Title

Understanding Evacuee Behavior: A Case Study of Hurricane Irma

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Executive Summary

In September 2017, Hurricane Irma prompted one of the largest evacuations in U.S. history of over six million people. This mass movement of people, particularly in Florida, required considerable amounts of public resources and infrastructure to ensure the safety of all evacuees in both transportation and sheltering. Given the extent of the disaster and the evacuation, Hurricane Irma is an opportunity to add to the growing knowledge of evacuee behavior and the factors that influence a number of complex choices that individuals make before, during, and after a disaster. At the same time, emergency management agencies in Florida stand to gain considerable insight into their response strategies through a consolidation of effective practices and lessons learned. To explore these opportunities, we distributed an online survey (n = 645) across Florida with the help of local agencies through social media platforms, websites, and alert services. Areas impacted by Hurricane Irma were targeted for survey distribution. The survey also makes notable contributions by including questions related to reentry, a highly under-studied aspect of evacuations. To determine both evacuee and non-evacuee behavior, we analyze the survey data using descriptive statistics and discrete choice models. We conduct this analysis across a variety of critical evacuation choices including decisions related to evacuating or staying, departure timing, destination, evacuation shelter, transportation mode, route, and reentry timing.

The majority of survey responses came from Brevard (53%)[1], Lee (17%), and Collier (13%) Counties. The sample of the survey skewed towards higher education (7% with high school degree or below), higher income (30% with household income of $100,000 and above), higher technology use (96% with a smartphone), white respondents (94%), and female respondents (82%). Despite the skew, the sample contained substantial variation in age, household size, employment status, type of residence, and length of residence. In addition, over 90% of respondents said they were the sole decision maker, the primary decision maker, or shared decision making equally in the household. Thus, the survey successfully targeted active decision-makers for the evacuation of Hurricane Irma.

For the evacuation overall, several key descriptive results indicate high rates of non-compliance (i.e., received a mandatory order and did not evacuate), shadow evacuations (i.e., did not receive a mandatory order and evacuated), and out of county evacuations. Evacuees also heavily used personal vehicles and highways to evacuate. However, the timing of departures – across days and within the day – exhibited an even distribution. Several key results include:

- A non-compliance rate of 31%;
- A shadow evacuation rate of 46%;
- A within county evacuation rate of 17%;
- An out of state (i.e., out of Florida) evacuation rate of 49%;
- Relatively even spread of evacuation departure days with 42% leaving three days or more before the landfall of Irma;
- Relatively even spread of evacuation departure times with 33% departing at night between 6:00 p.m. and 5:59 a.m.;
- Preference to shelter with family or a friend (59%) and at a hotel or motel (27%);
- Initial sheltering through a peer-to-peer service such as Airbnb (4%) and low use of shelters (4%);
- Predominate use of one vehicle (66%) and two or more vehicles (24%) to evacuate;

[1] All values in the executive summary are rounded to the nearest percentage.

- Low use of transit to evacuate (less than 1%);
- Predominate use of highways (64%) as the primary road type of travel but also a high use of major roads (14%) as the primary road type for evacuation;
- A GPS-navigation usage rate of 64% for routing;
- A wide spread of reentry days (with a maximum of 22% returning two days after landfall) and only 21% of respondents stating they returned due to an order from an official source or news source.

The descriptive results also indicate that agencies were relatively successful in issuing evacuation orders, communicating clearly to the public, and managing transportation facilities. While respondents perceived the delivery of orders as successful, the orders were not necessarily persuasive, with high non-compliance and shadow evacuation rates. Results include:

- A high rate of respondents (87%) who received a mandatory evacuation order and who found the message to be extremely clear;
- A somewhat high rate of respondents (70%) who received a voluntary evacuation order and who found the message to be extremely clear;
- A wide distribution of communication methods with at least 25% of respondents receiving mandatory order information across five different platforms;
- High usage of social media through which 48% and 39% of respondents received a mandatory and voluntary evacuation order respectively;
- A high rate of seeking a secondary source, with 47% and 50% of respondents for mandatory and voluntary evacuation orders respectively;
- Fluctuating overall opinion of an extremely effective or very effective government management of communication (68%), roadways (39%), evacuation of carless populations (19%), shelters (45%), and the overall evacuation (55%).

Non-evacuees were also specifically asked why they decided not to evacuate. Several key reasons that they decided not to evacuate include:

- Not wanting to sit in traffic (49%)
- Wanting to protect property (35%)
- Not wanting to go to a public shelter (31%)
- Having some work requirements during the storm (22%)
- Being unsure where they could take a pet (18%)
- Not having the money to evacuate (14%)

Our data analysis using discrete choice models suggests that a number of factors impacted individual choice-making throughout the evacuation, opening up opportunities for practitioners to improve evacuation outcomes. These factors include risk perceptions prior to evacuating, individual demographic characteristics, and household characteristics. The models also indicate that there is significant overlap of evacuation decisions, wherein one evacuation choice impacts another choice. We found the following significant statistical variables, including sociodemographic characteristics, for the following choices:

- Evacuate or Not: Receiving a mandatory evacuation order, worry of the severity of the storm, worry of finding housing, worry of housing costs, belief of major structural damage, belief of injury or death, belief of work requirements, previous evacuation experience, children present in household, housing structure type, and geography in Florida;

- Departure Day: Receiving a mandatory evacuation order, destination of evacuation, number of trips before evacuating, belief of work requirements, previous evacuation experience, children present in household, length of residence, and geography in Florida;
- Departure Time of Day: Shelter choice, destination of evacuation, transportation mode, worry of traffic, previous evacuation experience, and length of residence;
- Destination: Receiving a mandatory evacuation order, shelter choice, transportation mode, worry of traffic, worry of finding housing, belief of injury or death, and geography in Florida;
- Shelter Type: Destination of evacuation, worry of the severity of the storm, worry of finding housing, worry of housing costs, pets present in household, household income, and length of residence;
- Transportation Mode: Destination of evacuation, worry of the severity of the storm, vehicle availability in the household, household income, and length of residence;
- Route: Destination of evacuation, transportation mode, worry of traffic, and worry of finding gas;
- Reentry Day: Destination of evacuation, learning power was restored, needing to return to work, living in a Federal Emergency Management Agency (FEMA) flood risk zone; and geography in Florida.

The report concludes with recommendations for future evacuations based on the data from this Hurricane Irma survey and research directions for future work. Several key recommendations for agencies include:

- Issuing complete and clear mandatory evacuation orders phrased in strong terms and delivered by individuals with authority. Orders should include specific departure times, level of storm risk, and available transportation and sheltering resources. In addition, orders should provide clearer geographic boundaries, thereby reducing shadow evacuations and related roadway congestion.
- Posting mandatory evacuation orders on all available platforms and media outlets concurrently with the same messaging to reduce confusion.
- Developing pilot programs focused on education to encourage shorter-distance evacuations, given the high out of county evacuation rate.
- Continuing to employ phased evacuation plans and traffic management techniques such as signal timing, shoulder usage, and contraflow to reduce roadway congestion.
- Encouraging nighttime evacuations and ensuring that resources including gas, food, water, emergency services, law enforcement and traffic management officials are available during nighttime hours.
- Establishing or bolstering transit-based evacuation plans to assist lower-income and carless individuals by increasing pickup points and shuttle service to low-income neighborhoods.
- Ensuring that transportation and sheltering resources are available, plentiful, and free for evacuees to encourage evacuation compliance. Special needs of lower-income individuals, older adults, families, and other vulnerable groups must also be identified and met.
- Developing reentry plans for repopulating impacted areas. These plans must be crafted to ensure human safety, accelerate recovery efforts, and reduce traffic congestion. Evacuees should be informed prior to evacuation to expect a safe return order, and these orders must be widely disseminated to reach evacuees spread over a large geographic region.

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Contents

Introduction

In 2017, a number of devastating disasters impacted the United States (U.S.), requiring the evacuation of large populations. Of these disasters, Hurricane Irma in September led to one of the largest evacuations in U.S. history. Over six million people in Florida, Georgia, and South Carolina were ordered to leave their residences prior to the landfall of the storm. Given the immense complexity of managing evacuations, crafting and disseminating information, and allocating transportation and housing assets, governmental agencies must handle multiple challenges that are heavily dependent on how people behave in a disaster situation. Hurricane Irma was no exception – the projected path of the hurricane toward either Florida coastline prompted officials to issue mandatory and voluntary evacuation orders along both coasts. Hurricane Irma was also one of the largest and most intense storms on record, contributing to the extensive use of evacuations to safeguard the population. The unique characteristics of this disaster situation presented a worst-case scenario for officials as they attempted to adequately transport and shelter people.

Given the immense scale of this disaster, we developed several research questions to narrow the scope of this research and focus attention on the evacuation process from the perspective of the individual. These questions include:

- What decisions did individuals make regarding the evacuation of Hurricane Irma (i.e., evacuating or not, departure timing, mode choice, route choice, destination choice, reentry timing)?
- What specific reasons did individuals cite that influenced their choices?
- What beliefs did individuals have prior to the evacuation?
- To what extent was technology prevalent in the evacuation process?
- What are the lessons learned and areas of improvement for agencies moving forward?

To better understand what occurred during the evacuations and answer these questions, we conducted an online survey (n = 645) in Florida to ascertain the choices and behavior of individuals before, during, and after Hurricane Irma. This report includes five key sections. First, we present an overview of past evacuation literature. This is followed by a section detailing the methodology used for the survey and the analysis. Next, we provide an overview of the results of the survey through descriptive statistics followed by a more comprehensive analysis using discrete choice models. The final section of the report offers useful lessons learned, recommendations, and suggestions of strategies for evacuating people in disasters, specifically hurricanes. Ultimately, the aim of this preliminary report is to provide governmental agencies a background of what occurred during the evacuation, how individuals behaved, and what strategies may be useful moving forward for evacuation planning and policy-making.

Overview of Literature

Over the past 50 years, academics have slowly but methodically built a collection of wide-ranging research studies on evacuation behavior. Often, these evacuation studies coincided with major disaster events including the Big Thompson River Flood in Colorado (Gruntfest, 1977), the partial meltdown of Three Mile Island Nuclear Power Plant (Flynn, 1979; Zeigler *et al*., 1981; Cutter and Barnes, 1982; Stallings, 1984; Johnson and Zeigler, 1986), the eruption of Mt. St. Helens (Greene *et al*., 1981; Perry *et al*., 1982; Perry and Greene, 1983; Perry, 1983), flood events (Drabek and Stephenson, 1971; Leik *et al*., 1981; Drabek, 1992), and a number of hurricane events (Baker, 1979; Leik *et al*., 1981; Baker, 1990; Baker, 1991; Aguirre, 1991; Drabek, 1992; Dow and Cutter, 1998). Researchers also summarized earlier evacuation literature on both evacuation behavior and response to warnings and communications in several key reviews (Quarantelli, 1980; Sorensen *et al*., 1987; Sorensen and Mileti, 1988; Quarantelli, 1990; Lindell and Perry, 1991). Many of these papers employed surveys of evacuees and offered descriptive statistics as well as basic statistical models to help describe the key factors that influenced behavior. Frequently, these papers offered insights on evacuation choice-making (with a focus on evacuating or staying) and how different groups within the population, based on individual demographics and household characteristics, reacted to the disasters. Work in these earlier studies also focused on risk perception – a key factor influencing the behavior of evacuees.

For hurricane behavior, researchers have continued to focus on using surveys of disasters to provide an understanding of evacuee behavior and individual response to risk and messaging (Dow and Cutter, 2000; Dash and Morrow, 2000; Gladwin *et al*., 2001; Dow and Cutter, 2002; Lindell *et al*., 2005; Kang *et al*., 2007; Lindell and Prater, 2007; Lindell *et al*., 2011; Lindell *et al*., 2013; Sadri *et al*., 2013; Wu *et al*., 2012; Lin *et al*., 2014; Liu *et al*., 2014; Yang *et al*., 2016; Huang *et al*., 2017). These studies have focused on a number of different aspects of evacuations beyond the typical evacuation choices to include mobilization time, household logistics, and information sources and messaging crafting. Several studies have also offered important reviews of the literature such as evacuation behavior (Dash and Gladwin, 2007), warning systems for disasters (Sorensen, 2000), evacuation practice (Wolshon, 2009), evacuation traffic modeling (Pel *et al*., 2012), evacuation modeling (Murray-Tuite and Wolshon, 2013), and the decision to evacuate or stay (Huang *et al*., 2016). This overview of evacuation behavior literature, while brief, demonstrates the considerable work that has already been accomplished in the field and the successful application of lessons learned into current evacuation plans.

More recently, researchers have begun to employ discrete choice models developed in econometrics for hurricane evacuation choice-making. The most widely used models include binary logit (two discrete choices) and multinomial logit (more than two discrete choices). Particularly for the decision to evacuate or not, researchers have also tested other models for hurricane behavior including probit (based on a normal distribution), nested logit (allowing for a nesting of choices), mixed logit (allowing for random parameters), and sequential logit (time-based logit model). The defining feature of all these models is that individuals are assumed to choose the alternative with the highest utility, or satisfaction. Most of this work has also employed revealed preference surveys from specific hurricanes. Table 1 displays some of the key recent evacuation studies that have used discrete choice analysis. While most of the research has focused on the decision to evacuate or not, evacuees must make a number of other decisions throughout the evacuation including departure timing, route choice, shelter choice, destination choice, transportation mode choice, reentry timing, and reentry compliance. Some of these choices have only been peripherally studied, which indicates a gap in the literature and a need to develop models for these choices.

Consequently, this research aims to begin filling some of these gaps by modeling both well-documented choices – such as evacuation decision and departure timing – as well as other less studied choices including shelter choice, mode choice, and reentry timing. Moreover, this works adds to the literature by presenting empirical results of a new, recent disaster case, Hurricane Irma, which prompted one of the largest evacuations in U.S. history. Finally, the research aims to help agencies understand academic research in evacuations and begin a conversation to build more data-driven evacuation responses and strategies. While models in this work are confined to more basic logit models, future work using the same data will consider other models such as portfolio choice models and latent class models.

Table 1 Key Discrete Choice Studies of Hurricane Behavior

Alabama: AL	Georgia: GA	New Jersey: NJ	Rhode Island: RI
Arkansas: AK	Louisiana: LA	New York: NY	South Carolina: SC
Connecticut: CT	Maryland: MD	North Carolina: NC	Texas: TX
Delaware: DE	Massachusetts: MA	Pennsylvania: PA	Vermont: VT
Florida: FL	Mississippi: MS	Puerto Rico: PR	Virginia: VA

Authors (Year)	**Hurricane(s)**	**Key U.S. Location(s) (Month and Year)**	**N**	**Choice**	**Behavioral Model**
Evacuation Decision (Evacuate or Not)					
Whitehead *et al*. (2000)	Hurricane Bonnie; Hypothetical Hurricane	NC, SC, VA (Aug. 1998)	235; 673	Evacuate or Not	Binary Logit
Zhang *et al*. (2004)	Hurricane Bret	TX (Aug. 1999)	312	Evacuate or Not	Binary Logit
Smith and McCarty (2009)	Hurricane Charley; Hurricane Frances; Hurricane Ivan; Hurricane Jeanne	FL, SC, NC (Aug. 2004); FL, GA (Sept. 2004); FL, AL (Sept. 2004); FL, PR (Sept. 2004)	9048	Evacuate or Not	Binary Logit
Deka and Carnegie (2010)	Hypothetical Hurricane	NA	877	Evacuate or Not	Ordered Logit
Stein *et al*. (2010)	Hurricane Rita	LA, TX, FL, MS (Sept. 2005)	651	Evacuate or Not	Binary Logit
Solis *et al*. (2010)	Hurricane Katrina (Southeast FL); Hurricane Wilma; Hurricane Dennis; Hurricane Katrina (Northwest FL)	LA, MS, FL, AL, GA (Aug. 2005); FL (Oct. 2005); FL, AL (Jul. 2005); LA, MS, FL, AL, GA (Aug. 2005)	360; 506; 305; 184	Evacuate or Not	Probit
Hasan *et al*. (2011)	Hurricane Ivan	FL, AL (Sept. 2004)	1995	Evacuate or Not	Mixed Logit
Hasan *et al*. (2012)	Hurricane Andrew; Hurricane Ivan; Hurricane Katrina	FL, LA (Aug. 1992); FL, AL (Sept. 2004); LA, MS, FL, AL, GA (Aug. 2005)	954; 3200; 811	Evacuate or Not	Binary Logit + Combined Data Logit
Huang *et al*. (2012)	Hurricane Ike	TX, LA (Sept. 2008)	562	Evacuate or Not	Binary Logit
Murray-Tuite *et al*. (2012)	Hurricane Ivan; Hurricane Katrina	FL, AL (Sept. 2004); LA, MS, FL, AL, GA (Aug. 2005)	3200; 811;	Evacuate or Not	Binary Logit
Xu *et al*. (2016)	Hypothetical Hurricane	NA	404	Evacuate or Not	Probit
Yin *et al*. (2016)	Hurricane Ivan	FL, AL (Sept. 2004)	3200	Evacuate or Not	Mixed Logit
Departure Timing Decision and Combined Departure Timing and Evacuation Decision					
Fu and Wilmot (2004)	Hurricane Andrew	FL, LA (Aug. 1992)	428	Evacuate or Not and Departure Time	Sequential Logit

Fu *et al*. (2006)	Hurricane Floyd	SC, NC, VA, MD, DE, PA, NJ, NY (Sept. 1999)	651	Evacuate or Not and Departure Time	Sequential Logit
Dixit *et al*. (2012)	Hurricane Andrew	FL, LA (Aug. 1992)	429	Evacuate or Not and Departure Time	Binary Logit with risk aversion
Gudishala and Wilmot (2012)	Hurricane Gustav	LA, MS, AL, FL, AK, TX, PR (Aug. 2008)	300	Evacuate or Not and Departure Time	Sequential Logit, Nested Logit
Hasan *et al*. (2013)	Hurricane Ivan	FL, AL (Sept. 2004)	751	Departure Time	Random-Parameter Hazard-Based Model
Ng *et al*. (2015)	Hurricane Irene	NC, VA, MD, DE, PA, NJ, NY, CT, MA, RI, VT (Aug. 2011)	392	Departure Time	Ordered Logit
Sarwar *et al*. (2018)	Hurricane Ivan	FL, AL (Sept. 2004)	3031	Evacuate or Not within Departure Time Intervals	Mixed Logit
Destination Decision					
Cheng *et al*., (2012)	Hurricane Floyd	SC, NC, VA, MD, DE, PA, NJ, NY (Sept. 1999)	1040	Traffic Analysis Zone Choice	Multinomial Logit
Shelter Type Decision					
Whitehead *et al*. (2000)	Hypothetical Hurricane	NA	673	Shelter Choice	Multinomial Logit
Smith and McCarty (2009)	Hurricane Charley; Hurricane Frances; Hurricane Ivan; Hurricane Jeanne	FL, SC, NC (Aug. 2004); FL, GA (Sept. 2004); FL, AL (Sept. 2004); FL, PR (Sept. 2004)	9048	Shelter Choice	Binary Logit
Deka and Carnegie (2010)	Hypothetical Hurricane	NA	1537	Shelter Choice	Binary Logit
Mesa-Arango *et al*. (2012)	Hurricane Ivan	FL, AL (Sept. 2004)	1419	Shelter Choice	Nested Logit
Transportation Mode Decision					
Deka and Carnegie (2010)	Hypothetical Hurricane	NA	1362	Mode Choice	Multinomial Logit
Sadri *et al*. (2014a)	Hypothetical Hurricane	NA	707	Mode Choice (non-personal)	Nested Logit
Routing Decision					
Sadri *et al.* (2014b)	Hurricane Ivan	FL, AL (Sept. 2004)	720	Route Choice	Mixed Logit
Akbarzadeh *et al.* (2015)	Hypothetical Hurricane	NA	300	Route Choice	Multinomial Logit
Sadri *et al.* (2015)	Hypothetical Hurricane	NA	248	Route Choice	Mixed Logit
Reentry Compliance Decision					
Siebeneck *et al.* (2013)	Hurricane Ike	TX, LA (Sept. 2008)	808	Reentry Compliance	Binary Logit

Methodology

We administered an online survey from October to December 2017 to individuals impacted by Hurricane Irma across the state of Florida. All individuals were allowed to participate, even those who did not evacuate or receive a mandatory evacuation order. To facilitate survey distribution, we developed a list of emergency management and transportation agencies in Florida. This list included statewide agencies as well as agencies in several key counties in Florida based on population (i.e., Miami-Dade, Broward, Palm Beach, Pinellas, Hillsborough, Duval, and Brevard Counties) and proximity to landfall (i.e., Lee, Collier, and Monroe Counties). The survey was distributed on both the east coast and west coast of Florida, since evacuation orders were issued for both coastlines. Agencies were contacted via email with a description of the research and instructions for distributing the survey. We also employed a snowball technique wherein agencies were permitted and encouraged to provide contact information for other agencies and notify officials of the survey distribution. Survey distribution was not limited to transportation and emergency management agencies, as several regional planning organizations and one non-governmental organization also distributed the survey. All partnering organizations were allowed to distribute the survey via social media (i.e., Facebook, Twitter), organizational websites, subscription services, and online news outlets. This public-facing survey across a wide geography and through multiple outlets increased the coverage of the survey to the general population and provided an opportunity for individuals not connected to emergency management to participate. To increase the response and completion rates, respondents were entered into a drawing to win one of five $200 gift cards. We chose an online survey to reach a wide population quickly and cost-efficiently. The flexible structure of the online survey allowed us to ask 146 questions with considerable skip logic, permitting individuals to avoid non-applicable questions. The survey yielded 1,263 responses with 936 totally completed, a completion rate of 74%. We then intensively cleaned the completed surveys such that all key choice and demographic questions were answered. In all, 645 responses were retained for the research.

