuation demand model starts with identifying people's decision to evacuate (they can choose to ignore the event, shelter at their current location, or evacuate). If an individual decides to evacuate, a new activity is generated in his/her schedule whose attributes (destination, departure time, and travel mode) are determined using the models specifically developed for evacuation decisions during no-notice emergencies. Once the attributes are determined, the next phase of the model is run to form the complete evacuation tour of the individuals in two steps. In the first step, the framework simultaneously determines the total number of intermediate stops, travel time, and travel distance of the evacuation tour; next, the framework utilizes different types of models estimated based on the estimated number of intermediate stops to identify the type and order of the stops.

The last part of the model updates the activity schedule of the population; the previous activity schedule (determined by the ADAPTS model for normal conditions) is kept for those who are determined to ignore the event whereas for those who shelter in their current location, the schedule is replaced with an indoor activity until the safe situation will be announced. For those who decide to evacuate, the new evacuation activity whose attributes are determined by the models presented in this study replaces the previous activity schedule.

The framework provides a decision-support platform to help planners and emergency responders to first assess potential hazards, locating affected area and population, and investigate probable operability of transit systems for transit-dependent population. The framework is also suitable to investigate policies and strategies to re-deploying resources and understand evacuees' behavior at the time of an event to direct individuals' decision in favor of the most useful decision in order to prevent economic damages and loss of life.

1. INTRODUCTION

1.1 Background

A disaster is an event naturally or artificially caused, which can lead to infrastructure damage and loss of life. It can be in the form of natural events such as tornados, hurricanes, floods, forest fires, and earthquakes, or artificial events such as nuclear seepages and terrorist attacks. These disasters can result in sizable economic losses and fatalities and have been increasing in recent years. Only in 2016, 315 disastrous events occurred around the world, which resulted in more than 210 billion dollars of economic loss. The increased hazard becomes more evident when these values are compared to the 16-year average of 271 events per year that resulted in annual average of 174 billion dollars of economic loss (Benfield 2016). In order to reduce the damages caused by these tragedies, government agencies have been launching and supporting research projects to develop proper evacuation plans.

Generally, disasters can be categorized into two groups considering their predictability; first group comprises the predictable emergencies such as hurricanes in which treatments and possible evacuation procedures can be planned from the moment that they are predicted. In the case of these events, people in the affected areas are informed in advance by the officials and if required, are guided to safe places. These events are mostly referred to as **advance-notice** emergency events in the literature. The second group consists of disasters that are not predictable such as terrorist attacks, chemical spills, or earthquakes, where notifying the public prior to its occurrence is not feasible. In these situations, referred to as **no-notice** emergency events, it is generally considered that evacuation procedure starts immediately after the occurrence of the event when there is no time to develop comprehensive evacuation plans. Therefore, developing preconceived evacuation plans to mitigate potential damages from such events is of immense importance.

One of the major differences between the two emergency events is the dispersity of household members in the case of no-notice emergency events whereas, in advanced-notice emergencies household members are likely to plan for the event and gather in the same location. The dispersity may result in additional trips for the purpose of picking up family members (specially children) in the network, which can conflict with the evacuation procedure by adding extra trips (additional trips may even be in the opposite direction of the expected route) (S. Liu, Murray-Tuite, and Schweitzer 2012). Failing to account for these additional trips may result in underestimation of travel time that can ultimately lead to higher number of fatalities during emergencies. Therefore, it is important to observe individuals' decision-making behavior during both past emergency situations and their expected behavior in future events.

1.2 Research Gap

Evacuation behavior during advanced-notice events has been extensively studied in the literature (see, for example, (Drabek and Boggs 1968; Baker 1991; Drabek 1999; Hasan et al. 2011)). However, no-notice emergency events have not been adequately investigated mainly due to the scarcity of data. As one of the few studies focusing on evacuation behavior of people during no-notice emergency events, S. Liu, Murray-Tuite, and Schweitzer (2012) utilized a stated preference data collected in Chicago, IL and developed a logistic regression model to investigate households' child-pick up behavior during such events. Later, S. Liu, Murray-Tuite, and Schweitzer (2014) used the same source of data and incorporated household gathering, trip chaining, and mode choice models in a simulation framework to assess the network performance through different policies. Although these studies attempt to model and simulate evacuation behavior in the case of no-notice emergency events, the methods proposed cannot investigate evacuees' complex decision behavior at a disaggregated level.

On the same note, activity-based models (ABMs) aim to simulate individuals' activity-travel patterns by modeling all travel behavior aspects such as travel mode and route choices, activity location choice, and trip timing choice at disaggregated level. These models also have the ability to locate persons and resources in the transportation network which is specifically suitable for simulating people's evacuation trips in the case of no-notice events because they can determine the location of all the family members at any time. The proposed evacuation demand framework is designed to be compatible with a large-scale microsimulation activity-based model.

1.3 Research Scope

The results in this study are based on an internet-based stated preference (SP) survey conducted in Chicago metropolitan area by Argonne National Lab in 2012. In the survey, respondents were faced with multiple scenarios, each representing a no-notice emergency event that vary in terms of severity, location, type, radius of affected area, time-of-day, and government recommendation/order and were asked to state their complete evacuation tours.

The main objective of this study is to develop a comprehensive evacuation behavioral model that can be used in the Agent-based Dynamic Activity Planning and Travel Scheduling

(ADAPTS) activity-based framework (Auld and Mohammadian 2012) by adding an evacuation demand module prior to the activity execution phase. The proposed framework comprises of four steps: (i) *evacuation decision*, (ii) *evacuation planning*, (iii) *tour formation*, and (iv) *scheduling*, which are discussed extensively in the following chapters. Therefore, the specific goals of this study can be summarized as follows:

- *Evacuation decision:* presents a multivariate ordered probit model to estimate individuals' evacuation decision behavior. To do so, this study first applies a two-step clustering algorithm to group the evacuees into three distinct clusters in order to capture the heterogeneity in their decision behavior followed by estimating separate model in each cluster.

- *Evacuation planning:*

    - *Destination and timing:* presents a joint discrete-continuous model of evacuation destination and departure time choices. These two critical decisions can directly influence spatial and temporal traffic distributions in the network in case of emergency events. The joint structure is proposed to explore the interdependencies between these evacuation attributes that stem from the shared factors influencing them. The proposed joint model comprises a multinomial logit model as the discrete component to estimate evacuation destination and an accelerated hazard model as the continuous component to estimate the departure time.

    - *Mode choice:* presents a variation of one-versus-all support vector machine that is able to account for imbalanced nature of the alternatives in the dataset, which happens because most individuals who have access to their private vehicle stated that choose this mode for their evacuation trip.

- *Tour formation:*
    - *Number of stops, total distance and travel time:* estimates a joint ordered-continuous-continuous model of number of stops, total distance, and total travel time choices to capture the endogenous effect of the number of stops on other tour attributes.
    - *Type of stop:* estimates a multinomial logit model for those with only one intermediate stop, and a variation of rank ordered logit model for those with more stops in their evacuation tours.

2. LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive review of evacuation-related studies. First, the most important evacuation attributes are identified and discussed in terms their type, various possible modeling procedures, and factors that influence them. This is followed by a comprehensive review of different types of modeling and platforms used in the past studies to investigate the potential effects of a disaster on the transportation network.

2.2 Evacuation Behavior

Generally, two distinct lines of research can be recognized in the literature of evacuation participation decision. In the first line, researchers focus on analyzing the characteristics of evacuees through descriptive analysis and statistical tests (see, for example, (Fischer et al. 1995; Dow and Cutter 1998; Baker 1979; Drabek 1999; Baker 1991; Lindell, Lu, and Prater 2005)). As one of the first studies on hurricane evacuation, Baker (1979) analyzed data collected after hurricanes Carla in Louisiana and Texas, Camille in Mississippi, and Eloise in Florida to impute the most important variables that can be used to predict whether individuals evacuate after receiving warnings. The analysis comprised of conducting χ^2 test to discern the significant variables followed by computing Goodman and Kruskal's measure of association strength and checking if the predictors are significant across all hurricanes. The author found that the likelihood of evacuation is associated with receiving warnings, neighbors' evacuation decision, risk perception, and severity of the previously experienced hurricanes.

Six months after hurricane Lili in Louisiana and Texas, Lindell, Lu, and Prater (2005) conducted a survey in which respondents' perception toward the reliability of different information sources (such as authorities, news media, internet, and friends/family) was inquired. In addition to the usual demographic characteristics (e.g., age, gender, household income), they collected information regarding the key factors that played a pivotal role in respondents' evacuation decision. Using correlation analysis, they assessed the role of each factor and concluded that the variables such as proximity to coastlines, government evacuation recommendation, evacuation of social peers, and a collection of demographic characteristics such as age, gender, and number of children in the household are strongly correlated with the evacuation decision. Interestingly, as opposed to Baker (1979), they did not find any significant correlation between respondents' experience of past hurricanes and evacuation decision.

The second group of studies consider the evacuation decision from a behavioral perspective to find the direct influence of the latter characteristics on the decision to evacuate via statistical and econometrics models. For instance, Whitehead et al. (2000) conducted a phone survey following the Hurricane Bonnie from those who were affected in North Carolina and estimated a binary logit model to predict the probability of individuals' evacuation. The respondents were first questioned about their decisions during the hurricane (whether they evacuated, distance travelled, and destination of their evacuation). Following that, they were presented with hypothetical hurricanes with different severity levels and were asked to indicate whether they evacuate in each scenario. They specifically aimed to investigate the effect of hurricane severity on people's evacuation decision.

Using data collected after Hurricane Andrew in Louisiana, Fu and Wilmot (2004) developed a "sequential binary logit model" to estimate individuals' evacuation decision at different time periods prior to hurricane landfall. Later, they used a more detailed data from Hurricane Floyd in South Carolina and divided the time periods into smaller intervals (two-hour intervals) in their framework to better capture the dynamics of evacuation decision (Fu, Wilmot, and Baker 2006). Their model estimates the likelihood of evacuation within each time interval prior the storm as a function of hurricane characteristics and evacuation order from the authorities. They reached a better prediction accuracy compared to their previous study. They also checked the transferability of their proposed model to other hurricanes and found that the model can be applied on the dataset from Hurricane Andrew.

Moreover, Dash and Gladwin (2007) stated that although the severity of the emergency event per se affects the evacuation decision, individuals' perception of the intensity has greater influence on their decision. To capture this heterogeneous perception, Hasan et al. (2011) used the data that was collected after Hurricane Ivan and developed a random parameters binary logit model for estimating households' evacuation decision. Their model is able to capture unobserved heterogeneity in the population by allowing coefficients to vary across observations. Murray-Tuite et al. (2012) used a panel survey for Hurricanes Ivan and Katrina, which were consecutive storms following the same path, and developed a binary logit model of evacuation decision. They aimed to investigate whether past experiences with the same type of emergency events affect the evacuation decision. Their model captures the effect of previous decisions on evacuation participation, evacuation timing and destination, households' vehicle, and route selection strategy. They concluded that decision on evacuation participation and routing strategy stayed the same, whereas some households started their evacuation trip sooner during the Hurricane Katrina.

Turning to evacuation departure time, Sorensen (1991) used regression to uncover the factors that affect evacuation departure time. He found out that the time of warning receipt and the amount of time that the evacuee needs to prepare to leave (mobilization time) are the most significant factors in departure time decision. By using data collected in Louisiana after Hurricane Andrew, developed a "sequential binary logit" model to estimate the probability that people will evacuate at each time period before hurricane landfall. In a later study, (Fu and Wilmot 2006) estimated and compared two survival analysis models, the Cox proportional model and the piecewise exponential model. Similar to the previous study, they considered discrete time intervals and derived the evacuation probability within each time interval based on the household's demographic characteristics, event characteristics, and variables that represent decisions made by authorities.

Using the same dataset, Dixit, Wilmot, and Wolshon (2012) presented an evacuation departure time choice model while controlling for risk attitudes. They found that factors such as duration of residence in a region, time of day, and issuance of a mandatory evacuation order have significant effects on the risk attitudes. In another study, Dixit et al. (2008) showed how the psychological impact of a previous hurricane can affect the evacuation decisions in a subsequent hurricane. They used the data collected from the evacuees of Hurricane Frances and Charley in 2005, which both made landfall during a three-week period. In this study, the authors investigated the effects of the first hurricane on the second one by including an endogenous variable of evacuation participation during the first hurricane in the departure time model of the second hurricane.

Arguing that the risk responses are heterogeneous across the hurricane-affected individuals, Sadri, Ukkusuri, and Murray-Tuite (2013a) proposed a random parameters ordered probit model to capture unobserved heterogeneity in the decision about evacuation departure time. They estimated the evacuation mobilization time (time elapsed from the evacuation decision to the actual evacuation) using data from Hurricane Ivan collected from households located in Alabama, Louisiana, Florida, and Mississippi. They reported that the variables related to built-environment, characteristics of the event, and demographic characteristics are key determinants of the mobilization time. They also found that the effects of previous hurricane experience, source and time of evacuation notice received, work constraints, race, and income vary across the observations.

Using the same dataset, (Hasan, Mesa-Arango, and Ukkusuri 2013) proposed a continuous time approach for modeling the evacuation timing decision to overcome the limitations associated with the coarse discrete time intervals considered in the prior studies. They proposed a random-parameter hazard-based duration model to explore households' evacuation timing behavior. It is found that the hazard-based model can reasonably estimate the end of the duration from the moment of receiving a hurricane warning to the moment of actual evacuation. They could also capture the heterogeneous risk responses in the context of departure time decision by incorporating the random parameters approach in their model. As they reported, factors such as household's geographic location, type of the shelter, location and time to reach the destination in normal time, time between decision and actual evacuation, living in a mobile house, education status, income level, and the type of evacuation notice (mandatory or optional) have significant effect on departure time decision.

From a different perspective, Ng, Diaz, and Behr (2015) investigated the departure time choice behavior in hurricane evacuations of people with special needs (i.e., medically fragile population) in their study. Using data from a large-scale phone survey conducted after hurricane Irene, they applied an ordered logit model to investigate the differences between evacuation behavior of people with special needs and other population groups. They identified key variables that influence the evacuation departure time of these two population groups and found that fundamental differences exist between their evacuation behavior.

Moving to evacuation destination choice models, earlier studies showed that if people decide to leave the affected area, they mostly go to public facilities or friends and relative homes. These studies have used a variety of methodological approaches that generally focus on aggregated (or zone-based) data. These methods range from trip distribution gravity models (Wilmot, Modali, and Chen 2006) to zone-based discrete choice models (Cheng, Wilmot, and Baker 2008). In this line of research, Charnkol, Hanaoka, and Tanaboriboon (2007) developed an emergency trip destination model using the binary logistic regression and neural network models. They estimated the probability of selecting evacuation destinations between public and private shelters. Two separate sets of models for permanent residents and transients are presented. They found that variables such as safety and security, medical support, comfort and convenience, and availability of food and beverage attribute significantly affect the shelter choice behavior of evacuees.

Cheng, Wilmot, and Baker (2008) presented two separate zonal-level multinomial logit models for friends/relatives and hotel/motel choices. They aggregated destination zones based on the risk due to hurricane and natural geographic features, and considered twenty-eight destination alternatives in their study. They found that the choice of evacuation destination is significantly affected by the distance of the corresponding trip and the attributes of the destination zone including risk, white population, total population, presence of a major metropolitan area, number of hotels, and presence of an interstate highway. Later, Mesa-arango et al. (2013) developed a household-level nested logit model to identify the variables influencing destination type choice among four alternatives of: “houses of friends and relatives”, “hotels”, “public shelters and churches”, and “others”. They used data from Hurricane Ivan in 2004 to calibrate the model. More recently, Parady and Hato (2016) estimated a spatially correlated logit model of evacuation destination choice in the context of tsunami evacuation. They found that land-use and built-environment factors such number of buildings and designated shelters significantly affect evacuation destination choice. A summary of the reviewed studies is presented in Table 2.1.

Table 2.1. Summary of Studies on Evacuation Departure Time and Destination Choice

Author	Spatial context & data	Model	Choice set description
(Sorensen 1991)	Hazardous materials incident (March 1987): 578 respondents in Naticoke, Atlatna	Ordinary least square regression	Continuous time
(Fu and Wilmot 2004)	Hurricane Andrew (Aug 1992): 156 households in southwest Louisiana	Sequential logit model	Discrete time intervals: 12:00 am-6:00 am, 6:00 am-12:00 pm, 12:00 pm-6:00 pm, and 6:00 pm-12:00 am (for 3 consecutive days)
(Fu and Wilmot 2006)	Hurricane Andrew (Aug 1992): 156 households in southwest Louisiana	Cox proportional hazard & piecewise exponential model	Discrete time intervals: 12:00 am-6:00 am, 6:00 am-12:00 pm, 12:00 pm-6:00 pm, and 6:00 pm-12:00 am (for 3 consecutive days)
(Dixit et al. 2008)	Hurricane Frances (Aug 2004): 454 respondents in Florida	Ordered probit model	Discrete time intervals: 1 h or less, 2-3 h, 4-6 h, 7-24 h, and more than 24 h
(Dixit, Wilmot, and Wolshon 2012)	Hurricane Andrew (Aug 1992): 157 households in southwest Louisiana	Regression model	Discrete time intervals: 12:00 am-6 am, 6 am-12 pm to noon, noon to 6 p.m., 6 p.m. to 12 am.
(Sadri, Ukkusuri, and Murray-Tuite 2013a)	Hurricane Ivan (Sep 2004): 457 randomly selected households in Florida, Alabama, Mississippi and Louisiana	Random parameters ordered probit model	Discrete time intervals: 1 h or less, 2-3 h, 4-6 h, 7-12 h, 12-24 h, and more than 24
(Hasan, Mesa-Arango, and Ukkusuri 2013)	Hurricane Ivan (Sep 2004): 3200 households in Florida, Alabama, Mississippi, and Louisiana	Random-parameter hazard-based model	Continuous time
(Ng, Diaz, and Behr 2015)	Hurricane Irene (Aug 2011): 539 HH in Virginia and North Carolina	Ordered logit model	Discrete time intervals: after landfall, up to 24 h prior to landfall, 24-48 h prior to landfall, and more than 48 h prior to landfall
(Charnkol, Hanaoka, and Tanaboriboon 2007)	Indian Ocean earthquake & tsunami (Dec 2004): 633 individuals in Phuket Thailand	Binary logistic regression model & Neural Network model	Public shelter vs. private shelter (two separate models for permanent residents and transients)
(Cheng, Wilmot, and Baker 2008)	hurricane Floyd (1999): 1040 HH in South Carolina	Multinomial logit model	28 TAZ options (two separate models for friends/relatives & hotel/motel)
(Mesa-arango et al. 2013)	Hurricane Ivan (Sep 2004): 1,419 HH in Florida, Alabama, Mississippi, and Louisiana	Nested logit	4 options: Public shelters and churches, Hotels, Friends and Relatives, Other
(Parady and Hato 2016)	Great East Japan tsunami (March 2011): 10,603 individuals in Kesennuma city, Japan	Spatially correlated logit model	The study area is tessellated into a 1-km-square zone mesh, which is used as the spatial unit of analysis and constitutes the universal choice set

Review of literature focusing on the evacuation mode choice behavior highlights the dearth of research in this area; that is largely because evacuees tend to use their own vehicle for leaving the unsafe place (Lindell and Prater 2007; Wilmot and Gudishala 2013; Wu, Lindell, and Prater 2012), which is not always the optimal choice (Murray-Tuite et al., 2012a). As one of the few studies on evacuation mode choice behavior, Kang et al. (2007) investigated the difference between peoples' stated evacuation mode and their actual decision and concluded that their behavior mostly aligns with their stated preferences. In a more recent study, Sadri et al. (2014b) developed a nested logit model for the transit-dependent sector of the population and analyzed their mode choice decision during a hypothetical major hurricane. With regards to the no-notice emergencies, Liu et al. (2014) estimated a decision tree for the evacuation mode choice decision in their simulation framework. They found that vehicle access and decision to pick-up another family member are the most influential factors in evacuees' mode choice decision.

2.3 Modeling Techniques

This chapter presents a detailed review of different methodological approaches used to model and investigate evacuees' behavior and the resulting network conditions during emergency events. To develop the most efficient emergency plans, past studies introduced several types of models, which can be classified into three groups; namely simulation-based models, optimization, and statistical models. Table 2.2 provides a brief list of a representative sample of these approaches. The following sub-chapters provide examples of their relevance to emergency evacuation modeling.

Table 2.2. Summary of Previous Research in Evacuation Modeling

Methodological approaches	Previous research
Statistical Models	(Baker 1991; Lindell, Lu, and Prater 2005; Fu and Wilmot 2004, 2006; Fu, Wilmot, and Baker 2006; Cheng, Wilmot, and Baker 2008; Henson, Goulias, and Golledge 2009; Robinson and Khattak 2010; Auld et al. 2012; S. Liu, Murray-Tuite, and Schweitzer 2012; Mesa-arango et al. 2013; Hasan, Mesa-Arango, and Ukkusuri 2013; Sadri, Ukkusuri, and Murray-Tuite 2013a, 2014)
Optimization Models	(Hobeika and Kim 1998; Ziliaskopoulos 2000; Barrett, Ran, and Pillai 2000; Peeta and Ziliaskopoulos 2001; Kwon and Pitt 2005; Lin 2001; Ying Liu, Lai, and Chang 2006; Tuydes and Ziliaskopoulos 2006; Y.-C. Chiu et al. 2007; Yue Liu et al. 2008; Zheng et al. 2010; Sayyady and Eksioglu 2010; Xie, Lin, and Travis Waller 2010; Bish and Sherali 2013)
Simulation-based Models	(Moeller, Urbanik, and Desrosiers 1982; Sheffi, Mahmassani, and Powell 1982; Stone 1983; Stern and Sinuany-Stern 1989; Southworth, Janson, and Venigalla 1992; Hobeika and Kim 1998; Algers et al. 1998; Brachman and Church 2009; Cova and Johnson 2002; Zou et al. 2005; Dixit, Ramasamy, and Radwan 2008; Henson, Goulias, and Golledge 2009)

2.3.1 Statistical models

One of the key elements of evacuation models is to determine the adequacy level of informing the public about the disaster and expecting their behavior in response. Before the emergence of behavioral models, studies usually assumed some underlying presumptions about individual behavior that were anticipated to be true; but they often produced imprecise results. For example, although it is generally assumed that tenants tend to evacuate the building in the case of fire emergency, some recent research showed that approximately two third of the injuries and half of the fatalities resulting from fires are due to people’s decisions and actions that they perform instead of evacuating the building (e.g., trying to put out the fire or collecting their belongings).

To capture the effect of individuals’ decision-making during emergencies, it is important to observe how individuals have behaved during previous emergencies so that we can predict how they are likely to act during future events. Indeed, exploration of these factors can lead to preventing occurrence of gridlocks in the network and ultimately reducing economic damage and loss of life. Considering the behavioural aspects of evacuees' decision behaviour toward these parameters is imperative to identify the most influential factors in their evacuation planning process.

The literature on emergency evacuation consists of multiple research streams focusing on various aspects of evacuation decision including the evacuation participation decision (see, for example, (Baker 1979; Lindell, Lu, and Prater 2005; Fu, Wilmot, and Baker 2006; Fu and Wilmot 2004; Baker 1991; S. Liu, Murray-Tuite, and Schweitzer 2012; Hasan et al. 2011)), evacuation timing decision (see, for example, (Dixit, Wilmot, and Wolshon 2012; Sadri, Ukkusuri, and Murray-Tuite 2013a; Hasan, Mesa-Arango, and Ukkusuri 2013; Ng, Diaz, and Behr 2015; Fu, Wilmot, and Baker 2006; Fu and Wilmot 2004), evacuation destination choice (see, for example, (Charnkol, Hanaoka, and Tanaboriboon 2007; Yue Liu et al. 2008; Mesa-arango et al. 2013; Parady and Hato 2016), and evacuation route choice (see, for example, (Carnegie and Deka 2010; Robinson and Khattak 2010; Wu, Lindell, and Prater 2012; Sadri, Ukkusuri, and Murray-Tuite 2014)). However, the majority of the studies do not focus on no-notice emergency events due to lack of available data.

2.3.2 Optimization Models

Optimization-based models provide the best possible solution for any given problem. Generally, two types of optimization models have been used for evacuation modeling. First group corresponds to static optimization models that assume network's level of service remains steady over the examination period. However, traffic conditions constantly change due to the dynamic nature of disasters (Zhang et al. 2010). Therefore, these models cannot correctly consider congestion or traffic propagation occurrence in a network and thereby they result in evacuation plans that may significantly differ from the best. This restriction holds back the application of static models in evacuation procedure.

On the other hand, dynamic optimization models use Dynamic Traffic Assignment (DTA) approach, which formulate the problem in separate time-settings. These models can account for the dynamic nature of traffic flow during evacuation and therefore, they have been widely utilized in evacuation studies. Barrett et al. (2000) proposed a dynamic evacuation framework, which can model both long and short-term plans during hurricane evacuation. Further, the Cell Transmission Model (CTM), developed by Daganzo (1995, 1994), was used to form a DTA model by Ziliaskopoulos (2000). The basic idea of this model is to change links into homogeneous segments able to be crossed in a unit of time by free flow speed. As one of the few studies looking into no-notice events, Kermanshah and Derrible (2016) combined a GIS and network science to propose a new method which can measure the vulnerability of transportation network after earthquakes.

2.3.3 Simulation-based Models

Simulation-based models are designed to examine the evacuation plans by replicating the traffic conditions in the transportation network over time by using previously estimated traffic operation models. These models are in fact the same ones that are generally used for traffic simulation with minor adjustments to simulate traffic during emergency situations. A few studies developed software packages that were specifically designed for evacuation process of nuclear plant emergencies. As one of the earliest studies on this topic, Sheffi, Mahmassani, and Powell (1982) developed a model called NETVAC1 to simulate nuclear evacuation procedure. NETVAC1 is a macrosimulation model with continuous time domain that utilizes traffic condition models to simulate the evacuation process; thus, approximates evacuation measures such as total evacuation time[1] and clearance time[2].