We present the results of the research in two ways: 1) descriptive statistics and 2) discrete choice analysis models. Descriptive statistics provide the overall results of key evacuation decisions along with several unique categories related to risk perception and opinion of government effectiveness. The discrete choice models are separated by eight key choices (i.e., evacuate or stay, departure day, departure time of day, destination, shelter, mode, route, and reentry day). For all models, we chose a basic binary or multinomial logit. While a number of other studies have considered more complex models (i.e., probit, mixed logit, nested logit, dynamic logit), we opted for simpler models that have been shown to be behaviorally consistent and easy to interpret for government agencies and for policy improvements. In addition, the methods offer a quantitative level of understanding that can be visualized in reports, presentations, and internal meetings for agencies. Additional explanation of the discrete choice modeling is located under "Discrete Choice Analysis."

Limitations

This research has several key limitations. First, the survey exhibits some self-selection bias since individuals must opt into the study. We attempted to address this by offering the incentive of the chance to win a $200 gift card. Second, the link was not randomly sent to households across Florida, also increasing self-selection bias. While a wide range of agencies posted the survey across a number of different platforms, only individuals with Internet access were able to take the survey. This restriction, along with the high response rates in three counties – Brevard, Lee, and Collier – skewed the results to reflect a higher proportion of wealthier and white individuals than Florida as a whole. The digital divide (i.e., inequality based on Internet availability and ability to use the Internet) remains a key disadvantage of online surveys. Consequently, the survey failed to reach an adequate number of vulnerable individuals, including low-income households, minorities, and individuals with disabilities. This limitation does diminish any conclusions we can make about how vulnerable individuals make choices in evacuations.

To overcome some of these limitations, we employ a weighting methodology based on gender, age, and vehicle ownership on the prediction probabilities derived from the discrete choice analysis. The weighting mechanism adjusts the probabilities to more accurately reflect the population of Florida. In addition, the survey was only administered for a single hurricane in just one state, which limits the generalizability of the study, especially for other disasters. Finally, we acknowledge that other discrete choice models beyond logit models have been shown to be behaviorally consistent for some evacuation decision-making in hurricanes. Future work using this online survey will consider and test more complex models that could explain evacuation behavior. This paper focuses on more accessible models and results for public agency use and interpretation.

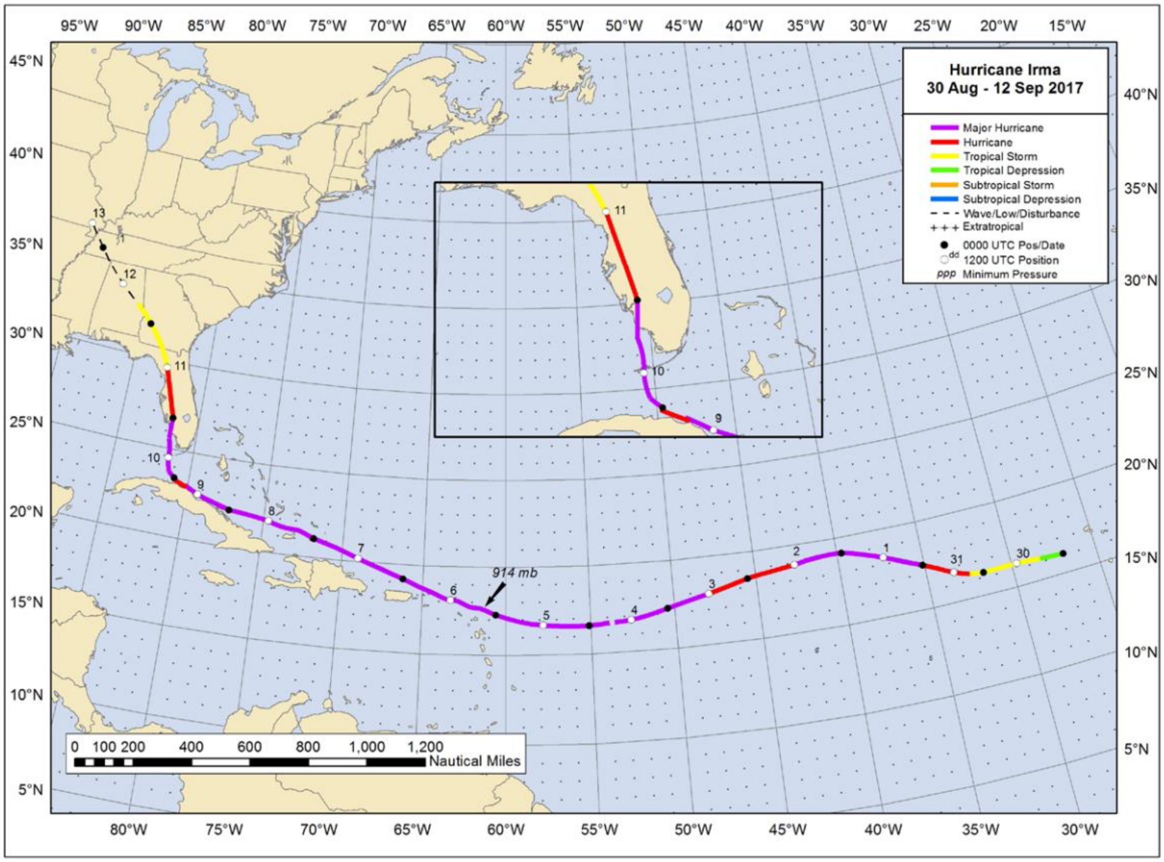
Brief Overview of Hurricane Irma Event

To provide context, we present a brief synopsis of Hurricane Irma in this section. The meteorological history of Hurricane Irma is based on the National Hurricane Center Tropical Cyclone Report (National Oceanic and Atmospheric Administration, 2018a). The summary of the evacuation is based predominately on reports from the Office of the Governor of Florida (2017a, 2017b, 2017c, 2017d, 2017e), which also offer information about the opening of shelters, status of the National Guard, transportation updates, telecommunications information, and law enforcement updates.

Meteorological History

Beginning as a wave off the coast of Africa on August 27, 2017, Hurricane Irma reached tropical storm-strength winds rapidly. Due to favorable conditions, it quickly developed into a hurricane on August 31. The storm intensified and became a Category 5 hurricane on September 4, with peak winds of 185 miles per hour on September 6. With warm water temperatures, low wind shear, and high atmospheric moisture, Hurricane Irma maintained its size and strength before impacting the Leeward Islands (i.e., Barbuda, Anguilla, Saint Martin, and the Virgin Islands). Hurricane Irma soon struck Puerto Rico (around September 6), the Turks and Caicos Islands, the Bahamas, and Cuba. During this time, the hurricane fluctuated between Category 5 and Category 4 strength before weakening to a Category 2 hurricane after scraping the coast of Cuba on September 9. Irma moved off the coast and intensified into a Category 4 hurricane across the Straits of Florida before making landfall in Cudjoe Key, Florida on September 10. Following a brief period over the Gulf of Mexico, Hurricane Irma made a second landfall in Marco Island, Florida later on September 10. With the eye remaining on land, Irma weakened quickly to a Category 1 storm by the time the eye approached Tampa, Florida on September 11. Irma then entered Georgia and lost most of its tropical force winds before eventually dissipating on September 13 in Missouri. Despite impacting Florida as a lower-rated Category 4 storm, Hurricane Irma was one of the strongest and most intense storms of all time. The storm had one of the strongest sustained wind speeds on record at 185 miles per hour and tied the longest time a hurricane retained its Category 5 status at 60 hours (National Oceanic and Atmospheric Administration, 2018a). See Figure 1 below for a map of the hurricane's path.

Figure 1 Meteorological Path of Hurricane Irma
(Source: National Oceanic and Atmospheric Administration, 2018a)



Evacuations

Early forecasts for Hurricane Irma predicted a landfall in the U.S. somewhere in Florida. However, it was unclear whether the storm would brush off Florida and enter the Gulf of Mexico, parallel the western coastline in the Gulf, or parallel the eastern coastline in the Atlantic Ocean. This uncertainty of the path of Irma, along with the size and intensity of the storm, led officials across Florida to issue numerous mandatory and voluntary evacuation orders. On September 4, Florida Governor Rick Scott declared a state of emergency, and the state began preparing for landfall. Over the course of the next six days, multiple counties in Florida issued evacuation orders for low-lying areas along both coastlines, areas prone to severe flooding (including inland counties), and neighborhoods with mobile homes. Orders were first issued to visitors of the Florida Keys on September 5 and eventually extended to residents. Both Miami-Dade and Broward Counties also issued mandatory evacuations on September 6 (effective September 7) for several zones and barrier islands. Mandatory evacuation orders quickly expanded on September 7 to include parts of Brevard County and Palm Beach County on the eastern coastline and parts of Lee, Collier, and Pinellas Counties on the western coastline. Mandatory evacuation orders were issued for Duval County on the following day, September 8, and for Charlotte County on September 9. In addition, officials issued mandatory orders for parts of Citrus, Dixie, Flager, Glades, Hendry, Hernando, Indian River, Martin, Orange (Orlando area), Pasco, Sarasota, Seminole, St. Lucie, Sumter, and Volusia Counties by September 9. The majority of these evacuations were for mobile homes, islands, and low-lying areas. Moreover, several counties including Lee County and Collier County encouraged residents to evacuate as early as

September 5. Officials also issued a number of voluntary evacuation orders throughout the event, and most counties used predetermined evacuation zones based on geography to communicate orders clearly. Monroe County implemented a phased evacuation approach across five zones with the furthest residents from mainland Florida evacuating first (Monroe County Office of Emergency Management, 2018). Figure 2 below provides the approximate mandatory evacuation zones immediately before Hurricane Irma's landfall.

Traffic Operations

The evacuation from Hurricane Irma was one of the largest evacuations in U.S. history with over six million people ordered to leave their homes across Florida, Georgia, and South Carolina. These orders were given as early as September 5 and continued until landfall on September 10. Congestion along roadways was expected, and considerable traffic occurred along I-75, I-95, the Florida Turnpike, and several other major roads (including U.S. 27) across the state on September 7 (Clark and Neal, 2017). Congestion was also widespread in the Florida Keys along the Overseas Highway. On September 8, traffic was relatively smooth on I-95, but problems persisted on I-75 and the Florida Turnpike and increased on I-10 (Clark, 2017a). On September 9, I-75 and I-4 grew increasingly congested during the late morning hours, while most other highways in Florida were free-flow (Clark and Bousquet, 2017). During the evacuation, the Florida Department of Transportation (FDOT) implemented Emergency Shoulder Use (ESU) along a number of corridors including I-75 and I-4 to increase the capacity of roadways and increase speeds (Florida Department of Transportation, 2018). Unlike Georgia on I-16, Florida decided against implementing contraflow on its major highways despite having prepared plans for the operation. Officials cited the high need for manpower to implement contraflow and the relatively smooth traffic flow on the majority of the highways at that point in time. In addition, contraflow would inhibit the transportation of gas and the movement of emergency response vehicles traveling in the opposite direction (Clark, 2017b). FDOT did use a number of other operation strategies to improve congestion including: 1) Dynamic Message Signs (DMS) for ESU, 2) communication through Florida 511 and mobile applications to provide real-time traffic information, 3) notification to residents through social media feeds and websites, and 4) coordination with Google and Waze about ESU. In contrast to some past hurricane evacuations, there were no fatalities during the evacuation of Hurricane Irma (Florida Department of Transportation, 2018). While it was difficult at times to encourage shoulder use and provide video footage of all roadways, FDOT considered its operations relatively successful. Still, FDOT recognized a number of areas for improvement including expanding ESU and emergency roadside assistance, filling in gaps where cameras or DMS did not exist, and developing signal timing operation plans for major parallel roads (Florida Department of Transportation, 2018).

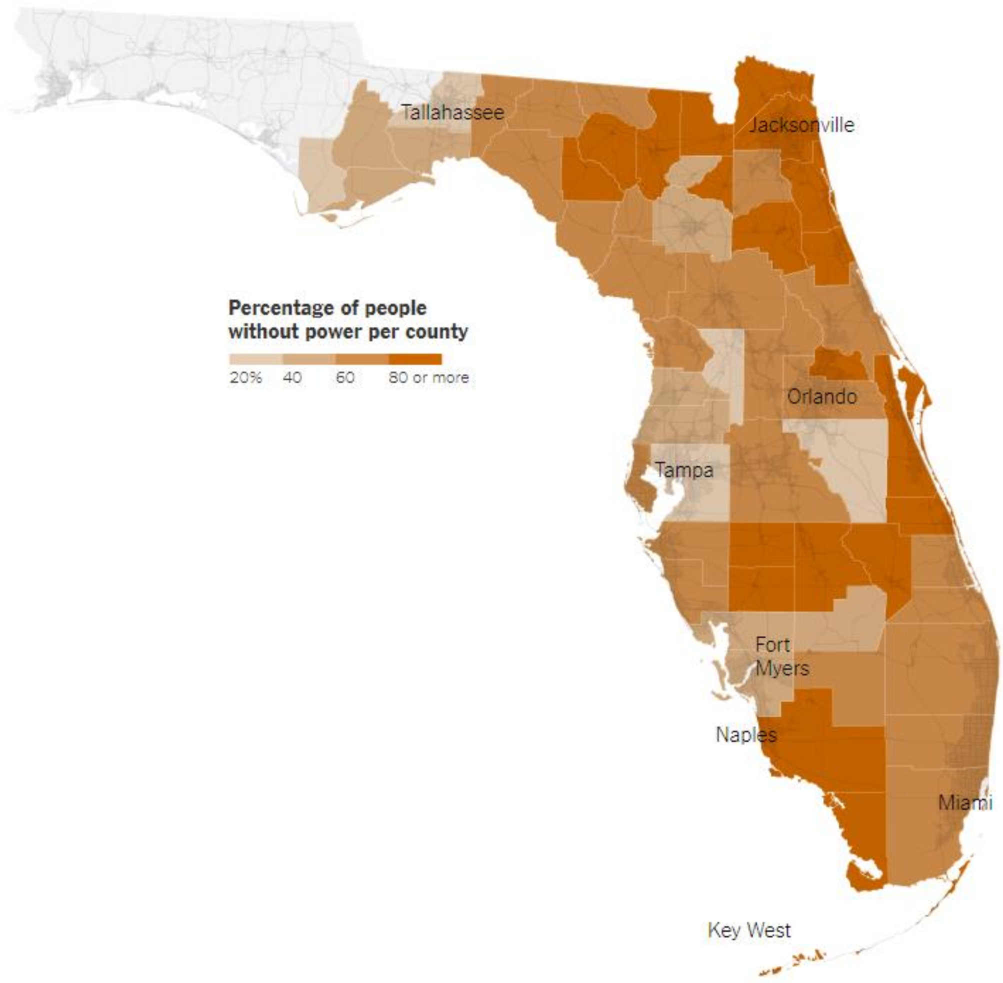
Figure 2 Approximate Mandatory Evacuation Zones by Sept. 10
(Source: The Washington Post, 2017)

Note: Some mandatory evacuation areas, particularly in Lee and Collier counties, are not included in the above map.

Impact and Additional Notes

With the extensive size of the Hurricane Irma evacuations, gas shortages across Florida were rampant. As early as September 6, parts of Florida experienced a lack of supply, and fears increased with both panic buying and price gouging. Shortages extended throughout the evacuation and into the reentry period back to impacted areas, as 43% of gas stations were dry across the state on September 12 (Disis and Egan, 2017). Officials also struggled with opening an adequate number of shelters for evacuees, especially along the western coastline following new hurricane trajectories (Fountain and Stevens, 2017).

Figure 3 Power Loss of Florida Following Hurricane Irma
(Source: The New York Times, 2017)



In terms of impact, damage from Hurricane Irma was highly isolated in several main areas including the Florida Keys, Marco Island, Naples, and Jacksonville. A number of other areas across Florida, particularly low-lying areas including Miami and Tampa, were also impacted. Despite dire predictions, Hurricane Irma remained largely inland, which caused the storm to dissipate quicker than expected. Storm surges and flooding in many areas were less than predicted. Still, Hurricane Irma caused estimated damage of upwards of $50 billion in just the U.S. and led to 97 fatalities (National Oceanic and Atmospheric Administration, 2018b). Reentry and power restoration lasted many weeks after the hurricane, with a significant proportion of homes losing power in most coastal areas of Florida (Figure 3). Despite considerable media attention, much of the recovery process was overshadowed by Hurricane Maria, which severely impacted Puerto Rico just two weeks after Hurricane Irma. Hurricane Harvey, which impacted Texas just two weeks prior to Hurricane Irma, was also a major focus of media coverage due to the record-breaking flooding in the Houston area. Ultimately, the intensity of Hurricane Irma wreaked havoc across Florida and Georgia and led to one of the largest hurricane disasters ever experienced in the U.S. Still, the preparedness of many emergency management and transportation agencies minimized the impact of the storm through a largely successful and safe evacuation of millions of residents. Indeed, Hurricane Irma could serve as a strong case study for emergency management in both effective practices and lessons learned (see Collins *et al*., 2017 for preliminary results). To help develop this case study, the following sections include the results of the survey, an analysis of evacuee behavior, and recommendations that augment already-established effective practices.

Characteristics of Evacuees

This section provides an overview of the characteristics of survey respondents and their respective households. Table 2 presents the individual characteristics of survey respondents, while Table 3 presents the household characteristics of respondents. We note that the sum of each demographic variable may not total 100% due to rounding. Despite sampling bias due to the survey methodology, the key characteristics including age, employment status, homeownership, and length of residence include substantial variation. In addition, over 90% of respondents said they were the sole decision maker, the primary decision maker, or shared decision making equally in the household. Thus, the survey successfully targeted active decision-makers for the evacuation of Hurricane Irma.

By using an online distribution method, we captured higher income and more educated individuals through the survey. Indeed, just 6.5% of the sample had a high school degree or below compared to 42% of the population of Florida (American Community Survey, 2018). Education and income are typically correlated, and the survey demonstrated this relationship as 30.1% of respondents had a household income of $100,000 and above. The higher proportion of wealthy and well-educated individuals was also a product of the locations where the survey was distributed. We targeted areas along the coastlines of Florida and major Florida cities to capture a higher proportion of individuals who evacuated and to increase response rate. The survey also captured a high number of smartphone users (96.3%) and individuals who had access to Internet at home (98.3%). This is unsurprising since the survey was only distributed online. Based on research, only about 65% of homes in the U.S. had broadband Internet service in 2018 (Pew Research Center, 2018a), and about 77% currently own a smartphone (Pew Research Center, 2018b). This digital divide between the survey respondents and the population presents a challenge in achieving a representative sample and also ensuring that individuals in emergencies have access to information and services via the Internet. The survey also oversampled White individuals while severely undersampling Hispanics and African-Americans. Language barriers, unequal access to the Internet, and geographic distribution of the survey are among the factors that may have contributed to this result.