NETVAC1 assumes that drivers decide the route based on their earlier knowledge of the network and limited understanding of current traffic conditions. This model can manage large networks at low computational expenses, and is capable of assessing a wide range of evacuation plans to provide a range of outputs such as flows, queues, speeds and travel time during the course of the evacuation process. The disadvantage of this model is that it has pre-specified evacuation plans with some general assumptions about individuals regardless of evacuees' decision behavior.

Later, several major hurricanes hit the United States coasts that resulted in a shift of the focus of emergency evacuation simulation models to hurricanes. For example, MASSVAC is a simulation model designed by Hobeika and Kim (1998), only for hurricane evacuation. The model has two levels of examination, a macroscopic and a microscopic level. The macroscopic level simulates the evacuation process on a network of only major roads. This level offers the maximum evacuation time estimation under various hurricane severity and traffic circumstances. The microscopic level focuses on a small network in detail, which is most suitable for analyzing congestion at intersections and lane obstructions due to accidents. The MASSVAC is able to use both all-or-nothing and user equilibrium (UE) traffic assignment techniques. Other simulation

[1] Elapsed time between the time that evacuees receive become aware of an emergency and the time that they start their evacuation procedure.
[2] Time necessary for all people to evacuate and reach their final destination.

models have also been designed for evacuation procedures such as OREMS, CLEAR, DYMOD, EVACD, SNEM, and ETIS (Moeller, Urbanik, and Desrosiers 1982; Stone 1983; Stern and Sinuany-Stern 1989; Southworth, Janson, and Venigalla 1992).

Finally, general traffic simulation software packages such as NETSIM, PARAMICS, DYNASMART-P, CORSIM, VISSIM may be used to simulate evacuation procedures. Chrurch and Sexton (2002) used PARAMICS simulation package to estimate the clearance time under different evacuation scenarios considering multiple arrangements of travel demand and traffic conditions. Cova and Johnson (2002) investigated a case study using PARAMICS for a wild fire emergency in Utah but concluded that this software is unable to account for traffic operation models (i.e., route-choice, car-following etc.). One of the major problem in evacuation models is that drivers' logic for route selection is assumed to be either (i) choosing the shortest path or (ii) limited understanding of the network. Unless tied to more general route selection models, which are able to capture the evacuees' complete decision behavior, these simulation packages may not be suitable for evaluating emergency evacuation procedures in large urban areas (Zhang et al. 2010).

3. PROPOSED FRAMEWORK

This section elaborates on the proposed evacuation demand model which aims to simulate individuals' evacuation behavior during no-notice emergency events. Since the proposed evacuation demand model is designed to be compatible with the structure of the ADAPTS activity-based framework, this section briefly presents its overall modelling structure. ADAPTS is an agent-based microsimulation travel demand model, which simulates individuals' activity-travel decisions in three distinct steps, as illustrated in Figure 3.1.

The simulation process starts by identifying the individual's need for generating a new activity of a certain type. This step is called *activity generation* in which competing hazard models derive the probability of each activity type based on the time spent since that specific activity type was previously performed. After generating an activity, the planning horizons of activity attributes (i.e., start time, duration, location, party composition, and travel mode) are determined by the attribute planning order model. This model which is a multivariate ordered probit model estimates the time in which each activity attribute will be decided (Auld and Mohammadian 2012). Therefore, as a unique feature of the ADAPTS model, various activity attributes can be determined in different time horizons.

The second step, called *activity planning*, corresponds to estimating the actual values of activity attributes. As the simulation time reaches an attribute's decision-making time (which is previously determined by the attribute planning order model), the corresponding model is called to estimate the value of that specific attribute (Auld and Mohammadian 2012). Therefore, depending on the order of attribute plan horizons, outcome of some attributes' decisions can affect the decisions on the undecided attributes (Shabanpour, Golshani, Auld, et al. 2017; Golshani et al. 2017).

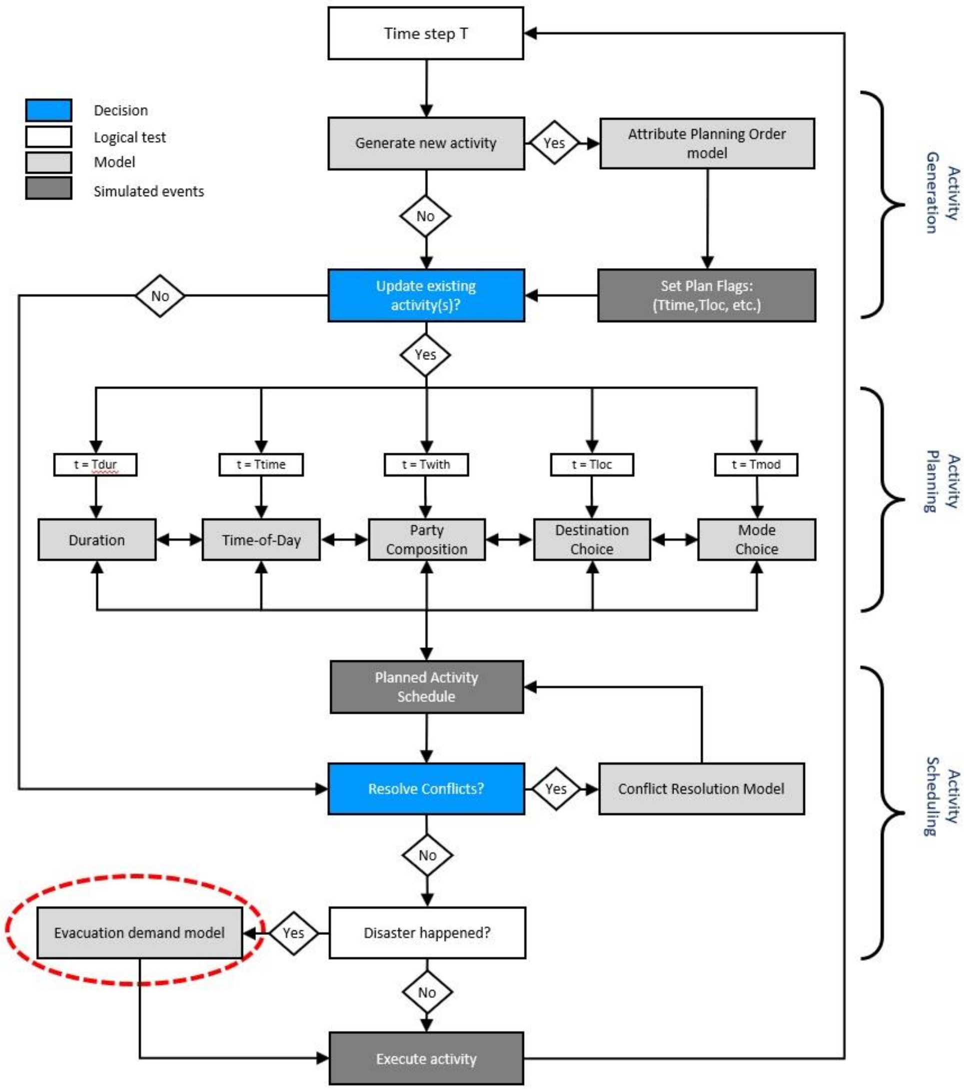


Figure 3.1. Overall Framework of the ADAPTS Activity-based Model

The last step of the ADAPTS framework, refer to as *activity scheduling*, updates the activity schedule of each agent by adding the completely planned activities and resolves the potential conflicts between the new activities and those that are already scheduled. The resolution strategies that are used in the conflict resolution module include shortening, shifting, and splitting either of the new or previously scheduled activities, with the overall aim of minimizing the total changes in start time and duration of involved activities in the conflict instance. Detailed information about different steps of the ADAPTS framework can be found in (Shabanpour, Javanmardi, et al. 2017; Shabanpour et al. 2018; Shabanpour, Golshani, Auld, et al. 2017; Auld and Mohammadian 2012).

Consistent with the ADAPTS structure, the proposed evacuation demand model is designed to be placed prior the activity execution step and is called only if a disaster has happened in the corresponding time step, as illustrated in Figure 3.1. Once the evacuation model is called, it estimates the new travel demand and updates individuals' activity schedule. An overview of the proposed evacuation behavior framework is presented in Figure 3.2. The framework comprises of four main steps: (1) evacuation decision, (2) evacuation planning, (3) tour formation, and (4) schedule update.

The first step deals with the decision to evacuate; individuals may decide to either ignore the emergency situation, shelter in their place, or evacuate. To do so, clustered-based multivariate ordered probit models estimate individuals' evacuation decision behavior in the context of no-notice emergency events. In the analysis, first, a two-step clustering algorithm was applied to group the evacuees into three distinct clusters in order to capture the heterogeneity in their decision behavior. Second, a multivariate ordered probit model was estimated within each cluster to determine the probability of selecting each of the three options of ignoring the situation, seeking shelter at the place, and evacuating to a safe place. In the first case, individuals ignore the event and follow their previously determined activity schedules (i.e., the activity schedule determined by the ADAPTS model for a typical day). In the second case, they will stay in the same place that they were at the time of the event and an indoor activity will replace their formerly scheduled activities until the safe situation will be announced. In the last case, individuals decide to evacuate to safe place. In this case, a new evacuation activity will replace the routine activity schedules of evacuees. The attributes of the evacuation activity will be determined in the next steps of the framework.

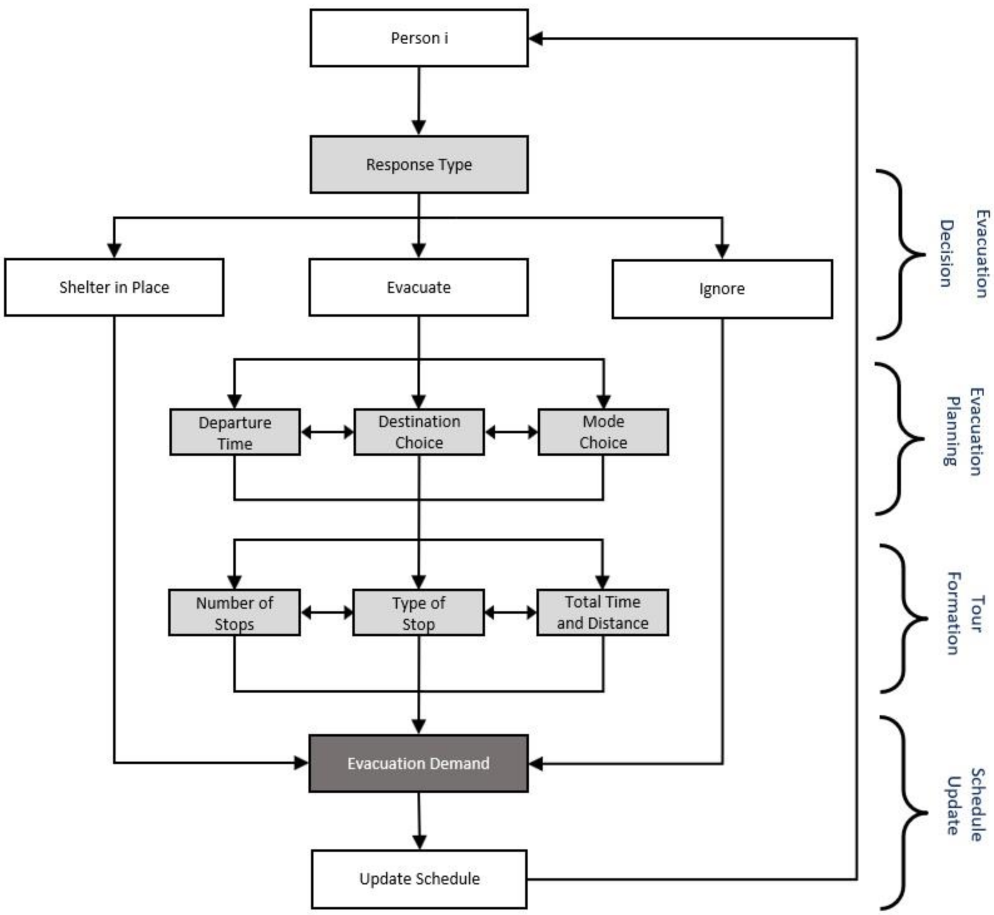


Figure 3.2. Overall Framework of the Proposed Behavioral Evacuation Model

The second step, named as the *evacuation planning* detailed in Chapter 6, identifies some of the main attributes of the newly generated evacuation activity. In this step, first, a joint discrete-continuous model estimates the evacuation destination and departure time choices. These two critical decisions can directly influence spatial and temporal traffic distributions in the network in case of the emergency events. The joint structure is proposed to explore the interdependencies between these attributes that stem from the shared factors influencing them and/or the causal effects that they might have on each other. The proposed joint model comprises a multinomial logit model as the discrete component to estimate evacuation destination and an accelerated hazard model as the continuous component to estimate the departure time. Next, a support vector machine is estimated to model evacuees' mode choice decision.

The third phase, named as *tour formation*, corresponds to identifying the total number of intermediate stops, type of these stops, total travel distance, and travel time of individuals' evacuation tours. This is presented in Chapter 7, where firstly a joint ordered-continuous-continuous model estimates the total number of stops, total distance, and total travel time of the evacuation tours. The joint structure is proposed to capture the endogenous effect of number of intermediate stops in total travel time and distance, as well as the interrelations between the three variables. Secondly, the type of the intermediate stops (e.g., pick-up family members, shop for supplies, etc.) is determined using a multinomial logit model for those with only one intermediate stop, and a rank ordered logit model for those with more stops in their evacuation tours.

Finally, in the schedule update phase of the proposed framework, evacuees' routine activity schedules (that were formed by the activity-based model for a typical day) are updated. Indeed, the new evacuation activity whose all attributes (i.e., departure time, destination, and evacuation mode, etc.) are determined will replace the previous schedule.

4. DATA

4.1 Introduction

The data used in this study is derived from an internet-based stated preference (SP) survey for the case of no-notice emergency events (Auld et al. 2012), which is conducted by the Argonne National Laboratory in 2012 from Chicago metropolitan area. The data is collected through an online platform with access to Google Maps API that allows for collecting detailed information regarding the location of respondents and their family members in a typical day.

The survey is conducted in three phases. First, detailed demographic and vehicle-use information of 521 respondents and their household members is collected. The dataset consists of 45% male and 55% female respondents who live in Chicago metropolitan area. As for the occupation status, the data contains 60% full-time workers, 10% part-time workers, 8% unemployed, 13% retired, 5% students, and 4% other categories. With respect to household income level, 30% of respondents' households have annual income below $50k, 40% have annual income between $50k and $100k, and the remaining 30% earn more than $100k per year. A full description of the survey, descriptive statistics, and validation of the data can be found in Auld et al. (2012).

In the second part of the survey, participants were presented with two random emergency scenarios. The designed scenarios vary in terms of timing, severity, risk, location, radius of the event, and government recommendation. The time of the event is randomly selected from three options of 9:00 am, 2:00 pm and 7:00 pm. The location of each household member was also asked at each time option. Considering the locations of the household members, an emergency scenario was designed in a proximity of one of the household members at the randomly chosen time-of-day. There were also three levels considered for describing the impact radius of the event (i.e., 5, 10, and 20 miles) and the risk level (i.e., low, moderate, and high), which were randomly assigned to each scenario. Finally, two types of government recommendations (i.e., evacuate or shelter in place) were considered in the emergency scenario design. Figure 4.1 illustrates the location of a random respondent and his/her family members at the time of an emergency event.

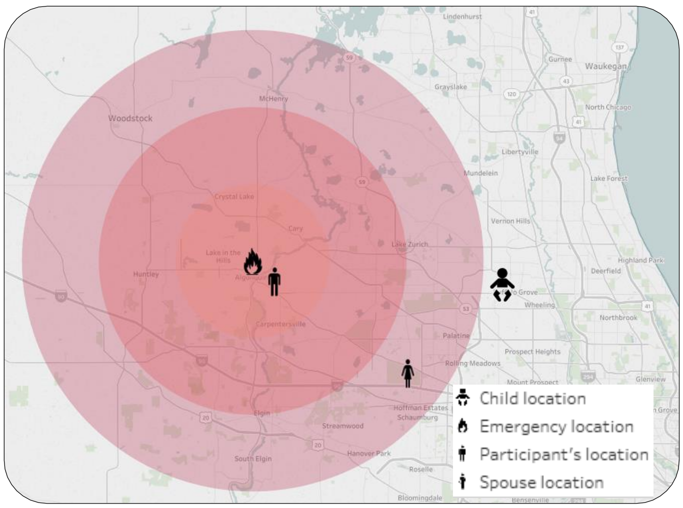


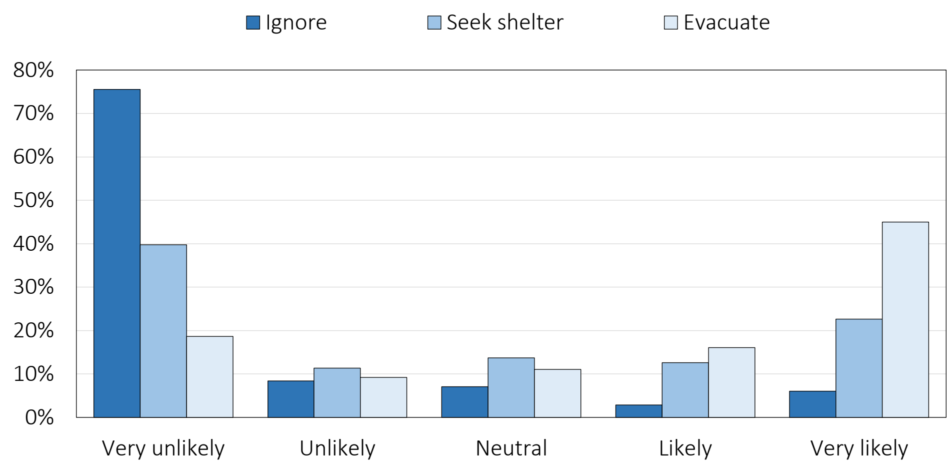
Figure 4.1. Example of Collected Locations Information with Impact Radii of 5, 10, and 15 Miles

4.2 Evacuation Decision

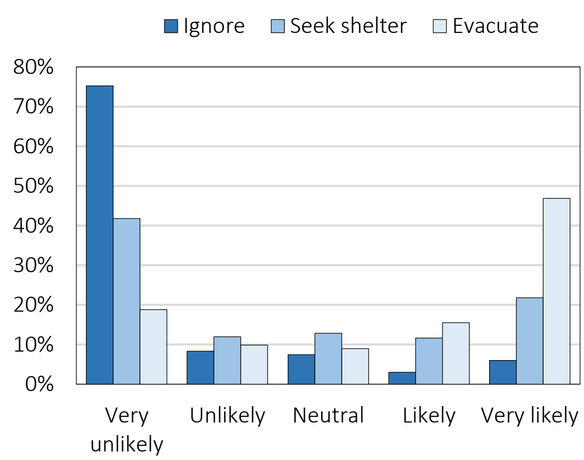
As the response variable for evacuation decision, respondents were asked to indicate how likely (in a five-point scale ranging from very unlikely to very likely) they make these three decisions:

1) Go about your day as usual and ignore the situation (hereinafter *ignore*)
2) Stay where you are and seek shelter at the place (hereinafter *seek shelter*)
3) Evacuate to a safe place (hereinafter *evacuate*)

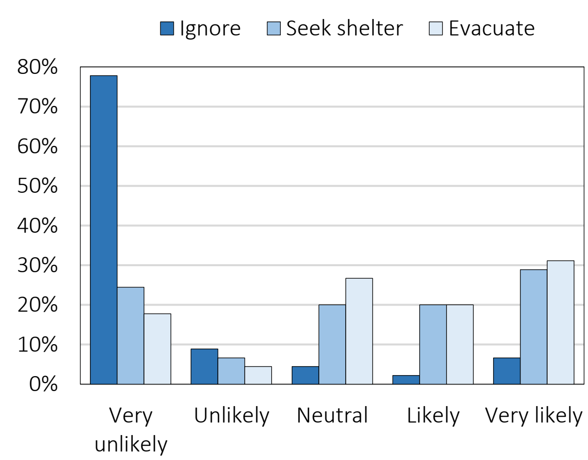
Participants' responses in multiple scenarios are the basis for estimating their decision to evacuate during no-notice emergency events. Using Likert scale questions that offer a complete spectrum of options allows the respondents to give their true opinions toward evacuation decision in a hypothetical situation. Figure 4.2(a) presents the general distribution of respondents' evacuation decision. For example, it indicates that 75% of respondents are "very unlikely" to ignore the emergency event whereas about 5% are "very likely" to ignore the situation.



(a) General Evacuation Decision



(b) Access to a Vehicle



(c) No Access to a Vehicle

Figure 4.2. Participants' Responses to Hypothetical No-notice Scenarios

Furthermore, analysis of the data reveals that out of those who are very unlikely to ignore the emergency event, 54% and 22% are very likely to evacuate and seek shelter, respectively. This heterogeneous behavior can arise from either observed factors (e.g., event severity, vehicle ownership) or unobserved factors (e.g., risk perception) that affect evacuation participation decision. For instance, Figure 4.2(b) and Figure 4.2(c) compare respondents' evacuation decision when they have access and they do not have access to a vehicle at the time of emergency event. These figures indicate that access to vehicle increases the tendency for evacuation while those who do not have access to vehicle are more willing to seek shelter at the place. Intuitively, vehicle accessibility makes trivial changes in the likelihood of ignoring the event.

4.3 Evacuation Attributes

Respondents were also asked about their potential trips after the occurrence of the emergency event. The collected trip information includes number of stops, the reason for each stop (e.g., pick up children from their school), and the type and location of final evacuation destinations. Destination types that are considered in this study are evacuation shelter, hotel/motel, stay/return home, and stay with family and friends, hereafter referred to as *shelter*, *hotel*, *home,* and *family*, respectively. Figure 4.3 presents the distribution of destination choices in the dataset, which indicates that 53.54% of the respondents would travel to shelters whereas only 4.17% would select hotel as their destination. Figure 4.3 also shows that 30.42% of respondents would return home and 11.88% prefer to stay with their family.

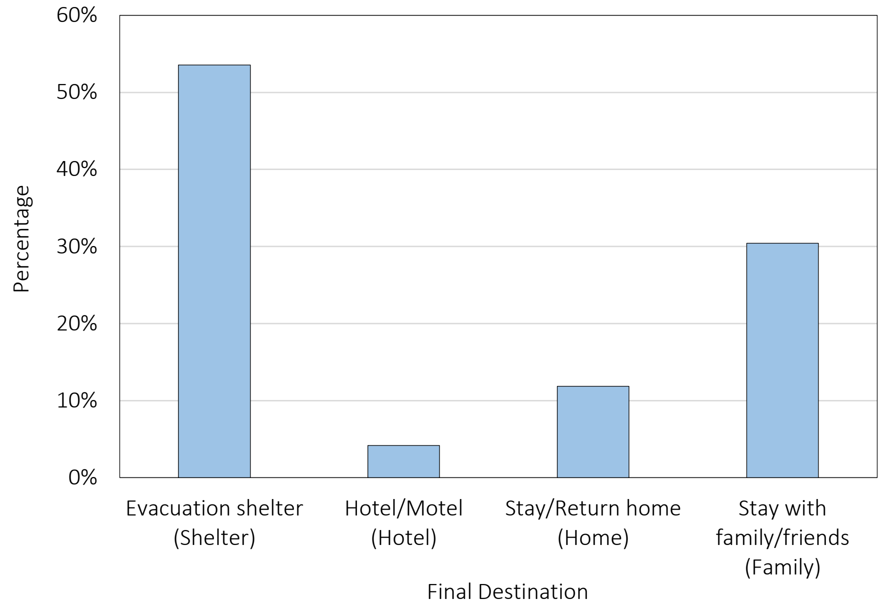


Figure 4.3. Destination Choice Distribution

As for the evacuation departure time, Figure 4.4 presents the distribution of departure times in the dataset, which reveals that 48% of respondents start their tours within the first 30 minutes after the emergency event occurrence; that is expected in the case of no-notice evacuation. Further, more than 90% of the respondents stated that they would evacuate within 180 minutes after the event occurrence. Furthermore, to investigate the dependence of departure time and destination choice decisions, Figure 4.5 illustrates the distribution of evacuation departure time conditioned on the destination. Different patterns of departure time distributions reveal that this variable highly depends on the selected destination, which reflects the need for a modeling approach that can account for the interdependence between the two variables.