Table 2 Individual Demographic Characteristics of Survey Respondents (n = 645)

Gender	
Female	81.9%
Male	18.1%
Age	
18-24	3.1%
25-34	26.0%
35-44	28.7%
45-54	21.7%
55-64	14.9%
65+	5.6%
Race	
White	94.0%
Black or African-American	1.6%
Mixed	1.1%
Asian	0.9%
Native American/Alaska Native	0.2%
Pacific Islander	0.2%
No answer/Prefer no answer	2.2%
Ethnicity	
Not Hispanic	89.5%
Hispanic	6.7%
No answer/Prefer no answer	3.9%
Primary Transportation Mode	
Drive alone using automobile	94.3%
Work from home	1.7%
Carpool/vanpool	0.9%
Bus	0.8%
Bicycle	0.6%
Walk	0.3%
Motorcycle/scooter	0.3%
Shared mobility	0.2%
Rail	0.0%
Other	0.9%

Note: Some values may not add to 100% due to rounding

Education	
High school graduate or below	6.5%
Some college	18.6%
2 year degree	12.9%
4 year degree	32.1%
Master's/Professional degree	26.4%
Doctorate	3.6%
Employment	
Employed full time	65.7%
Employed part time	10.2%
Unemployed looking for work	2.8%
Unemployed not looking for work	6.8%
Retired	8.7%
Disabled	2.3%
Student	2.2%
No answer/Prefer no answer	1.2%
Mobile Phone Type	
Own a smartphone	96.3%
Own a non-smartphone	3.4%
Do not own a cell phone	0.3%
Mobile Phone Plan	
Call, text, and internet and data plan	95.7%
Call, text, and internet but no data plan	2.0%
Only call and text capabilities	2.2%
Do not own a cell phone	0.2%
Access to Internet at Home	
Yes	98.3%
No	1.7%
In-Vehicle or Smartphone Navigation	
Yes	87.9%
No	12.1%

Table 3 Household Demographic Characteristics of Survey Respondents (n=645)

Household Characteristics	
Household with Disabled	16.4%
Household with Children	44.8%
Household with Elderly	15.0%
Households with Pets	77.1%
Households with Dogs	55.0%
Households with Cats	35.7%
Household Income	
Less than $10,000	1.1%
$10,000 - $19,999	3.6%
$20,000 - $29,999	6.4%
$30,000 - $39,999	6.0%
$40,000 - $49,999	7.4%
$50,000 - $59,999	7.9%
$60,000 - $69,999	6.0%
$70,000 - $79,999	7.3%
$80,000 - $89,999	6.5%
$90,000 - $99,999	5.9%
$100,000 - $149,999	17.7%
$150,000 - $199,999	5.1%
$200,000+	7.3%
No answer/Prefer no answer	11.8%
County of Residence	
Brevard	53.2%
Lee	17.2%
Collier	13.3%
Miami-Dade	3.7%
Monroe	2.6%
Pinellas	2.9%
Broward	2.5%
All other counties (under 10 respondents per county)	4.5%
Live in FEMA Flood Risk Area	
Yes	39.5%
No	47.9%
I don't know	12.6%

Distance from Major Water Source	
Next to Major Source	15.3%
1 mile	16.4%
2 miles	8.7%
3 miles	7.0%
4 miles	5.0%
5 to 9 miles	23.6%
10 to 20 miles	17.8%
Over 20 miles	3.6%
No answer	2.6%
Residence Structure	
Site build (single home)	76.6%
Site build (apartment)	19.1%
Mobile/manufactured home	4.3%
Homeownership	
Yes	69.3%
No	30.7%
Length of Current Residence	
Less than 6 months	9.5%
6 to 11 months	7.9%
1 to 2 years	22.6%
3 to 4 years	18.6%
5 to 6 years	9.8%
7 to 8 years	6.4%
9 to 10 years	4.0%
More than 10 years	21.2%
Number of Vehicles	
No vehicle	0.5%
One vehicle	24.6%
Two vehicles	52.4%
Three or more vehicles	22.5%

Choices of Evacuees

The following section contains an overview of the key choices from the survey along with additional descriptive results of the survey. This section, while not employing statistical models in discrete choice, provides considerable information on the choices that individuals made. Table 6 presents the decisions of the survey respondents. Subsections focus on describing the worries and concerns of individuals before evacuating; messaging and communication; the decision-making of non-evacuees; and individual perception of government response.

Evacuate or Stay

Of the 645 respondents, 368 evacuated while 277 did not evacuate, representing 57.1% and 42.9% of the sample respectively (Table 4). For those given a mandatory evacuation order, 69.5% evacuated while 30.5% did not evacuate. For those not given a mandatory evacuation order, 46.4% still evacuated while 53.6% did not evacuate. These numbers are comparable to results obtained from a telephone poll of registered voters in Florida, finding that for those who received a mandatory order, 57% evacuated while 43% did not (Mason-Dixon Polling and Strategy, 2017). Table 4 also tests the relationship between evacuation decision and mandatory order and finds that there is a statistically significant relationship between the two categorical variables, suggesting that mandatory orders do impact evacuation decision.

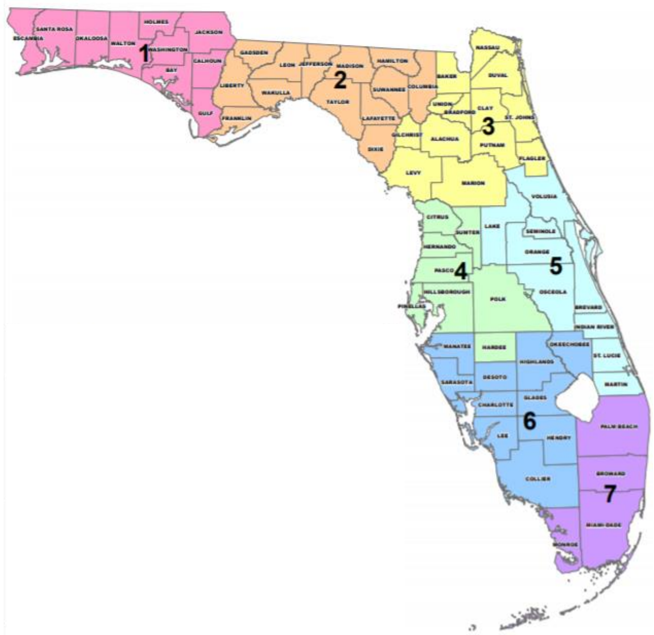
As seen in Table 4 with the conversion to percentage values, 30.5% of those who received a mandatory order did not evacuate (i.e., non-compliance). Mandatory evacuation orders require that individuals leave their residence, and in some states and localities, failure to comply with a mandatory order is illegal. The non-compliance levels indicate a substantial number of people who remained behind despite mandatory orders and the risks associated with Irma. This behavior is problematic for human safety as rescue crews are typically not available to save individuals who do not evacuate. Moreover, high non-compliance is generally associated with higher fatality levels. Fortunately, storm surge and flooding from Hurricane Irma were not as severe as predicted, which significantly lowered the number of fatalities. While there are a number of reasons for not evacuating, the level of non-compliance is an important indicator of agency messaging and effectiveness in protecting citizens. Non-compliance may also be indicative of the characteristics of the population and their perception of risks. On the flip side, 46.4% of those who did not receive a mandatory order still evacuated (i.e., shadow evacuations). These results suggest a level of disconnect between evacuation-issuing entities and citizens, particularly regarding the level of risk associated with the orders. The high values for shadow evacuations are concerning for agencies, as these individuals contribute to overall congestion on roadways and use of sheltering resources.

Table 4 Bivariate Cross Tabulation for Evacuation Decision and Mandatory Order

		Evacuation Decision	
		Yes	No
Received Mandatory Order	Yes	69.5%	30.5%
	No	46.4%	53.6%
	Total	57.1%	42.9%

χ^2= 34.8, p-value < 0.001

Figure 4 Designation of Florida Regions
(Source: Florida Division of Emergency Management, 2018)



Designation for Study

- Northeast/Central-East: Region 3 and Region 5
- Southwest: Region 6
- Southeast: Region 7
- Central-West: Region: 4

Table 5 Selected Descriptive Results by Geographic Region

Region in Florida	Percent of Sample	Evacuation Characteristics: Evacuated	Evacuation Characteristics: Non-Compliance	Evacuation Characteristics: Shadow Evacuation	Destination of Evacuees: Within County	Destination of Evacuees: Out of County, Within Florida	Destination of Evacuees: Out of Florida
Northeast/Central-East	54.7%	46.2%	45.1%	40.2%	11.7%	36.2%	52.1%
Southwest	32.6%	72.4%	16.9%	58.7%	22.4%	27.6%	50.0%
Southeast	9.8%	61.9%	20.7%	47.1%	10.3%	51.3%	38.5%
Central-West*	2.9%	73.7%	0.0%	58.3%	42.9%	35.7%	21.4%
Total	100.0%	57.1%	30.5%	46.4%	17.1%	34.2%	48.6%

***With such a small sample size, we cannot draw descriptive statistical conclusions for the Central-West region. The values are only included in this table to present all data available.

We also divided several key results by Florida region to present more geographic-specific findings in Figure 4 and Table 5. Overall, the Northeast/Central-East had the highest non-compliance rate of 45.1% while the Southwest region had the lowest non-compliance rate. These results are intuitive since Hurricane Irma made landfall in the Southwest region and was predicted to have the lowest impact on the eastern Florida coastline. Shadow evacuation rates were highest in the Southwest (58.7%), as many individuals outside the mandatory evacuation zones may have been worried about the impact of the storm. Regarding destination, the Southwest region had both a high rate of within county evacuations (22.4%) and out of Florida evacuations (50.0%). The split result is not immediately explainable, but it may be a consequence of messaging and policies within the region. Regardless, long-distance evacuations from both the Southwest and Southeast regions are problematic for transportation management. Indeed, more long-distance evacuations lead to increased congestion and higher resource usage of services such as gas. The Northeast/Central-East region had a high rate of out of Florida evacuees (52.1%), due in part to its closer proximity to other states.

Table 6 Descriptive Results of Key Evacuation Decisions (n=368)

Evacuation Choice *(n = 645)*	
Evacuated	57.1%
Did Not Evacuate	42.9%
Departure Date	
Before Tuesday, Sept. 5	1.6%
Tuesday, Sept. 5	2.7%
Wednesday, Sept. 6	15.8%
Thursday, Sept. 7	22.3%
Friday, Sept. 8	32.3%
Saturday, Sept. 9	22.6%
Sunday, Sept. 10	0.8%
Monday, Sept. 11 and Later	1.9%
Departure Timing	
12:00 a.m. - 5:59 a.m.	16.0%
6:00 a.m. - 11:59 a.m.	32.9%
12:00 p.m. - 5:59 p.m.	34.2%
6:00 p.m. -11:59 p.m.	16.8%
Mode Choice	
One personal vehicle	65.8%
Two personal vehicles	21.5%
Aircraft	4.1%
More than two personal vehicles	2.7%
Non-household carpool	2.2%
Recreational vehicle (RV)	1.6%
Rental car	1.6%
Bus	0.5%
Usage of GPS for Routing	
Yes, and followed route	63.6%
Yes, but rarely followed route	6.5%
No	29.9%
Primary Route by Road Type	
Highways	64.1%
Major Roads	13.6%
Local Roads	4.1%
Rural Roads	1.4%
No Majority Type	16.8%

Shelter Type	
Family member's residence	43.5%
Hotel or motel	27.4%
Friend's residence	15.8%
Peer-to-peer service (e.g., Airbnb)	4.3%
Public shelter	3.5%
Second residence	2.7%
Portable vehicle (e.g., camper, RV)	2.2%
Other	0.5%
Destination by State	
Florida	51.4%
Georgia	12.0%
Tennessee	6.8%
North Carolina	5.7%
Alabama	4.9%
South Carolina	3.5%
Virginia	2.4%
Louisiana	1.6%
Mississippi	1.6%
Ohio	1.6%
Pennsylvania	1.6%
All other states	6.8%
Within County Evacuation	
Yes	17.1%
No	82.9%
Multiple Destinations	
Yes	28.0%
No	72.0%
Reentry Date	
*Before Sunday, Sept. 10	10.9%
Sunday, Sept. 10	1.6%
Monday, Sept. 11	18.5%
Tuesday, Sept. 12	22.0%
Wednesday, Sept. 13	12.5%
Thursday, Sept. 14	8.2%
Friday, Sept. 15	5.4%
Saturday, Sept. 16	4.1%
Sunday, Sept. 17	7.1%
After Sunday, Sept. 17	9.8%

*Respondents may have decided to return home before landfall if their residence was no longer at risk due to a change in the hurricane path.

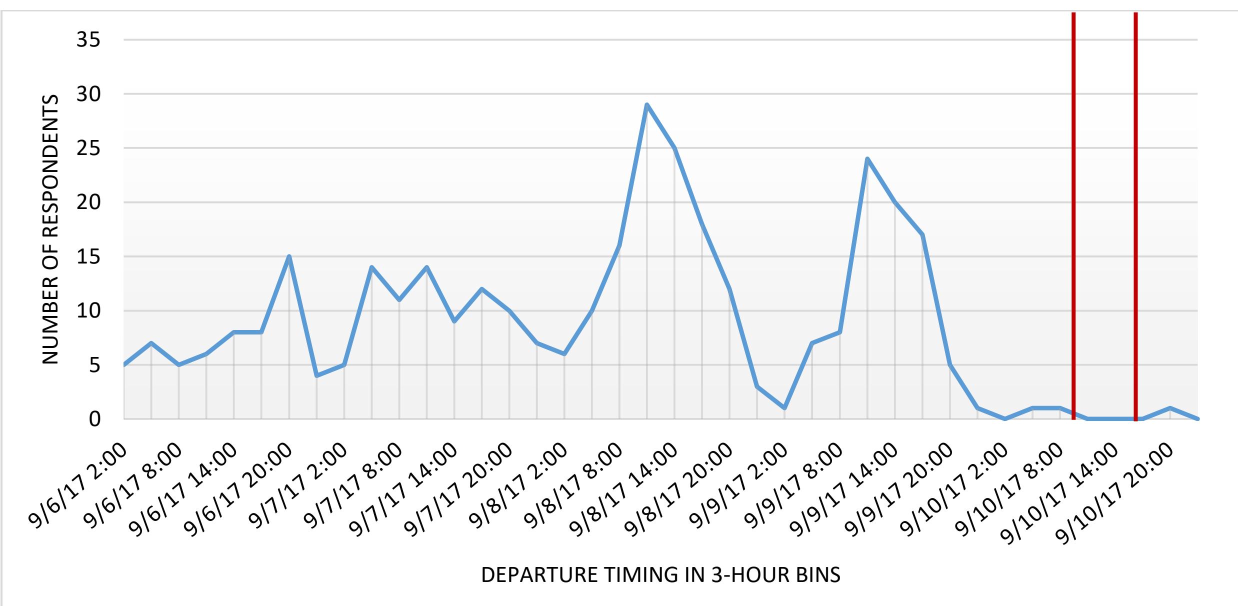
Departure Day

Hurricane Irma made landfall on September 10, 2017 in the Florida Keys and Marco Island, and most respondents evacuated before that date. In fact, the majority of respondents evacuated one, two, or three days prior to landfall at 22.6%, 32.3%, and 22.3% respectively. There were also a considerable number of early evacuees with 20.1% evacuating four days or more in advance. Only 0.8% evacuated on the date of landfall. Possible reasons for the high rate of early evacuees include the increased use of time-phased evacuation plans and the decision to issue evacuation orders earlier. For Hurricane Irma, officials issued some mandatory evacuation orders as early as five days prior to landfall, on September 5. In addition, respondents may have been concerned about the potential for traffic jams, given the immense scale and strength of the storm. Figure 5 displays the evacuation departure timing of the respondents, while Figure 6 displays the cumulative departure curve.

Departure Time of Day

Most respondents evacuated during daylight hours, but a surprisingly high number decided to evacuate at night. Indeed, 16% of respondents evacuated between midnight and 5:59 a.m. Another 16.8% departed between 6:00 p.m. and 11:59 p.m. A number of respondents may have taken advantage of better traffic conditions to begin their evacuations at night. It is also possible that respondents preferred to drive in more familiar areas at night and less familiar areas, such as near their final destination, during daylight hours. In addition, respondents may have wanted to finish work, particularly during the weekdays up until Friday, September 8. Nighttime departures may also have resulted from the time needed to mobilize, which includes collecting family members, packing, and preparing to leave. Still, daytime evacuations were popular with 32.9% departing in the morning between 6:00 a.m. and 11:59 a.m. and 34.2% departing between 12:00 p.m. and 5:59 p.m.

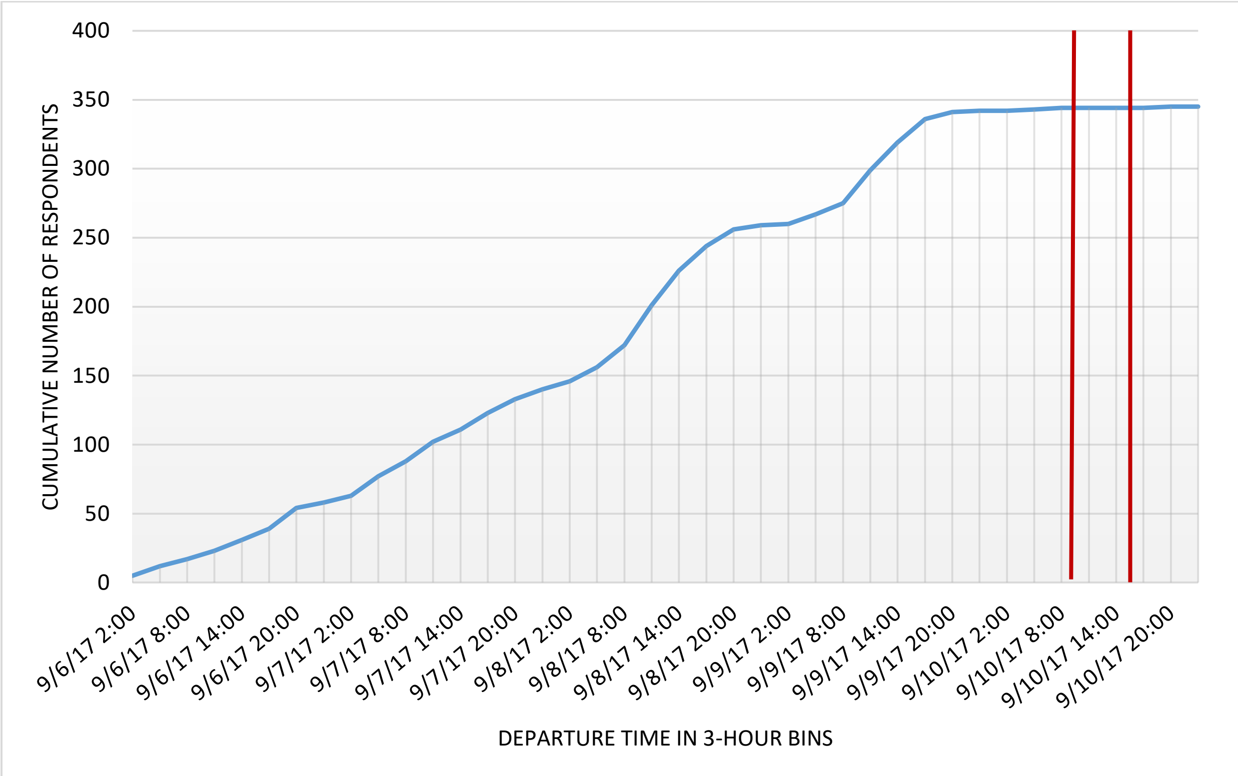
Figure 5 Evacuation Trip Generation for Hurricane Irma Respondents (n=345)



*The first red line indicates landfall at Cudjoe Key. The second red line indicates landfall at Marco Island.

**16 respondents evacuated prior to 9/6/17. Seven respondents evacuated after 9/10/17.

Figure 6 Cumulative Count of Trip Generation for Hurricane Irma Respondent (n=345)



*The first red line indicates landfall at Cudjoe Key. The second red line indicates landfall at Marco Island.

**16 respondents evacuated prior to 9/6/17. Seven respondents evacuated after 9/10/17.

Transportation Mode

Similar to other evacuations, most individuals evacuated via private automobile(s) as their primary transportation mode, with 65.8% taking one vehicle and 21.5% taking two vehicles. Only 2.7% evacuated with more than two personal vehicles and only 0.5% evacuated using a bus, while 4.1%, evacuated via aircraft. Some individuals also carpooled with non-household members (e.g., neighbors, strangers), while several were able to find rental cars to evacuate. The modal split towards individuals who drive is unsurprising, given the geography of most areas of Florida and the survey methodology bias toward individuals with higher income, which typically correlates with higher car ownership. Over 24% of individuals evacuated with more than one vehicle, but it is unclear why households took additional vehicles. One reason may be that 16.4% of households contained five or more individuals. Other hypotheses include the desire to protect all vehicles in the household since they are expensive assets; the increased capacity for carrying luggage and possessions; the improved comfort of more space in the vehicles; and greater flexibility in returning home or traveling near the destination. However, respondents were also asked the quantity of available (non-occupied) seatbelts in the vehicle. Sixty-three percent reported that they had three or more seatbelts open and available. This spare capacity, though, did not factor in the space used for luggage or pets, and actual open seats are most likely significantly lower than the reported numbers. Still, there appears to be some level of capacity in vehicles that is not occupied by people. By increasing occupancy levels, evacuations could become more efficient through the increased carrying capacity of vehicles and lead to reduced congestion on the roadways.

Route Choice

For route choice, we asked respondents the percentage of their trip that they traveled via different road types. A primary route indicates that individuals used that road type over 50% of the time. Most individuals primarily evacuated using highways (64.1%), but a relatively large number of respondents took mostly major roads (13.6%). For highway users, many respondents took I-75 (33.4%) and I-95 (26.1%) as "the largest" road during their evacuation. The high use of major roads – including both U.S. routes and state roads – may be a result of improved navigation capabilities via smartphone technology and in-vehicle routing. Over 63% said they used a GPS system for routing and frequently followed the route. Over 6% used GPS but preferred not to follow the route given, and just under 30% did not use GPS for routing. Before the mass use of smartphone technology and the rise of in-vehicle navigation, most evacuees relied on previous experience with routes, official designation of evacuation routes, and instructions from local law enforcement and government agencies. The shift towards using GPS as a tool for evacuation is an important consideration for transportation and emergency management agencies. With the rise of applications including Google Maps, Apple Maps, and Waze, individuals are now able to circumvent traditional evacuation routes to decrease their overall travel time and avoid congestion on major routes. However, changes in routing may place burdens on other transportation facilities and geographic areas with sparse amenities. Additional discussion on this topic is offered later in this report.

Destination

While a number of evacuations were short-distance and within the state of Florida, 48.6% of respondents left the state. The majority of those individuals went to Georgia (12%), but other southern states including Tennessee, North Carolina, Alabama, and South Carolina were also popular. There were a number of respondents who evacuated to much further locations, particularly the Northeast and Midwest. These long-distance evacuations may have resulted from friends and family in spatially-distant locations and the sheer magnitude of the storm. Some respondents may not have felt comfortable remaining in Florida or nearby locations. Lending support to this idea, only 17.1% of evacuees remained in the county of their residence. When asked why they traveled so far out of the county (see Table 7), respondents believed their home was not safe from the storm (38.9%), wanted to stay with friends and family who happened to live further away (37.2%), were ordered to leave the county (17.1%), and found it necessary to locate an available shelter or hotel (16.2%). Paralleling these findings, 52.7% of respondents spent ten or more hours evacuating with 10.6% taking over 30 hours, while only 17.9% spent less than two hours evacuating. It should also be noted that 28% of respondents sheltered in more than one location. While this number may reflect a stop-over between segments of the trip, other multiple-destination individuals may have initially evacuated to a location that was unsafe. The unpredictability of the storm and which side of Florida would be most severely impacted may have led people to switch their destinations.

Sheltering

For shelter type, most respondents stayed at a family member's residence (43.5%), a hotel or motel (27.4%), or a friend's residence (15.8%). These results show a preference towards sheltering with friends and family as well as dedicated facilities such as hotels and motels rather than public shelters. Sheltering with friends and family is a low-cost option that also ensures social connections and a more comfortable stay. Hotels and motels are seen as secure options that provide amenities and services. Moreover, these structures are sometimes perceived as more stable and better prepared to weather storms. Despite the opening (and crowding) of hundreds of shelters, only 3.5% of respondents chose a public shelter. Public shelters were generally not preferred (despite being free and nearby) as they can become crowded, resource-depleted, and uncomfortable. Therefore, public shelters are frequently a last resort for those who are resource deficient, given that they are commonly perceived to be a poor sheltering option. Moreover, many shelters do not allow pets. Low public shelter use can partially be attributed to the high levels of pet ownership at 77.1% of respondents. One interesting result from the sheltering choice was that 4.3% sought peer-to-peer housing services such as Airbnb or HomeAway. Not available ten years ago, these options – whether through the free Airbnb Open Homes Program or as a standard rental – could grow with increasing service coverage. Across the different shelter types, most respondents stayed three to four days (30.7%), five to six days (27.7%), and one to two days (17.1%). However, 22.3% stayed one week or more at their destination, suggesting difficulty in returning to their residence.

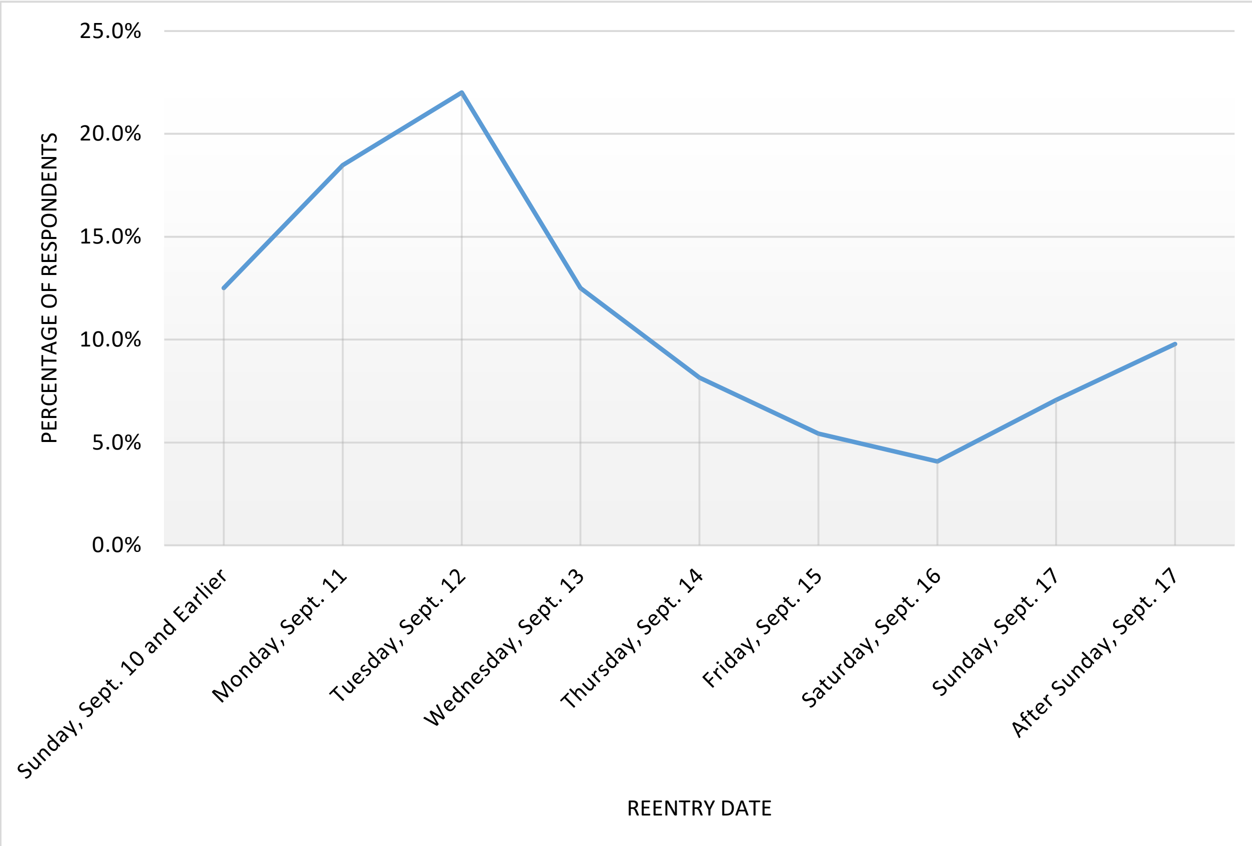
Reentry

One important yet highly under-researched aspect of evacuations is reentry, the process of returning to a residence after a disaster. In general, reentry has fewer peaking characteristics than departure timing since impacted areas are livable at different times. Moreover, government agencies typically do not plan reentry to impacted areas. This lack of planning is problematic, as people attempt to return to unlivable disaster areas or return all at once, causing additional traffic problems. Siebeneck *et al*. (2013) attributed the neglect of research on the reentry process to practical and theoretical reasons. Indeed, reentry is not the reverse of an evacuation. Most notably, the risk of the disaster is severely diminished, and communication with a dispersed evacuee population is much more difficult (Siebeneck *et al*., 2013). The results from the survey indicate that people returned to impacted areas rather quickly in some cases (18.5% on September 11 and 22% on September 12). This peak tapered off but began to rise slightly starting September 17 (7.1%). A number of people also waited until after September 17 (9.8%). Individuals listed several reasons why they returned on a particular date (see Table 7). Specifically, 40.8% wanted to survey the damage as soon as possible, and 40.5% and 18.2% cited learning that power and water were restored, respectively. One area of concern is that just 26.4% were informed by a secondary source that it was safe to return. Even worse, only 20.9% received a notification from an official source or news source that indicated they could return. Indeed, official notices were not a driving reason for returning. Individuals also had to return to work (28.3%) and wanted to protect their property as soon as possible (23.4%). Additional comments highlighted the desire to return much earlier or later to avoid traffic, the wish to check on friends and family in the impacted areas, and depleted resources at the destination location. The results offer a snapshot of the factors that influence reentry behavior, and it is clear that there is a gap in evacuation planning that does not account adequately for reentry. The process of reentry is also considerably more challenging than evacuation, since individuals are dispersed throughout a wider geographical area. While reentry restrictions could be justified with the goal to maintain safe and livable conditions, safe-return notices need to be balanced effectively as individuals may disregard these notices.

Table 7 Respondent Reasons for Traveling Far Distance, Reentry, and Not Evacuating

Multiple selection allowed	
Reasons to Travel Far Distance Out of County (n = 368)	
I felt my home wasn't safe for this storm and that's how far I had to go to reach safety	38.9%
That was the location of the friend/relative I wanted to stay with	37.2%
I stayed in the county	17.7%
Because my location was ordered to evacuate the county	17.1%
That's how far I had to go to find available hotel/motel/public shelter or other location to stay	16.2%
Other	18.2%
Reasons for Reentry (n = 368)	
Wanted to survey damage as soon as possible	40.8%
Learned that power was restored	40.5%
Had to return for work	28.3%
Was told by a secondary source that it was safe to return	26.4%
Wanted to protect property as soon as possible	23.4%
Received a safe-return notice from a public official or news source	20.9%
Learned that water restored	18.2%
Had to return for child's school	3.0%
Other	14.4%
Reasons to Not Evacuate (n = 277)	
Didn't want to sit in traffic	49.1%
Didn't want to leave	48.0%
Wanted to protect my property	34.7%
Didn't want to go to public shelter	31.4%
Believed the storm would not be bad	29.6%
Some requirement to go to work during storm	21.7%
Was not sure where I could take my pets	18.1%
Didn't receive any orders	15.9%
Didn't have the money to evacuate	14.4%
No friends or family to shelter with	6.1%
Tried to but ended up going back home due to traffic	2.5%
Tried to but was turned away at shelter	0.4%
No transportation to get to shelter	0.0%
Other	37.5%

Figure 7 Reentry Date (n = 368)



Messaging, Worries, and Likelihood Belief of Events

We asked respondents a number of other questions addressing evacuation-specific variables that go beyond traditional demographic characteristics. One area of inquiry was the type of messaging respondents received with regard to different orders (mandatory, voluntary, and shelter-in-place) as seen in Table 8. Respondents received evacuation orders through a number of different sources, most notably television, social media, Internet websites, and reverse 911 calls. This was largely consistent across all types of orders. Other methods of receiving orders included text message, being told by another person, and radio announcements. Receiving orders from a subscribed service was fairly low, which is indicative of the opt-in nature of these services. Many respondents sought additional information, with 46.9% and 50.2% seeking more information for mandatory and voluntary orders respectively. Despite this need to find additional sources, most respondents indicated that the messaging was clear. Indeed, 86.6% of those who received a mandatory order said that the messaging was extremely clear, while 70.0% answered likewise for voluntary orders. Table 8 provides, within order type, the breakdown of the method of receiving orders as well as the clarity of overall messaging. These results demonstrate relatively strong communication by public agencies in notifying the public of evacuation orders. The variety of methods by which orders were received also suggests that public agencies should continue to focus on using all means of communication with consistent messaging to inform the public effectively and encourage higher evacuation compliance.

Table 8 Communication and Messaging of Evacuation Orders

	Mandatory	Voluntary	Shelter-in-Place
Received the Order *(n = 645, multiple selection allowed)*	46.2%	36.3%	14.6%
Did Not Receive the Order	53.8%	63.7%	85.4%
Method of Receiving Order Within Order Type	*n = 298*	*n = 234*	*n = 94*
Television announcement	56.4%	57.4%	50.0%
Social media (Facebook, Instagram, Twitter, etc.)	47.5%	38.8%	39.6%
Internet website (news, EM/government page)	33.1%	24.1%	20.8%
Reverse 911 call	30.2%	18.6%	18.8%
Text message	25.9%	17.7%	22.9%
Radio announcement	19.3%	13.1%	20.8%
Someone told you (neighbor, friend, extended, family)	19.3%	14.3%	12.5%
Alert from a subscribed service	15.7%	10.1%	12.5%
Smartphone application	13.4%	7.2%	7.3%
Personal interaction with a public official	7.2%	3.4%	4.2%
Billboard or road message board	3.6%	0.8%	1.0%
Flyer	1.0%	0.0%	1.0%
Other	4.3%	5.5%	6.3%
(multiple selection allowed)			
Sought Additional Information Within Order Type			
Yes	46.9%	50.2%	32.3%
No	49.8%	45.1%	63.5%
No answer	1.0%	3.4%	2.1%
Clarity of Messaging Within Order Type			
Extremely clear	86.6%	70.0%	71.9%
Somewhat clear	8.9%	19.8%	18.8%
Neither clear nor unclear	1.6%	5.5%	5.2%
Somewhat unclear	0.7%	2.1%	0.0%
Extremely unclear	0.0%	0.0%	0.0%
No answer	0.0%	1.3%	2.1%

Table 9 Risk Perceptions of Respondents Prior to Evacuating

Worry About Certain Events Before Evacuating (n = 645)

	Extremely worried	Very worried	Moderately worried	Slightly worried	Not at all worried
Severity of the Hurricane	47.1%	27.0%	20.5%	4.5%	0.9%
Evacuation Process	21.1%	29.5%	27.0%	12.9%	9.6%
Traffic	42.3%	26.5%	16.4%	7.4%	7.3%
Finding Housing	19.4%	14.7%	16.4%	13.8%	35.7%
Finding Gasoline	47.8%	21.6%	17.8%	7.8%	5.1%
Finding Food	16.7%	17.1%	24.8%	18.4%	22.9%
Cost of Transportation	13.8%	11.3%	20.6%	17.1%	37.2%
Logistics of Transportation	17.1%	15.7%	23.7%	17.1%	26.5%
Cost of Housing	17.8%	10.9%	16.4%	15.0%	39.8%
Logistics of Housing	16.3%	15.5%	21.4%	18.6%	28.2%

Belief of the Probability of Certain Events (n = 645)

	Extremely likely	Somewhat likely	Neither likely nor unlikely	Somewhat unlikely	Extremely unlikely
Risk of Flooding	27.1%	28.8%	10.7%	20.3%	13.0%
Risk of Wind	63.3%	27.6%	4.8%	3.6%	0.8%
Injury or Death	12.2%	20.5%	19.1%	21.2%	27.0%
Utility Loss	86.5%	11.2%	0.8%	1.2%	0.3%
Structural Damage	35.5%	40.6%	10.2%	11.2%	2.5%
Belongings Damaged	35.5%	38.6%	12.1%	10.1%	3.7%
Belongings Stolen	9.3%	22.3%	22.9%	23.4%	22.0%
Rescuers Not Available	11.3%	20.6%	24.0%	26.4%	17.7%
Require Rescuing	8.2%	13.8%	21.7%	27.8%	28.5%
Require to Return to Work	21.1%	16.7%	10.1%	11.9%	40.2%

We also asked respondents a series of risk perception questions on a Likert scale from extremely worried to not at all worried (Table 9). These questions encouraged respondents to think back to the time before they decided to evacuate or not from Hurricane Irma. Specifically, we asked the level of worry they had regarding a number of factors such as the severity of Hurricane Irma or traffic they might experience during the evacuation. Overall, respondents were extremely or very worried about the severity of Hurricane Irma (74.1%), finding gasoline (69.4%), traffic (68.8%), and the evacuation process (50.6%). These proportions are to be expected, given the dire weather predictions and the traffic challenges with evacuating from a hurricane in Florida. A number of respondents were also extremely or very worried about the cost of transportation (25.1%) and the cost of housing (28.7%) despite the skew of the sample towards higher-income individuals. This suggests that a more representative sample would most likely have yielded considerably more worry about the cost of transportation and sheltering. Even in the survey sample, the cost of evacuating may have been a key reason that individuals did not comply with evacuation orders.

Similarly, we asked respondents about the belief that certain events would affect them or their household to assess risk perception (Table 9). Again, respondents were told to think back to the time before they made the decision to evacuate or not. Respondents believed, with an extreme likelihood, that they were at risk of wind (63.3%) and that they would lose utilities such as power and water (86.5%). Respondents also believed that structural damage (35.5%) and belongings damage (35.5%) were extremely likely to happen. However, a sizable percentage said it would be extremely unlikely that anyone in their household would be injured or die (27%), and almost a majority of people said it was extremely unlikely that they would be required to return to work immediately following the hurricane (40.2%). While individuals also stated there was an extremely low probability that they would require rescuing (28.5%), many did believe it was extremely or somewhat likely that rescuers would not be available during the hurricane (31.9%). The results from these questions shed light on possible reasons that led individuals to evacuate or not. While safety was not a primary concern, most respondents believed that events related to poor livability had a higher likelihood of occurring. Some of these livability concerns could be remedied by purchasing adequate supplies (such as generators for utility loss). However, a high likelihood of risks including flooding, wind, and structural damage are likely to outweigh other factors and push individuals to evacuate. On the other hand, households faced with inadequate information on the risks of staying may assume they are safe and not evacuate.