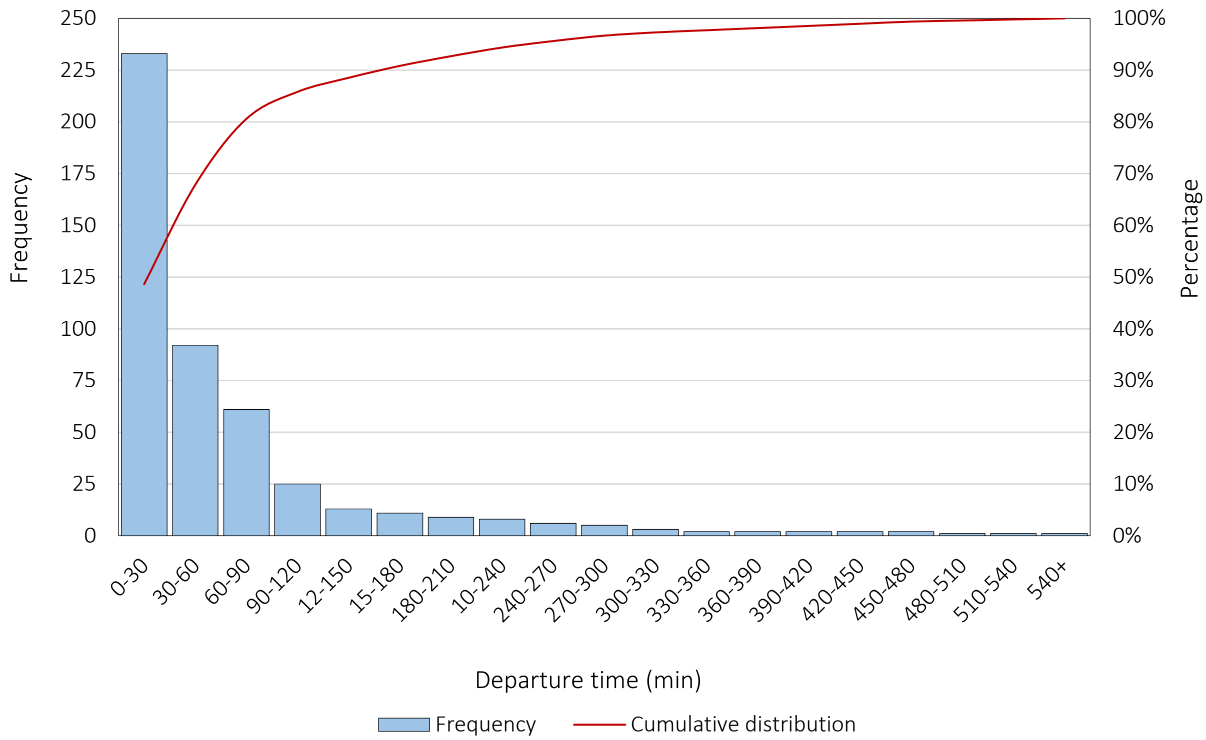


Figure 4.4. Evacuation Departure Time Distribution

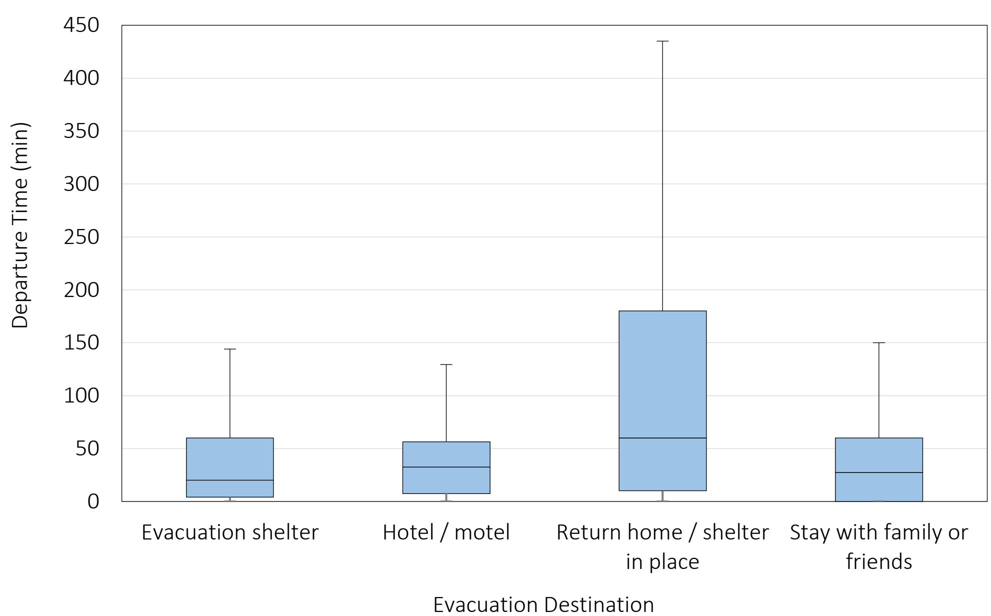


Figure 4.5. Distribution of Departure Times Across Destination Choices

Moreover, respondents were asked to indicate their choice of travel mode when faced with the hypothetical scenarios events. Analysis of the data reveals that 89.36% of the participants intend to drive their own vehicle during no-notice emergencies whereas 3.64%, 3.64%, and 3.36% will rely on CTA, Metra, and friends and family to evacuate, as illustrated in Figure 4.6.

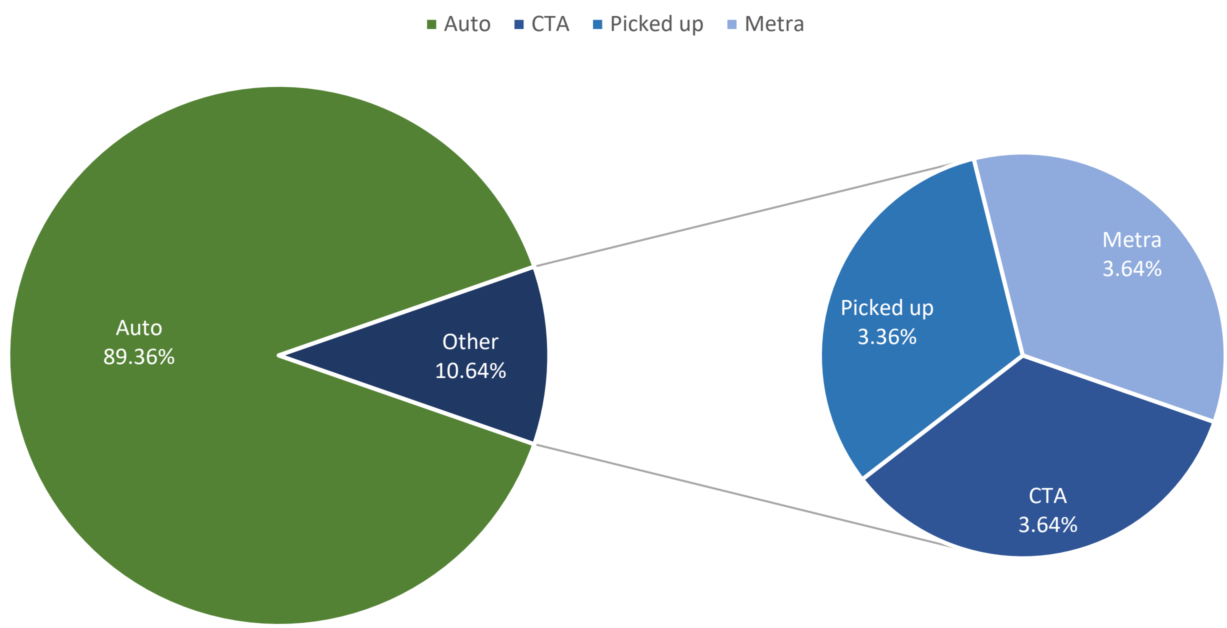


Figure 4.6. Mode choice distribution

4.4 Evacuation Tour

Respondents' stated tours were formed (as illustrated in Figure 4.7(right)) and the corresponding tour- and trip-related variables such as total number of trips, trip travel time and distance, and total tour travel time and distance were extracted from Google Maps API. Figure 4.7 depicts the formed tours with red dots showing the final evacuation destinations. Moreover, Figure 4.8 presents the distribution of total distance of evacuation tours for each type of destination. The figure shows that most respondents tend to evacuate to a nearby safe place as the number of respondents who stated that they would travel for less than 100 miles is higher than other distances in nearly all destination types. The figure also reveals that respondents who prefer to stay with family/friends are willing to commute longer distances compared to those who select other destination alternatives.

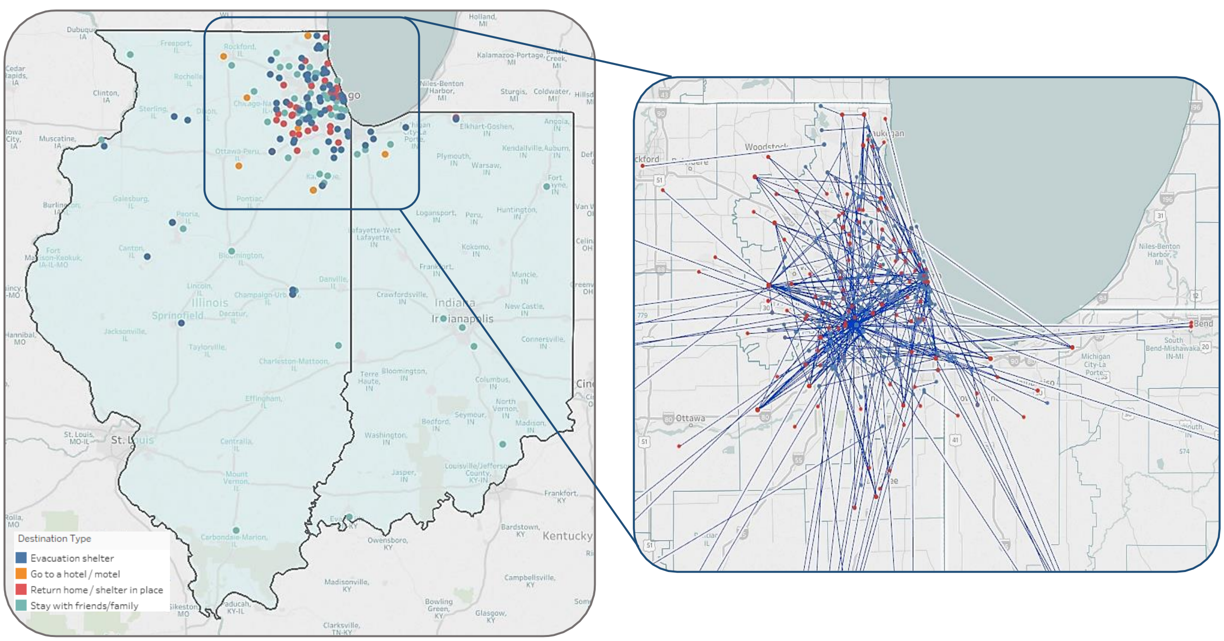


Figure 4.7. Evacuation Destination Type (left) and Tour Formation (right)

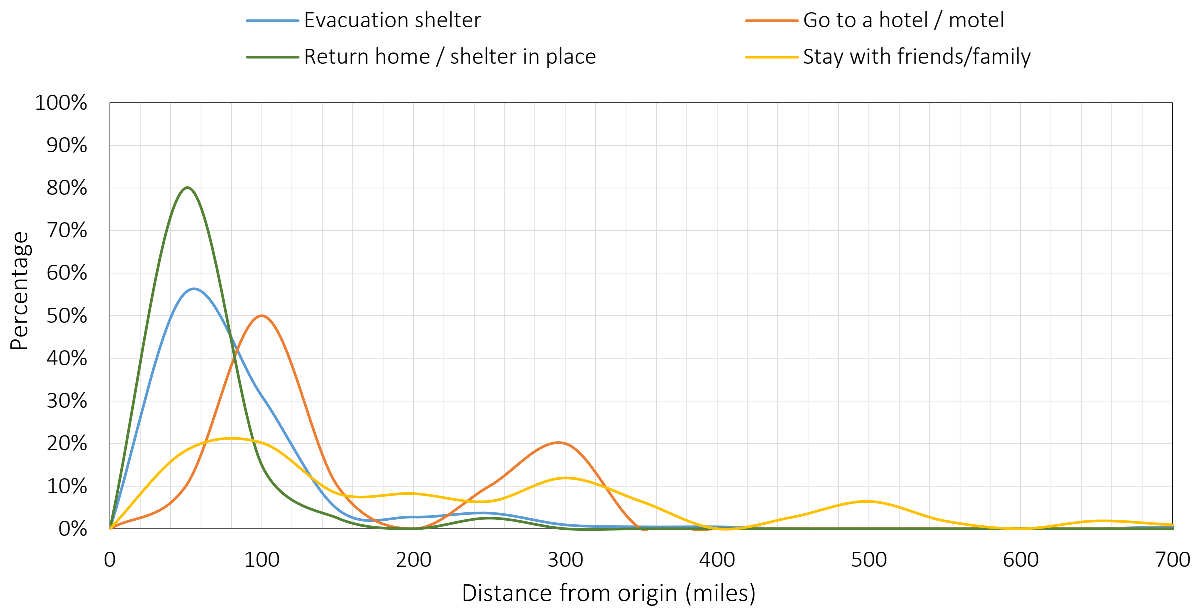
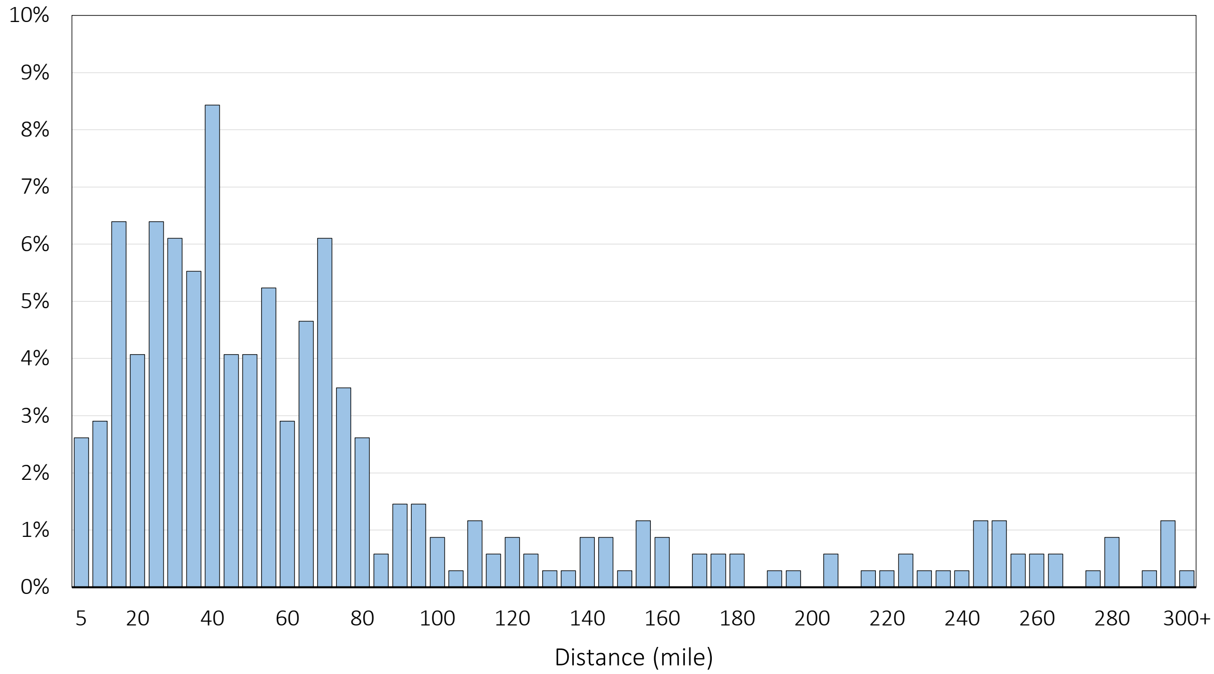
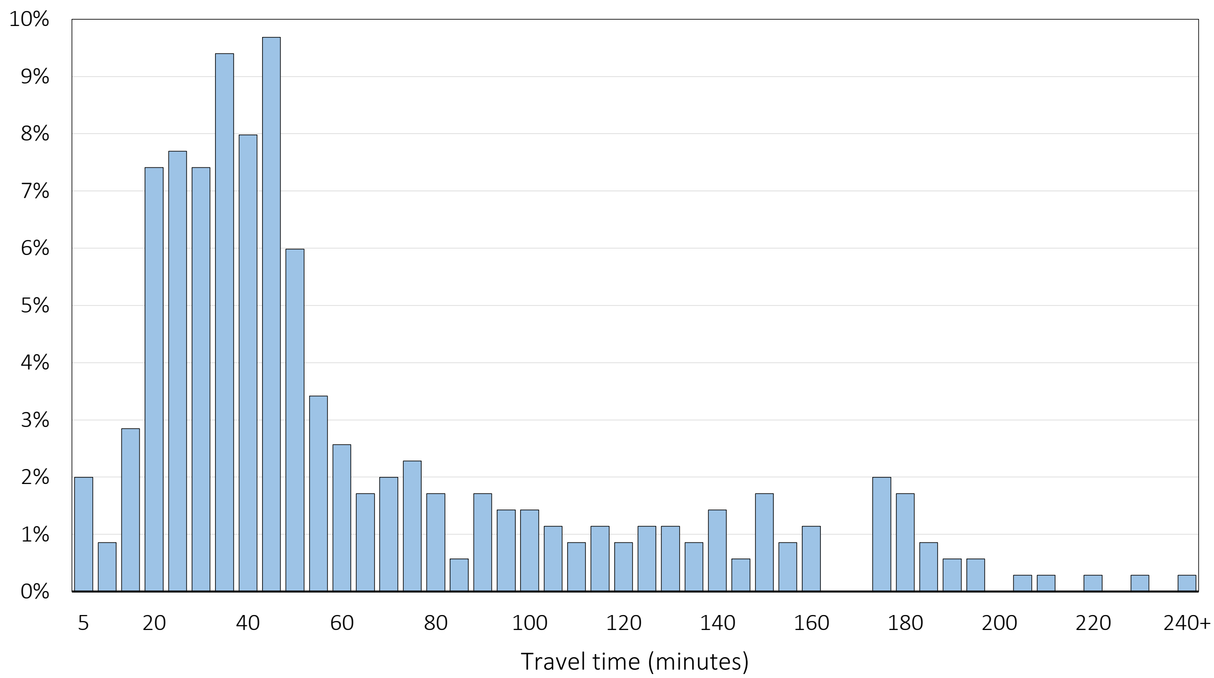


Figure 4.8. Total Distances for Each Destination Type

After collecting general information with regards to the evacuation decision and the corresponding evacuation attributes, respondents were asked to indicate any possible intermediate stop in their evacuation tour. They were asked to first select the stop type and then enter the location on the interactive map provided for them. Regarding the stop type, respondents were able to select an option among meet with family and friends, shop for supplies, pick-up child, and pick-up other family members. With respect to the number of intermediate stops, data analysis reveals that 48.4% of the respondents stated that they would make no intermediate stops. From the remaining 51.6%, 73% had only one intermediate stop, 19.4% had two intermediate stops, and 7.6% had three intermediate stops in their evacuation tours. The total travel time and travel distance of the stated evacuation tours are illustrated in Figure 4.9.



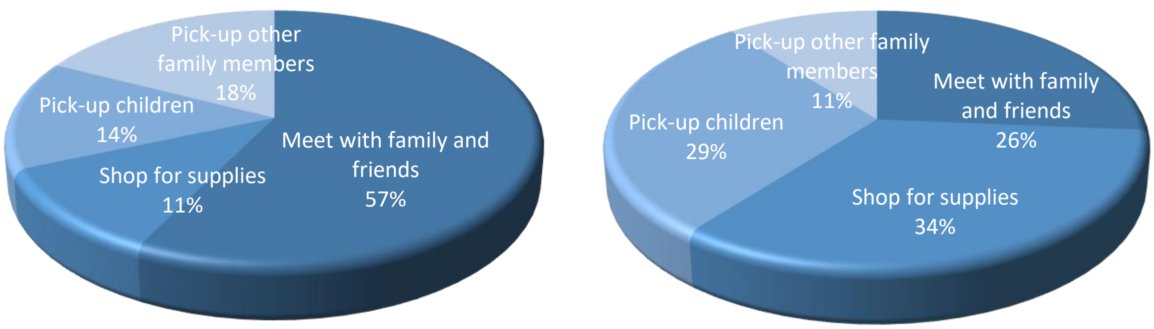
(a) Distance



(b) Travel time

Figure 4.9. Distribution of Travel Time and Distance of the Evacuation Tours

Following that, Figure 4.10 presents the distribution of stops types for (a) respondents with one intermediate stop in their tour and (b) respondents with two intermediate stops in their tour. According to this figure, most of the respondents selected meet with family and friends as their first stop whereas the most probable type for the second stop is shop for supplies. Furthermore, 32% of respondents stated they would pick-up either children or other family members in the first stop whereas this rate increases to 40% for the second stop in the evacuation tour.



(a) First Stop (b) Second Stop

Figure 4.10. Distribution of Type of Intermediate Stop

5. EVACUATION DECISION

5.1 Introduction

This chapter focuses on developing a modeling framework to estimate individuals' evacuation decision behavior in the context of no-notice emergency events. In the survey, respondents were asked to indicate the likelihood of making three potential decisions in Likert scales, namely *ignoring the event*, *seeking shelter at the place*, and *evacuating* when faced with hypothetical scenarios representing no-notice emergency events. the three dependent variables are collected in the Likert-scale format, which offers a complete spectrum of options and allows the respondents to give their true opinions toward the evacuation decision in the designed hypothetical situation.

Furthermore, one critical issue in regards with the modeling procedure is that the dependent variables are clearly interrelated because of the shared unobserved factors that influence them. Considering the ordinal nature of the variables and the interrelation between them, this study proposes a multivariate ordered response model to analyze evacuees' decision behavior. Another critical issue in modeling these variables is the heterogeneous behavior of evacuees in terms of their decision-making criteria, which, if captured, offers substantial improvements towards reliability of results for policy assessments. Therefore, two-step clustering algorithm is conducted to assign respondents to certain clusters in a way that each cluster includes relatively homogenous members—in terms of their lifestyle specifications (Shabanpour, Golshani, Derrible, et al. 2017). This is followed by estimating a multivariate ordered probit model within each cluster to investigate respondents' evacuation decision behavior. The model estimation results indicate that a variety of factors affect the evacuation decision including socio-economic attributes of evacuees, disaster characteristics, built-environment factors, and government evacuation order. Furthermore, variations of estimated coefficients across clusters highlight the significant behavioral differences among members of various clusters.

5.2 Modeling Approach

5.2.1 Cluster Analysis

This study applies the clustering algorithm to capture participants' heterogeneous behavior toward the evacuation decision. Cluster analysis is one of the most widely used methods in behavioral science to classify observations into relatively homogenous subsets by minimizing the variance of the key attributes within clusters and maximizing the variance between clusters. From the available clustering methods, the two-step clustering algorithm is selected for capturing the heterogeneous evacuation behaviour due to its high accuracy. Furthermore, this algorithm has a low convergence time even when dealing with large datasets. From another perspective, the two-step clustering is able to get both discrete and continuous variables as input as well as estimating the optimal number of clusters on its own (T. Chiu et al. 2001) rather than using other methods such as Gap Statistics.

In the first step, the dataset is divided into a number of sub-clusters (mostly an overestimation of the true numbers) based on the density of the data points. It calculates Bayesian Information Criterion (BIC) to decide whether the data point should merge with one of the previously-formed clusters. This is followed by changing the criterion to a distance-based measure to determine whether the sub-clusters should be merged; this only happens if the change is greater than a specified threshold. The distance between any pair of clusters ($dist_{ab}$) is formulated as follows (Mohammadian and Zhang 2007; T. Chiu et al. 2001; Shabanpour et al. 2019):

$$dist_{<a,b>} = \eta_a + \eta_b - \eta_{<a,b>} \tag{5.1}$$

where:

$$\eta_v = -I\left[\sum_{c=1}^{C}\frac{1}{2}log(\hat{\sigma}_c^2 + \hat{\sigma}_{vc}^2) + \sum_{d=1}^{D}\hat{E}_{vd}\right] \tag{5.2}$$

$$\hat{E}_{vd} = -\sum_{l=1}^{L_d}\frac{I_{vdl}}{I_v}log\frac{I_{vdl}}{I_v} \tag{5.3}$$

here, C (D) is the number of continuous (discrete) variables with corresponding variances of $\hat{\sigma}_c^2$ and $\hat{\sigma}_{vc}^2$ for the cth continuous variable in cluster v, L_d is the number of categories for a discrete variable, I is the number of observations in the sample, I_v is the number of observations in cluster v, and $< a, b >$ represents an index for a new cluster that is formed as a result of combining clusters a and b.

5.2.2 Statistical Model

As mentioned earlier, we consider the three response variables that represent the likelihood of evacuation, seeking shelter, and ignoring the event to estimate participants' evacuation decision. The likelihood of each decision in the survey was collected according to a five-point Likert-scale ranging from very unlikely to very likely. As the likelihood of each dependent variable is in an ordinal scale, they can be suitably modeled using ordered probit model. The formulation for such model can be written as (Greene and Hensher 2010):

$$Z_i = \beta X_i + \varepsilon_i, y_i = j \qquad \text{if} \qquad \mu_{j-1} < Z_i < \mu_j \tag{5.4}$$

where, Z_i is an unobserved continuous latent utility for observation i, β is the vector of estimable coefficients corresponding to the vector of exploratory variables (X_i), ε_i is the error term, j is the integer order choice corresponding to y_i, which is the likelihood of decisions (i.e., observed discrete outcome ranging from very unlikely to very likely), and μ_j is the threshold that separates categories j and $j+1$. The probability of outcome j and the likelihood function L for ordered models can be formulated as follows (Greene and Hensher 2010):

$$P(y_i = j) = \left[\Phi\left(\mu_j - \beta X_i\right) - \Phi\left(\mu_{j-1} - \beta X_i\right)\right] \tag{5.5}$$

$$L = \prod_{i=1}^{I} \prod_{j=1}^{J} \left[\Phi\left(\mu_j - \beta X_i\right) - \Phi\left(\mu_{j-1} - \beta X_i\right)\right]^{m_{ij}} \tag{5.6}$$

where I and J are the total number of observations and categories, respectively, m_{ij} is a binary indicator, which is equal to one if observation i belongs to category j and zero otherwise, and $\Phi(.)$ is the cumulative normal distribution function.

Moreover, the three dependent variables may be correlated because they are responses of the same participant to a single event. This correlation may arise from shared unobserved factors that influence the dependent variables. Multivariate ordered models are capable of accounting for this potential correlation and can be formulated as follows:

$$\begin{cases} Z_{i1} = \beta_1 X_{i1} + \varepsilon_{i1}, & y_{i1} = j_1 \quad \text{if} \quad \mu_{j_1-1} < Z_{i1} < \mu_{j_1} \\ Z_{i2} = \beta_2 X_{i2} + \varepsilon_{i2}, & y_{i2} = j_2 \quad \text{if} \quad \mu_{j_2-1} < Z_{i1} < \mu_{j_2} \\ Z_{i3} = \beta_3 X_{i3} + \varepsilon_{i3}, & y_{i3} = j_3 \quad \text{if} \quad \mu_{j_3-1} < Z_{i1} < \mu_{j_3} \end{cases} \tag{5.7}$$

here, Z_{i1}, Z_{i2}, and Z_{i3} are unobserved continuous latent utilities for observation i for the dependent variables, β_1, β_2, and β_3 are the vectors of estimable coefficients corresponding to the vectors of exploratory variables (X_{i1}, X_{i2}, and X_{i3}), ε_{i1}, ε_{i2}, and ε_{i3} are the error terms of the dependent variables, j_1, j_2, and j_3 are the integer order choice corresponding to the observed outcomes y_{i1}, y_{i2}, and y_{i3}, respectively, and μ_{j1}, μ_{j2}, and μ_{j3} are the threshold values. This model accounts for the correlation among the three dependent variables assuming their error terms follow a multivariate normal distribution, which can be formulated as follows (Greene and Hensher 2010):

$$\begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \varepsilon_{i3} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{21} & 1 & \rho_{23} \\ \rho_{31} & \rho_{32} & 1 \end{pmatrix} \right] \tag{5.8}$$

It should be noted that the off-diagonal correlation terms represent the shared unobserved factors between any two dependent variables. Therefore, the positive sign of these terms indicates that participants with higher likelihood to select one of the dependent variables are also likely to select the other one. On the other hand, if these coefficients become zero, the joint structure changes into a set of independent models. The joint probability and the likelihood function can be formulated as (Greene and Hensher 2010):

$$
\begin{aligned}
&P(y_{i1} = j_1, y_{i2} = j_2, y_{i3} = j_3) \\
&\qquad = \Big[\Phi_3\big[(\mu_{j_1} - \beta_1 X_{i1}), (\mu_{j_2} - \beta_2 X_{i2}), (\mu_{j_3} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big] \\
&\qquad - \Phi_3\big[(\mu_{j_1-1} - \beta_1 X_{i1}), (\mu_{j_2} - \beta_2 X_{i2}), (\mu_{j_3} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big]\Big] \\
&\qquad - \Big[\Phi_3\big[(\mu_{j_1} - \beta_1 X_{i1}), (\mu_{j_2-1} - \beta_2 X_{i2}), (\mu_{j_3} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big] \\
&\qquad - \Phi_3\big[(\mu_{j_1-1} - \beta_1 X_{i1}), (\mu_{j_2-1} - \beta_2 X_{i2}), (\mu_{j_3} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big]\Big] \\
&\qquad - \Big[\Phi_3\big[(\mu_{j_1} - \beta_1 X_{i1}), (\mu_{j_2} - \beta_2 X_{i2}), (\mu_{j_3-1} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big] \\
&\qquad - \Phi_3\big[(\mu_{j_1-1} - \beta_1 X_{i1}), (\mu_{j_2} - \beta_2 X_{i2}), (\mu_{j_3-1} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big]\Big] \\
&\qquad - \Big[\Phi_3\big[(\mu_{j_1} - \beta_1 X_{i1}), (\mu_{j_2-1} - \beta_2 X_{i2}), (\mu_{j_3-1} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big] \\
&\qquad - \Phi_3\big[(\mu_{j_1-1} - \beta_1 X_{i1}), (\mu_{j_2-1} - \beta_2 X_{i2}), (\mu_{j_3-1} - \beta_3 X_{i3}), \rho_{12}, \rho_{13}, \rho_{23}\big]\Big]
\end{aligned}
\tag{5.9}
$$

$$
L = \prod_{i=1}^{I} \prod_{j=1}^{J} P(y_{i1} = j_1, y_{i2} = j_2, y_{i3} = j_3)^{m_{ij}} \tag{5.10}
$$

5.3 Results and Sensitivity Analysis

This section starts with presenting the results of the applied clustering algorithm followed by a detailed discussion on the estimation results of the evacuation decision model. As previously highlighted, a two-step clustering algorithm is applied to capture participants' heterogeneous behavior towards the evacuation decision by grouping them into homogeneous clusters in terms of their key demographic characteristics. The two-step clustering is applied using 10% noise allowance and three clusters are obtained from the analysis. The optimal number of clusters are determined by the algorithm using Bayesian Information Criterion (T. Chiu et al. 2001). Table 5.1 presents the summary statistics and centroids of the clusters.

Table 5.1. Summary statistics of the clusters (mean for continuous and mode for categorical variables)

Cluster ID	Size	%	Variables					
			Household income	No. of kids in HH	No. of adults in HH	Age	Education level	Employment status
1	97	25.52	< 25k	0.35	1.70	56-65	College	Retired
2	144	37.89	50k-75k	0.54	2.32	46-55	College	Full-time
3	139	36.58	100k-150k	0.78	2.09	36-45	Graduate/ Professional	Full-time
Total	380	100						

For each of these three clusters, a multivariate ordered model of evacuation decision is estimated. A full set of possible variables and variable interactions is tested, and the statistically significant variables are presented in Table 5.3 to Table 5.5, and a brief summary statistics of the key variables is presented in Table 5.2. With respect to the interpretation of the estimated parameters, a positive sign of coefficients indicates that increasing the corresponding exploratory variable raises the probability of the last category (i.e., very likely) and lowers the probability of the first category (i.e., very unlikely). We found that conducting the clustering step leads to variations in the sign, magnitude, and significance level of the estimable parameters, which confirms existence of heterogeneity in people’s decision behavior across clusters. For instance, indicator of low-income level (less than $50k) in Table 5 has a negative effect on the likelihood of evacuation in cluster 2 whereas it increases the likelihood of evacuation in cluster 3. This heterogenous behavior can be attributed to dissimilarities in the lifestyle specifications of participants in different clusters.

Table 5.2. Descriptive statistics of the key variables

Variable	Definition	Mean	St. dev.
Age: 18 – 25	1: if participant is between 18 and 25 years old; 0: o/w	0.07	0.25
Gender: male	1: if participant is male; 0: o/w	0.45	0.50
Race: white	1: if participant is white; 0: o/w	0.50	0.50
HH income: low	1: if household income is less than $50,000; 0: o/w	0.26	0.44
HH income: high	1: if household income is greater than $100,000; 0: o/w	0.27	0.45
Disabled	1: if participant has a disability; 0: o/w	0.07	0.25
Employment: retired	1: if participant is retired; 0: o/w	0.13	0.34
Employment: full-time	1: if participant is full-time worker; 0: o/w	0.59	0.49
Employment: part-time	1: if participant is part-time worker; 0: o/w	0.10	0.29
Residence: apartment	1: if participant lives in an apartment; 0: o/w	0.17	0.37
Residence: house	1: if participant lives in a house; 0: o/w	0.49	0.50
HH adult	Number of adults in the household	2.08	0.96
HH child	Number of children in the household	0.58	1.04
HH child: low	1: if number of children in the household is greater than 1; 0 o/w	0.18	0.39
HH child: high	1: if number of children in the household is greater than 2; 0 o/w	0.05	0.22
HH size ≥ 3	1: if household size is greater than 3; 0 o/w	0.26	0.44
HH size ≥ 4	1: if household size is greater than 4; 0 o/w	0.09	0.29
Severity level: low	1: if event has a low severity; 0: o/w	0.32	0.47
Severity level: high	1: if event has a high severity; 0: o/w	0.33	0.47
Order to evacuate	1: if government has issued an evacuation order; 0: o/w	0.65	0.48
Population Density	Population density (thousand persons per square mile)	4.62	6.10
Population Density_3000	1: if population density is less than 3000; 0: o/w	0.57	0.49
Vehicle access	1: if participant has access to a vehicle when event occurs; 0: o/w	0.88	0.32
No vehicle access & midday	1: if event happens in midday and participant does not have access to a vehicle; 0: o/w	0.06	0.23
Proximity: less than 5 miles	1: if event happens within a 5-mile radius of the participant; 0: o/w	0.19	0.39
Proximity: 10 – 20 miles	1: if distance between event and participant's location is greater than 10 miles and less than 20 miles; 0: o/w	0.20	0.40

The results of the ordered model for ignoring the emergency events are presented in Table 5.3. Per results, those with high income levels (greater than $100k per year) are less likely to ignore the evacuation order compared to others as it significantly increases the probability of the "very unlikely" outcome. This finding is in line with Peacock et al. (1997) where they found that higher-income individuals are more likely to evacuate. Table 3 also reveals that low-educated people (defined as high school diploma or less) are more likely to ignore the situation or seek shelter compared to high-educated people, which supports the results of Murray-Tuite et al. (2012).

Table 5.3. Estimation Results of Multivariate Ordered Model (Decision: Ignore)

Variable	Cluster 1		Cluster 2		Cluster 3		Aggregate	
	Param.	t-stat	Param.	t-stat	Param.	t-stat	Param.	t-stat
Constant	0.59*	1.51	-0.63***	-4.05	-0.51***	-1.98	-0.13	-0.85
Race: white	–	–	–	–	–	–	0.58***	2.35
HH income: high	–	–	–	–	–	–	-0.35***	-2.24
Degree: high school	1.04**	1.95	–	–	–	–	1.00***	1.98
Employment: retired	–	–	–	–	–	–	-0.52***	-2.11
Employment: full-time	1.01***	2.88	–	–	–	–	–	–
Residence: apartment	-1.67***	-2.99	–		-0.95**	-1.90	-1.20***	-4.19
Residence: house	–	–	–	–	-0.52***	-2.04	-0.86***	-3.41
HH size ≥ 4	–	–	–	–	0.70**	1.93	–	–
Severity level: low	–	–	0.64***	3.09	0.92***	3.58	0.55***	4.03
Order to evacuate	-0.87***	-2.70	–	–	-0.47**	-1.79	-0.51***	-3.53
Population Density	–	–	-0.07***	-2.03	–	–	–	–
Vehicle access	-1.10***	-3.24	–	–	–	–	–	–
Proximity: less than 5	–	–	–	–	-0.88***	-1.96	-0.28*	-1.52
μ_1	0.46***	3.00	0.28***	3.50	0.42***	3.85	0.35***	5.99
μ_2	0.94***	4.12	0.66***	5.31	0.81***	5.16	0.73***	8.44
μ_3	1.04***	4.28	0.91***	5.98	1.05***	5.55	0.94***	9.20

We also found that employment status significantly affects participants' evacuation decision; that is retired people are less likely to ignore the event while full-time workers are more likely to ignore. Further, in accordance with Peacock et al. (1997) that reported those who live in multi-unit buildings have a higher tendency towards evacuation compared to those living in single houses, we found that participants who live in multi-unit buildings are less likely to ignore the disastrous event. Overall, such variables capture the heterogeneous response to the emergency event as a result of difference in lifestyles arising from variations in age, income level, social status, and other demographic attributes.

Moving to the variables representing characteristics of the emergency event, the results show that people who are in low-risk areas at the time of the event are more likely to ignore the situation. We also found that proximity of the event to participants' location significantly affect the evacuation decision. According to Table 5.3, participants who are within a 5-mile radius of the event are less likely to ignore the event. Another critical parameter that affects all the response variables is the type of the order issued by authorities. The results indicate that issuance of an evacuation order significantly decreases the likelihood of ignoring the emergency events. This finding is in line with those from the previous studies (see, for example, Dash (2002), Fu et al. (2006), Whitehead et al. (2000)).

Table 5.4 presents the results of the ordered model for the seek shelter choice. According to the table, people with disability are more willing to seek shelter in place, which may be due to their mobility restrictions. Such people, intuitively, rely on friends and family for evacuation. We also found that having a child in the household significantly decreases the likelihood of seeking shelter; this is possibly because as parents would be concerned about their children's safety, they most probably decide to pick them up instead of seeking shelter in place. Moreover, the results indicate that having access to a vehicle significantly decreases the chance of seeking shelter.

Moving to the characteristics of the emergency event, the results show that respondents' location significantly affect the evacuation decision. Per results, participants who are within a 5-mile radius of the event are less likely to seek shelter. On the other hand, those who are farther from the event location (i.e., between 10 and 20 miles) are more likely to seek shelter at their place. Interestingly, we found that issuance an evacuation order has no significant effect on the decision to seek shelter as oppose to the decisions on ignoring the event or evacuating the place.

Table 5.4. Estimation Results of Multivariate Ordered Model (Decision: Seek Shelter)

Variable	Cluster 1		Cluster 2		Cluster 3		Aggregate	
	Param.	t-stat	Param.	t-stat	Param.	t-stat	Param.	t-stat
Constant	1.05***	2.96	0.82***	4.29	0.78***	3.66	0.65***	5.34
Gender: male	–	–	–	–	0.25*	1.50	–	–
HH income: high	–	–	0.60***	2.82	–	–	–	–
Degree: high school	–	–	–	–	–	–	1.01**	1.92
Degree: low	–	–	-0.83***	-2.01	–	–	–	–
Disabled	0.96***	3.38	1.28**	1.94	0.77**	1.71	0.91***	4.34
HH child	–	–	–	–	–	–	-0.12***	-2.25
HH child: low	–	–	–	–	-0.33	-1.61	–	–
HH child: high	–	–	-0.64*	-1.46	–	–	–	–
Order to evacuate	-0.58***	-2.41	-1.06***	-5.19	-0.88***	-4.25	-0.84***	-6.88
Population Density	0.02**	1.76	–	–	–	–	0.02***	2.23
No veh access & midday	–	–	0.74***	1.99	–	–	0.47***	2.14
Vehicle access	-0.57***	-2.01	–	–	–	–	–	–
Proximity: less than 5	–	–	–	–	-0.67***	-2.35	–	–
Proximity: 10 — 20	–	–	–	–	–	–	0.24**	1.93
μ_1	0.34***	3.37	0.28***	3.79	0.42***	4.83	0.33***	6.99
μ_2	0.66***	5.11	0.82***	6.95	0.78***	6.85	0.71***	10.95
μ_3	1.01***	6.64	1.30***	8.84	1.24***	8.55	1.14***	13.75

Table 5.5 presents the results of the multivariate ordered model for the likelihood of evacuation in the case of no-notice emergency event. We found that young adults (defined as 18 to 25 years old) are more likely to evacuate during a no-notice emergency event in cluster 1 whereas this variable has no significant effect on evacuation decision of the participants in other clusters. Further, employment status is found to significantly affect participants' evacuation decision; that is both full-time and part-time workers are less likely to evacuate compared to unemployed individuals. The results also indicate that male respondents are less likely to evaluate. It should be noted that although Huang et al. (2016) found no consistent effect the gender indicator throughout the hurricane evacuation literature, the significance of this variable in our study can be supported by the higher tendency of females for childcare in the case of no-notice emergencies as stated by Liu et al. (2012).

Moving to the built-environment factors and variables representing characteristics of the event, Table 5.5 indicates that higher population density corresponds to higher chances of evacuation, this can be attributed to the higher number of shelters in such areas that generally associate with availability of basic medical care (Smitherman and Soloway-Simon 2002; Sadri, Ukkusuri, and Murray-Tuite 2013b). We also found that respondents who are located in the vicinity of the event's location (i.e., less than 5 miles) and experience events with higher severities are more likely to evacuate. As expected, issuance of a mandatory evacuation order also increases the likelihood of evacuation.

Table 5.5. Estimation Results of Multivariate Ordered Model (Decision: Evacuate)

Variable	Cluster 1		Cluster 2		Cluster 3		Aggregate	
	Param.	t-stat	Param.	t-stat	Param.	t-stat	Param.	t-stat
Constant	0.21	0.80	0.66***	1.98	0.37**	1.74	0.22**	1.68
Age: 18 – 25	0.48**	1.76	–	–	–	–	0.69***	3.22
Gender: male	-0.37**	-1.70	–	–	–	–	–	–
Race: white	0.39**	1.70	0.39***	2.11	–	–	0.25***	2.38
HH income: low	–	–	0.62***	2.76	-0.76***	-2.62	–	–
Degree: low	–	–	0.78**	1.85	–	–	–	–
Employment: part-time	-1.22***	-3.23	-1.49***	-3.17	–	–	-0.49***	-2.96
Employment: full-time	–	–	-0.46*	-1.59	–	–	–	–
HH size ≥ 3	–	–	-0.42***	-2.15	–	–	–	–
Severity level: high	–	–	–	–	0.43***	2.27	–	–
Order to evacuate	0.55***	2.23	0.44***	2.29	0.78***	3.80	0.63***	5.29
Population Density_3	–	–	0.38**	1.89	0.31**	1.94	0.28***	2.66
Vehicle access	–	–	–	–	–	–	0.31***	2.22
Proximity: less than 5	–	–	0.49**	1.77	0.87***	2.88	–	–
Proximity: 10 – 20	0.50**	1.89	–	–	–	–	–	–
μ_1	0.13**	1.91	0.43***	4.41	0.47***	4.39	0.30***	6.11
μ_2	0.34***	3.51	0.85***	6.79	0.77***	6.06	0.62***	9.58
μ_3	0.71***	5.44	1.32***	8.89	1.35***	8.79	1.08***	13.53

The rest of this section is devoted to analyzing the marginal effects to better interpret the results and understand the effect of the estimated parameters on all categories of the evacuation decision. Marginal effects are estimated as (Washington, Karlaftis, and Mannering 2010; Greene and Hensher 2010):

$$\frac{\partial P(y=j)}{\partial X_i} = \left[\phi\left(\mu_{j-1} - \beta X_i\right) - \phi\left(\mu_{jk} - \beta X_1\right)\right]\beta \tag{5.11}$$

$$\begin{aligned}\Delta_j(D) = {} & \left[\Phi\left(\mu_j - \beta X_i + \alpha\right) - \Phi\left(\mu_{j-1} - \beta X_i + \alpha\right)\right] \\ & -\left[\Phi\left(\mu_j - \beta X_i\right) - \Phi\left(\mu_{j-1} - \beta X_i\right)\right]\end{aligned} \tag{5.12}$$

here, $\Delta_j(D)$ is the marginal effects for dummy variable D, which represents the change in the probability of an outcome with respect to changing D from 0 to 1 and α is its corresponding coefficient. Equation (11) represents the marginal effects for continuous variables, which calculates the change in probability of an outcome with respect to a unit change in the exploratory variable. Table 5.6, Table 5.7, and Table 5.8 presents the marginal effects of the estimated parameters on the evacuation decision for all clusters.

As providing the marginal effects of all variables in the models would not be of much benefit, we only focus on the most important and policy-sensitive variables. As an example, Figure 5.1 presents the marginal effects of the proximity variable (dummy indicator specifying those who are in a 5-mile radius of the emergency event) for members of cluster 3. The figure shows that when the dummy indicator changes from zero to one for such people, the probability of "very likely" ignoring or seeking shelter at the place decreases by 7.63% and 15.34%, respectively. This variable can capture participants' risk perception where those who are closer to the event location perceive a higher risk and thus they are more likely to evacuate the affected area. These findings are in line with previous studies (Dash 2002; Whitehead et al. 2000; Fu, Wilmot G, and Baker Jay 2006).

Table 5.6. Marginal Effects of Variables for Cluster 1 (%)

Variable	Ignore					Seek Shelter					Evacuate				
	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely
Age: 18 — 25	–	–	–	–	–	–	–	–	–	–	-13.7	-0.3	-2.1	-1.0	17.1
Race: white	–	–	–	–	–	–	–	–	–	–	-11.7	-0.2	-1.8	-0.9	14.5
Gender: male	–	–	–	–	–	–	–	–	–	–	10.6	0.2	1.6	0.8	-13.1
Degree: high school	-22.3	6.0	6.1	1.1	9.2	–	–	–	–	–	–	–	–	–	–
Disabled	–	–	–	–	–	-30.7	-2.8	0.0	2.8	30.6	–	–	–	–	–
Employment: part-time	–	–	–	–	–	–	–	–	–	–	35.5	0.7	5.3	2.7	-44.2
Employment: full-time	-21.9	5.9	5.9	1.1	9.0	–	–	–	–	–	–	–	–	–	–
Vehicle Access	23.9	-6.4	-6.5	-1.2	-9.9	18.2	1.6	-0.1	-1.7	-18.0	–	–	–	–	–
Residence: apartment	36.1	-9.6	-9.8	-1.8	-14.9	–	–	–	–	–	–	–	–	–	–
Order to evacuate	18.5	-5.0	-5.0	-0.9	-7.6	18.6	1.6	-0.1	-1.7	-18.4	-15.0	-0.3	-2.3	-1.1	18.7
Population Density	–	–	–	–	–	-0.8	-0.1	0.0	0.1	0.8	–	–	–	–	–
Proximity: 10 — 20	–	–	–	–	–	–	–	–	–	–	-14.7	-0.3	-2.2	-1.1	18.3

Table 5.7. Marginal Effects of Variables for Cluster 2 (%)

	Ignore					Seek Shelter					Evacuate				
Variable	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely
Race: white	–	–	–	–	–	–	–	–	–	–	-8.6	-2.4	-1.4	0.1	12.3
Degree: low	–	–	–	–	–	27.7	0.4	-3.0	-5.6	-19.5	-17.9	-5.0	-2.9	0.2	25.7
Disabled	–	–	–	–	–	-41.4	-0.6	4.5	8.4	29.1	–	–	–	–	–
HH income: low	–	–	–	–	–	–	–	–	–	–	-14.0	-3.9	-2.3	0.1	20.0
HH income: high	–	–	–	–	–	-19.0	-0.3	2.1	3.9	13.4	–	–	–	–	–
HH size: low	–	–	–	–	–	–	–	–	–	–	9.5	2.7	1.6	-0.1	-13.6
HH child: high	–	–	–	–	–	20.9	0.3	-2.3	-4.3	-14.7	–	–	–	–	–
Employment: part-time	–	–	–	–	–	–	–	–	–	–	33.5	9.3	5.5	-0.3	-48.0
Employment: full-time	–	–	–	–	–	–	–	–	–	–	9.9	2.8	1.6	-0.1	-14.2
No veh access & midday	–	–	–	–	–	-23.0	-0.3	2.5	4.7	16.1	–	–	–	–	–
Severity level: low	-19.3	3.4	4.9	3.0	8.0	–	–	–	–	–	–	–	–	–	–
Order to evacuate	–	–	–	–	–	34.5	0.5	-3.7	-7.0	-24.3	-10.3	-2.9	-1.7	0.1	14.8
Population Density	2.1	-0.4	-0.5	-0.3	-0.9	–	–	–	–	–	–	–	–	–	–
Population Density_3	–	–	–	–	–	–	–	–	–	–	-8.4	-2.4	-1.4	0.1	12.1
Proximity: less than 5	–	–	–	–	–	–	–	–	–	–	-11.8	-3.3	-1.9	0.1	17.0

Table 5.8. Marginal Effects of Variables for Cluster 3 (%)

Variable	Ignore					Seek Shelter					Evacuate				
	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely	Very unlikely	Somewhat unlikely	Neutral	Somewhat likely	Very likely
Gender: male	–	–	–	–	–	-8.7	0.1	1.0	1.9	5.7	–	–	–	–	–
Disabled	–	–	–	–	–	-26.0	0.4	2.9	5.8	17.0	–	–	–	–	–
Residence: apartment	24.9	-7.0	-6.1	-3.2	-8.6	–	–	–	–	–	–	–	–	–	–
Residence: house	13.5	-3.8	-3.3	-1.7	-4.7	–	–	–	–	–	–	–	–	–	–
HH income: low	–	–	–	–	–	–	–	–	–	–	14.2	6.0	3.1	2.4	-25.8
HH size: high	-17.7	5.0	4.3	2.2	6.1	–	–	–	–	–	–	–	–	–	–
HH child: low	–	–	–	–	–	11.1	-0.2	-1.2	-2.5	-7.2	–	–	–	–	–
Severity level: low	-23.5	6.6	5.8	3.0	8.2	–	–	–	–	–	–	–	–	–	–
Severity level: high	–	–	–	–	–	–	–	–	–	–	-7.7	-3.3	-1.7	-1.3	14.0
Order to evacuate	12.1	-3.4	-3.0	-1.5	-4.2	30.3	-0.5	-3.3	-6.7	-19.8	-14.7	-6.3	-3.3	-2.5	26.8
Population Density_3	–	–	–	–	–	–	–	–	–	–	-5.6	-2.4	-1.2	-0.9	10.1
Proximity: less than 5	22.0	-6.2	-5.4	-2.8	-7.6	23.5	-0.4	-2.6	-5.2	-15.3	-16.4	-7.0	-3.6	-2.8	29.8

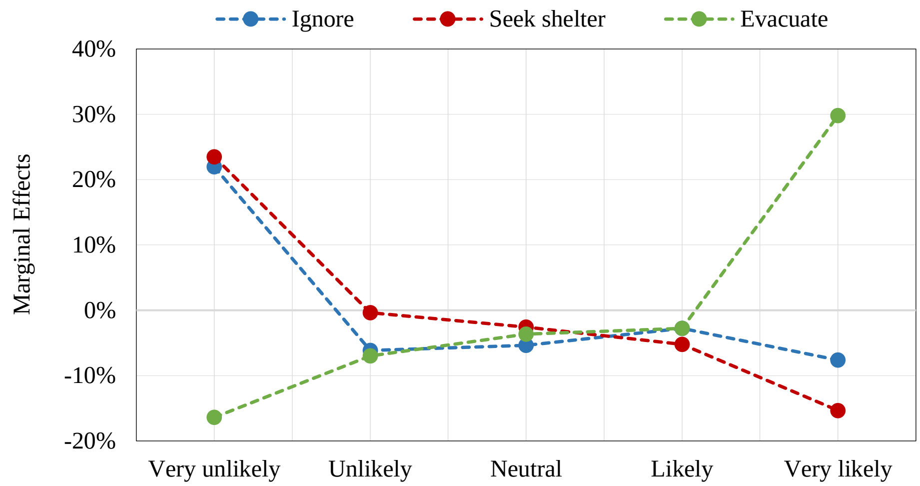


Figure 5.1. Marginal effect of proximity indicator on the evacuation decision for cluster 3

Another critical parameter that affects all the response variables is the type of the order issued by authorities. Figure 5.2 presents the marginal effects of "issuance of an evacuation order" on the likelihood of evacuation decision in each cluster. It provides a clear vision that the likelihood of evacuation increases if participants are aware of issuing an evacuation order, while the likelihood of ignoring the event or seeking shelter at place significantly drops. According to Figure 5.2, the extent of changes in the likelihood of decision variables alters across clusters, which indicates the unalike response of participants to the evacuation order in different clusters.