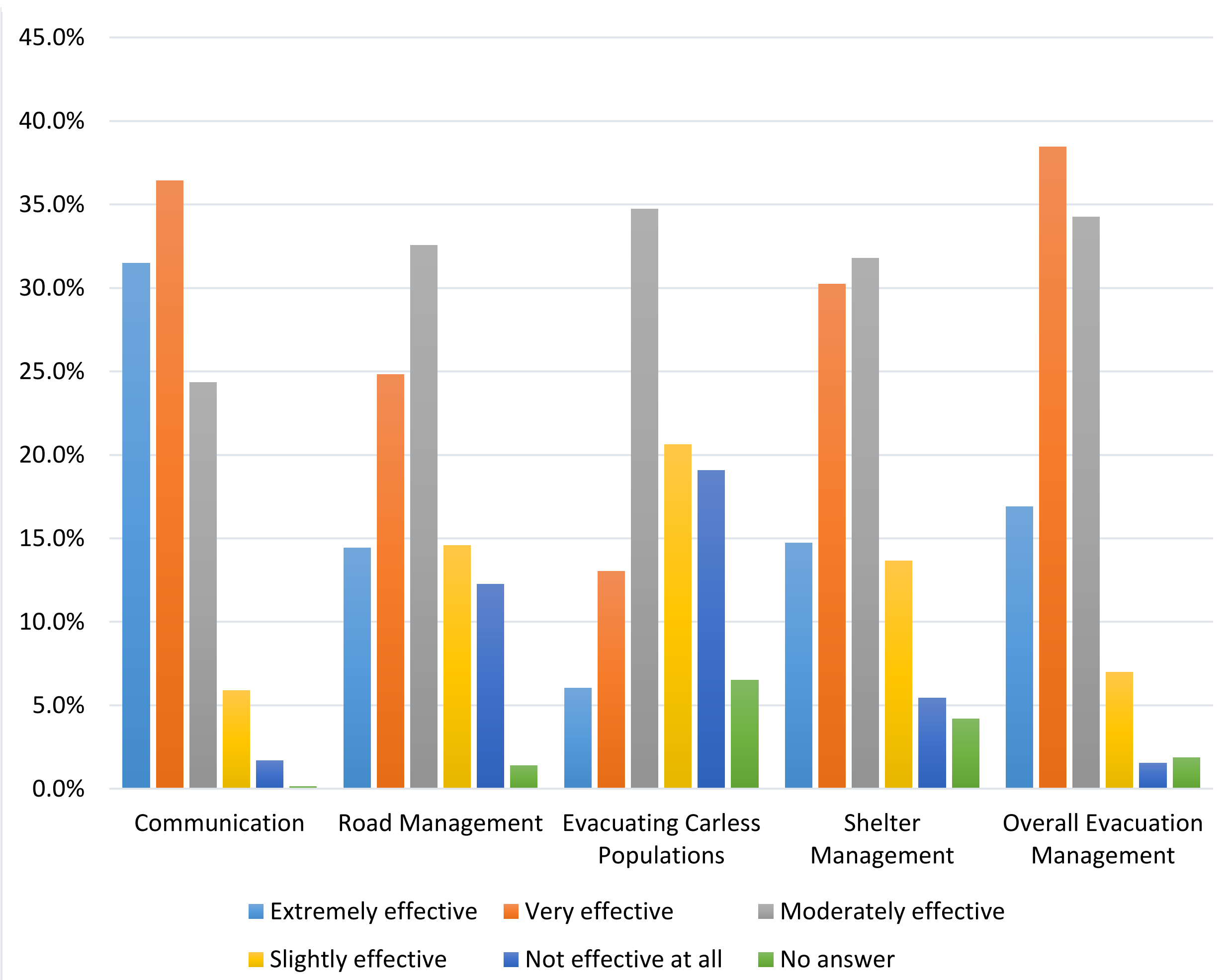
Non-Evacuees

While the focus of this work is on the decisions of evacuees, we asked non-evacuees several questions to decipher their reasoning for staying. In all, 277 respondents did not evacuate. As seen in Table 7, the most highly cited reason for not evacuating was that the respondent did not want to sit in traffic (49.1%). Many others indicated that they simply did not want to leave (48%), they wanted to protect their property (34.7%), and they did not want to go to a public shelter (31.4%). There was also a preconceived notion that Hurricane Irma would not be bad (29.6%). Similar to other studies on non-evacuee behavior, other reasons included work requirements and challenges evacuating with pets. One troubling statistic is that 14.4% of respondents said they did not have enough money to evacuate. Considering the skew of the sample towards higher-income individuals, this resource deficiency may be a much more pervasive problem for the general population. It should also be noted that high-income individuals may still worry about finances and may have little funds saved up for an emergency evacuation. Individuals without family or friends nearby or strong social connections to family or friends could struggle finding cost-effective housing. These individuals may also not have access to private transportation, and local government agencies may not offer city-based evacuation resources in the form of transit. At the same time, people without strong connections to their local community may also miss opportunities to evacuate at a lower cost with the help of community-based organizations or major social institutions in the area. Comments from non-evacuees also indicated that some respondents were confident their property could withstand the hurricane. Others mentioned that their children and elderly individuals in the household did not want to evacuate, which led the household to remain in their residence. While not all these areas can be addressed by agencies, the underlying motivations and reasoning of non-evacuees present an opportunity to engage in further discussions with local citizens on how best to ensure human safety in disasters.

Government Response

We included one question in the survey regarding the effectiveness of overall government response in five main areas: communication, road management, evacuating carless populations, shelter management, and overall evacuation management. Specifically, we asked respondents their opinion of the effectiveness of government response (note that the type of agency was not specified). On a positive note, most of the results, as seen in Figure 8, trended in a good direction for government agencies. Notably, 67.9% of respondents viewed the communication of government agencies to be extremely or very effective, while only 1.7% stated that it was not effective at all. In decreasing order, respondents found overall evacuation management (55.3%), shelter management (45%), road management (39.2%), and evacuating carless populations (19.1%) to be either extremely or very effective. For these four areas, many respondents stated that the government was moderately effective. The government's performance was rated the worst for evacuating carless populations. Indeed, 19.1% said that the government was not effective at all in this area. With generally lower marks in road management, government entities and agencies have more work to do in improving not just the availability of transportation for carless populations but also implementing additional operational strategies to decrease congestion on the roadways.

Figure 8 Opinion of Government Effectiveness in Hurricane Irma Evacuation



Discrete Choice Analysis

The analysis for this report incorporates a series of models grounded in econometrics that were developed using discrete choice analysis. The purpose of these models is to determine the factors that influenced different choices that individuals made throughout the evacuation process. Currently, these choices are modeled separately using basic logit models. However, future work will consider how these choices may be correlated and how more complex models may or may not better explain evacuation behavior. However, for the purpose of this report, we employed simple models for each choice as a starting point for the research.

Discrete choice analysis is a modeling technique that utilizes variables of the decision maker or a set of alternatives to predict an individual's or household's choice. For the majority of discrete choice analyses, an individual is assumed to behave rationally and to choose an alternative that will maximize their utility – or satisfaction. Discrete choice models are quantitatively grounded in statistical and econometric techniques. Put another way, a series of independent variables (characteristics of the decision maker or alternatives) quantitatively influence the outcome that is modeled as a dependent variable (a decision maker's choice). Part of the challenge of discrete choice analysis is to accurately and appropriately estimate the coefficients and signs in front of independent variables. To do so, researchers have applied a number of methods of estimation, most notably maximum likelihood and least squares. However, the early development of choice behavior theories in psychology (Thurstone, 1927; see Luce and Suppes, 1965 for an overview) frequently produced experimental results of inconsistent preferences. For example, individuals would choose different alternatives over and over again, despite being faced with the same choice situation. To overcome this problem, researchers introduced probabilistic mechanisms to capture unobserved factors affecting individuals' choices. Consequently, the field of discrete choice has grown immensely through the many variations of the underlying statistical distribution, structure of probabilistic error terms, and the interaction of independent variables. An extensive literature review of the theory of discrete choice and the application of this type of modeling to travel demand can be found in Ben-Akiva and Lerman (1985) and Train (2009). Discrete choice analysis has continued to evolve rather quickly, and several other key pieces of literature have synthesized the rapid progression of utilizing 1) latent class models to better capture lifestyle preferences (Hagenaars and McCutcheon, 2002), 2) simulations to estimate intractable models (Train, 2009) and 3) alternative decision rules, such as regret, to explain behavior in different situations (Chorus *et al*., 2008).

As previously mentioned, the majority of discrete choice models employ utility maximization as the decision rule. Utility maximization assumes commensurability of attributes (i.e., the attractiveness of an alternative can be quantified by the reduction of a vector of variables into a single scalar value). Thus, a decision maker will consider all the variables and characteristics and choose the most attractive alternative that "maximizes" their utility. The single scalar values allow for the immediate comparison of how an individual engages in tradeoffs. For example, an individual may greatly value a fast commute to work but may also want to pay very little to achieve this fast travel time. Thus, the individual will make some tradeoff between alternatives in their choice-making, which can be quantified. Utility maximization has been the primary decision rule in discrete choice analysis, largely because it has statistical properties that produce relatively simple, accurate, and tractable solutions (Ben-Akiva and Lerman, 1985; Washington *et al*., 2010). Indeed, discrete choice models employing utility maximization (also known as random utility maximization (RUM) models for the inclusion of an error term) were first introduced in two seminal papers (McFadden, 1973; McFadden, 1974) that would eventually lead to a Nobel Prize in

Economics. The discrete choice analysis for this report follows the procedures in Ben-Akiva and Lerman (1985), particularly in the selection of independent variables. Variables are retained for the modeling if they are significant, behaviorally important, and/or have a correct *a priori* coefficient sign. Each table for the various evacuation choices contains the selected parameters across the available alternatives for that specific choice. Note that one alternative is considered a "base" and all values are compared to this base. From the model, the probabilities that each individual chooses each alternative can be calculated and aggregated to determine the final probabilities for each alternative. Since the survey sample of respondents is not representative of the population of Florida, these probabilities are weighted based on three demographic factors: gender, age, and vehicle ownership. The weights were generated using data collected from the American Community Survey 2012-2016 (five-year estimates) and applied using a raking technique (Deville *et al*., 1993).

Decision to Evacuate or Stay

The decision to evacuate or stay is a well-researched choice that has major implications for agencies. Similar to other research, we constructed a simple fixed-parameter binary logit model between evacuating and not evacuating. Many other binary models, along with the associated variables, are found in Murray-Tuite and Wolshon (2013) and Yin *et al*. (2016). Table 10 presents the results of this binary logit model with the associated coefficient, sign, p-value, and significance level for each chosen variable. Since the decision to not evacuate is the base choice, all positive coefficients indicate that the variable increases the likelihood to evacuate, while a negative coefficient signifies a decrease in the likelihood to evacuate.

As seen in Table 10, individuals who received a mandatory evacuation order were significantly more likely to evacuate. This behaviorally consistent result with past research continues to indicate that individuals do respond to mandatory orders given by emergency management agencies. However, receiving a voluntary order was not a significant variable, suggesting that agencies may not be successful in encouraging evacuations with this method. The lack of legal weight behind voluntary orders leads many to disregard them, even though certain populations – particularly vulnerable ones – may be safer evacuating. A number of different concerns and worries, which are proxies for risk perception and evacuation barriers, were significant. Extreme worry about the severity of Hurricane Irma and extreme likelihood belief of major structural damage were both highly significant and positive. The extreme or some likelihood belief of injury/death was also highly significant and positive. However, those who were extremely worried about finding housing were less likely to evacuate. Without prior knowledge of a safe location to go, individuals were more reluctant to begin the evacuation process, especially as hotels and motels booked up quickly. Extreme or some concern over housing costs was also a key evacuation barrier and led to a lower likelihood to evacuate. Throughout the Hurricane Irma evacuation process, gas was in short supply. The results of the model show that those with extreme or some worry of finding gas were less likely to evacuate (slightly insignificant). Potential evacuees may have worried that they would run out of gas while evacuating, so they decided to forgo evacuating altogether. Finally, an extreme belief of work requirements was negative and significant, suggesting that those who believed they needed to return to work quickly were less likely to evacuate. While some of these individuals may have been required workers (i.e., government employees, nurses, doctors), some with hourly positions may have remained behind to make ends meet.

Table 10 Discrete Choice Analysis - Evacuation Decision

Evacuation Decision: Binary Logit

Choice 1: Did Not Evacuate - Base
Choice 2: Evacuated

Variable	***Evacuated*** *Estm. Coef.*	*p-value*	
Constant	1.28	0.205	
Evacuation Experience			
Received a Mandatory Order	0.52	0.012	*
Concerns and Worry			
Extreme Worry of the Severity of Irma	0.91	<0.001	***
Extreme Worry of Finding Housing	-0.71	0.016	*
Extreme or Some Worry of Finding Gas	-0.30	0.197	
Extreme or Some Worry of Housing Cost	-0.63	0.012	*
Extreme Likelihood Belief of Major Structural Damage	1.21	<0.001	***
Extreme Likelihood Belief of Work Requirements	-0.66	0.012	*
Extreme or Some Likelihood Belief of Injury/Death	1.30	<0.001	***
Individual Characteristics			
Older Adult: Age 65 and Over	-0.34	0.466	
Female	-0.12	0.656	
Race: White	0.19	0.676	
Experienced at Least One Prior Hurricane	-1.16	0.138	
Previous Evacuee	-1.05	<0.001	***
Household Characteristics			
Children Present in Household	0.85	0.014	*
Pets Present in Household	-0.10	0.690	
1 or 2 Person Household	0.37	0.289	
Household Income Under $20,000	-0.67	0.171	
Site Build - Apartment [Base: Site Build - House]	1.02	<0.001	***
Mobile Home [Base: Site Build - House]	1.30	0.047	*
Less than 1 Year in Residence	0.51	0.071	
Southeast Region [Base: Southwest]	-0.49	0.203	
Central-West Region [Base: Southwest]	0.48	0.462	
Northeast/Central-East Region [Base: Southwest]	-1.51	<0.001	***
Number of Observations	645		
ρ^2 (fit)	0.31		
$\bar{\rho}^2$ (adjusted fit)	0.26		
Final Log-Likelihood	-307.4		

* 95% significance
** 99% significance
*** 99.9% significance

Overall, individual characteristics were found to be largely insignificant in the decision to evacuate. However, previous evacuees were much less likely to evacuate, suggesting a lack of concern over Hurricane Irma given past evacuations. Past evacuations, especially for hurricanes that had a relatively low impact, tend to lead individuals to second guess evacuation orders for subsequent hurricanes. This "crying wolf" phenomenon described in Dow and Cutter (1998) has been somewhat mixed for hurricanes, as that study found prior false alarms did not necessarily decrease evacuation rates. However, the same study found that people did seek additional sources of reliable information before making the decision to evacuate or not. Other research including Murray-Tuite *et al*. (2012) and Solis *et al*. (2010) found previous hurricane experience increased evacuations, while Hasan *et al*. (2012) found prior experience decreased evacuations. For this research study, we found that experience with at least one prior hurricane (and being a previous evacuee) decreased the likelihood to evacuate. These results may be somewhat due to isolated damage from Hurricane Matthew in 2016, along the eastern Florida coastline. Along the western Florida coastline, Hurricane Charley and Wilma were the last hurricanes to impact the area in 2004 and 2005, respectively. The lack of hurricane activity may have contributed to a sense of safety for residents on the western coastline. In addition to hurricane and evacuation experience, we included gender (female) and race (white) in the model due to their presence in other research. The gender variable was found to be negative but insignificant. Previous research has found females more likely to evacuate (Murray-Tuite and Wolshon, 2013; Yin *et al*., 2016). In our study, white individuals were more likely to evacuate, but the variable was again insignificant. This aligns more closely with past work in Murray-Tuite and Wolshon (2013) and Yin *et al*. (2016), which found the results to be mixed. Older adults were found to be less likely to evacuate in our research, but this variable was insignificant.

We found several household characteristics to be significant and positive including children present in the household, living in a mobile home, and living in an apartment. Families are typically more concerned about the safety of their children and more readily evacuate. Those living in mobile homes face increased wind and flooding risks due to construction materials and lack of a strong foundation. Those in apartments may have been concerned about the lack of hurricane protections in the building and the inability to purchase and use items, such as a generator. These results parallel previous research, such as in Solis *et al*. (2010) and Hasan *et al*. (2011). Household income under $20,000 was found to be negative but slightly insignificant. Often, low-income households do not have the funds to afford transportation or housing for a long time period. The cost of evacuating is prohibitive, and household members are more likely to work in hourly positions that may have mandatory work requirements. This result differs from Deka and Carnegie (2010), which found low-income households to be more likely to evacuate in a hypothetical hurricane scenario. Households with pets were less likely to evacuate, but this result was insignificant. Past studies have found that pets decrease evacuations or are insignificant (Murray-Tuite and Wolshon, 2013). Public shelters, hotels/motels, and public transit vehicles are less likely to accept pets, which leads some people to stay. Small households (1 to 2 people) and those who have lived less than one year in their residence were more likely to evacuate. In previous research, long-time residents were found to be less likely to evacuate (Zhang *et al*., 2004). Smaller households have greater flexibility in transportation and sheltering options, while those with limited time in their residence may not have had time to build hurricane protections or have little disaster experience. By region, those in the Northeast and Central-East regions were much less likely to evacuate (highly significant) in contrast to those in the Southwest region. This result is unsurprising since Irma made landfall in the Southwest region, and the Northeast and Central-East regions were only predicted to have isolated impact. The Southeast region was also less likely to evacuate, but the Central-West region was more likely to evacuate than the Southwest region. However, both the Southeast and Central-West region variables were insignificant.

Overall, the evacuation model produced similar results to past research. However, several inconsistencies were found in evacuee and hurricane experience, which may be a result of the unique characteristics of recent Florida hurricanes. Not surprisingly, the mandatory evacuation order and high-risk perceptions led to an increased likelihood to evacuate. However, real or perceived barriers to the evacuation and the logistics surrounding the evacuation decreased evacuation likelihood. The results confirm a number of previous studies, while also suggesting that some variables and characteristics may require additional research.

Departure Day

While research has predominately focused on the decision to evacuate or not, a number of studies have also considered decision-making regarding departure day and time of day. Often, these studies consider a departure time and evacuation decision together as a sequential logit model (Fu and Wilmot, 2004; Fu *et al*., 2006), a nested logit model (Gudishala and Wilmot, 2012), or a mixed binary logit model (Sarwar *et al*., 2018). Hasan *et al*. (2013) used a random-parameter hazard-based model to determine if individuals would leave sooner or later based on the perceived hazard. For this study, we separated the decision to evacuate or not from the departure day/time to simplify the modeling and provide more specific recommendations for agencies. For departure day, we constructed a multinomial logit model with five distinct choices related to the number of days before landfall (September 10, 2017): 1) more than three days before landfall; 2) three days before landfall; 3) two days before landfall; 4) one day before landfall; and 5) day of landfall or after. The base category for the model is more than three days prior to landfall (i.e., very early evacuees). It should be noted that the day on which a certain region of Florida was impacted differs. Southwest Florida was impacted one day before landfall and after, while parts of Northeast Florida were not struck until a day after landfall. Despite these differences, the demarcation of landfall has traditionally been used for the modeling of departure time choice-making.

In Table 11, the only significant constant value is for three days prior to landfall, indicating that individuals were more inclined to evacuate three days prior to landfall compared to more than three days (early evacuees). Individuals who received a mandatory evacuation order were much more likely to depart two days prior (highly significant) and one day prior (somewhat insignificant). Values for three days prior and landfall or after were found to be insignificant. Individuals who evacuated within county were much more likely to evacuate two days prior, one day prior, and on the day of landfall or after than evacuating earlier. These short-distance trips could be accomplished much closer to landfall with minimal risk to the evacuee. A similar result was found for those who evacuated out of county but still within Florida. In terms of conducting trips before the evacuation (i.e., to gather supplies, pick up family members, etc.), those who conducted five or more trips were more likely to evacuate on one day prior (significant), two days prior (somewhat insignificant) and three days prior (somewhat insignificant). Additional trips tend toward a longer mobilization time, which can push back the evacuation day to closer to landfall. In all, a number of these evacuation-specific variables were found to be key factors in departure day.

Table 11 Discrete Choice Analysis - Departure Day

Departure Day: Multinomial Logit

Choice 1: More than Three Days Prior to Landfall - Base
Choice 2: Three Days Prior to Landfall
Choice 3: Two Days Prior to Landfall
Choice 4: One Day Prior to Landfall
Choice 5: Day of Landfall or After

	Three Days Prior			***Two Days Prior***			***One Day Prior***			***Landfall or After***		
Variable	*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*	
Constant	0.88	0.034	*	-0.23	0.656		-0.02	0.977		-0.74	0.373	
Evacuation Experience												
Received Mandatory Order	-0.09	0.810		0.96	0.008	**	0.75	0.085		0.45	0.546	
Evacuated Within County [Base: Out of Florida]	------	------		2.82	<0.001	***	4.51	<0.001	***	2.69	0.012	*
Evacuated Out of County, Within Florida [Base: Out of Florida]	------	------		0.94	0.001	***	1.84	<0.001	***	0.37	0.641	
Five or More Trips Before Evacuating	0.42	0.287		0.32	0.404		1.04	0.014	*	------	------	
Concerns and Worry												
Extreme Worry of Traffic	-0.36	0.315		-0.54	0.113		-0.77	0.065		-0.09	0.898	
Extreme Likelihood Belief of Flooding	-0.47	0.224		-0.10	0.776		-0.37	0.399		-1.30	0.142	
Extreme Likelihood Belief of Work Requirements	1.23	0.009	**	0.72	0.127		1.07	0.058		0.13	0.912	
Individual Characteristics												
Previous Evacuee	-0.94	0.007	**	-0.39	0.298		-1.11	0.016	*	-1.27	0.093	
Household Characteristics												
Children Present in Household	-0.19	0.581		-0.51	0.129		-0.64	0.111		-1.81	0.032	*
Less than One Year in Residence	-0.76	0.057		-0.53	0.148		-1.58	0.003	**	-0.66	0.455	
Southeast Region [Base: Southwest]	------	------		0.36	0.416		-3.13	0.005	**	------	------	
Central West Region [Base: Southwest]	------	------		0.03	0.967		-0.18	0.824		------	------	
Northeast/Central-East Region [Base: Southwest]	------	------		0.63	0.076		-0.91	0.045	*	------	------	
Number of Observations	368											
ρ^2 (fit)	0.26											
$\bar{\rho}^2$ (adjusted fit)	0.18											
Final Log-Likelihood	-437.5											

* 95% significance

** 99% significance

*** 99.9% significance

Extreme worry about traffic was negative across all departure days, which suggests that those worried about traffic were more likely to depart more than three days before landfall. However, this variable is not significant. A similar result was found for the extreme likelihood belief of flooding. This risk perception influenced individuals to leave early, which is behaviorally consistent but again not significant. Individuals with an extreme likelihood belief of work requirements were more likely to evacuate on later days, particularly three days prior, which was highly significant, and one day prior, which was almost significant. With regard to individual characteristics, previous evacuees were early evacuees for Hurricane Irma. Thus, all values for this characteristic were negative, with the results for three days prior and one day prior being significant in the model, and two days prior and landfall or after being somewhat insignificant. Past experience with traffic jams, gas shortages, and housing challenges may have led residents to leave as soon as possible when the risks were apparent for a Florida landfall.