Moreover, all correlation coefficients between error terms are significantly different from zero (as presented in Table 5.9), which confirms the existence of shared unobserved factors that should be considered in the modeling procedure. The positive sign of the correlation coefficients indicates that unobserved factors that increase the probability of the last category (i.e., very likely) in a decision (i.e., ignore, seek shelter, and evacuate) also increases the probability of the last category in another decision and vice versa. Per results, ignore and seek shelter have a positive correlation among their error terms whereas both have a negative correlation with the evacuation decision likelihood.

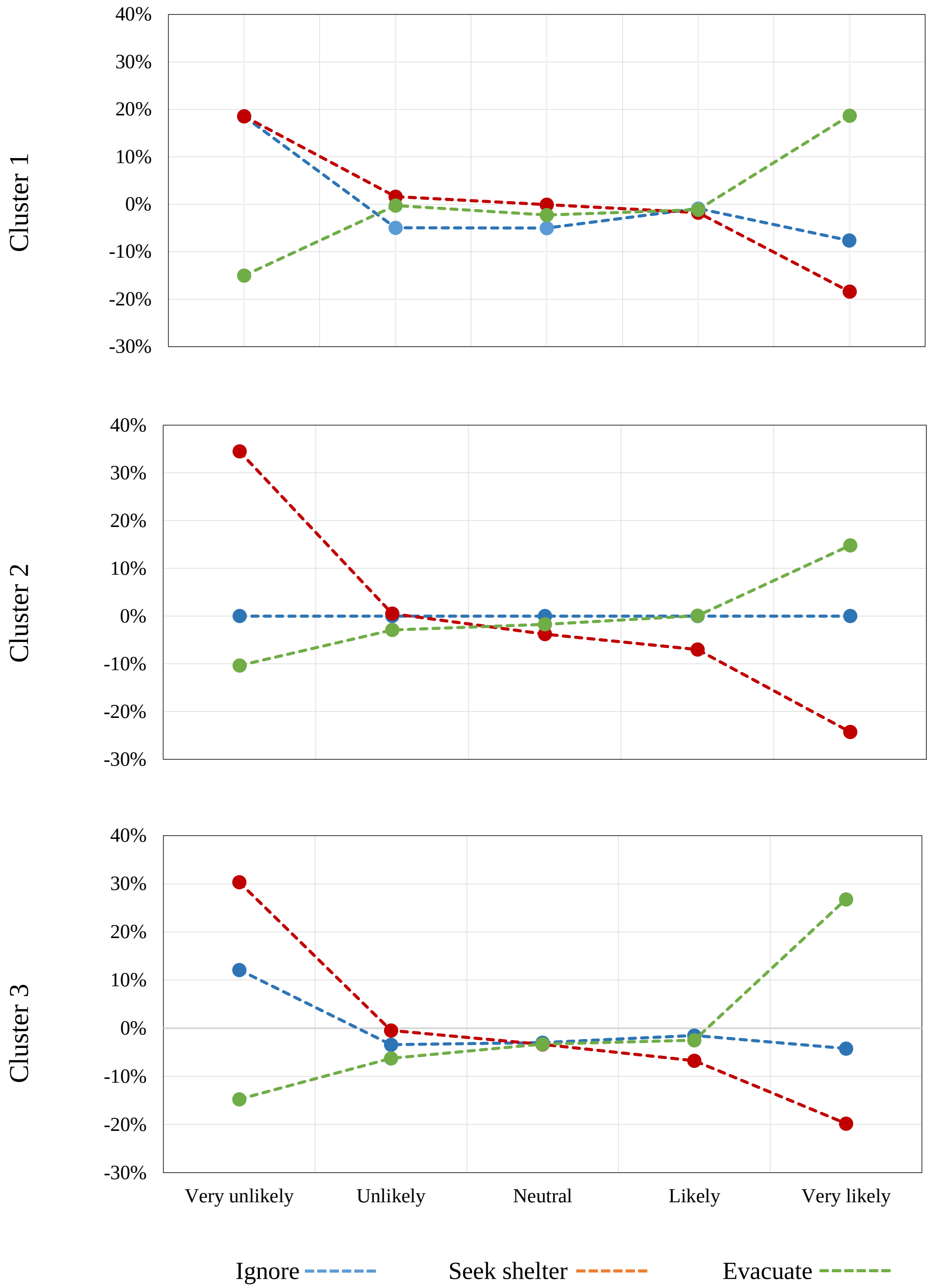


Figure 5.2. Marginal effects of government recommendation on evacuation decision

Finally, to compare the cluster-based multivariate ordered probit models with the aggregate model, likelihood ratio is calculated as $LR = -2\left[LL(\beta_{aggregate}) - \sum_{i=1}^{3} LL(\beta_{cluster\ i})\right]$ and is compared with the corresponding critical chi-square value with 99% confidence level and 56 degrees of freedom. The LR value (234.02) is found to be greater than the critical chi-square value (83.51), which shows the superiority of the proposed cluster-based approach over the aggregate model.

Table 5.9. Estimation Results of Multivariate Ordered Model (Decision: Evacuate)

Variable	Cluster 1		Cluster 2		Cluster 3		Aggregate	
	Param.	t-stat	Param.	t-stat	Param.	t-stat	Param.	t-stat
Correlation coefficients								
Ignore/seek shelter	0.53***	3.50	0.45***	4.14	0.38***	3.17	0.45***	6.58
Ignore/evacuate	-0.58***	-4.15	-0.48***	-4.81	-0.39***	-3.12	-0.45***	-6.49
Seek shelter/evacuate	-0.50***	-4.42	-0.43***	-4.19	-0.67***	-10.04	-0.55***	-10.78
Restricted log-likelihood	-368.69		-589.34		-553.50		-1530	
log-likelihood at convergence	-268.33		-471.41		-423.25		-1280	

Note: *significant at 85%, **significant at 90%, ***significant at 95%

5.4 Conclusions

This study presents a cluster-based multivariate ordered probit analysis of individuals' evacuation decision during no-notice emergency events using an internet-based stated preference survey conducted in Chicago, US. In the survey, respondents were presented with hypothetical emergency scenarios and were asked to indicate the likelihood of making each of the three potential decisions of: (1) ignoring the event, (2) seeking shelter at the place, and (3) evacuating the place. The responses were collected according to a five-point Likert-scale, ranging from very unlikely to very likely.

The modeling process starts by applying a two-step clustering algorithm to assign participants into homogenous clusters based on their demographic information. This is followed by estimating a multivariate ordered response model for each cluster. The results indicate that a wide range of demographic (e.g., disability, education level, housing type, and employment status), land-use (e.g., population density), and characteristics of the event (e.g., government order and event severity level) affects individuals' evacuation decision behavior during no-notice emergency events. Further, the variations in signs and magnitudes of the estimated coefficients across clusters confirm the existence of the heterogeneity in the dataset that if ignored, leads to inconsistent estimates. Furthermore, the significance of the correlation coefficients between error terms of the estimated models confirms the existence of shared unobserved factors that should be considered in the modeling procedure.

6. EVACUATION PLANNING

6.1 Introduction

This chapter presents the estimation process and models developed for the planning phase of the proposed evacuation demand framework. First, a joint discrete-continuous model of evacuation destination and departure time choices is estimated in the context of no-notice emergency events. These two travel dimensions of evacuation behavior are of great importance because they directly affect the spatial and temporal distributions of traffic in the transportation network. Exploration of these attributes can specifically lead to preventing occurrence of gridlocks in the network and ultimately reducing economic damage and loss of life. Considering the behavioral aspects of evacuees' decision behavior toward these parameters is imperative to identify the most influential factors in their evacuation planning process. From the methodological perspective, these two attributes have traditionally been modeled independently via a variety of modeling approaches. However, these decisions are closely intertwined due to the shared factors affecting them and/or the causal effects that they have on each other. Hence, it is necessary to investigate these two decisions in a joint structure to be able to capture the unrestricted correlation between their unobserved influencing factors.

This study contributes to the emergency evacuation literature by presenting a discrete-continuous joint structure to explore the relationship between decisions on evacuation destination choice and departure time. To achieve that goal, a copula-based joint model is proposed, which comprises a multinomial logit model as the discrete component to estimate destination choice and an accelerated hazard model as the continuous component to estimate departure time decision. The main motivation to adopt the copula approach is that it links the stochastic error terms without imposing restrictive distribution assumptions on the dependency structures of the discrete and continuous components (Bhat and Eluru 2009). Other examples of this modeling method can be found in (Golshani, Shabanpour, Auld, et al. 2018; Golshani, Shabanpour, Mahmoudifard, et al. 2018; Shabanpour, Golshani, Derrible, et al. 2017; Shabanpour et al. 2018). The results indicate that socio-economic attributes of evacuees, disaster characteristics, built-environment factors, and issuance of evacuation order by government are key determinants of the two decisions. The significance of the estimated copula parameters confirms the existence of unobserved shared effects between the two evacuation decisions, which entails the use of joint modeling scheme.

In the next step, the study focuses on analyzing evaluation mode choice. Analysis of evacuation mode choice decision is challenging due to the overwhelming number of evacuees who would rather travel with their own vehicle. From the modeling perspective, this excessive number of observations in one mode (i.e., auto) can result in estimation bias and underestimating the probability of rarely selected alternatives (King and Zeng 2001). To avoid such issues in modeling of the evacuation mode choice behavior, the few studies in this area limit the scope of their analysis by focusing on transit-dependent populations and modeling the non-auto evacuation options (e.g., (Sadri et al. 2014)).

There are quite a few methods introduced in the statistical modeling literature to account for such instances including weighting the sample as well as correcting the probability and/or estimated coefficients. Besides adding complexity to the overall modeling structure, these methods cannot generally lead to acceptable prediction accuracy. In contrast, machine learning (ML) techniques which are able to determine highly non-linear patterns in the data without any assumption of their functional forms, can significantly increase the prediction accuracy in these instances.

From all the available machine learning algorithms, this study applies a variation of the Support vector machine (SVM), which is originally developed from learning theory (Boser, Guyon, and Vapnik 1992). SVM defines a criterion for identifying a hyperplane that has the maximum distance from any two nearest data points of different classes. Compared to other machine learning models such as neural networks, SVM does not require a large amount of data for training, the global optima are always guaranteed, and it outperforms other ML models when dealing with multidimensional datasets. This method has been extensively used in various fields such as pattern recognition in handwriting identification (Cortes and Vapnik 1995; Mozer, Jordan, and Petsche 1997), sound recognition (Wan and Campbell 2000), text mining (Joachims 1998), and face recognition in surveillance videos (Osuna, Freund, and Girosit 1997).

More recently, researchers in other fields such as transportation and travel behavior have set to use SVM approach. For example, Moons, Wets, and Aerts (2007) used SVM as a nonlinear estimator of individual’s mode choice behavior. They concluded that although this approach results in prediction with high level of accuracy, it is not suitable for applying on skewed datasets due to over fitting the data. Yang et al. (2010) applied support vector machine to predict individual’s daily activity patterns. They used spatial information provided by GPS data to determine the trip chain specifications such as travel routes and stop locations. Then, based on the derived spatial information, they used a SVM classifier to determine the most likely activity type from the activity options. In an interesting study, Allahviranloo and Recker (2013) used SVM for activity pattern recognition and found that incorporating the effects of socio-demographic attributes and characteristics of previous activities of individuals on the same day can improve the model prediction accuracy.

6.2 Evacuation Destination and Departure Time

6.2.1 Modeling Approach

As discussed earlier, this study aims to jointly model the evacuation destination and departure time choices in case of no-notice emergency events. To achieve this goal, this research study adopts the copula-based modelling approach which is able to simultaneously estimate these interrelated decisions and capture the underlying correlation between them. In the proposed joint structure, destination choice is estimated using a multinomial logit model and departure time is estimated using accelerated hazard formulation.

As the first component, evacuation destination choice is estimated using a multinomial logit model. The utility function of the choices can be written as:

$$U_{di} = \beta_d X_{di} + \varepsilon_{di} \tag{6.1}$$

where U_{di} is the person-specific utility of destination d for individual i, X_{di} is the set of explanatory variables, β_d corresponds to the estimable parameters, and ε_{di} is the random error term of the utility corresponding to unobserved factors, which is assumed to have standard type-I extreme value distribution.

As the second component of this joint structure, continuous departure time can be suitably modeled using hazard duration approach. Hazard models focus on the elapsed time until occurrence of an event, which would be equal to the "time until one evacuates" in this study. In fact, hazard models estimate the conditional probability of event occurrence (i.e., evacuation action) between t and $t + dt$ given that it has not happened up to t. This conditional probability can be formulated as follows:

$$\lambda(t) = \frac{f(t)}{1 - F(t)} \tag{6.2}$$

here, $\lambda(t)$ is the hazard rate, $f(t)$ is the probability density function of the elapsed time, and $F(t)$ is the corresponding cumulative density function that represents the probability of event occurrence until t.

From the available hazard models, accelerated hazard formulation allows the covariates to directly influence the length of the elapsed time until the event occurrence. Therefore, the effects of the estimated parameters on the elapsed time can be easily interpreted. In addition, this model assumes that the hazard rate can be accelerated/decelerated over time in direct response to changes in covariates. The accelerated time hazard model can be expressed as:

$$\lambda(t|Z) = \lambda_0[t.\exp(\alpha Z)]\exp(\alpha Z) \tag{6.3}$$

where Z is the set of explanatory variables affecting elapsed time, α is the vector of estimable parameters, and λ_0 represents the baseline hazard function.

As Kiefer (1988) stated, assuming that the covariates exponentially influence the duration, this formulation is mathematically equivalent to the log-linear regression model as (for each individual i and destination d):

$$\ln(t_{di}) = \alpha_d Z_{di} + \nu_{di} \tag{6.4}$$

here, $\ln(t_{di})$ represents the natural logarithm of elapsed time for person i and destination choice d, only if choice d is selected as the evacuation destination, α is the vector of estimable parameters,

Z is the vector of explanatory variables, and ν is the error term corresponding to unobserved factors.

The linkage between the two decisions depends on the type and the extent of the dependency between the stochastic terms ν_{di} and ε_{di}. To capture the dependency between these two decisions, this study applies the copula approach, which presents the joint probability distribution of random variables with pre-defined marginal distributions as follows (Sklar 1973):

$$F_{\nu_{di},\varepsilon_{di}}(X_1, X_2) = C_\theta\left(u_1 = F_{\nu_{di}}(X_1), u_2 = F_{\varepsilon_{di}}(X_2)\right) \tag{6.5}$$

here, $F_{\nu_{di},\varepsilon_{di}}(.,.)$ is the multivariate joint distribution, $C_\theta(.,.)$ is the copula function with θ as its corresponding copula parameter, $F_{\nu_{di}}(.)$ and $F_{\varepsilon_{di}}(.)$ are marginal distributions.

Several copula functions have been formulated in the literature including FGM, Gaussian, and the Archimedean class of copulas. The Archimedean class of copula has been widely used in the literature because of their closed-form functions and their ability to cover a wide range of dependency structures (Bhat and Eluru 2009). This study adopts the Frank copula (Frank 1979) to jointly estimate the evacuation destination and departure time choices because it is the only copula function that allows for both positive and negative dependence and has no limitations in parametrizing the complete range of dependence between the two dependent variables (Bhat and Eluru 2009).

The copula function for Frank model with u_1 and u_2 as marginal distributions of the stochastic error terms and θ as the copula parameter is as follows (Bhat and Eluru 2009):

$$C_\theta(u_1, u_2) = -\frac{1}{\theta}\ln\left[1 + \frac{(\exp(-\theta u_1) - 1)(\exp(-\theta u_2) - 1)}{\exp(-\theta) - 1}\right] \tag{6.6}$$

Using the equations (6.4) to (6.6) for estimating the joint distribution, the likelihood function of the joint model can be formulated as (Spissu et al. 2009):

$$L = \prod_{i=1}^{N}\left[\left\{\prod_{d=1}^{D}\frac{1}{\sigma_{\nu_{di}}}\times\frac{\partial C_{\theta d}\left(u_{i1}^{d},u_{i2}^{d}\right)}{\partial u_{i2}^{d}}f_{\nu_{di}}\left(\frac{ln(t_{di})-\alpha_d Z_{di}}{\sigma_{\nu_{di}}}\right)\right\}^{R_{di}}\right] \tag{6.7}$$

here, R_{di} is the binary variable indicating whether destination d is selected by individual i , $f_{\nu_{di}}$ is the probability density function of ν, $\sigma_{\nu_{di}}$ is the scale parameter of ν, $C_{\theta d}$ is the copula corresponding to the joint distribution ($F_{\nu_{di},\varepsilon_{di}}\left(u_{i1}^{d},u_{i2}^{d}\right)$) where:

$$u_{i1}^{d} = F_{\nu_{di}}\left(\frac{ln(t_{di})-\alpha_d Z_{di}}{\sigma_{\nu_{di}}}\right) \tag{6.8}$$

$$u_{i2}^{d} = F_{\varepsilon_{di}}(\beta_d x_{di}) \tag{6.9}$$

6.2.2 Results and Sensitivity Analysis

Table 6.1 presents a summary of key variables used in the model and Table 6.2 outlines the estimation results of the joint discrete-continuous destination and departure time model. A full set of possible variables and variable interactions was tested, and the statistically significant variables are presented in this table. The results show that a wide range of socio-demographic and land-use variables, event characteristics, and travel-related parameters affects evacuees' destination and timing decisions during no-notice emergency events.

The results indicate that disability significantly increases the probability of selecting home shelter during emergency events possibly because of evacuee's mobility restrictions. Furthermore, retired respondents tend to stay with their family whereas they are less likely to choose home, which is not surprising because seniors typically rely on their family members for emergency evacuation. The results also suggest that housing type plays an important role in evacuation destination choice. That is respondents who live in single houses tend to return home or shelter in their place whereas those who live in multi-unit buildings are more likely to opt for shelters or hotels as their destination.

In an interesting study, Huang et al. (2016) present a statistical meta-analysis on more than 30 studies on hurricane evacuation to find the most common influential variables on evacuation decision. In contrast to the literature on advanced-notice emergency events where no significant effect of gender and education level on the evacuation decision has been reported (Huang et al., 2016), we found that these variables play important roles in the evacuation destination and timing decisions in the case of no-notice disasters. More specifically, we found that male respondents generally tend to evacuate later, which can be attributed to the fact that females are more likely to evacuate sooner to pick-up their children during no-notice emergency events (S. Liu, Murray-Tuite, and Schweitzer 2012, 2014). Similar to the study by Liu, Murray-Tuite, and Schweitzer (2014), where the authors reported that education level significantly affects different dimensions of the evacuation decision at the time of no-notice emergency events, we found a significant effect of this variable on both destination and timing decisions.

Further, Positive sign of population density in utility functions of shelter and family indicates that these destinations in areas with higher population densities (e.g., metropolitan areas) are more attractive to evacuees. Similar findings can be found in Cheng, Wilmot, and Baker (2008) for selecting to stay with family as evacuation destination.

Table 6.1. Key Variables in the Joint Destination and Departure Time Model

Variable	Description	Mean	St. dev.
Gender_male	1: if respondent is male; 0: o/w	0.45	0.50
Degree_low	1: if respondent has a high school degree or less; 0: o/w	0.07	0.25
Degree_graduate	1: if respondent has a graduate or professional degree; 0: o/w	0.45	0.50
Disability	1: if respondent has a disability; 0: o/w	0.07	0.25
Housing_townhouse	1: if respondent lives in a town house; 0: o/w	0.06	0.23
Housing_apartment	1: if respondent lives in an apartment; 0: o/w	0.12	0.33
Housing_condo	1: if respondent lives in a condo; 0: o/w	0.04	0.20
Job_retired	1: if respondent is retired; 0: o/w	0.13	0.34
Job_homemaker	1: if respondent is a homemaker; 0: o/w	0.04	0.19
HH_size	Number of adults in the household	2.65	1.48
Government_evacuate	1: if government has issued an evacuation order; 0: o/w	0.65	0.48
Risk_high	1: if risk of the event is high; 0: o/w	0.33	0.47
Risk_low	1: if risk of the event is low; 0: o/w	0.31	0.47
PopulationDensity	Population density of the census tract (in thousand people)	4.59	6.09
PopulationDensity_log	Log of the population density of the census tract (in thousand people)	0.84	1.19
PopulationDensity _10	1: if population density of respondents' location during the event is greater than 10,000; 0: o/w	0.11	0.32
PopulationDensity _3	1: if population density of respondents' location during the event is less than 3,000; 0: o/w	0.57	0.50
Distance	Total distance of the tour (miles)	133.07	267.80
Distance_log	Log of the total distance of the tour	4.07	1.27
Distance_10	1: total distance of the tour is greater than 10 miles; 0: o/w	0.95	0.22
Distance_30	1: total distance of the tour is greater than 30 miles; 0: o/w	0.74	0.44
Distance_50	1: total distance of the tour is greater than 50 miles; 0: o/w	0.54	0.50
TT_40	1: if the total travel time of the tour is greater than 40 minutes; 0: o/w	0.58	0.49
Stops_high	1: if there are more than 1 stops in respondents' tour; 0: o/w	0.23	0.42
Stop_pickup	1: if respondent's first trip is to pick up their child; 0: o/w	0.05	0.22
Mode_family	1: if respondent's first trip is to meet up with family; 0: o/w	0.97	0.17

Table 6.2. Estimation Results of Joint Destination and Departure Time Choice Model

Variable	Shelter		Hotel		Home		Family	
	Param.	t-stat	Param.	t-stat	Param.	t-stat	Param.	t-stat
Destination Choice:								
Constant	6.33***	7.54	–	–	3.90***	7.84	5.11***	4.44
Disability	–	–	–	–	1.22**	2.02	–	–
Degree_graduate	0.89**	2.48	–	–	-0.70*	-1.80	–	–
Housing_townHouse	–	–	–	–	6.38***	7.62	–	–
Housing_apartment	5.33***	9.74	–	–	–	–	–	–
Housing_condo	–	–	4.82***	8.94	–	–	–	–
Job_retired	–	–	–	–	-2.17**	-2.34	1.63***	3.84
Government_evacuate	0.61**	2.15	–	–	-1.39***	-3.19	–	–
Risk_high	1.22**	2.35	0.93*	1.72	–	–	–	–
PopulationDensity_log	0.38***	2.63	–	–	–	–	0.21***	4.19
PopulationDensity_10	–	–	-4.79***	-8.56	–	–	–	–
Distance_50	–	–	–	–	–	–	1.71***	5.35
Distance_log	-0.27**	-1.99	–	–	-0.56***	-3.18	–	–
Timing:								
Constant	4.38**	2.09	3.85*	1.82	5.18***	3.65	3.71***	2.79
Disability	2.71**	2.30	–	–	–	–	4.43***	6.21
Gender_male	–	–	1.99**	2.39	–	–	2.52**	2.05
Degree_low	2.55***	5.19	–	–	–	–	–	–
Job_retired	–	–	–	–	–	–	4.33***	4.42
HH_size	0.73**	2.03	0.64***	2.71	–	–	–	–
Government_evacuate	-0.95**	-2.26	-0.53*	-1.88	–	–	–	–
Risk_low	–	–	–	–	1.49***	2.93	1.65*	1.84
Distance_30	-1.97**	-2.39	-1.28*	-1.89	–	–	-2.42*	-1.92
TT_40	–	–	–	–	-2.61***	-2.64	–	–
Stops_high	-2.78***	-3.32	–	–	–	–	–	–
Stop_pickup	-4.01***	-3.59	-3.45***	-2.73	–	–	–	–
Mode_family	–	–	–	–	–	–	2.17**	2.08
Copula parameter: θ	-1.86***	-3.80	-6.35**	-2.07	-6.14**	-2.40	-4.97***	-2.98
Scale parameter: σ	5.34***	20.87	4.28**	2.25	2.71***	4.91	5.58***	16.91
Kendall's τ	-0.20		-0.53		-0.52		-0.46	
Restricted LL	-1804.87							
LL at convergence	-1485.67							

Note: *Significant at 90%, **significant at 95%, ***significant at 99%

Other collected demographic information was found to have no significant effect on the destination choice model. For instance, the non-significant effect of respondents' age is in line with what Huang, Lindell, and Prater (2016) found in about 60% of studies on hurricane evacuation. Similar to Huang, Lindell, and Prater (2016) that found consistent insignificant effect of race in the evacuation literature, we found this variable to have no significant effect on both studied evacuation dimensions. Furthermore, household income was tested both as a continuous variable and multiple dummy indicators, but no significant effect was found in the final model. This is in line with findings of 69% of studies on hurricane evacuation according to Huang, Lindell, and Prater (2016). On the other hand, Huang, Lindell, and Prater (2016) found that housing tenure has a significant effect on evacuation decision in the case of advanced-notice disasters, whereas we found no significant effect of this variable on the departure time and destination decisions of no-notice emergencies.

Moreover, variables representing the characteristics of the emergency event significantly affect the evacuation destination choice. Per results, respondents are less likely to return home if an evacuation order has been issued by the government while they are more willing to opt for shelters. On the same note, respondents who are experiencing events associated with high risks tend to take refuge in hotels and shelters where medical assistance is usually provided. This finding is in line with previous studies, suggesting that public perceptions towards shelters are associated with the availability of food, water, and basic medical facilities (Smitherman and Soloway-Simon 2002; Sadri, Ukkusuri, and Murray-Tuite 2013a).

Finally, it was found that distance significantly affects the evacuation destination choice. The results indicate that long distance evacuation tours (greater than 50 miles) are more likely to associate with selecting family as evacuation destination. Further, increasing the distance leads to reducing the probability of selecting home and shelters. Similar results are found in Mesa-arango et al. (2013) in the context of hurricane evacuation. Also, Liu, Murray-Tuite, and Schweitzer

(2012) showed that distance significantly affects the decision to pick-up children during no-notice emergency events.

Turing to the departure time decision, the results show that participants with high school degree or less tend to evacuate in later times which in line with findings of previous studies on evacuation timing (see, for example, Hasan et al. 2013). Positive sign of the variable representing participants with disability suggests that they are associated with later evacuation departure times. This can be because of their need for more preparation time, mobility restrictions, and reliance on others to evacuate, which is specifically important during no-notice events. We also found that the higher the household size of the evacuees, the longer it takes for them to evacuate as opposed to the findings in advanced-notice emergency events where this variable generally has no significant effect on the evacuation decision (Huang, Lindell, and Prater 2016).

As expected, participants who have received the government evacuation order tend to depart sooner to take refuge in shelters or hotels compared to those who have received a non-mandatory seek shelter order. These findings are similar to those from Hasan et al. (2013) in the context of hurricane evacuation where they stated that this variable may capture the severity of the event. On the same note, low risk of an emergency event leads to later departure times for trips destined to home or family. The level of risk of the event is also found to be a significant factor in evacuation decision during advanced-notice emergencies (Huang, Lindell, and Prater 2016).

We also found that trip- and tour-related variables significantly influence the timing of evacuation. According to Table 3, participants tend to depart sooner if their final destinations are associated with travel distances longer than 30 miles and travel times greater than 40 minutes. The results also suggest that increasing the number of stops in the evacuation tour advances the departure time. Trip purpose is also confirmed to be influential. As expected, respondents who stated that they would first pick up their child and then evacuate to a shelter or a hotel tend to depart very soon. Participants who prefer to wait to be picked up by their family members tend to evacuate in later times. These variables are of great importance in the case of no-notice emergency events since household members are possibly dispersed throughout the network in daytime. The dispersity of household members may result in additional trips (e.g., picking up family members) in the network, which can conflict with the evacuation procedure by adding extra trips in either the direction or the opposite direction of the expected routes (S. Liu, Murray-Tuite, and Schweitzer 2012; Zimmerman, Brodesky, and Karp 2007). Failing to consider these additional trips may result in underestimation of travel time that can ultimately lead to higher number of fatalities during emergencies.

Moving to the parameters of the joint modelling structure, the significance of the copula parameters confirms the existence of unobserved common factors in destination and departure time choices which, if ignored, can lead to inconsistent estimates. Furthermore, the significance of the scale parameters, which represent the variance of the error terms in continuous departure times, indicates the considerable effect of unobserved factors on departure time for each destination. To better show the dependency structure of destination and departure time choices, the Kendall's τ measure of dependency is calculated and presented in Table 3. This measure (τ) converts the copula parameter (θ) into a number between -1 and 1 (Bhat and Eluru 2009) and can be derived as follows:

$$\tau = 1 - \frac{4}{\theta}\left[1 - \frac{1}{\theta}\int_{t=0}^{\theta} \frac{t}{e^{t} - 1}\,dt\right], \qquad -1 \leq \tau \leq 1 \tag{6.10}$$

The negative sign of the resulted Kendall's τ indicates that the unobserved factors that increase the propensity to choose a destination tend to increase the departure time. Furthermore, the magnitude of the estimated Kendall's τ for shelter is less than those for other destinations, which demonstrates that evacuees who decide to take refuge in a shelter, are more likely to start their trips sooner compared to other destinations. Moreover, to evaluate the model in terms of the predictive ability, we calculate the out-of-sample prediction accuracy measure for the discrete component. This measure which shows the estimated mean probability of the selected alternative (Chorus 2010) is calculated as 0.54 for the evacuation destination type model. With respect to the departure time component, Mean Absolute Percentage Error (MAPE) index is calculated as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|O_i - P_i|}{O_i} \tag{6.11}$$

where O_i is the observed departure time, P_i is the predicted departure time, and N is the total number of observations in the sample. The overall MAPE index is calculated as 17.93%.

6.3 Evacuation Mode

6.3.1 Model Structure

As previously mentioned, the mode choice decision in the evacuation planning phase is estimated via a variation of SVM technique. The basic notion in SVM algorithm is to find the hyperplane (also known as decision surface) with maximum distance from any two nearest data points of different classes. These points that define the position of the separator are referred to as the support vectors. Support vectors are the only data points that are involved in estimating the decision surface and other data points play no role in this process. Decision surface can be defined as follows:

$$\vec{w}^T\vec{x} + b = 0 \tag{6.12}$$

where $\vec{w}$ is the weight vector that is perpendicular to the decision surface, x_i is the vector of input variables, and b is an intercept term. For a set of training data points with the vector of independent variables (x_i) and the binary target variable defined as $y_i \in \{+1, -1\}$, the linear classifier can be written as:

$$f(\vec{x}) = sign(\vec{w}^T\vec{x} + b) \tag{6.13}$$

here, a positive sign (negative) resulted from Eq. (6.13) indicates that the data point belongs to the category +1(-1). Another important parameter in SVM is the margin function (M) which is the distance between support vectors of classes and thus, will be maximized in the best condition. The margin function is defined as the perpendicular distance to the hyperplane and based on the Euclidean distance (the shortest distance (r) from a point to the hyperplane $\vec{w}^T\vec{x} + b$) can be formulated as:

$$r = \frac{|\vec{w}^T\vec{x} + b|}{|\vec{w}|} = \frac{1}{|\vec{w}|} \tag{6.14}$$

Referring to the definition of the margin function, it can be derived that margin function is twice the minimum possible distance (r). Also, as previously mentioned, the margin function is best to be maximized (so that plenty of room remains for the estimation error). Therefore, to determine the margin function, the following maximization problem needs to be solved:

$$M = \underset{w,b}{argmax}\ \underset{x_i}{min}\ \frac{2}{|\vec{w}|} \tag{6.15}$$

For the sake of calculation convenience, it is assumed that $|\vec{w}^T\vec{x}+b| \geq 1$; therefore, the maximization problem can be rewritten as:

$$\frac{M}{2} = argmin \sum_{i=1}^{I} w_i^2 \qquad (6.16)$$
$$s.t.\; y_i(wx_i + b) \geq 1$$

Solving the latter optimization problem results in w and b, which are then used to estimate the separator hyperplane. There are instances that data points cannot be classified with linear classifier in the current dimensional space. Therefore, the original input variables should be transformed into a higher-dimensional space where separating them by a linear classifier is feasible. Assuming that the linear classifier is $K(x_i, x_j) = x_i^T x_j$, and the transformation function is $F(.)$, we can form the classifier as:

$$K(x_i, x_j) = F(x_i)^T F(x_j) \qquad (6.17)$$

The following formulations are among the most popular transformation functions in SVM algorithms:

Polynomial of power: $K(x_i, x_j) = \left(1 + x_i^T x_j\right)^p$ (6.18)

Radial-basis function: $K(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$ (6.19)

Polynomial of power: $K(x_i, x_j) = \tanh(\beta_0 x_i^T x_j + \beta_1)$ (6.20)

6.3.2 Results and Sensitivity Analysis

SVM is a binary classification technique whereas evacuation mode in this analysis is a categorical variable with four modes of auto, Metra, CTA, and get picked up by family/friends. To model the evacuation mode choice with SVM, this study utilizes the one-vs-all technique where the target variable is treated as a series of binary choices. In this approach, for each mode of travel, we form a binary indicator of whether the alternative is selected and then classify the binary indicator using SVM algorithm. The SVM models are estimated with the open-source Scikit-learn package (Pedregosa et al. 2011) in Python.

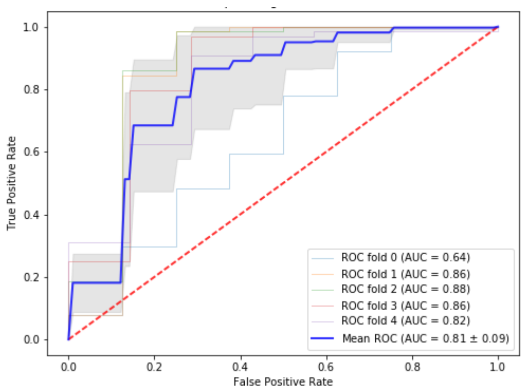
To assess the prediction accuracy of the models, k-fold cross validation technique is applied. In this technique, we first split the data into k equally-sized partitions – one is held out for testing the accuracy of the model and the other $k-1$ partitions are used to train the model. The procedure is repeated k times and the overall prediction accuracy is calculated by taking the average of the prediction accuracy measures of all the models. The prediction accuracy measure of binary outcomes can be illustrated through the Receiver Operating Characteristic (ROC) curves which plot the true positive rate (TPR) versus the false positive rate (FPR) for various decision thresholds (Hanley and McNeil 1982):

$$TPR = \frac{TP}{TP + FN} \tag{6.21}$$

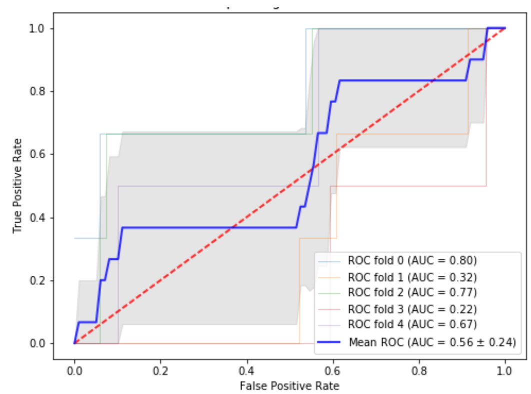
$$FPR = \frac{FP}{FP + TN} \tag{6.22}$$

here, TP is the true positive fraction (number of +1 that are correctly predicted as +1), FN is the false negative fraction (number of +1 that are incorrectly predicted as -1), FP is the false positive fraction (number of -1 that are incorrectly predicted as +1), and TN is the true negative fraction (number of -1 that are correctly predicted as -1). Figure 6.1 presents the ROC curves of the four evacuation modes for 5-fold cross validation. The dashed red line represents the ROC curve of random guess. Any curve below this line implies that the model performs worse than the random guess and any curve above this line indicates that the classifier outperforms the random guess.

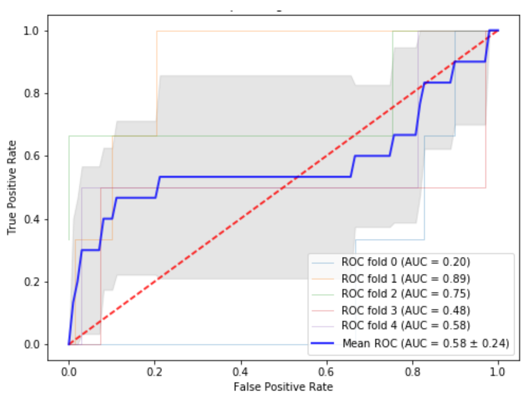
Also, the larger the area under the ROC curve (AUC), the higher will be the prediction accuracy of the model. Figure 6.1 shows that, as expected, auto has the best prediction accuracy among all evacuation modes, possibly due to its high number of observations.



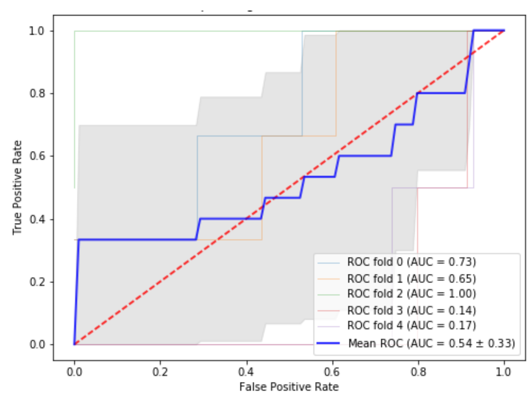
(a) Auto



(b) Metra



(c) CTA



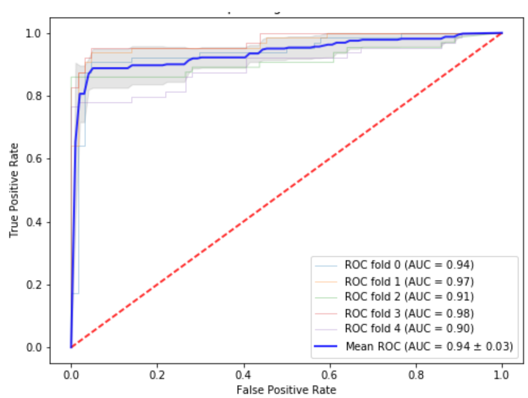
(d) Get picked up by family/friends

Figure 6.1. ROC Curves for Travel Modes

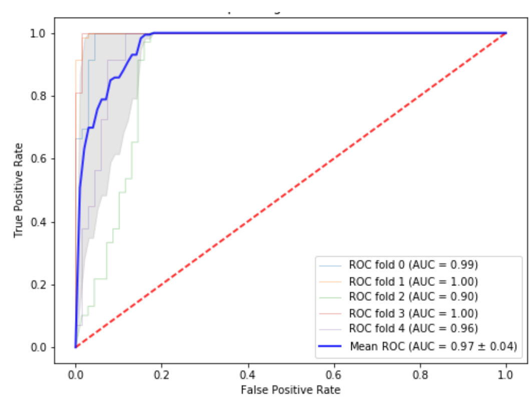
With respect to the imbalanced frequency of target variable in the dataset, several methods have been proposed to prevent bias in the estimated coefficients and probabilities. One solution is naive over-sampling the rare events. In this approach, we replicate the observations that selected the rare alternative by sampling with replacement or under-sample the highly selected alternative by removing the observations corresponding to that alternative by sampling without replacement.

Another popular solution is to use penalization algorithms in which a penalty term is added to the classification function to avoid errors in classification of the rare alternative.

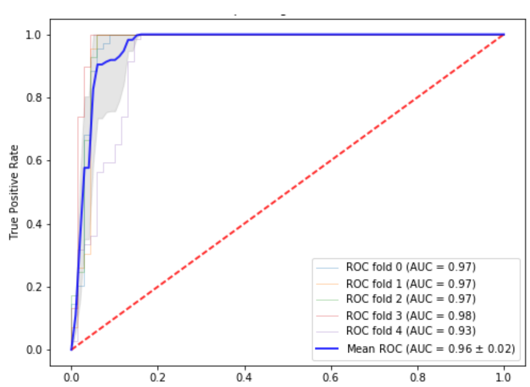
Although the previous methods could address the issue of rarely selected alternatives in SVMs, they still cannot lead to very high levels of prediction accuracy such as in normal data. To increase the prediction accuracy of rarely selected alternatives, (Chawla et al. 2002) introduced the Synthetic Minority Over-sampling Technique (SMOTE) that over-samples the rare alternative by generating synthetic observations based on k-nearest neighbor algorithm. SMOTE takes the k-nearest neighbors of a data point in the rarely selected alternative and synthesizes new data points between them by either averaging or linear interpolation. Figure 6.2 presents the ROC curves for different travel modes after implementing the SMOTE algorithm on the dataset.



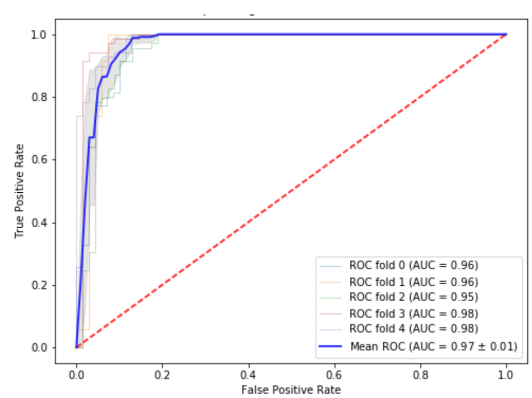
(a) Auto



(b) Metra



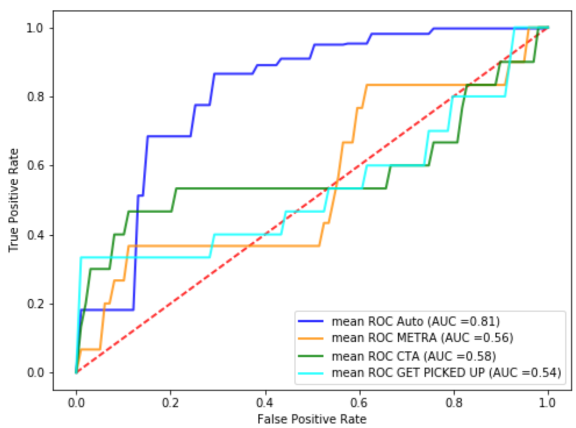
(c) CTA



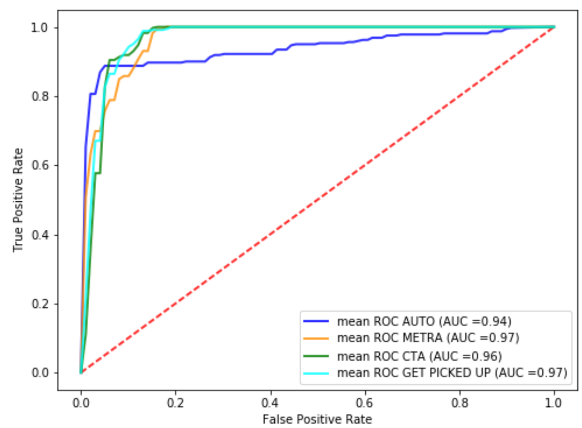
(d) Get picked up by family/friends

Figure 6.2. ROC Curves for Travel Modes After Implementing SMOTE Algorithm

For comparison, Figure 6.3 illustrates mean ROC curves of the mode choice models before and after implementation of the SMOTE algorithm. According to the figure, applying the SMOTE algorithm and increasing the number of observations that opt for the rarely selected alternatives significantly improve the prediction accuracy for all evacuation modes. To investigate the effect of explanatory variables on evacuees' mode choice decision and address the black-box nature of the SVM algorithm, we conduct sensitivity analysis on important variables which is presented in what follows. This is done by simulating the estimated model and calculating the change in the mode share with respect to changing the values of continuous variables by a certain percent and changing the binary indicators from 0 to 1 (Golshani, Shabanpour, Mahmoudifard, et al. 2018).



(a) Before



(b) After

Figure 6.3. Comparison of Mean ROC Curves Before and After Implementing SMOTE Algorithm

The results indicate that disaster characteristics and issuance of evacuation order by government are among the most influential parameters on the evacuation mode decision. Figure 6.4 illustrates the change in the probability of each mode with respect to a change in the latter variables. According to the figure, issuance of a mandatory evacuation order and higher severity of the events decrease the probability of using CTA and getting picked up by relatives, while increase the probability of using other modes of travel. The increase in the probability of Metra could be due to the fact that respondents usually associate the issuance of an evacuation order with higher severity levels and risks; therefore, they tend to evacuate to farther locations such as suburban areas which can be relatively accessible by Metra services. On the other hand, proximity of the respondent to the event location significantly decreases the probability of using Metra. Interestingly, we found that if respondent is in a close proximity of the event location, the probability of selecting private car decreases whereas the probability of getting picked up by family/friends increases. This is possibly because, those who are located in the impacted area face greater danger and prefer to shelter in place until the help arrives.

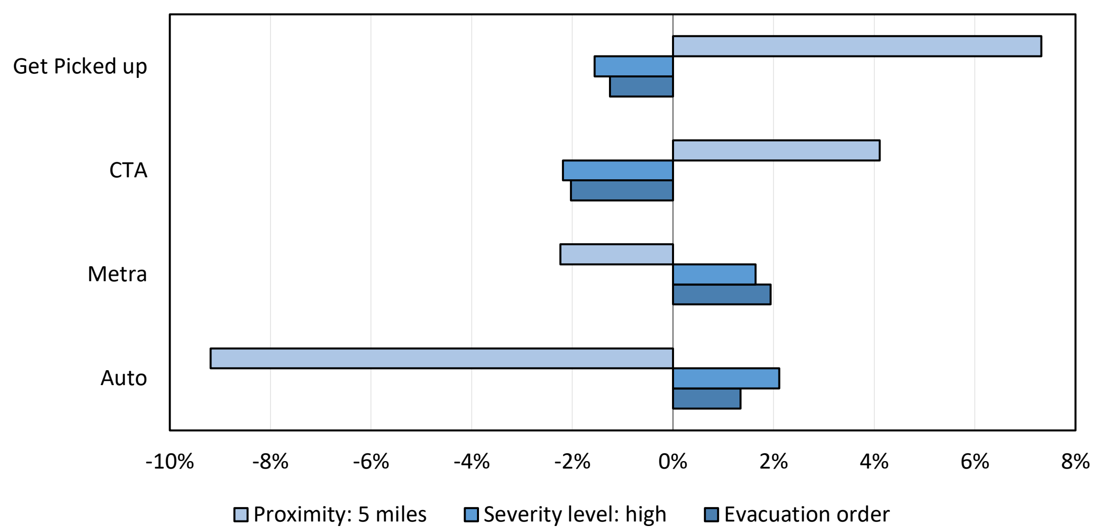


Figure 6.4. Percentage Change in the Probability of Each Mode Due to Characteristics of the Event

The general assumption in the evacuation mode choice literature is that a high majority of people who have access to a private vehicle tend to use it as their mode. To test this hypothesis, we simulated the model based on various percentages of vehicle accessibility in the data as illustrated in Figure 6.5. According to the figure, only a few of those who have access to a vehicle choose to use other travel modes for evacuation. As presented, by increasing the vehicle accessibility from 50% to 100%, the probability of evacuating with auto increases by 55.7%, which is mostly associated with the reduction in the probability of getting picked up by relatives. Indeed, the probability of getting picked up by relatives decreases by 30.5% as a result of providing access to a vehicle for all respondents. We also found that the rate of reduction of the probability for those who would wait to be picked up is higher than transit users. This trend can be attributed to the fact that if access to a private vehicle is provided for those who have decided to wait for their relatives to pick them up, they most probably will evacuate themselves in order to keep their relatives out of the impacted area.

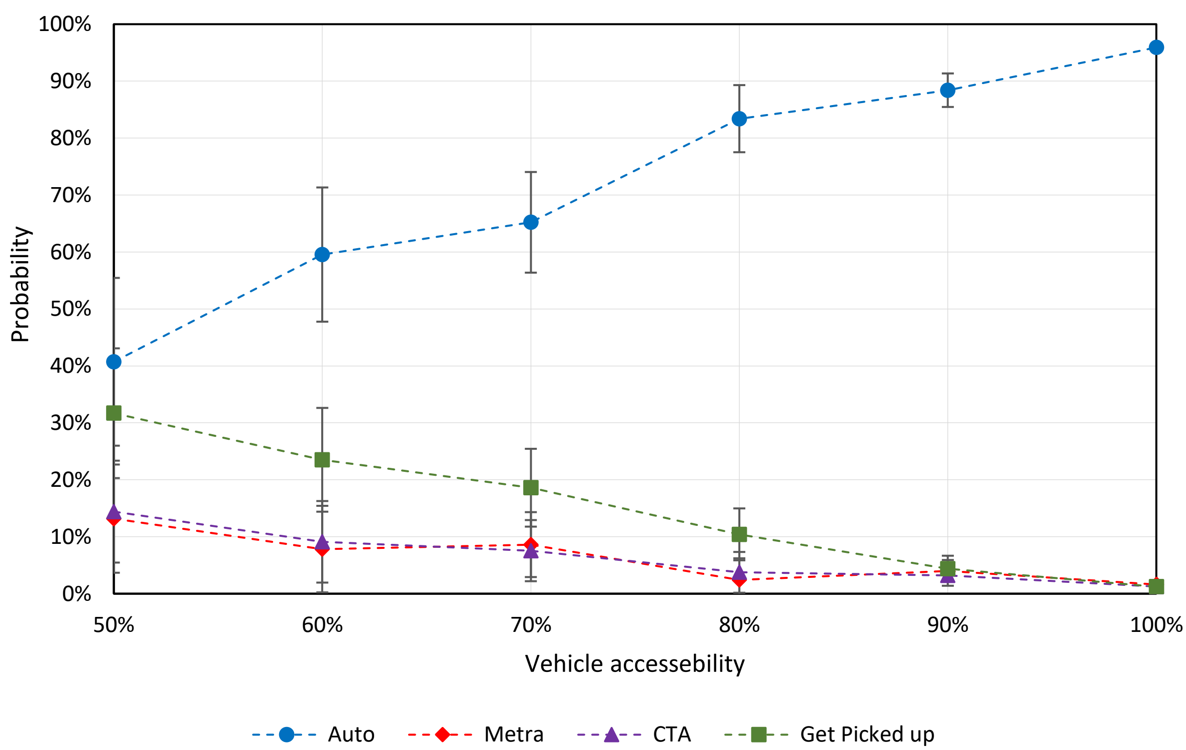


Figure 6.5. Percentage Change in the Probability of Each Mode for Different Vehicle Accessibility

6.4 Conclusions

This chapter presents the estimation process and models developed for the planning phase of the proposed evacuation demand framework. In this phase, all the attributes of the newly generated evacuation activity including final destination, departure time, and travel mode are estimated using an internet-based stated preference survey conducted in Chicago, US. The results indicate that a wide range of demographic (e.g., disability, education level, housing type, and employment status), land-use (e.g., population density), and characteristics of the event (e.g., government order and event severity level) affects evacuees' decision mechanism during no-notice emergency events.