For household characteristics, households with children were more likely to be early evacuees, especially when compared to departing on the day of landfall or after. Interestingly, the significance increases as the days become closer to landfall, which indicates a temporal trend – the closer to landfall, the less likely households with children evacuate. Respondents who have lived in their residence for less than one year were also more likely to be early evacuees and especially less likely to evacuate one day before landfall. Inexperience with disasters or concern over the lack of hurricane protections for the residence may have prompted this behavior. Individuals in the Southeast and Northeast/Central-East regions were significantly less likely to evacuate one day before landfall compared to those in the Southwest. However, all regions were more likely to evacuate two days prior to landfall compared to the Southwest region, though this result was mostly insignificant across the regions.

Table 11 displays behaviorally consistent results, and we found that destination choice was a powerful factor affecting departure day. Mandatory orders were also effective in concentrating evacuations on one and two days prior to landfall. While the concerns and worries of respondents were mostly insignificant, the variables displayed consistent signs. Those most worried about traffic and who perceived high risk of flooding were more likely to be early evacuees, while those concerned about work requirements were more likely to depart three or fewer days prior to landfall. Experience played a role in departure day, as previous evacuees were more likely to be early evacuees for Hurricane Irma. Likewise, those with less than one year in the current residence were also more likely to be early evacuees. Families became less and less likely to depart closer to landfall.

Departure Time of Day

Similar to departure day, researchers have often modeled departure time of day in tandem with the decision to evacuate or stay. Indeed, time of day is often modeled as a dynamic variable within the selected time segments before landfall (Fu and Wilmot, 2004; Fu *et al*., 2006). For the purpose of this report, we modeled departure time as its own choice, because the behavior can shift based on changing circumstances (such as traffic) and can also be influenced by policy-making. In addition, while the majority of evacuations occur during the daytime (67.1% of the Hurricane Irma respondents departed between 6:00 a.m. and 5:59 p.m.), a significant number of individuals in our study chose to depart at night. The departure time of day has important implications for traffic management and the congestion on roadways. Emergency management and transportation agencies have traditionally struggled to handle spikes in daytime evacuation congestion. However, if nighttime evacuations begin to gain popularity, congestion patterns may change and certain traffic measures – such as the effective but costly contraflow process – may not be required. A multinomial logit model was originally chosen for departure time of day, but we ultimately selected a binary logit between nighttime and daytime evacuations due to the improved fit and more significant variables. In this binary logit model for our study, a positive coefficient indicates a higher likelihood to evacuate at night, while a negative coefficient indicates a lower likelihood to evacuate at night.

In Table 12, the constant variable is both negative and significant, which indicates that respondents have a natural tendency to prefer daytime over nighttime evacuations. Individuals who received a mandatory evacuation order were more likely to depart during the daytime, while those who received a voluntary evacuation order were more likely to depart at night. Not issued exact times to depart, individuals with voluntary evacuation orders may have had increased flexibility to leave at night. Voluntary evacuees may also have departed at night to avoid traffic caused by mandatory evacuations. People who decided to shelter with friends and family were more likely to depart during the nighttime as compared to those who went to a public shelter or other shelter. These results may be influenced by individuals feeling more comfortable navigating to the home of a family member or friend – a place they may already know. While shelter choice at a hotel/motel was also positive, the result was insignificant. Individuals who evacuated within county and out of county (but within Florida) were much more likely than those evacuating out of state to depart during the daytime. Out of state evacuees (traveling to Alabama, Georgia, etc.) may have wanted to beat the daytime evacuation traffic on the highways. Congestion near neighboring states was high during most of the evacuation of Hurricane Irma. Evacuees may have also felt more comfortable driving at night in their home state of Florida, and then driving in an unfamiliar place the next day during daylight hours. To round out the evacuation experience, people who evacuated with shared non-personal vehicles (i.e., aircraft, carpool, bus, etc.) were more likely to depart during the day. Most shared transportation options are primarily only available during the day, and carpooling individuals may have been subject to the schedule of other passengers.

With regard to concerns and worry, those with extreme worry of the severity of Irma and of finding gas were more likely to evacuate during the day, but the results were slightly insignificant. These two variables highlight the risks that evacuees were considering. Evacuating at night during a storm can be especially dangerous. In addition, some evacuees may have believed that gas stations would not be refilled until early morning. However, respondents with extreme worry of traffic were much more likely to evacuate at night. This unsurprising result is still key: as people receive more traffic information via smartphone applications, they may choose to avoid congestion by departing at night. While this behavior shift would improve traffic conditions during the day, services providing gas and water, law enforcement, and traffic management may need to increase correspondingly during the night.

Despite a slightly insignificant result, young evacuees were more likely to evacuate at night. Younger individuals (under 35) may be more comfortable evacuating at night (perceived lower risk than other people) and confident choosing routes via GPS and smartphones. Previous evacuees and those who had experience with at least one prior hurricane were also more likely to evacuate at night. Past traffic challenges during evacuations may have pushed these individuals to avoid congestion at all costs. Similarly, those who have lived in their residence for more than 10 years were more likely to evacuate at night. Familiarity with nearby roads and the evacuation process may have made a nighttime evacuation relatively comfortable.

Table 12 Discrete Choice Analysis - Departure Time of Day

Departure Time of Day: Binary Logit

Choice 1: Daytime (6:00 a.m. to 5:59 p.m.) - Base
Choice 2: Nighttime (6:00 p.m. to 5:59 a.m.)

	Nighttime		
Variable	*Estm. Coef.*	*p-value*	
Constant	-1.60	0.026	*
Evacuation Experience			
Received a Mandatory Order	-0.46	0.111	
Received a Voluntary Order	0.42	0.136	
Shelter Choice with Family [Base: Public Shelter and Other Shelter]	0.82	0.048	*
Shelter Choice with Friends [Base: Public Shelter and Other Shelter]	1.01	0.032	*
Shelter Choice at Hotel/Motel [Base: Public Shelter and Other Shelter]	0.29	0.512	
Evacuated Within County [Base: Out of Florida]	-1.28	0.001	***
Evacuated Out of County, Within Florida [Base: Out of Florida]	-0.81	0.006	**
Evacuated with Shared Non-Personal Vehicle	-1.16	0.023	*
Concerns and Worry			
Extreme Worry of the Severity of Irma	-0.31	0.230	
Extreme Worry of Traffic	0.75	0.007	**
Extreme Worry of Finding Gas	-0.53	0.058	
Individual Characteristics			
Young: Under 35	0.48	0.077	
Previous Evacuee	0.55	0.038	*
Experienced at Least One Prior Hurricane	0.47	0.379	
Household Characteristics			
More than 10 Years in Residence	0.75	0.034	*
Number of Observations	368		
ρ^2 (fit)	0.20		
$\bar{\rho}^2$ (adjusted fit)	0.13		
Final Log-Likelihood	-205.3		

* 95% significance

** 99% significance

*** 99.9% significance

For departure time of day, a clear demarcation exists between nighttime and daytime evacuations. People overall prefer to evacuate during the day since it is safer to drive during daylight hours. However, a number of variables increased departing at night including evacuating out of Florida, sheltering with friends and family, extreme worry of traffic, and having previous experience with evacuating and hurricanes. Those who experienced major congestion problems in past events may not have wanted to repeat that scenario. Most likely, respondents were weighing traffic during the day against higher risks and feeling uncomfortable driving during the night. While nighttime evacuations would clearly help transportation and emergency management agencies manage traffic during the day, any increase in evacuees at night would necessitate additional resources and services to ensure safety for nighttime evacuees.

Destination Choice

Emergency management and transportation agencies are highly interested in where evacuees decide to go, and the survey provided enough information to output a condensed destination choice. Consequently, we developed three categories: 1) evacuated out of Florida, 2) evacuated within county, and 3) evacuated out of county but within Florida. These three consolidated categories have clear behavioral differences, especially for those who decide to remain within the county. Agencies have a particular interest in within county evacuations, as an increase in them would necessitate additional sheltering resources in the area. In addition, there has been a recent push to consider short-distance evacuations to reduce costs and social impacts (Long, 2016). Often evacuees travel further away than necessary from risk, which places stress on transportation systems. At the same time, the belief that one needs to travel far away may contribute to lower compliance of mandatory evacuation orders. As already discussed in this paper, destination choice heavily influences other evacuation decisions. Given that only several papers have considered destination choice in a discrete choice context, further work on future disasters will be necessary to achieve a stronger consensus.

The results of destination choice are presented in Table 13, with out of Florida evacuations acting as the base choice. Based on the constant, individuals were much more likely to favor evacuating out of Florida (long-distance evacuations) compared to evacuations out of county but within Florida (medium-distance evacuations) and evacuations within county (short-distance evacuations). This result may be a natural preference to avoid risk or a response to the dire predictions for Hurricane Irma. However, individuals who received mandatory evacuation orders were much more likely to remain within county or out of county but within Florida. People who evacuated out of state were much less likely to have received a mandatory order, suggesting that so-called "shadow evacuees" were conducting long-distance evacuations. Shadow evacuees do not receive a mandatory order but still decide to evacuate. People who sheltered with friends were also more likely to stay nearby, a consequence of geographically close friend circles. However, those who sheltered at a hotel/motel were much less likely to evacuate within county. Within county evacuees may have had additional sheltering options (with friends) and did not want to spend money on a hotel/motel so close to home. In addition, most hotels/motels in evacuating counties were located along the coast, so those hotels/motels may not have been open. Those evacuating with two or more vehicles were also much more likely to remain close by within county or within Florida. Evacuating with additional vehicles is a logistical challenge, requiring more than one driver.

Table 13 Discrete Choice Analysis - Destination Choice

Destination Choice: Multinomial Logit

Choice 1: Out of Florida - Base
Choice 2: Within County
Choice 3: Out of County, Within Florida

	Within County			Out of County, Within Florida		
Variable	*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*	
Constant	-2.64	0.026	*	-2.06	0.006	**
Evacuation Experience						
Received a Mandatory Order	1.01	0.004	**	1.43	<0.001	***
Shelter Choice with Friends	0.71	0.095		0.87	0.025	*
Shelter Choice at a Hotel/Motel	-2.45	<0.001	***	0.55	0.073	
Evacuated with 2 or More Vehicles	1.36	0.001	***	0.72	0.022	*
Concerns and Worry						
Extremely or Very Worried of Traffic	-1.57	<0.001	***	-0.95	0.006	**
Extremely or Very Worried of Finding Housing	0.94	0.019	*	-0.32	0.311	
Extremely or Very Worried of Finding Gas	-0.11	0.808		0.64	0.066	
Extreme or Somewhat Likelihood Belief of Injury/Death	-0.13	0.713		-0.66	0.016	*
Individual Demographics						
Experienced at Least One Prior Hurricane	2.12	0.055		0.85	0.190	
Household Characteristics						
Household Income Under $40,000	-0.19	0.652		-0.68	0.090	
Southeast Region [Base: Southwest]	-0.19	0.778		1.09	0.016	**
Central-West Region [Base: Southwest]	1.28	0.136		1.42	0.081	
Northeast/Central-East Region [Base: Southwest]	-0.72	0.061		0.30	0.308	
Number of Observations	368					
ρ^2 (fit)	0.25					
$\bar{\rho}^2$ (adjusted fit)	0.18					
Final Log-Likelihood	-302.8					

* 95% significance
** 99% significance
*** 99.9% significance

A number of concerns and worries influenced destination choice. Interestingly, those who were extremely or very worried about traffic were much less likely to stay nearby. This direction of correlation suggests an issue, as logically those who conducted a long-distance evacuation would be worried about traffic. Those with a worry about finding housing were more likely to stay within county, which normally offers more options for public sheltering and sheltering with friends. Those worried about finding gas typically evacuated out of county but within Florida. This may also suggest a correlation direction problem, as the destination may have impacted their worry. However, one clear variable was the likelihood belief of injury or death, which was found to be negative for both choices but only significant for out of county but within Florida evacuations. Higher perceptions of risk clearly impacted destination choice, and those worried about Irma tried to escape the hurricane by conducting longer evacuations out of Florida.

Experience with at least one prior hurricane led to a higher albeit slightly insignificant likelihood to evacuate closer. This experience may lead people to make decisions that are less taxing on the individual and household. Households with less than $40,000 income were found to be more likely to evacuate out of Florida, but the results were somewhat insignificant. One possible explanation is that cheaper hotels/motels and family members were only available outside of Florida. Finally, those in Southeast and Northeast/Central-East Florida were more likely to evacuate within Florida but less likely to stay in county. However, those in the Central-West region were more likely to remain both within county and within Florida.

In total, individuals were more likely to prefer out of Florida evacuations. However, those who received a mandatory order, sheltered with friends, evacuated with two or more vehicles, and experienced a prior hurricane were more likely to conduct short- and medium-distance evacuations. The concerns and worries variables may have a correlation directionality issue, but it is clear that those with a belief of possible injury or death were more likely to evacuate out of Florida. Geography and income also played a role in destination choice, both of which require further research to find adequate explanations for the behavior.

Shelter Choice

Sheltering resources, particularly in the form of public shelters, are difficult to manage and allocate effectively. If evacuations are large enough, hotels and motels fill up quickly, which causes individuals to travel longer distances in search of shelter. For this research, we consider five different choices for shelter: 1) a friend's residence, 2) a family member's residence, 3) a hotel/motel, 4) a public shelter, and 5) an "other" location such as an Airbnb or a second residence. Other research in shelter choice from Whitehead *et al.* (2000) also built a multinomial logit model, while Smith and McCarty (2009) used a binary logit for each shelter type; Deka and Carnegie (2010) used a binary logit for just sheltering at a public shelter; and Mesa-Arango *et al*. (2012) developed a nested logit model. Based on the survey, most people stayed at a family member's residence (43.5%) followed by a hotel/motel (27.4%) and a friend's residence (15.8%). Only 3.5% of the sample stayed at a public shelter, but 4.3% used a peer-to-peer service such as Airbnb. The rise of Airbnb as a sheltering option could help alleviate demand on public shelters. To explore the factors that influenced shelter choice, we constructed a multinomial logit model with a friend's residence as the base choice.

Table 14 Discrete Choice Analysis - Shelter Choice

Shelter Type: Multinomial Logit

Choice 1: Stayed at a Friend's Residence - Base
Choice 2: Stayed at a Family Member's Residence
Choice 3: Stayed at a Hotel/Motel
Choice 4: Stayed at a Public Shelter
Choice 5: Stayed at an Other Location (i.e., Airbnb, Second Residence)

	Family			***Hotel/Motel***			***Public Shelter***			***Other***		
Variable	*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*	
Constant	1.30	0.003	**	1.33	0.009	**	-1.75	0.032	*	-0.07	0.912	
Evacuation Experience												
Evacuated Within County [Base: Evacuated Out of Florida]	-1.23	0.001	***	-3.21	<0.001	***	------	------		-2.43	<0.001	***
Evacuated Out of County, Within Florida [Base: Evacuated Out of Florida]	-0.71	0.055		-0.12	0.748		------	------		-1.37	0.011	*
Concerns and Worry												
Extreme or Somewhat Worry of the Severity of Irma	0.95	0.022	*	0.18	0.69		0.07	0.926		0.70	0.246	
Extreme or Somewhat Worry of Finding Housing	-1.10	0.002	**	0.15	0.705		0.16	0.805		-0.31	0.511	
Extreme Worry of Cost of Housing	------	------		1.10	0.002	**	------	------		------	------	
Individual Demographics												
Older Adult - 65+	-0.95	0.086		-1.12	0.121		------	------		------	------	
Household Characteristics												
Pet(s) Present in Household	------	------		-0.60	0.044	*	-0.60	0.341		------	------	
Household Income Under $40,000	-0.03	0.951		-1.09	0.048	*	1.63	0.014	*	0.15	0.79	
More Than 10 Years in Residence	-0.77	0.019	*	------	------		------	------		------	------	
Number of Observations	368											
ρ^2 (fit)	0.27											
$\bar{\rho}^2$ (adjusted fit)	0.22											
Final Log-Likelihood	-434.0											

* 95% significance

** 99% significance

*** 99.9% significance

As seen in Table 14, individuals preferred staying with family and at a hotel/motel over a friend's residence. On the other hand, people were less likely to choose a public shelter with all else equal. For those who evacuated within county, people were much less likely to stay with family or at a hotel/motel. Families are often more geographically dispersed than friends (who are usually closer in proximity), which helps explain the results. For hotel/motel, many of these businesses were located along the coastline in hazardous areas. Therefore, for within county evacuees, these hotels/motels may not have been viable options for sheltering. In addition, some survey respondents explained that they had to travel far distances to find available hotels/motels since they filled quickly. A similar result was found for individuals who stayed in an "other" shelter. Second residences are typically located out of state, while Airbnbs are geographically dispersed. Individuals who evacuated out of county but within Florida made similar sheltering choices but with a lower likelihood (i.e., not as significant).

With regard to concerns and worry, those who were extremely or somewhat worried about the severity of Hurricane Irma were more likely to shelter with family. This may be a result of the geographical linkage between family members' residences and places further away or the desire to be with loved ones during a major disaster. Those who were extremely or somewhat worried about finding housing were much less likely to shelter with family. This indicates that respondents who could stay with family knew they had a guaranteed shelter. However, those choosing to stay with friends may have been worried that their housing was uncertain, especially if there was a possibility that the friend would also need to evacuate. Individuals with an extreme worry of cost of housing were much more likely to shelter at a hotel/motel. This suggests that those sheltering in hotels and motels knew that it was perhaps their only sheltering option. For all these cases, the direction of correlation is unclear. Indeed, the concerns and worry may be a result of the availability of sheltering or the chosen sheltering option, and further work will be necessary to disentangle the endogeneity.

Older adults (65 and over) were less likely to shelter with family compared to friends, which suggests that social connections may be important for these respondents. Older adults were also less likely to evacuate to a hotel/motel. This may be due to the cost of hotels/motels or the barriers that older adults face during the evacuation process. Respondents with pets were less likely to stay at a hotel/motel (significant) or at a public shelter (insignificant). Often, hotels/motels and public shelters do not allow pets, which decreases the likelihood that individuals would choose these sheltering options. Lower-income households (under $40,000) were less likely to shelter at a hotel/motel but much more likely to stay at a public shelter, confirming results from Whitehead *et al.* (2000) and Mesa-Arango *et al*. (2012). This unsurprising result reflects the high cost of hotels/motels compared to the free option of a public shelter. The results also suggest that additional resources may be needed at public shelters, since those staying there have less financial ability to pay for critical items for survival. Individuals who lived in their residence for more than 10 years were much less likely to shelter with family. Long-time residents in Florida may not have family nearby, which makes this decision less likely.

Ultimately, we found that the evacuation destination had an impact on shelter choice. As noted in the previous section, however, shelter choice also impacted destination choice. Consequently, the direction of correlation is unclear and may require additional research to tease out the order in which people make their evacuation decisions. Those with worries about the severity of Irma were more likely to shelter with family, but those with worries about finding housing were much less likely to shelter with family, suggesting availability as a key variable. Age and household characteristics such as income, pets in the household, and length of residence also impacted shelter choice.