First, the study focuses on modeling evacuation destination and departure time as a joint decision in order to capture the interrelation between the two decisions. This issue arises because of some shared unobserved factors that affects the two evacuation attributes simultaneously, and it has been largely ignored in the evacuation literature. To tackle these issues, this study presents a joint discrete-continuous model of destination and departure time choices during no-notice emergency events. These two decisions are of great importance because they directly impact the spatial and temporal distribution of traffic in the network in case of emergency events. The proposed joint model consists of a multinomial logit model to estimate the destination choice and an accelerated hazard formulation to estimate the departure time of the evacuation.

The significance of copula and scale parameters in the proposed joint structure confirms that there exist unobserved factors between the two attributes which, if ignored, lead to inconsistent estimates. Furthermore, the least estimated dependence measure is obtained for the shelter alternative, which indicates those respondents who select this alternative as their final destination tend to start their trip sooner than others.

The second part of this chapter focuses on investigating individuals’ decision behavior towards evacuation mode. In this section, we address the estimation bias that is introduced due to unbalanced nature of the dependent variable. To do so, this study takes advantage of a powerful machine learning algorithms called SMOTE, which reshapes the sample by creating new data points from the under representative alternatives (i.e., Metra, CTA, and getting picked up by family/friends) using the k-nearest neighbor approach. After balancing the data, we utilized one-versus-all SVM technique to model evacuees’ mode choice. The results showed high prediction accuracy and significant improvements compared to other types of models.

7. EVACUATION TOUR FORMATION

7.1 Introduction

This chapter focuses on the third phase of the proposed framework, which is called tour formation. In this bi-level phase, we first determine the components of the evacuation tours including number of intermediate stops, travel time, and travel distance. Because of the interrelations of these components or causal effects that they may have on each other, it would be of great significance to consider them as a joint structure. Another critical issue that can be addressed by utilizing joint modeling structure is the endogenous effect of the number of stops on the total travel time and distance of the evacuation tours.

Therefore, using the method outlined by Lee (1983), a joint discrete-continuous-continuous model that contains the ordered probit formulation for the discrete component (number of stops) and log-linear regression for the continuous components (travel time and distance) is developed. Ordered probit is chosen for modeling the number of intermediate stops because it specifically accounts for the ordinal nature of the variable, and the log-linear regression is selected to ensure the non-negativity of outcomes for the continuous components (Farber et al. 2014).

Once the total number of intermediate stops in the evacuation tour is estimated, the second part of this phase determines the type of each stop. There are four types of intermediate stops available in the data, namely meet with family and friends, shop for supplies, pick-up children, and pick-up other family members. For the case of having only one intermediate stop, a multinomial logit model is incorporated to estimate the probability of each stop type. For those who have more than one stop in their tour, a variation of rank ordered logit model is utilized to determine the type and order of the intermediate stops in the evacuation tour.

7.2 Modeling Approach

7.2.1 Tour Components

In this section, we elaborate on the structure of the joint ordinal-continuous-continuous model that will be used to simultaneously estimate number of intermediate stops, travel time, and travel distance, respectively. As previously shown in the data section, the number of intermediate stops in people's evacuation tours vary from 0 to 2. Due to the ordinal nature of this variable, we apply the ordered probit model to estimate the first component of the joint structure as:

$$\begin{aligned} &U_i = \beta X_i + \varepsilon_i \\ &S_i = j \quad if \quad \mu_{j-1} < U_i \leq \mu_j \end{aligned} \tag{7.1}$$

In Eq. (7.1), U_i is the unobserved utility function of the number of intermediate stops for observation i, X_i is a vector of explanatory variables, β is the vector of estimable parameters, and ε_i is the random error term assumed to have a normal distribution with mean zero and variance σ_ε^2. In Eq. (7.1), j is the number of intermediate stops (here ranges from 0 to 2), μ_j is the threshold that separates j and $j+1$ categories, and J is the total number of categories.

Assuming the cumulative density function of the error term as $\Phi(.)$, the probability of each outcome in observation i can be written as:

$$P(S_i = 0) = \Phi(\mu_0 - \beta X_i) = \Phi(-\beta X_i) \tag{7.2}$$

$$P(S_i = 1) = \Phi(\mu_1 - \beta X_i) - \Phi(-\beta X_i) \tag{7.3}$$

$$P(S_i = 2) = 1 - \Phi(\mu_1 - \beta X_i) = \Phi(\beta X_i - \mu_1) \tag{7.4}$$

With regards to the second and third components of the joint model, travel time and travel distance are considered as continuous variables with a log-normal distribution (to ensure their non-negativity), which can be formulated as:

$$ln(T_i) = \alpha Z_i + \nu_i \tag{7.5}$$

$$ln(D_i) = \gamma Q_i + \omega_i \tag{7.6}$$

here, T_i and D_i are respectively the total travel time and distance traveled by an evacuee, Z_i and Q_i are vectors of explanatory variables that affect the travel time and distance, respectively, with α and γ as their vectors of estimable parameters. ν_i and ω_i correspond to the stochastic error terms of the evacuation travel time and distance, which are assumed to be normally distributed with probability density functions as (Johnson, Kotz, and Balakrishnan 1994; Habib, Day, and Miller 2009):

$$f(\nu_i) = \frac{1}{\sigma_\nu T_i} \phi \left(\frac{ln(T_i) - \alpha Z_i}{\sigma_\nu} \right) \tag{7.7}$$

$$f(\omega_i) = \frac{1}{\sigma_\omega D_i} \phi \left(\frac{ln(D_i) - \gamma Q_i}{\sigma_\omega} \right) \tag{7.8}$$

where $f(.)$ Is the probability density function of the error terms, σ_ν and σ_ω are the standard deviations of the normal distributions corresponding to ν and ω, respectively.

In order to capture the effects of the shared unobserved factors on the three dependent variables, a multivariate normal distribution can be imposed on the error terms of Eq. (7.1), Eq. (7.5), and Eq. (7.6) as follows:

$$\begin{pmatrix} \varepsilon_i \\ \nu_i \\ \omega_i \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & \rho_{\varepsilon\nu}\sigma_\varepsilon\sigma_\nu & \rho_{\varepsilon\omega}\sigma_\varepsilon\sigma_\omega \\ \rho_{\nu\varepsilon}\sigma_\nu\sigma_\varepsilon & \sigma_\nu^2 & \rho_{\nu\omega}\sigma_\nu\sigma_\omega \\ \rho_{\omega\varepsilon}\sigma_\omega\sigma_\varepsilon & \rho_{\omega\nu}\sigma_\omega\sigma_\nu & \sigma_\omega^2 \end{pmatrix} \right] \tag{7.9}$$

where ρ_{mn} is the correlation coefficient between any two random error terms m and n. To avoid unnecessary complex analysis, we can normalize one of the standard deviations to 1. Therefore, the multivariate normal distribution can be rewritten as (Greene 2012):

$$\begin{pmatrix} \varepsilon_i \\ \nu_i \\ \omega_i \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{\varepsilon\nu}\sigma_\nu & \rho_{\varepsilon\omega}\sigma_\omega \\ \rho_{\nu\varepsilon}\sigma_\nu & \sigma_\nu^2 & \rho_{\nu\omega}\sigma_\nu\sigma_\omega \\ \rho_{\omega\varepsilon}\sigma_\omega & \rho_{\omega\nu}\sigma_\omega\sigma_\nu & \sigma_\omega^2 \end{pmatrix} \right] \tag{7.10}$$

We can consider the multivariate normal distribution as a union of multiple bivariate normal distributions (Nurul Habib 2012). Therefore, considering the correlation between the three dependent variables (as presented in Eq. (7.10)) and assuming the total travel time as the base (as in Eq. (7.7)), we can employ the approach presented by (Lee 1982) to transform the probability density functions of the error terms of the total travel distance from Eq. (7.8) to Eq. (7.11) as follows:

$$f(\omega_i) = \frac{1}{\left(\sigma_\omega\sqrt{1-\rho_{\omega\nu}^2}\right)D_i}\,\phi\left(\frac{ln(D_i) - \gamma Q_i - \rho_{\omega\nu}\sigma_\omega\left(\frac{ln(T_i) - \alpha Z_i}{\sigma_\nu}\right)}{\sigma_\omega\sqrt{1-\rho_{\omega\nu}^2}}\right) \tag{7.11}$$

Therefore, the probability of each outcome for observation i can be written as:

$$P(S_i = 0) = \left[f(\nu_i) f(\omega_i) \Phi\left(\frac{-\beta X_i - \rho_{\nu\varepsilon}\left(\frac{\ln(T_i)-\alpha Z_i}{\sigma}\right) - \rho_{\omega\varepsilon}\sqrt{1-\rho_{\nu\varepsilon}^2}\left(\frac{\ln(D_i)-\gamma Q_i-\rho_{\omega\nu}\sigma_\omega\left(\frac{\ln(T_i)-\alpha Z_i}{\sigma_\nu}\right)}{\sigma_\omega\sqrt{1-\rho_{\omega\nu}^2}}\right)}{\sqrt{\left(1-\rho_{\nu\varepsilon}^2\right)\left(1-\rho_{\omega\varepsilon}^2\right)}} \right) \right] \tag{7.12}$$

$$P(S_i = 1) = \left[f(\nu_i) f(\omega_i) \Phi \left(\frac{\mu_1 - \beta X_i - \rho_{\nu\varepsilon}\left(\frac{\ln(T_i) - \alpha Z_i}{\sigma}\right) - \rho_{\omega\varepsilon}\sqrt{1-\rho_{\nu\varepsilon}^2}\left(\frac{\ln(D_i) - \gamma Q_i - \rho_{\omega\nu}\sigma_\omega\left(\frac{\ln(T_i) - \alpha Z_i}{\sigma_\nu}\right)}{\sigma_\omega\sqrt{1-\rho_{\omega\nu}^2}}\right)}{\sqrt{(1-\rho_{\nu\varepsilon}^2)(1-\rho_{\omega\varepsilon}^2)}} \right) \right] - \left[f(\nu_i) f(\omega_i) \Phi \left(\frac{-\beta X_i - \rho_{\nu\varepsilon}\left(\frac{\ln(T_i) - \alpha Z_i}{\sigma}\right) - \rho_{\omega\varepsilon}\sqrt{1-\rho_{\nu\varepsilon}^2}\left(\frac{\ln(D_i) - \gamma Q_i - \rho_{\omega\nu}\sigma_\omega\left(\frac{\ln(T_i) - \alpha Z_i}{\sigma_\nu}\right)}{\sigma_\omega\sqrt{1-\rho_{\omega\nu}^2}}\right)}{\sqrt{(1-\rho_{\nu\varepsilon}^2)(1-\rho_{\omega\varepsilon}^2)}} \right) \right] \tag{7.13}$$

$$P(S_i = 2) = 1 - \left[f(\nu_i) f(\omega_i) \Phi \left(\frac{\mu_1 - \beta X_i - \rho_{\nu\varepsilon}\left(\frac{\ln(T_i) - \alpha Z_i}{\sigma}\right) - \rho_{\omega\varepsilon}\sqrt{1-\rho_{\nu\varepsilon}^2}\left(\frac{\ln(D_i) - \gamma Q_i - \rho_{\omega\nu}\sigma_\omega\left(\frac{\ln(T_i) - \alpha Z_i}{\sigma_\nu}\right)}{\sigma_\omega\sqrt{1-\rho_{\omega\nu}^2}}\right)}{\sqrt{(1-\rho_{\nu\varepsilon}^2)(1-\rho_{\omega\varepsilon}^2)}} \right) \right] \tag{7.14}$$

Finally, the likelihood function of the joint ordered-continuous-continuous model can be formulated as:

$$L = \prod_{i=1}^{I} \prod_{j=0}^{2} P(S_i = j)^{m_{ij}} \tag{7.15}$$

7.2.2 Type and Order of Intermediate Stop

As previously discussed, once the number of the intermediate stops is determined (the output of the latter model), we will determine the type of each stop. In the survey, four types of intermediate stops are identified in respondents' evacuation tours, namely meeting with family & friends, pick-up children, pick-up other family members, and shop for supplies. Descriptive analysis of the data indicates that the number of intermediate stops ranges from 0 to 2. In case of zero stops, intuitively, there is no need for identifying the stop type. In the case of one intermediate stop, we employ a multinomial logit model to determine the type of the stop. In this model, the utility of alternative a (a from $\{1, 2, \dots, A\}$) for individual i, and probability that individual i selects alternative a are as follows:

$$UIS_{ia} = \theta_a N_{ia} + \zeta_{ia} \tag{7.16}$$

$$P[y_i = a] = \frac{exp(\theta_a N_{ia})}{\sum_{k=1}^{A} exp(\theta_k N_{ik})} \tag{7.17}$$

here, UIS_{ia} denotes the utility of intermediate stop a for individual i, θ_a is the vector of estimable parameters that corresponds to the vector of independent variables (N_{ia}), and ζ_{ia} is the stochastic error term assumed to follow an extreme value type I distribution.

In the case that the evacuee has two intermediate stops, we use a variation of the rank ordered logit model (Beggs, Cardell, and Hausman 1981) to determine the type and order of the two stops. In this model, we consider the ordering of the stops as $y_i^R = (a_{i1}, a_{i2}, \dots, a_{iR})$, where a_{ir} denotes the alternative which is ranked as the rth alternative by individual i, and R denotes the total number of alternatives which are ranked. This model assumes that the decision maker selects the alternative with the highest utility as the most preferred alternative, the alternative with the second highest utility as the second most preferred alternative, and so forth. Therefore, the probability of observing ranking y_i^R for respondent i equals (Beggs, Cardell, and Hausman 1981):

$$P[y_i^R = (a_{i1}, a_{i2}, \dots, a_{iR})] = \prod_{r=1}^{R} \frac{exp\left(\theta_{a_r} N_{a_{ir}}\right)}{\sum_{k=r}^{A} exp\left(\theta_{a_k} N_{a_{ik}}\right)} \tag{7.18}$$

More specifically, in the context of our analysis where evacuees have two intermediate stops ($R = 2$), Eq. (7.18) can be simplified as follows:

$$P[y_i^2 = (a_{i1}, a_{i2})] = \frac{exp\left(\theta_{a_1} N_{a_{i1}}\right)}{\sum_{k=1}^{A} exp\left(\theta_{a_k} N_{a_{ik}}\right)} \times \frac{exp\left(\theta_{a_2} N_{a_{i2}}\right)}{\sum_{k=2}^{A} exp\left(\theta_{a_k} N_{a_{ik}}\right)} \tag{7.19}$$

Assuming that $\delta_{i,(a_1,a_2)}$ is a binary indicator which equals 1 if ranking of (a_1, a_2) is observed for individual i and equals 0 otherwise, the likelihood function of the model can be formulated as follows:

$$L = \prod_{i} \prod_{(a_1,a_2)} \left(\frac{exp\left(\theta_{a_1} N_{a_{i1}}\right)}{\sum_{k=1}^{A} exp\left(\theta_{a_k} N_{a_{ik}}\right)} \times \frac{exp\left(\theta_{a_2} N_{a_{i2}}\right)}{\sum_{k=2}^{A} exp\left(\theta_{a_k} N_{a_{ik}}\right)} \right)^{\delta_{i,(a_1,a_2)}} \tag{7.20}$$

7.3 Results and Sensitivity Analysis

Table 7.1 presents a brief summary statistics of the key variables used in the models. The results of the tour components model (including number of intermediate stops, total distance, and total travel time) and the results of the models on the type of intermediate stops are respectively presented in Table 7.2 and Table 7.3. This section starts with discussing the tour components model in terms of effects of the estimated parameters (their sign and magnitude), followed by elaborations on parameters of the joint structure and model elasticities. Following that, results of the models on the type of intermediate stops are discussed.

The estimation results confirm that a confluence of factors including individuals' and households' socio-demographics, characteristics of the emergency event, and built-environment indicators influence the evacuation tour components. To facilitate the interpretation of the estimated parameters of the number of intermediate stops component, mean marginal effects of the binary variables used in the model are presented in Figure 7.1. According to this figure, receiving the evacuation order by government has the highest effect on the number of intermediate stops in the evacuation tour. On the other hand, whether the residence type is single-family detached house has the lowest impact on the number of intermediate stops in respondents' evacuation tour. It should also be noted that since comparing the marginal effects of binary variables with continuous covariates is unreasonable, they are not presented in this figure.

Table 7.1. Key Variables Used in the Estimated Models

Variable	Definition	Mean	St. dev.
Age: 19-25	1: if participant is between 19 and 25 years old; 0: o/w	0.07	0.25
Age: 26-35	1: if participant is between 26 and 35 years old; 0: o/w	0.13	0.34
Employment: full time	1: if participant is full time worker; 0: o/w	0.59	0.49
Employment: retired	1: if participant is retired; 0: o/w	0.13	0.34
Employment: unemployed	1: if participant is unemployed; 0: o/w	0.08	0.27
Residence: multi-unit residential building	1: if participant lives in a multi-unit residential building; 0: o/w	0.17	0.37
Residence: house	1: if participant lives in a house; 0: o/w	0.49	0.50
HH income: low	1: if household income is less than $50,000; 0: o/w	0.26	0.44
Vehicle access	1: if participant has access to a vehicle when event occurs; 0: o/w	0.88	0.32
HH size: greater than 2	1: if household size is greater than 2; 0 o/w	0.44	0.50
HH size: greater than 3	1: if household size is greater than 3; 0 o/w	0.26	0.44
HH child	Number of children in the household	0.58	1.04
Having a child	1: if respondent has a child; 0: o/w	0.30	0.46
Proximity to respondent: less than 5	1: if event happens within a 5-mile radius of the respondent; 0: o/w	0.19	0.39
Proximity to child: less than 5	1: if event happens within a 5-mile radius of the respondent's child; 0: o/w	0.07	0.25
Proximity to other family members: less than 5	1: if event happens within a 5-mile radius of the respondent's other family members; 0: o/w	0.09	0.28
Proximity to family members: less than 5	1: if event happens within a 5-mile radius of any family member of the respondent; 0: o/w	0.16	0.37
Order to evacuate	1: if government has issued an evacuation order; 0: o/w	0.65	0.48
Severity level: high	1: if event has a high severity; 0: o/w	0.33	0.47
Destination: shelter	1: if shelter is selected as respondent's final destination; 0: o/w	0.58	0.50
Population Density	Population density of respondent's location at the time of an event (in thousand)	4.62	6.10
Population Density (log)	Log of population density of respondent's location at the time of an event (in thousand)	0.84	1.19

Table 7.2. Estimation Results of the Tour Components Model

Variable	Parameter	t-stat
Number of Intermediate Stops		
Constant	-1.41***	-5.59
Residence: house	1.91***	7.36
Order to evacuate	0.39**	2.21
HH child	0.11***	3.46
Employment: retired	-0.43*	-1.65
Proximity to child: less than 5	0.55**	1.98
Proximity to other family members: less than 5	0.41**	2.53
Population Density (log)	-0.45**	-1.97
μ_1	1.16***	8.38
Total Distance		
Constant	3.55***	25.73
Order to evacuate	0.26*	1.93
Proximity to respondent: less than 5	-0.55***	-3.41
HH income: low	-0.32**	-2.27
Age: 26-35	0.54**	2.19
Vehicle access	0.63***	8.69
Proximity to other family members: less than 5	0.76***	-3.45
Number of Intermediate Stops	0.07**	2.52
σ_ω	1.20***	26.79
Total Travel Time		
Constant	3.94***	40.12
Order to evacuate	0.21**	1.98
Proximity to respondent: less than 5	-0.34***	-2.66
HH income: low	-0.36***	-3.16
Age: 26-35	0.49**	2.49
Proximity to other family members: less than 5	0.53***	-3.02
Population Density	0.01***	2.95
Number of Intermediate Stops	0.09***	3.81
σ_ν	0.96***	26.58
Correlation Coefficients		
$\rho_{\nu\omega}$	-0.74***	-14.22
$\rho_{\varepsilon\omega}$	-0.21*	-1.83
$\rho_{\varepsilon\nu}$	-0.25**	-2.22
Model Specification		
Log-likelihood at convergence	-924.46	
Restricted log-likelihood	-1376.00	

Note: *Significant at 90%, **significant at 95%, ***significant at 99%

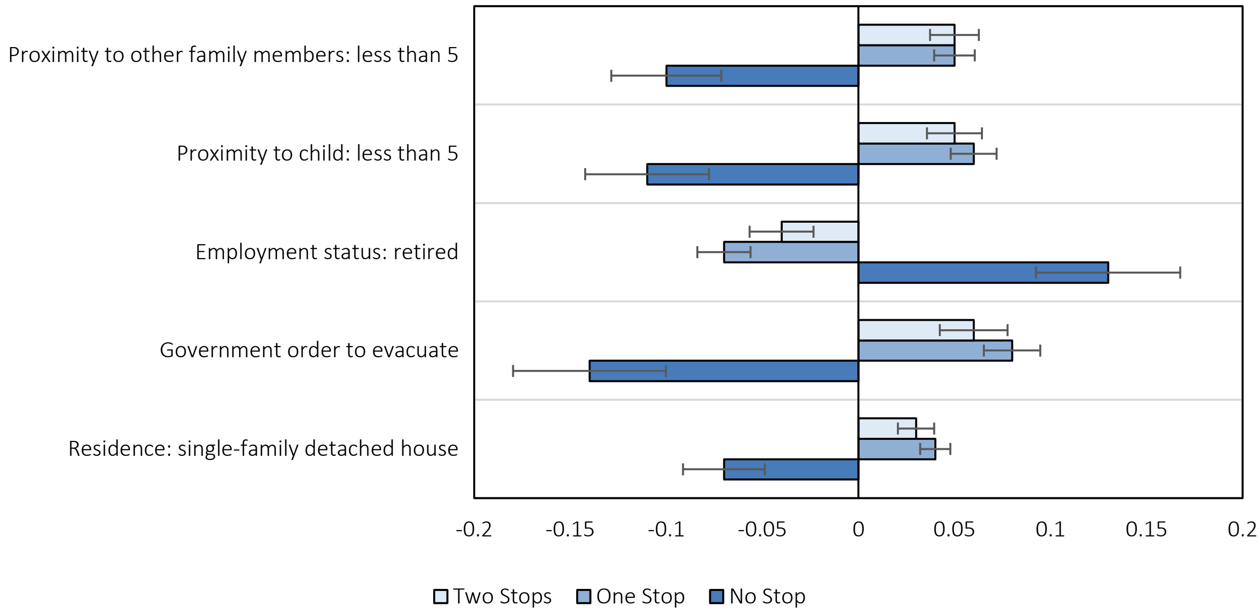


Figure 7.1. Marginal Effects of the Categorical Variables

The estimation results also indicate that several socio-demographic indicators affect all the dependent variables. For example, retired evacuees are more likely to travel to their final evacuation destination without any intermediate stops as the probability of no-intermediate-stop tours on average increases by 13.2% for such individuals. This is possibly because retired (and more generally, older) individuals are more likely to wait to be picked up by their family members in case the emergency event.

Furthermore, Table 7.2 reveals that number of children in the household has a strong impact on the number of intermediate stops in the evacuation tour. Figure 7.2 presents the probability of each outcome (i.e., number of intermediate stops) with respect to the number of children in the household. The overall trends are intuitive in that as the number of children in the family increase the probability of having no intermediate stop decreases; the trend is opposite for the case of two intermediate stops. On the other hand, the curve of one-intermediate-stop tours peaks in the case of having one or two children.

More specifically, the average probability that a member of a childless family evacuates without an intermediate stop is 60.9% whereas this probability reduces by 14.3% for families with one child. The probability of non-intermediate-stop tours dramatically decreases to 12.7% for the members of families with four or more children. On the other hand, the probability of having two intermediate stops escalates in the families with more than three children. This is intuitive because, in a typical day, children are probably located in different places (e.g., school, daycare, home, etc.) and parents need to pick them up during emergencies, which increase the number of intermediate stops in their evacuation tour.

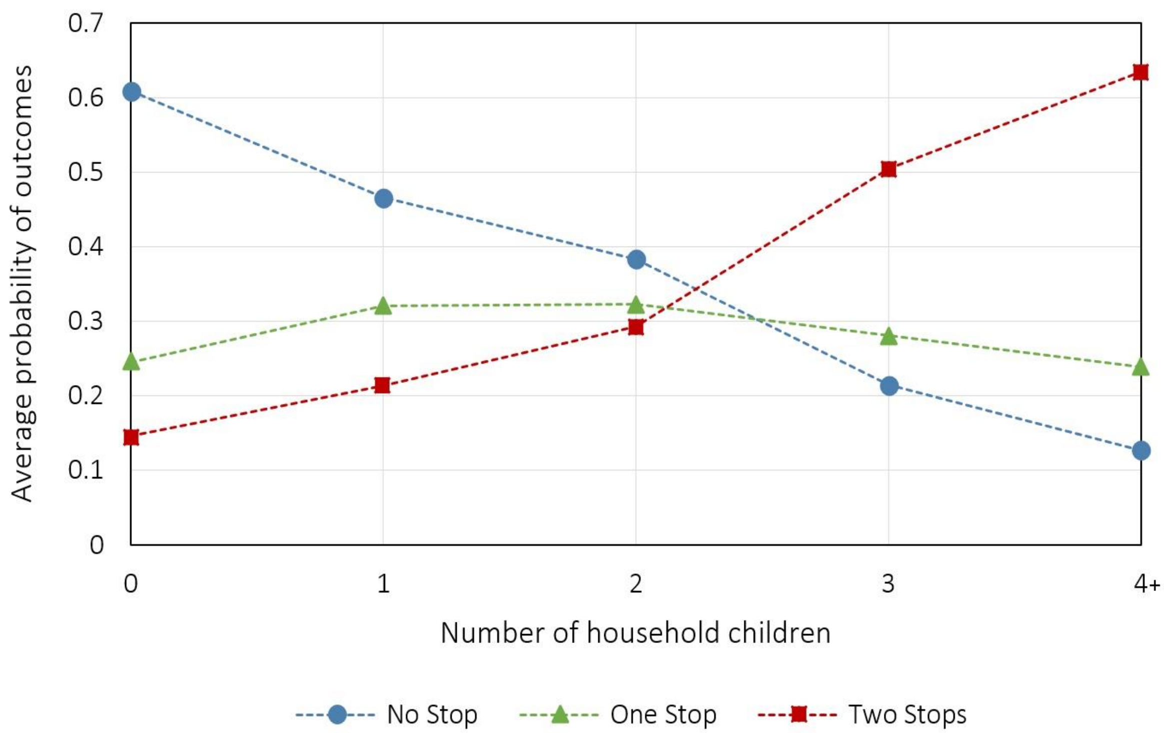


Figure 7.2. Effect of the Number of Children on the Probability of Outcomes

Furthermore, it is found that evacuees who have access to a personal vehicle at the time of the emergency event have longer travel distances, perhaps to pursue other activities such as shopping or picking up family members in their evacuation tour. On the same note, the results indicate that members of low-income families have shorter travel distances, which might be because they mostly rely on transit services for their evacuation (as a result of their lower vehicle ownership) and thereby cannot pursue other types of activities in their evacuation tour. We also found that young individuals who are between the age of 25 and 35 have higher travel distance and travel time.