Mode Choice

The survey results did not include a substantial number of individuals who evacuated without a personal vehicle. This is likely due to high auto ownership of Florida residents in the counties surveyed and the online survey design that reached wealthier respondents who can afford vehicles. Thus, while the multinomial logit model for mode choice may not be representative of the general population, the model still highlights some variables that impact mode choice of this wealthier sample. For research on non-personal mode choice, Sadri *et al*. (2014a) provides results from a hypothetical choice experiment for carless individuals using a nested logit model. Deka and Carnegie (2010) also considered mode choice – specifically for transportation-disadvantaged individuals – but used a multinomial logit to determine mode preference in a hypothetical scenario. Consequently, this research on Hurricane Irma offers a glimpse into mode choice in a revealed preference setting for hurricanes, which has been severely lacking in the literature. For this research, mode choice is divided into four categories: 1) one personal vehicle, 2) two personal vehicles or more, 3) shared mode (i.e., carpool, bus, airplane), and 4) other personal mode (i.e., rental vehicle, RV). A one personal vehicle evacuation is the base choice.

Based on the constant parameter in Table 15, individuals are much less likely to prefer evacuating with two or more vehicles, shared modes, or other personal modes when compared to one personal vehicle. This highlights the willingness of individuals to use the availability of their vehicle in an evacuation but not necessarily take additional vehicles to increase capacity or protect those vehicles from the storm. However, those who evacuated within county were more likely to use two or more vehicles. Since the distance of the evacuation was short, more evacuees may have been comfortable taking an additional vehicle for increased passenger capacity or luggage capacity. Moreover, evacuees may have wanted to protect their vehicles, and within county evacuees had more time to accomplish this. A similar result was found for those who evacuated out of county but within Florida. Respondents who evacuated within county were less likely to evacuate with a shared mode or other personal mode, but the results were not significant.

Individuals who were extremely or somewhat worried about the severity of Hurricane Irma were more likely to evacuate with two or more vehicles (significant) and with a shared mode (insignificant). Evacuees with a higher risk perception may have worried about damage to their belongings, especially additional vehicles. Risk perception may have also pushed some to fly out of Florida rather than evacuate by vehicle. The severity variable was negative but insignificant for other personal modes.

Young adults (under 35) were more likely to use a shared mode but this was slightly insignificant. This age group was also less likely to use two or more vehicles and other personal modes, perhaps due to cost restrictions. One and two-person households were less likely to evacuate with multiple vehicles (slightly insignificant) but more likely to use shared modes and other personal modes (slightly insignificant). With less household members, evacuees had greater flexibility to use different modes beyond an owned vehicle. Of course, availability was a key variable. Households who owned two or more vehicles were much more likely to evacuate with two or more vehicles. However, it should be noted that the survey found that of those who owned two or more vehicles, only 30% actually evacuated with multiple vehicles. Households with lower income (below $40,000) were more likely to evacuate with a shared mode or other personal mode but less likely to use two or more vehicles.

Table 15 Discrete Choice Analysis - Mode Choice

Transportation Mode: Multinomial Logit

Choice 1: 1 Personal Vehicle - Base
Choice 2: 2 or More Personal Vehicles
Choice 3: Shared Mode of Transportation (i.e., carpool, bus, aircraft, etc.)
Choice 4: Other Personal Mode of Transportation (i.e., rental car, RV, walk/bike, etc.)

	2 Vehicles or More			***Shared Mode***			***Other Personal Mode***		
Variable	*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*	
Constant	-3.24	<0.001	***	-3.76	<0.001	***	-4.37	<0.001	***
Evacuation Experience									
Evacuated Within County [Base: Evacuated Out of Florida]	1.27	0.001	***	-0.68	0.380		-0.60	0.579	
Evacuated Out of County, Within Florida [Base: Evacuated Out of Florida]	1.10	<0.001	***	------	------		------	------	
Concerns and Worry									
Extreme or Somewhat Worry of the Severity of Irma	0.87	0.042	*	0.44	0.504		-0.44	0.542	
Individual Demographics									
Young Adult - Under 35	-0.08	0.795		0.78	0.084		-0.93	0.272	
Household Characteristics									
1 and 2 Person Household	-0.52	0.078		0.50	0.282		1.28	0.071	
2 or More Vehicles	1.44	0.001	***	0.11	0.825		0.35	0.627	
Household Income Under $40,000 [Base: Income of $40,000-$99,999]	-0.13	0.764		1.05	0.056		1.76	0.029	*
Household Income $100,000 and Over [Base: Income of $40,000-$99,999]	0.12	0.705		0.80	0.135		1.36	0.085	
Less Than 1 Year in Residence	-0.80	0.050	*	0.20	0.675		0.31	0.678	
Number of Observations	368								
ρ^2 (fit)	0.42								
$\bar{\rho}^2$ (adjusted fit)	0.37								
Final Log-Likelihood	-294.9								

* 95% significance

** 99% significance

*** 99.9% significance

Lower-income households are less likely to own a vehicle and may have also attempted to reduce evacuation expenses by using carpooling or buses. However, high-income respondents ($100,000 and over) were also more likely to use a shared mode or other personal mode. This may result from flying out of Florida or using an RV to evacuate, both of which are costly. Evacuees who have lived less than one year in their residence were less likely to evacuate with two or more vehicles. These individuals may not have owned multiple vehicles or may have believed that an extra vehicle would be safe at their residence.

Overall, the model suggests that evacuation destination was a key parameter for mode choice. Similar to shelter choice, it is unclear if mode choice occurs before or after destination choice. Indeed, a destination may be dependent on the availability of certain modes of transportation. Of course, those who owned two or more vehicles were more likely to evacuate using two or more vehicles. Other variables such as worry about the severity of Hurricane Irma and length of residence also changed the likelihood of using two or more vehicles. Income had a split influence – both lower-income and high-income respondents were more likely to use a shared mode and other personal mode, perhaps because these categories contain both expensive and inexpensive modes. The results for household size and young adults were slightly insignificant but were retained to add variability in the model.

Route Choice

Route choice is an important but difficult choice to analyze. Routing has significant implications for transportation agencies as they attempt to manage traffic during an evacuation. However, with just survey data and without GPS trace data, routes must be discretized into categories that do not detail specific routes. Using a mixed logit model, Sadri *et al*. (2015) was able to conduct a route choice experiment across specific bridges from Miami Beach, but this was dependent upon leaving from a single origin area. Akbarzadeh *et al*. (2015) also considered a hypothetical hurricane but only surveyed individuals in New Orleans where routing options are limited. With a state-wide survey, an exact route approach was not feasible. Consequently, we developed a question that asked respondents to indicate the percentage of their trip they took on four different road types: 1) highways, 2) major roads, 3) local roads, and 4) rural roads. Thus, an individual may have spent 70% of their evacuation on highways and 30% of their evacuation on local roads. This designation helps capture different road types, which can then be used to determine general differences in routing. Thus, the routing choice is not on specific roads but on road types. Discrete choices were formed by considering the majority route (over 50%) that an individual took, broken into four categories: 1) highways, 2) major roads, 3) local/rural roads, and 4) no majority. A no majority choice indicates that no one road type was used over 50%. This category includes individuals who took 50% highways and 50% major roads, or those who took 40% highways, 30% major roads, and 30% local/rural roads. While this categorization is imperfect, it does signify the overall route choice of individuals while evacuating, especially those who did not use highways for the majority of the evacuation. Individuals who used highways as the majority road type are the base. This aggregation of route types is similar to Sadri *et al*. (2014b), which considered three choices – usual/familiar route, recommended route, and updated route – for a mixed logit model. However, for this paper, we chose division by road type since it offers more specific policy-oriented results for transportation agencies.

Table 16 Discrete Choice Analysis - Route Choice

Route Choice: Multinomial Logit

Choice 1: Over 50% of Route on Highways - Base
Choice 2: Over 50% of Route on Major Roads
Choice 3: Over 50% of Route on Local/Rural Roads
Choice 4: No Majority on Any One Type of Road

	Major Roads			***Local/Rural Roads***			***No Majority Road***		
Variable	*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*	
Constant	-1.52	0.016	**	-3.41	<0.001	***	-2.92	<0.001	***
Evacuation Experience									
Evacuated with 1 Vehicle [Base: Shared Mode and Other Personal Mode]	-1.99	0.003	**	-1.30	0.147		-0.21	0.699	
Evacuated with 2 or More Vehicles [Base: Shared Mode and Other Personal Mode]	-1.93	0.009	**	-1.01	0.306		-0.42	0.503	
Evacuated Within County [Base: Evacuated Out of Florida]	5.08	<0.001	***	4.31	<0.001	***	2.33	<0.001	***
Evacuated Out of County, Within Florida [Base: Evacuated Out of Florida]	1.56	0.011	*	0.73	0.351		0.98	0.003	**
Concerns and Worry									
Extreme or Somewhat Worry of Traffic	-0.80	0.080	*	-0.69	0.275		0.89	0.045	*
Extreme Worry of Finding Gas	0.47	0.295		1.25	0.044	*	0.83	0.014	*
Individual Demographics									
Previous Evacuee	0.03	0.936		0.96	0.081		0.08	0.784	
Number of Observations	368								
ρ^2 (fit)	0.44								
$\bar{\rho}^2$ (adjusted fit)	0.39								
Final Log-Likelihood	-286.9								

* 95% significance
** 99% significance
*** 99.9% significance

In Table 16, the constant term is negative and highly significant for routing on major roads, local/rural roads, and no majority road. This finding highlights the natural preference for highways over other road types, which is typical for major evacuations. Evacuees with one vehicle or two or more vehicles were much more likely to use highways, especially when compared to major roads (negative and significant). This also suggests that respondents who used alternative modes of transportation – such as buses, rental cars, RVs, and carpools – were more likely to forgo using the highway in favor of other roads. Individuals who evacuated within county were significantly more likely to evacuate using major roads, local/rural roads, or no majority road. This result is unsurprising as those evacuating within county can avoid highly congested highways and have knowledge of nearby smaller roads. Similarly, those who evacuated out of county but within Florida were also less likely to use highways. With a number of major state roads in Florida, evacuees may have attempted to avoid congestion on highways at all costs. In addition, some respondents may have evacuated inland where major roads are more viable than the mostly north-south configuration of Florida interstates.

Individuals who were extremely or somewhat worried about traffic were less likely to take major roads and local/rural roads, but more likely to take no majority road. However, the correlation direction on this variable is unclear, as people may have decided their evacuation route prior to the evacuation. This would indicate that respondents not worried about traffic were unconcerned due to their choice of route. However, people extremely worried about finding gas were less likely to use highways, perhaps resulting from news stories on fuel shortages during the evacuation. Evacuees may have believed that gas stations in areas away from the highway would be open, due to less evacuation traffic. Finally, previous evacuees were more likely to use local/rural roads than highways. While this result was slightly insignificant, it may point to the role of experience in evacuations. Those caught in traffic during a previous storm may have switched their route to avoid congestion.

Overall, respondents had a natural tendency to evacuate using highways, which was augmented by those using one or more vehicles to evacuate. However, individuals evacuating within county and within Florida, those with worries about finding gas, and previous evacuees were more likely to evacuate on road types other than highways. One interesting result was that the use of a GPS system for navigation was found to be highly insignificant across all choices. While GPS may help evacuees find alternative routes away from highways and congestion, the results indicate that at this point, the link between GPS and routing *choice* is minimal. Future work should focus more attention on the interplay between GPS and routing, especially as technology allows drivers to make a number of decisions that do not follow official evacuation routes or emergency management directions. This may be beneficial for relieving congestion on highways but would increase the need for services – such as gas, food, and water – along other routes that evacuees employ.

Reentry Day

In recent evacuations, reentry timing has become a critical choice, and emergency and transportation practitioners are increasingly interested in methods of returning evacuees to their residences. However, this process can be challenging, as evacuees are spread out across a wide area with varying levels of connectivity to local news reports, safety orders, and information on the ground. Reentry timing must strike an appropriate balance between ensuring the safety of returners, guaranteeing livability and resources, and permitting returners access to their property. Deviation from this interplay can often lead to misinformation, poor living conditions, and an angry public that wants to return to their homes. Overall, there is limited research on reentry choice. Consequently, our study formulated a question asking evacuees on what day they returned and what factors led them to that choice. We then created five discrete options for reentry: 1) one day or less after landfall, including before landfall, 2) two days after landfall, 3) three days after landfall, 4) four days after landfall, and 5) five or more days after landfall. Depending on the specific hurricane or hazard, these choices may be drastically different. A more devastating hurricane may lead to later reentry trips, while a glancing hurricane may lead to earlier reentry trips. The base case for the analysis was the decision to return one day or less after landfall (including before landfall). It should be noted that some individuals (10.9%) reported that they indeed returned home before landfall. Some respondents on the eastern Florida coastline may have returned before landfall, when Hurricane Irma shifted course towards the western Florida coastline.

In Table 17, the constant value is only significant for five or more days after landfall. The negative value indicates that people preferred to return much earlier than to return much later. This is intuitive as evacuees want to reestablish their routines and return to work as quickly as possible. Evacuees who remained within county were much more likely to return one day or less after landfall compared to all the other choices. These significant results suggest that proximity to home helps establish an understanding of the local conditions. While the situation still may not be safe, even some knowledge is a powerful influence on returning. At the same time, within county evacuees are closer to home, making their return journey shorter and quicker. The same results were found for those who evacuated out of county but within Florida. However, the coefficients for two days after and four days after landfall were not significant. This finding suggests more varied reentry timing for out of county but within Florida evacuees than for within county evacuees.

Regarding reentry characteristics, individuals who stated they received a safe return order from an official source were more likely to return two days or later after landfall than one day or less after landfall (all slightly insignificant). This result is behaviorally consistent, as many agencies did not issue an all-clear to return within a day of landfall. Evacuees who learned that power was restored were also more likely to return two days or later after landfall than one day or less after landfall (all significant). Indeed, the results suggest that evacuees waited at evacuation destinations until they learned power had been restored. Individuals with work requirements were more likely to return two days after landfall (compared to one day or less after landfall). Work requirements also led some respondents to forgo evacuating, so it is unsurprising that this same factor led to earlier reentries. Those who wanted to survey damage quickly were much less likely to return four days or five days or more after landfall. This desire to assess damage presents a challenge for law enforcement and emergency management agencies who sometimes must restrict access due to unsafe conditions.

Table 17 Discrete Choice Analysis - Reentry Day

Reentry Date: Multinomial Logit

Choice 1: 1 Day or Less After Landfall (Includes Before Landfall) - Base
Choice 2: 2 Days After Landfall
Choice 3: 3 Days After Landfall
Choice 4: 4 Days After Landfall
Choice 5: 5 or More Days After Landfall

	2 Days After			**3 Days After**			**4 Days After**			**5+ Days After**		
Variable	*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*		*Estm. Coef.*	*p-value*	
Constant	-0.45	0.31		0.02	0.969		-0.77	0.176		-0.95	0.045	*
Evacuation Experience												
Evacuated Within County [Base: Evacuated Out of Florida]	-1.99	<0.001	***	-4.01	<0.001	***	-2.62	0.002	**	-1.84	<0.001	***
Evacuated Out of County, Within Florida [Base: Evacuated Out of Florida]	-0.28	0.442		-1.65	<0.001	***	-0.84	0.105		-1.74	<0.001	***
Reentry Characteristics												
Received a Safe Return Order from Official Source	0.74	0.068		0.87	0.083		0.87	0.13		0.71	0.125	
Learned Power Restored	0.80	0.044	*	1.42	0.001	***	2.29	<0.001	***	2.87	<0.001	***
Needed to Return to Work	0.74	0.044	*	0.34	0.446		0.00	0.996		0.16	0.689	
Wanted to Survey Damage Quickly	0.37	0.264		0.59	0.162		-0.49	0.355		-0.69	0.067	
Individual Demographics												
Young Adult - Under 35	-0.66	0.067		-0.16	0.702		-0.53	0.303		-0.26	0.485	
Household Characteristics												
Children Present in Household	0.60	0.067		-0.36	0.367		-0.32	0.496		-0.28	0.425	
Live in FEMA Risk Zone	-0.46	0.182		-0.46	0.288		-1.45	0.01	**	0.03	0.937	
Southeast Region [Base: Central-West, Northeast/Central-East]	-0.04	0.945		-1.95	0.084		0.26	0.754		1.05	0.079	
Southwest Region [Base: Central-West, Northeast/Central-East]	-0.07	0.86		-0.65	0.172		0.46	0.401		1.38	0.001	***
Number of Observations	368											
ρ^2 (fit)	0.26											
$\bar{\rho}^2$ (adjusted fit)	0.18											
Final Log-Likelihood	-437.6											

* 95% significance
** 99% significance
*** 99.9% significance

Young adults (under 35) were more likely to return one day or less after landfall, which may be tied to their lower risk perception. However, the results were slightly or moderately insignificant, so this individual demographic (along with other non-modeled demographics) may not play a role in reentry timing. Children present in the household was also an insignificant variable, but those with children were slightly more likely to return two days after landfall. This finding may be related to school requirements and the higher cost of sheltering an entire family. Respondents living in a FEMA risk zone were much less likely to return two, three, and four days after landfall. Since these choices are compared to one day or less, the results indicate that people were slightly more willing to return home one day or less after landfall if they lived in a FEMA risk zone. Individuals in these zones may have been concerned about their property. Finally, geography had a small effect on reentry timing. Those living in the Southeast and Southwest regions were more likely to return later (four days or five days or more after landfall). These residents had longer distances to travel if they evacuated outside of Florida. Moreover, the Florida Keys in the Southeast region and most cities in the Southwest region were directly impacted by Hurricane Irma.

The results of the multinomial logit model for reentry day indicate that those who evacuated closer, wanted to survey damage quickly, and had work requirements were more likely to return very early or relatively earlier. Individuals living in the Southeast and Southwest regions were more likely to return later. However, several variables including age (young adult under 35), children present in the household, and living in a FEMA risk zone produced somewhat contradictory results. Further research into reentry timing may be necessary to understand the impact of these variables. Regardless, major motivators for reentry, which are listed in Table 7, included wanting to survey damage quickly, learning power was restored, returning to work, being told by a secondary source that it was safe, and wanting to protect property. These stated reasons are important to consider, as they indicate that personal priorities can supersede official orders. In this case, agencies must develop a clearer reentry protocol that can be effectively communicated across a wide geography. Reentry timing also has implications for transportation agencies as the influx of vehicles may overcome available resources – particularly fuel – that are critical for the recovery process. Ultimately, additional research should be conducted on reentry timing to help establish data-driven approaches for planning.

Prediction Results for All Choices

To enhance the analysis, we also calculated the prediction probabilities of each modeled choice using the estimated model parameter coefficients. Given the small sample size of the dataset, we chose to use the entire dataset for both estimation and prediction. We also employed a weighting mechanism as described in the methodology section that weights probabilities based on three factors: gender, age, and vehicle ownership. This weighting attempts to move the predictions to more accurately represent the population of Florida. These demographic variables were feasible to use, as they each had a 100% response rate and a reasonable deviation from the population of Florida. While income would have been a preferable weighting factor, a significant portion of individuals responded “prefer not to answer.” Rather than use imputation to estimate these values, we opted to use other demographic variables where imputation was not necessary. The results for the weighted predictions are found in Table 18 and are compared to the survey results. We find for all the choices a relatively low difference between the survey results and the weighted predictions. The small differences indicate that the models are relatively stable and that they may indeed help describe and explain evacuation choice-making. We also note that the sum of each choice may not equal 100% due to rounding.