Moving to the variables representing the characteristics of the emergency event, the results reveal that receiving evacuation order from responsible government agencies significantly increases all dependent variables. Past studies showed that people generally tend to associate the issuance of evacuation orders with higher risks and thereby, they are more likely to evacuate (see, for example, Whitehead et al. (2000); Dash (2002); Fu, Wilmot, and Baker (2006)). Therefore, it is expected that in such situations people plan for intermediate stops in their evacuation tours (possibly for picking up family members or preparing for a severe hazard), which ultimately increases the total travel time and distance. On the same note, occurrence of the event in a proximity of a family member increases the chance that the evacuee will have intermediate stops in his/her evacuation tour, and ultimately increases total travel time and distance; this is expected because people tend to pick up (or better to say, save) their family members who are in high risk areas in no time.

Built-environment factors are also found to be influential in the formation of the evacuation tour. Figure 7.3 indicates that those who are in areas with high population density at the time of the emergency event will experience higher travel time, and at the same time, will have fewer intermediate stops in their evacuation tours. Figure 7.3 also illustrates how variation of population density affects the probability of different alternatives of number of intermediate stops for an average respondent in the sample. As presented in the figure, keeping all other variables unchanged, increasing the population density from 1,000 persons per square mile (areas of sparse population) to 10,000 persons per square mile (densely populated areas) raises the probability of non-intermediate-stop evacuation tours by approximately 13%. This is intuitive as locations with higher population densities will probably become congested during emergency events and thereby evacuation travel time increases. Consequently, people may avoid unnecessary intermediate stops in order to save time and reach their evacuation destination at the earliest possible time.

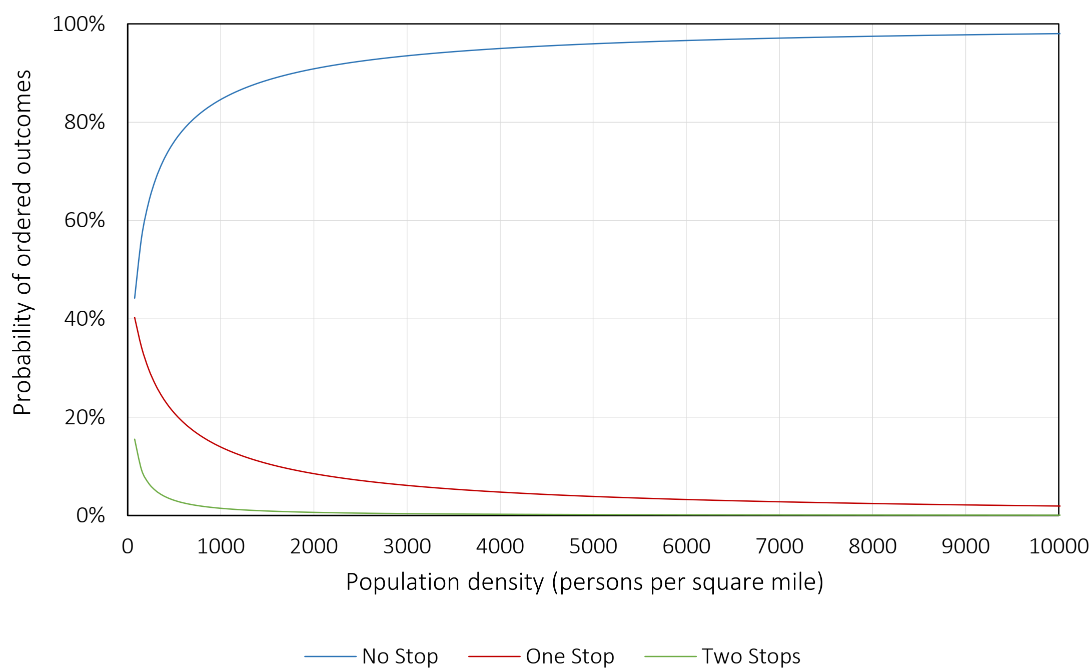


Figure 7.3. Effect of Population Density of Respondents' Location on the Probability of Outcomes

Another important finding is the positive sign of the number of intermediate stops in the travel time and distance models, which indicates that evacuees with higher number of stops have longer travel time and distance. The statistical significance of this factor in the travel time and distance models confirms the initial assumption of the endogenous effects of number of stops on the latter two dependent variables. Furthermore, the negative sign of the correlation coefficients of the joint structure indicates that the unobserved factors which increase the chance of higher number of intermediate stops will consequently increase the total travel time and duration of the evacuation tour.

To assess the prediction performance of the proposed joint framework, we first calculate the match rate for the ordered model. This measure estimates the percentage of correctly-predicted alternatives in the held-out sample. The match rate equals 76.32% in this analysis which is a fairly decent value for such model. With regards to the prediction accuracy of the travel time and travel distance models, the mean absolute percentage error (MAPE) index is calculated as $\frac{1}{n}\sum_{i=1}^{n}[|O_i - P_i|/O_i]$, where O_i is the observed value and P_i is the predicted value for observation i. The MAPE measure for the travel time and distance models are 24.1% and 23.9%, respectively. In sum, the proposed joint discrete-continuous-continuous model of tour components offers a reasonably good prediction accuracy.

The rest of this section is devoted to analyzing the type of intermediate stops in the evacuation tours. As previously mentioned, two separate models (a multinomial logit model and a rank ordered logit model) are developed for the cases when evacuees plan for one or two intermediate stops in their evacuation tour. Indeed, once the number of intermediate stops is estimated via the joint model discussed above, the corresponding outcome determines which model should be called in the simulation framework to determine the type of those stops.

The results of the models on the type of intermediate stops are presented in Table 7.3. With respect to the interpretation of the estimated results, it should be noted that a coefficient positive sign in the multinomial logit model indicates that increasing the corresponding variable raises the probability of selecting that alternative (among the four types of intermediate stops in the dataset: meeting with family & friends, shop for supplies, pick-up children, and pick-up other family members). However, a positive sign in the rank ordered model indicates that increasing the variable raises the probability of ranking the corresponding alternative higher than others. Furthermore, to better understand the effect of explanatory variables on the stop type, Table 7.4 is added to present the average change in probability of selecting an alternative in the case of having one intermediate stop, and Figure 7.4 is added to illustrate the average change in the ranking order of the alternatives in the case of having two intermediate stops (All possible ranking orders are defined in Table 7.5).

With respect to the socio-demographic characteristics, Table 7.3 reveals that in case of having one intermediate stop, full-time workers are more likely to pick up a family member and less likely to shop for supplies. This could be because full-time workers (such as parents) have probably more responsibility in the household and tend to take care of more critical tasks if they only have one intermediate stop in their evacuation tour. In case of having two intermediate stops, however, this variable is found to have no significant effect on the ordering of stops in the tour. We also found that respondents who are between the ages of 19 and 25 are more likely to rank meet with family and friends and shop for supplies above other alternatives. This is consistent with the results of Figure 7.4(a) where this variable increases the probability of ranking order 1 (meet with family/friends and shop for supplies) by 24.3%. This can be inferred as less responsibility of such individuals in the household.

Table 7.3. Estimation Results of the Stop Type Models

Variables	One stop		Two stops	
	Param.	t-stat	Param.	t-stat
Meet with family & friends				
Constant	2.69***	3.25	1.20**	1.97
Age: 19-25	–	–	3.70**	2.38
Residence: multi-unit residential building	–	–	-4.78***	-4.28
Population density (log)	1.32***	3.01	–	–
Shop for supplies				
Age: 19-25	–	–	2.65*	1.84
Employment: full time	-2.04*	-1.67	–	–
Residence: multi-unit residential building	–	–	-4.13***	-3.60
Proximity to family members: less than 5	-1.79**	-2.17	-2.25*	-1.66
Population density (log)	1.36***	2.80	–	–
Pick-up children				
Constant	-6.00**	-2.37	-4.66***	-3.48
Having a child	6.91***	3.68	–	–
HH size: greater than 2	–	–	5.61***	4.37
HH size: greater than 3	8.71***	3.39	–	–
Employment: unemployed	4.32***	3.54	–	–
Severity level: high	3.96***	2.58	1.48*	1.77
Proximity to child: less than 5	11.10**	2.28	4.03**	2.32
Destination: shelter	3.91***	3.21	–	–
Pick-up other family members				
Constant	-2.84*	-1.74	-2.63**	-2.03
Employment: full time	3.28***	2.61	–	–
HH size: greater than 2	–	–	4.23***	3.48
Proximity to other family members: less than 5	2.45***	2.77	–	–
Destination: shelter	1.95**	2.10	2.07**	2.53
Model Specification				
Log-likelihood at convergence	-64.19		-57.74	
Restricted log-likelihood	160.40		141.50	

Note: *Significant at 90%, **significant at 95%, ***significant at 99%

Table 7.4. Average Marginal Effects for the MNL Model

Variable	Meet with family and friends	Shop for supplies	Pick-up children	Pick-up other family members
Employment: full time	4.22%	-4.68%	0.13%	0.33%
Employment: unemployed	-12.94%	-0.44%	13.43%	-0.05%
Having a child	-31.96%	-1.08%	33.20%	-0.15%
HH size: greater than 3	-50.73%	-1.58%	52.55%	-0.24%
Proximity to child: less than 5	-52.75%	-2.32%	55.28%	-0.20%
Proximity to other family members: less than 5	0.27%	-1.98%	0.05%	1.65%
Severity: high	-10.65%	-0.37%	11.05%	-0.03%
Destination: shelter	-7.14%	-0.19%	7.04%	0.29%

Further, being member of a large family and presence of at least on child in the family significantly increase the probability of pick-up child. Indeed, according to Table 7.4, the probability of child pick-up increases by 33.2% for household who have at least one child and by 52.6% for households with more than 3 members. Similar pattern is recognized in the results of the rank ordered model as Figure 7.4(a) shows an increase in the probability of higher ranks of either pick-up child and pick-up other family members by those who live in households with more than 2 members.

Table 7.5. All Possible Ranking Order for Having Two Intermediate Stops

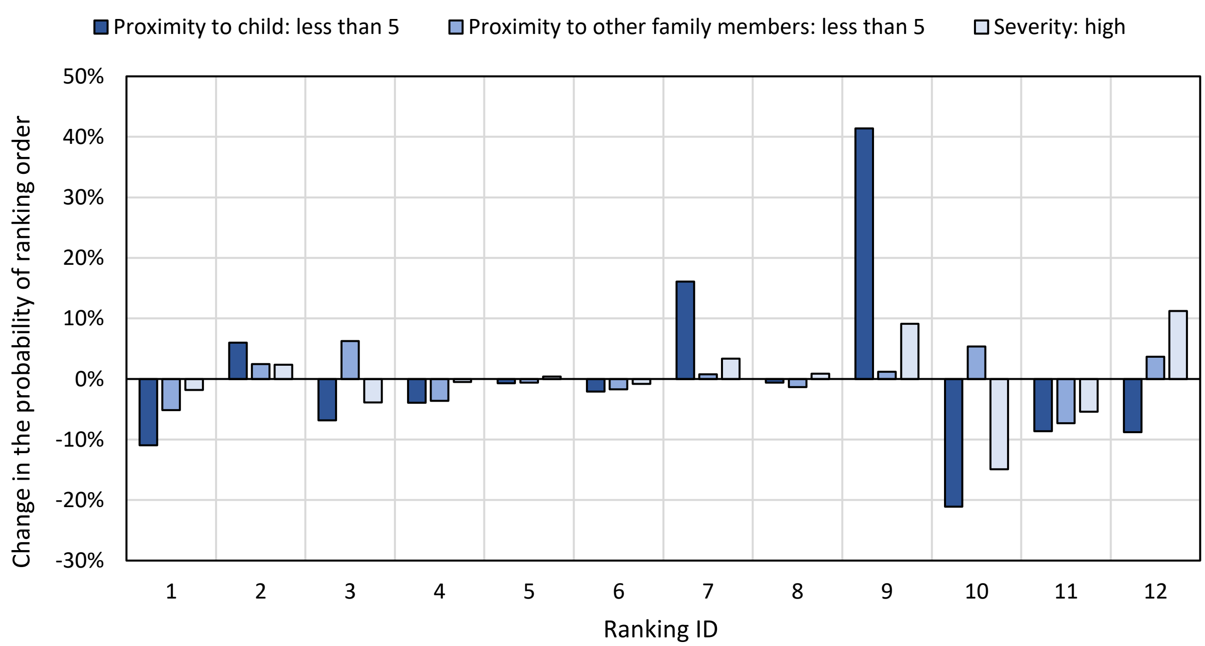
ID	First stop	Second stop
1	Meet with family & friends	Shop for supplies
2	Meet with family & friends	Pick-up children
3	Meet with family & friends	Pick-up other family members
4	Shop for supplies	Meet with family & friends
5	Shop for supplies	Pick-up children
6	Shop for supplies	Pick-up other family members
7	Pick-up children	Meet with family & friends
8	Pick-up children	Shop for supplies
9	Pick-up children	Pick-up other family members
10	Pick-up other family members	Meet with family & friends
11	Pick-up other family members	Shop for supplies
12	Pick-up other family members	Pick-up children

Moving to the factors that represent characteristics of the emergency event, the results indicate that having a family member in a close proximity of the event's location increases the chance of pick-up children or other family members by 55.28% and 11.05%, respectively, for those with only one stop in their evacuation tour. On the same note, for evacuees with two intermediate stops, Figure 7.4(b) suggests that probability of ranking pick-up children or other family members above other alternatives increases in these situations. Furthermore, we found that severity level of the event significantly affects the type of intermediate stop(s) in the evacuation tour. Per results, respondents with only one stop in their evacuation tour are more likely to pick-up their children in the case of an event with high severity. Figure 7.4(b) exhibits the same pattern in the case of two stops. We found that generally those ranking orders with pick-up children as the first or second stop (i.e., 2, 5, 7, 8, 9, and 12) have higher chances of being selected.

As the only built-environment variable that was found to be significant in the stop type model, population density has a positive effect on the probability of shop for supplies and meet with family and friends. We also found that the outcomes of the previously determined evacuation attributes significantly affect the decision on the type of intermediate stop. Table 7.3 reveals that if the final destination of the evacuation tour is determined as shelter, the corresponding binary indicator positively affects the probability of picking up children and other family members within the evacuation tour. This is expected as previous studies have shown that evacuees tend to go to shelters in case of more severe events (Sadri, Ukkusuri, and Murray-Tuite 2013a; Smitherman and Soloway-Simon 2002), in which they are more concerned about saving their family members. According to Table 7.4, this variable increases the probability of pick-up children and other family members by 7.0% and 0.3% for respondents with only one intermediate stop in their tour.

Similarly, for those with two intermediate stops, selecting shelter as the final destination would result in ranking pick-up family members above others.

a) Demographic Characteristics



b) Event's Characteristics

Figure 7.4. Average Marginal Effects for Ranking Orders

7.4 Conclusions

This chapter focuses on the tour formation phase of the proposed evacuation demand framework which comprises of two steps. First, three components of the evacuation tour (i.e., number of stops, travel time, and travel distance) are estimated via a joint ordered-continuous-continuous model. The results indicate that a wide range of demographic (e.g., age, housing type, and employment status), land-use (e.g., population density), and characteristics of the event (e.g., government order and event severity level) affects evacuees' decision behavior during no-notice emergency events. Interestingly, we found that the number of intermediate stops has endogenous effect on the travel time and distance decisions, which indicates that tours with higher number of stops are associated with higher travel time and distance. Furthermore, significance of the correlation parameters confirms the existence of the shared unobserved factors that affect all components, which entails the application of the joint modeling approach.

In the next step, the type of the intermediate stops in the evacuation tour is determined by considering the estimated number of stops from the tour component model. For those with only one stop in their tour, a MNL model is developed to determine the probability for each stop type (meeting with family & friends, shop for supplies, pick-up children, and pick-up other family members). For those with more than one stop in their tour, a variation of the rank ordered logit model is utilized that simultaneously determines the type and ordering of the intermediate stops.

The findings are specifically useful to account for the additional trips that people make during the evacuation procedures which are sometimes in the opposite direction of the evacuation plans. The final objective is to reduce the number of fatalities and economic damage during emergencies through creating effective policies, which should direct individuals' decision in favor of the most useful information against other factors that they consider.

8. CONCLUSIONS AND FUTURE WORKS

8.1 Introduction

Two types of emergency events are introduced in the literature that are different in terms of their predictability. First group consists of advance-notice emergency events such as hurricanes or tornados where authorities can inform the public when they are predicted so that household members and government officials can start to plan for emergency evacuation planned. Second type corresponds to no-notice emergency events such as terrorist attacks or earthquakes that are not predictable. Therefore, there is no time to develop comprehensive evacuation plans after event occurrence, which highlights the importance of pre-disaster planning for these situations.

Studies that focus on evacuation behavior during advanced-notice events are abundant in the literature whereas, only a few studies investigated behavioral response during no-notice emergency events. There is still a huge gap in literature with respect to investigation of evacuation behavior for no-notice emergency events mainly due to the scarcity of data. In an effort to fill such a gap, this study employs an internet-based stated preference (SP) survey conducted in Chicago Metropolitan Area to analyze individuals' evacuation behavior. The proposed framework is designed to be compatible with a large-scale activity-based model.

This study first introduces a new disaggregated evacuation demand model, which is designed to be compatible with the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) activity-based model. The proposed behavioral evacuation demand model is placed before the activity execution phase and is only called if a disaster has happened. Once a disaster happens the evacuation model is called to estimate the new demand in three steps of *evacuation decision*, *planning*, and *tour formation* before updating every person's schedule accordingly.

8.2 Summary and Major Findings

The proposed framework starts by identifying individuals' decision to evacuate where they can either ignore the event, seek shelter at their current location, or evacuate. To do so, we first apply a two-step clustering algorithm to account for heterogeneity in the dataset by grouping the respondents into homogeneous clusters. Then, a multivariate ordered probit model is estimated on each cluster to determine the probability spectrum for each outcome of the evacuation decision. If individuals decide to evacuate, the framework starts by planning the evacuation activity attributes with models specifically designed for no-notice emergencies.

The evacuation planning phase of the framework deals with estimating departure time, destination type, and travel mode for the newly generated evacuation activity. First, a joint discrete-continuous model of destination type and departure time is estimated to account for possible interrelation between these two decision variables. The joint modeling structure is utilized to account for shared unobserved factors and possible causality effects between evacuation destination and departure time choices, which directly affect the spatial and temporal components of the transportation network. In the next step of the evacuation planning phase, the framework determines the travel mode of the evacuees' by utilizing support vector machine as one of the most precise and popular machine learning techniques.

The last part of the framework before updating people's schedule corresponds to forming the evacuation tours. This means various components in evacuees' tours including number of intermediate stops, type of these stops, and travel time and distance are determined. First, a joint ordered-continuous-continuous model is estimated to determine the tour characteristics (number of stops, travel time, and travel distance). Then, based on the determined number of intermediate stops, a MNL model (for one stop in the tour) or a variation of rank ordered logit model (for those with more than one stop in the tour) is utilized to determine the type of each stop.

Finally, the framework updates people's schedule where those who are determined that they ignore the event follow their previously determined activity schedules. The schedule of those who decided to stay in the same place that they were at the time of the event is replaced with an indoor activity until the safe situation will be announced. In the case that individuals decided to evacuate, a new evacuation activity (which its attributes are determined in the planning phase) will replace the routine activity schedules of evacuees.

The main findings of this study that can help responsible agencies to develop pre-disaster plans are summarized below:

- Retired individuals and those with disability tend to stay with their family as well as travel to their final evacuation destination without any intermediate stops. This is not surprising due to their reliance on their family members for emergency evacuation.
- Individuals living in single houses tend to return home or shelter in their place, while those living in multi-unit buildings are more likely to choose shelters or hotels as their destination.
- Population density positively affects the probability of choosing shelters and staying with family as evacuees' final destination. On the other hand, higher population density leads to decreasing the probability of high number of stops in the evacuation tour, while increasing

the tour's total travel time. This could be attributed to occurrence of traffic congestion during emergency events, which increases evacuation travel time. Ultimately people avoid unnecessary intermediate stops in order to save time and reach their evacuation destination.

- Access to a vehicle at the time of an emergency event significantly increases the chance evacuation by using a private vehicle.
- Individuals who are located within a five-mile radius of the event's location at the time of its occurrence are more likely to decide to evacuate, whereas those who are further from the event location are more likely to seek shelter at their place. On the same note, if the emergency event happens near individual's family members, they are more likely to add intermediate stops to their evacuation tour to pick them up. Interestingly, people who are in the vicinity of an event are less likely to choose private vehicle and Metra as their evacuation mode.
- Those who are experiencing emergency events associated with high risks are more likely to evacuate to shelters which are generally perceived as refuge with the availability of food, water, and basic medical facilities. These individuals are also more likely to add an intermediate stop in the evacuation tours to pick up their children. We also found that the same individuals are more likely to evacuate by their own vehicle and Metra. On the other hand, people who are experiencing low-risk events tend to evacuate late and choose their own home or stay with family and friends as their final evacuation tour.
- Issuance of an evacuation order significantly increases the chance of evacuation and at the same time decreases the probability of shelter at place and ignoring the event. On the same note, individuals tend to depart soon and are more likely take refuge in shelters or hotels

compared to those who have received a non-mandatory seek shelter order. This variable also increases the chance of using private vehicle and Metra as evacuation mode. Generally, issuance of an evacuation order is perceived as events with higher severity levels and risks; therefore, people tend to evacuate to farther locations such as suburban areas which can be relatively accessible by Metra services and auto. We also found that this factor significantly increases the chance of higher number of stops, as well as travel time and distance of evacuation tour.

8.3 Major Contributions

The findings of this study can shed light on individuals' complex decision behavior in response to no-notice disasters and are useful for government agencies to facilitate the evacuation process through creating effective policies. These policies should direct individuals' decision in favor of the most informed decisions that may result in minimum economic damage and loss of life. The contributions of this thesis can be summarized below:

- Individuals' evacuation behavior during advanced-notice events has been extensively studied in past studies, whereas no-notice emergency events have not been adequately investigated mainly due to the scarcity of data. This study utilizes an internet-based SP survey to analyze individuals' decision mechanism towards various evacuation attributes.
- One major issue in modeling no-notice emergency events is the dispersity of household members in the network, which causes additional trips in the evacuation tour. To account for this issue, this study to present a framework which can be implemented in a large-scale activity-based model; these models are able to locate all family members and resources in

the network at the time of an event. Therefore, the framework can simultaneously account for background trips and induced demand as a result of a no-notice disaster and provide a suitable platform to analyze a variety of evacuation plans and policies.

- The study accounts for heterogeneity in the decision to evacuate by dividing individuals into homogeneous groups, which has been largely ignored in the literature of no-notice emergency events.
- Although evacuation attributes are closely intertwined due to unobserved shared factors or endogenous effects of decision variables on each other, no study has yet investigated them in a joint structure. The study contributes to the literature by presenting joint models of evacuation attributes and tour components in the context of no-notice emergency events.
- Literature on no-notice emergency events usually focus on individuals' decision with regards to one type of intermediate stop in the evacuation tour (i.e., pick-up children). However, the proposed framework considers multiple types of intermediate stops, and determines their number, type, and order in a single phase.

8.4 Limitations and Directions for Future Research

With regards to the data used in this study, recent studies showed that emergence of social media can significantly contribute to individuals' evacuation behavior. Therefore, lack of the related information in the utilized data is a limitation of this study and therefore, incorporating factors related to usage of social media can be a potential direction for future study. Another limitation of the dataset corresponds to the low number of observations where it leads to restricting the variations of decision variables, specifically in the tour formation step. The geographical area covered for data collection is another limitation of this study, which prevents us from testing transferability of the proposed framework to other geographical regions.

This study has several other potentials for future research directions. First, collecting revealed preference dataset after no-notice emergency for model validation is an important future step of this study. With respect to the utilized modeling procedure in the evacuation planning phase, the method can be expanded by developing a joint model that considers the correlation of all evacuation attributes (i.e., departure time, destination, and model) while controlling for rarely selected alternatives in the mode decision. Furthermore, applying other joint modelling techniques and comparing their results with the employed copula approach detailed in Chapter 6 would be informative about their performance. Finally, the proposed evacuation demand model should be implemented in the ADAPTS structure in order to develop a policy-sensitive framework that captures the dynamics in evacuees' behavior with respect to traffic conditions of the network.

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