Table 18 Weighted Predictions of Discrete Choice Models (n=368)

	Survey Results	Weighted Prediction
Evacuation Choice *(n = 645)*		
Evacuated	57.1%	56.3%
Did Not Evacuate	42.9%	43.7%
Departure Day		
More than Three Days Prior to Landfall	20.1%	19.9%
Three Days Prior to Landfall	22.3%	21.2%
Two Days Prior to Landfall	32.3%	32.1%
One Day Prior to Landfall	22.6%	23.6%
Day of Landfall or After	2.7%	3.2%
Departure Time of Day		
6:00 p.m. - 5:59 a.m. (Nighttime)	32.8%	32.0%
6:00 a.m. - 5:59 p.m. (Daytime)	67.1%	68.0%
Destination Choice		
Within County	17.1%	20.2%
Out of County, Within Florida	34.3%	31.1%
Out of Florida	48.6%	48.7%
Shelter Choice		
Family Member's Residence	43.5%	41.3%
Hotel/Motel	27.4%	24.4%
Friend's Residence	15.8%	17.5%
Other Location (i.e., Airbnb, Second Residence, etc.)	9.7%	11.7%
Public Shelter	3.5%	5.1%
Mode Choice		
One Personal Vehicle	65.8%	68.9%
Two or More Personal Vehicles	24.2%	18.5%
Shared Mode	6.8%	8.0%
Other Personal Mode	3.2%	4.6%
Primary Route (Over 50%) by Road Type		
Highways	64.1%	64.1%
Major Roads	13.6%	14.4%
Local/Rural Roads	5.5%	5.1%
No Majority Type	16.8%	16.4%
Reentry Day		
One Day or Less After Landfall (Includes Before Landfall)	31.0%	31.5%
Two Days After Landfall	22.0%	19.4%
Three Days After Landfall	12.5%	12.4%
Four Days After Landfall	8.2%	8.2%
Five or More Days After Landfall	26.4%	28.5%

Key Takeaways and Recommendations

The results from the survey and the conclusions from the discrete choice analyses offer several key takeaways and recommendations for emergency management *and* transportation agencies to consider in their preparedness, response, and recovery strategies. These recommendations could be employed to develop future evacuation plans, bolster current plans, or test response mechanisms to determine their effectiveness. While this research does not develop any explicit pilots, we recommend that agencies consider making small changes in their evacuation policies and strategies to improve for next time. We also would like to note that these recommendations do incorporate concurring ideas from past hurricane evacuation research.

Noncompliance with Mandatory Evacuation Orders

- Mandatory evacuation order compliance has not shifted significantly, suggesting that compliance with orders remains a major issue and agencies should make this a primary area of focus.
- Individuals in the Southeast and Northeast/Central-East regions were less likely to evacuate. While this finding may reflect the shift in the storm's direction, the lower rates in both regions also suggest that agencies may need to develop plans to increase compliance.
- Previous evacuees and those with hurricane experience were less likely to evacuate. Indeed, the poor management of past evacuations may lead many to remain home during a subsequent storm. Agencies should consider informing the public about evacuation and sheltering improvements to encourage compliance.
- Some non-evacuees (34.7%) wanted to protect their property. Increased law enforcement, as well as clear messaging about the presence of law enforcement in evacuation zones would alleviate worry about property.
- Other reasons frequently cited in the survey for noncompliance were:
  - Didn't want to sit in traffic (49.1%)
  - Didn't want to go to public shelter (31.4%)
  - Believed the storm would not be bad (29.6%)
  - Some requirement to go to work during storm (21.7%)
  - Was not sure where I could take my pets (18.1%)
  - Didn't receive any orders (15.9%)
  - Didn't have the money to evacuate (14.4%)

  These noncompliance issues are addressed as part of the wide-ranging recommendations offered in the following sections.

Evacuation Communication

Overview of Mandatory Evacuation Orders

- Mandatory evacuation orders are effective in encouraging evacuations. Local agencies should craft complete and clear orders phrased in strong terms and delivered by individuals with authority. This may include high-ranking law enforcement officials or local politicians.
- Individuals were informed of evacuations through a number of different platforms and often confirmed the information through another source. Evacuation orders should continue to be posted on all available media outlets concurrently with the same messaging to reduce confusion.

- Individuals who received a mandatory evacuation order were more likely to evacuate two days or one day prior to landfall, which was the required time of departure for most evacuation orders. Thus, orders were effective in encouraging specific departure timing. Agencies should continue to specify exact times when individuals should evacuate.
- Risk perception of the storm was a major influencer of evacuating. Clear and strong language for major events is necessary to increase evacuation rates. Likewise, communication for smaller events should not overstate the risk of an impending storm. This would prevent a "crying wolf" scenario wherein evacuees may be less likely to evacuate for a second storm.

Communication Encouraging/Discouraging Evacuee Behavior

- A significant number of individuals evacuated even though they were not given mandatory orders. Evacuation orders should state clearer geographic boundaries, thereby reducing shadow evacuations.
- Provided that necessary nighttime resources are available, mandatory orders could be worded and timed to encourage departures at night, thus reducing roadway congestion during daylight hours. In addition, communication should include information about times when registration is open at public shelters (further discussion on nighttime evacuations can be found below under "Transportation").
- Those who evacuated within county and out of county but within Florida were more likely to leave closer to landfall. Long-distance evacuees should be encouraged to depart earlier to ensure their safety and to reduce local traffic congestion.
- Risk perception impacted distance evacuated, as those worried about injury/death were more likely to leave the state. Messaging should be crafted to accurately reflect the risks in specific communities, thereby reducing long-distance evacuations but maintaining human safety.
- Evacuees who experienced prior hurricanes were more likely to stay closer, which suggests that newer residents should be encouraged to evacuate shorter distances. Educational outreach may be useful in this circumstance.
- Lower-income individuals (under $40,000) were less likely to conduct shorter evacuations. Again, targeted outreach may be necessary to reduce the distance of evacuations (and associated costs).
- The Southeast region was more likely to evacuate within Florida but not within county. Those in the Northeast/Central-East were also less likely to evacuate within county. In general, most regions need to improve their messaging to encourage evacuees to remain closer.
- The number of within Florida and outside of Florida evacuees were very similar. In fact, half of the respondents from the Southwest region evacuated out of state, indicating that a large number of individuals traveled long distances. Agencies should consider methods and pilot ideas to encourage shorter-distance evacuations.
- People who took five or more trips – such as gathering supplies or picking up family members – were more likely to leave one day prior to landfall. Agencies should encourage households to stock up on supplies earlier to move up departure times.

Other Communication

- Respondents who experienced a prior evacuation were more likely to leave more than three days before landfall. Thus, people with no evacuation experience may not fully understand evacuation techniques such as phased evacuations or evacuation zones. Consequently, improved outreach in emergency education, especially to new residents, would be useful.

Transportation

Traffic Management

- Improved traffic management techniques (i.e., signal timing, shoulder usage, contraflow) and evacuation strategies, such as phased evacuations, would reduce both the real traffic levels and the perceived traffic levels.
- Individuals departed more evenly than in past evacuations. This shift away from the typical "s-curve" is notable, as a more phased evacuation reduces congestion on roadways. Agencies should continue developing plans for phased evacuations.
- Evacuees still preferred highways over other roads. The majority of resources still need to be concentrated along major thoroughfares. Congestion management is also most important along highways where contraflow and shoulder use may be effective strategies.
- Those evacuating within county and out of county but within Florida were more likely to use major roads, local/rural roads, and no majority road. Agencies should encourage this behavior to reduce congestion on highways for those traveling further.
- Within county evacuees were more likely to evacuate during the day. These evacuees should be encouraged to use local and rural roads to alleviate daytime congestion on highways and major roads.
- A large percentage of respondents (24.2%) evacuated with two or more vehicles, which indicates unused capacity. Agencies should consider encouraging less vehicle usage or increased use of capacity through assisting other individuals in evacuating.
- Respondents worried about the severity of Irma were more likely to evacuate with two or more vehicles, suggesting the desire to protect vehicles. To reduce multiple-vehicle evacuations, localities could lift parking restrictions or offer parking in city-owned lots or garages in areas less vulnerable to the storm.
- Extreme worry of traffic was associated with very early departures. This concern could be used by agencies as a strategy to encourage earlier evacuations, especially if the evacuation is phased.

Nighttime Evacuations

- People prefer to evacuate during the day, which often contributes to considerable roadway congestion. Agencies could provide information about evacuating at night and also ensure resources for nighttime evacuees. Law enforcement and traffic management officials may also be needed at night.
- Respondents who received voluntary evacuation orders were more likely to evacuate at night compared to those who received mandatory orders. Providing a larger window to evacuate, including times at night, may also encourage mandatory evacuees to depart at nighttime.
- Individuals worried about traffic were more likely to evacuate at night. This preference could be further encouraged through information and education from agencies.
- Younger individuals, previous evacuees, and longtime residents were more likely to leave at night. This preference could be further encouraged by agencies through communication, education, and behavioral nudging. For example, a statement might be issued suggesting that those comfortable with evacuating at night should do so in order to help other evacuees and reduce roadway congestion.

Gasoline Supplies

- The gas shortage in Florida was a key transportation issue during the evacuation. Not surprisingly, respondents worried about finding gas were less likely to evacuate. Bolstering gas reserves, increasing deliveries prior to the storm, and identifying areas prone to gas shortages are possible solutions.
- Individuals worried about finding gas were more likely to evacuate during the day, so agencies need to work on ensuring gas supplies during daytime hours.
- Individuals worried about finding gas were more likely to avoid highways. While this result is likely due to gas shortages on highways, rural gas stations may run out of gas as well, if a significant number of evacuees decide to reroute. Therefore, adequate gas supplies must be accessible along local/rural roads.

Other Transportation

- Young adults (under 35) were more likely to use shared transportation modes, such as public transit. Public transit should be made accessible for more individuals including older adults. Cities should also develop transit-based evacuation plans that utilize local transportation assets. This strategy would be especially effective for cities with a high proportion of carless individuals. Setting distinct and known pickup points is a crucial aspect of this type of planning.
- Respondents used a mix of roadways to evacuate. While this is beneficial for congestion management, it may also spread resources thin. Food, water, gas, and emergency services need to be appropriately positioned to ensure that all evacuees – not just those on highways – have access to these resources.
- Individuals worried about traffic were less likely to use major roads but more likely to use a mixture of roads with no majority road (over 50%). This finding suggests that these respondents may have been using their own knowledge of the roads or GPS to navigate. Agencies may need to partner with GPS navigation providers – such as Google Maps, Apple Maps, and Waze – to determine safe routes for vehicles.

Sheltering

- Lack of space coupled with poor perception of public shelters led some respondents not to evacuate. Additional evacuation shelters should be identified, prepared, and used. Shelters should have the necessary resources to provide a comfortable stay for all people, particularly those with disabilities or medical conditions.
- Individuals worried about housing and the cost of sheltering were less likely to evacuate. Additional public shelters should be opened with adequate resources and accessibility. This may require identifying new shelters within county that could be designated for public use. Agencies should also consider working with local hotels and motels to encourage lower priced rooms during evacuations to make sheltering more equitable.
- Individuals have a natural preference to shelter with family and at hotels/motels when compared to friends but a preference against public shelters also when compared to friends. While this reduces the need for governmental sheltering assistance, poor perception of public shelters may stop individuals from complying with evacuation orders. The other sheltering options may also be located in neighboring states, which increases congestion and risk on the roads.

- Respondents worried about finding housing were more likely to evacuate within county, suggesting a need for additional public shelters or alternative options for sheltering within communities.
- Individuals staying with friends and family were more likely to evacuate at night. People traveling to shelters may be worried about nighttime admittance. Agencies and non-governmental organizations should be clearer about when registration at shelters is open.

Special Evacuation Needs

Lower-Income Individuals

- Some non-evacuees stated they did not have enough money to evacuate. Since the survey skews toward wealthier individuals, this result is likely underrepresented. The cost of evacuation – particularly sheltering – is a major barrier that must be addressed. Increasing free shelters and free transportation would help overcome this obstacle.
- Low-income individuals (under $20,000) were less likely to evacuate, which highlights the high cost associated with evacuating. Low-income individuals are also less likely to own a private vehicle and may not have alternate transportation options. Expanding free transportation and shelters, specifically near poorer neighborhoods, would alleviate cost barriers and make evacuations more equitable. Increasing vital resources at shelters – including food, water, bedding, and medicine – would also help low-income individuals.
- Lower-income individuals (under $40,000) were more likely to use shared transportation or other personal modes. Additional evacuation pickup points and increased shuttle service to low-income neighborhoods will help provide and reduce the cost of transportation, increase compliance, and ensure safety for this vulnerable group.
- Lower-income individuals (under $40,000) were more likely to go to a public shelter and much less likely to stay at a hotel/motel. Additional resources at shelters may be necessary to care for lower-income individuals and to ensure that evacuation costs are not debilitating.

Older Adults

- Older adults (65 and over) were somewhat less likely to evacuate than other individuals. The identification of neighborhoods, senior living centers, and nursing homes with a higher proportion of older adults is important, as they may need additional transportation and sheltering assistance. For example, transit and paratransit may offer comfortable transportation options, while ADA (Americans with Disabilities Act) accessible shelters could also assist older adults.
- Older adults (65 and over) were much less likely to shelter with family or at hotels/motels compared to the other options. Public shelters should be equipped for older adults.

Families

- Households with children were more likely to evacuate, so public shelters should be equipped with resources needed for families. Also, school districts should remain closed for additional days, especially if post-storm conditions are poor in an impacted area.
- Households with children were more likely to evacuate very early. Evacuation shelters should be prepared for the earlier arrival of families with children, and schools should be prepared for the early departure of students.

Individuals with Work Requirements

- Those with a work requirement were less likely to evacuate. For a job not tied to human safety, response, or recovery, an employer should grant additional time away from work. Agencies can encourage employers to develop a pre-storm protocol regarding work requirements, so employees can be properly informed.
- Respondents worried about work requirements were more likely to evacuate closer to landfall as compared to more than three days prior to landfall. Improved communication from employers regarding work expectations may encourage individuals to leave earlier.

Pet Owners

- Households with pets were somewhat less likely to evacuate. Often, public transportation, public shelters, and hotels/motels do not allow pets. Transit agencies should ensure that pets can be taken aboard evacuation buses, while shelters should include a designated area for pets. Agencies can also encourage hotels and motels to allow pets in specific rooms.
- Individuals with pets were much less likely to choose a hotel/motel or public shelter. Some shelters should allow pets, and this information must be disseminated. Resources for pets – including veterinarian services and food – may also be necessary.

Reentry

- Most jurisdictions do not have a plan in place for repopulating impacted areas. Agencies at all levels of government must cooperate to develop reentry plans. People typically want to return quickly to begin the recovery process and determine the level of damage. Plans must be crafted to ensure human safety, accelerate recovery efforts, and reduce traffic congestion.
- Individuals who evacuated within county and out of county but within Florida were much more likely to return one day or less after landfall. Thus, early arrivers were locals who wanted to survey damage quickly or protect their property. Agencies must be prepared for the possibility of this influx. A phased reentry plan may be necessary to reduce the number of evacuees who return home immediately.
- A safe return order did encourage people to return two days or later after landfall. These orders must be more widely disseminated, a challenging task since evacuees are often spread over a large geographic region. A multi-pronged communication effort would most effectively spread the word. In addition, communication prior to evacuations may be needed, informing evacuees to expect a return order.
- Learning that power was restored was a key motivator for reentry, highlighting the need for collaboration between local agencies and utilities.
- Individuals who needed to return to work were most likely to return two days after landfall. The first wave of returning evacuees may be critical for recovery (i.e., nurses, doctors, government officials, media) or may need to resume work for their livelihood (i.e., hourly workers, lower-income individuals). While those returning early may be at risk, restricting their reentry would be problematic for recovery and community resilience.
- Individuals wishing to survey damage quickly were more likely to return two days or three days after landfall. Media and government officials could offer improved communication regarding damage, thus reducing the perceived need to return quickly. In addition, guaranteeing law enforcement would alleviate fears of looting, likewise reducing the need for earlier reentry.

- Families with children were most likely to return two days after landfall, perhaps because parents were worried about their children missing school. Local school districts should clearly communicate the length of time they will be closed, thereby reducing premature returns of children who are highly vulnerable in a disaster zone.

New Strategy with Shared Resources

In recent times, improvements in communication and technology have fueled the growth of the sharing economy, a collection of peer-to-peer and business-to-peer transactions that allow for the sharing of resources. The sharing economy has been particularly present in transportation mobility through the form of ridesourcing, carsharing, bikesharing, and other mobility-on-demand services. With the advent of private sharing economy companies, it has been hypothesized that these companies could play a major role in disasters. Wong *et al*. (2018) offers an overview of past actions of sharing economy companies during disasters and provides a number of key benefits and limitations for leveraging the sharing economy in a disaster situation. Shared resources could also be provided via private citizens through a system that successfully matches supply (i.e., additional transportation and sheltering capacity) with demand (i.e., the need for transportation and sheltering resources to evacuate). Agencies and community organizations should begin to consider how the growth of private sharing economy companies and improvements in technology could benefit all people in evacuations. While future work is needed to further develop this concept and strategy, Wong *et al*. (2018) offers a starting point for considering how to leverage these new shared resources to supplement public resources in evacuations.

Future Research Direction

For this report, we offered a comprehensive collection of descriptive statistics and discrete choice models to offer insights into the behavior of evacuees throughout a hurricane evacuation. We recognize that the analysis is based on basic methodology that has already been conducted in the evacuation field. One key reason for the use of simple models was to develop an analysis that could easily bridge the gap between researchers and practitioners, with clear policy links for improving evacuation planning and response. However, we did provide several key models – particularly in destination choice, mode choice, and reentry timing – that have seldom been studied in the field. Along with these new models, we have added empirically to the literature through the study of Hurricane Irma as a new disaster situation.

A significant finding from the development of the discrete choice models was that choices in the evacuation process exhibit clear correlation. For example, the destination choice of an evacuee was found to significantly impact all other key evacuation choices (i.e., departure day, departure time of day, transportation mode, shelter type, route, and reentry day). At the same time, destination choice was impacted by shelter type and transportation mode. This endogeneity presents a challenge: how should evacuation choices be modeled to successfully handle this one-way or bidirectional correlation? Moreover, latent variables (such as attitudes and perceptions) and choice variables are likely to be influenced by the same underlying factors that may not be measurable (Chorus and Kroesen, 2014). In the context of evacuation choice-making, the concerns and worry of respondents prior to evacuations may be affected by underlying personality traits (such as sensitivity, nervousness, or general risk aversion), which may also impact the choice itself (a preference to travel far away from the storm). Chorus and Kroesen (2014) also notes that the choice may influence the latent variable due to learning effects. While this is less prominent for evacuation decision-making since disasters do not occur frequently, individuals with more evacuation experience may begin to exhibit behavior that is consistent with a learning effect. For example, those who chose to evacuate in a previous disaster may be less inclined to evacuate again if they were caught in extensive traffic, thus altering latent variables such as worry about traffic for the next disaster. Within the revealed preference context of our survey, respondents may have also stated their attitudes and perceptions in response to the choice that they made as a justification for their actions. This process, known as cogitative dissonance (Festinger, 1962) may also lead to endogeneity of latent variables and an unclear causal relationship (Chorus and Kroesen, 2014).

Traditional evacuation behavioral studies have modeled choices separately, with the exception of departure timing and evacuation decision which have sometimes been modeled both sequentially and concurrently. Consequently, future research with this dataset will consider models that attempt to overcome the limitations of separated choice models while also addressing the causal and endogeneity problems related to latent variables. Urata and Pel (2018) began to push this methodological understanding in a revealed preference setting by developing a latent class model of evacuation choice that is dependent on disaster risk and risk recognition. By using this risk recognition variable, the study is able to link the results more closely to both risk education and risk information, which are two areas that can be altered through agency policy changes. We aim to construct a similar approach to the evacuation decision while also considering the interplay of different choices throughout the evacuation decision-making process. As econometric models in discrete choice analysis continue to develop, we find that an opportunity exists to begin leveraging these models to help explain evacuation behavior and improve governmental evacuation planning, preparedness, and response.

Summary

This report offered an overview of evacuee behavior from an online survey of individuals impacted by Hurricane Irma. Using descriptive statistics and discrete choice models, we presented the different choices that evacuees and non-evacuees made throughout the disaster and what influenced these choices. We developed specific models for a number of critical evacuation choices including evacuating or staying, departure day, departure time of day, destination, evacuation shelter, transportation mode, route, and reentry day. Each of these discrete choice models considered a number of variables including other evacuation decisions, risk perceptions in the form of concerns and worry, individual demographic characteristics, and household characteristics. In addition to these models, we presented other findings from the survey including results on messaging, communication, opinion of governmental response, and reasons for not evacuating. Finally, we concluded the report with a set of recommendations for emergency management and transportation agencies. The purpose of this report was to present the findings of the 2017 Hurricane Irma survey and develop several basic models to explain evacuee behavior. Future work on this dataset will undertake the comparison of different types of behavioral models described in the literature review as well as new applications such as latent class choice models. Ultimately, this work falls within the literature as a new analysis of a recent disaster – Hurricane Irma – that adds to the current understanding of evacuee behavior. The empirical contributions of the report, along with the recommendations, offer a new resource for both emergency management and transportation agencies to better prepare for, respond to, and recover from hurricanes. Given the limited collection of revealed preference data for disasters and the rarity of modeling some evacuation decisions including destination, transportation mode, and reentry timing, this report and its associated dataset constitute a major addition to the literature on evacuation behavior.

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