1 **How effective are evacuation orders? An analysis of decision making among vulnerable populations**
2 **in Florida during Hurricane Irma.**

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1 **ABSTRACT**

2 Natural disasters preparedness measures are of paramount importance in reducing fatalities,
3 economic tolls, and health concerns for vulnerable populations. One such preparedness measure that
4 policymakers can take is issuing an evacuation order. Our study focuses on vulnerable populations
5 including people in low lying areas, flood evacuation zones, low income communities, sparsely populated
6 areas, and in manufactured or mobile homes. We analyze the evacuation decision and distance of over
7 170,000 individuals using passively collected location-based service (LBS) data in Florida before, during
8 and after Hurricane Irma. We control for evacuation order, evacuation order date, and storm path. The
9 results of the analysis are in line with hurricane evacuation studies using survey data, which provides
10 validation that using big data can be a reliable and efficient method to analyze hurricane evacuation decision
11 making. Our major findings are that (1) individuals issued a mandatory order are far more likely to evacuate
12 than if given a voluntary order, (2) manufactured and mobile home residents are more likely to evacuate
13 short distances than site-built home residents but less likely to evacuate longer distances, (3) people living
14 in low income census tracts were less likely to evacuate longer distances than those in higher income census
15 tracts and (4) population, employment and road density were positively associated with decision to
16 evacuate. The authors recommend that policies and hurricane preparation measures pay particular attention
17 to less densely populated and low-income regions as these were identified as vulnerable areas that were less
18 likely to evacuate.

19 **Keywords:** Passively collected location-based services data, natural disasters, evacuations, vulnerable
20 populations

1. INTRODUCTION

Climate change and increases in global sea temperatures have important consequences on the frequency and severity of natural disasters [1-3]. Coupled with a steady increase in coastal population, natural disasters have dire implications for the affected populations particularly in terms of economic toll and health concerns. Individuals are differentially exposed and vulnerable to natural disasters based on inequalities in levels of wealth and education, disability, and health status [3]. As a result, governance and management of natural disasters must account for these differences. This study explores the evacuation patterns of vulnerable populations of Florida based on their physical location (e.g. rural residents, low-lying residents, residents in flood/evacuation zones, and mobile and manufactured home (MH) residents) and based on socio-economic characteristics of their census tract (e.g. median household income and population density) during Hurricane Irma in 2017 using passively collected location-based service (LBS) data.

Florida is home to over 21 million people. Many of these people are particularly vulnerable to the effects of natural disasters. Nearly a quarter of the population (23%) in Florida is 62 years or older [4]. Over 5 million people live in government-designated flood or hurricane evacuation zones and nearly 2 million people live in MHs in Florida; many of whom are also elderly or live in low lying or coastal areas. Vulnerable populations, particularly MH residents, have traditionally been understudied in the literature [3]. MH residents are more vulnerable to the effects of hurricanes than residents in site-built housing. Moreover, the lower cost per area of MH makes them a more attractive option for lower income individuals to own property without the need for government issued housing subsidies. MHs are home to 22 million people in the U.S. According to 2017 ACS 5-year estimates retrieved from the IPUMS database, 6.3% and 9.1% of homes were MHs in the U.S. and in Florida, respectively [4, 5]. Within Florida, the proportion varies widely by county, from only 1.3% of Miami-Dade residents who lived in MHs to over 50% of residents in Glades, Liberty, Gilchrist, Levy, Dixie and Suwannee Counties [6]. The median income for MH residents is just under \$30,000. Not including land costs, purchasing a MH averages just \$70,600 compared to \$286,000 for a single family home [7, 8].

Hurricane Irma was a category 5 hurricane that made landfall in August and September 2017. The hurricane made seven landfalls, four of which occurred as category 5 across the northern Caribbean Islands. By the time it reached the Florida Keys, it had weakened to a category 4 and struck southwestern Florida at category 3 intensity. Irma was one of the strongest Atlantic basin hurricanes on record. As of the end of 2018, it was the fifth costliest U.S. hurricane on record. Irma caused 47 direct deaths, 10 of which occurred in the United States [9]. In addition to the strength and intensity of the hurricane, the cost and death toll of a hurricane can also depend on disaster management. Proper evacuation and preparation strategies can considerably decrease the economic and death toll of a natural disaster. Irma made its landfall just days after a very destructive Hurricane Harvey, possibly prompting a more alarmed response from county officials.

Disaster preparedness measures may be considered a bridge between disaster risk reduction and disaster management [3]. One important such measure is a government issued evacuation order. According to an Intergovernmental Panel on Climate Change (IPCC) report, the literature has shown that in hurricane evacuations: individuals tend to evacuate as family units, often in more than one vehicle; social influences and risk perception are key to evacuation decision-making; social and demographic factors either constrain or motivate evacuation depending on the particular context. Evacuation orders, as a form of disaster preparedness, must be given in a timely manner to be effective [3]. In the case of Irma, county evacuation orders were given as early as 4 days before landfall to just hours before landfall.

An estimated 6.5 million Floridians, or around 30% of the population, were ordered to evacuate [10]. Out of the 67 Floridian Counties, 57 of them issued some sort of evacuation order (**Figure 1**). The orders were either voluntary or mandatory, varied by location (county-wide, by hurricane evacuation zone or by housing type), and differed in what they considered “evacuating” by urging evacuation out of the county, within the county in county designated hurricane shelters, or simply “off the road” (allowing residents to stay in their homes). Some of the orders were vague and even conflicting depending on the source or without a clear time stamp while others were well outlined and directed on several news-outlets and social-media platforms.

The objectives of this study are to use big data (1) to understand if and how residents' evacuation behavior are influenced by government issued evacuation orders and (2) to analyze the evacuation behavior of vulnerable populations who were ordered to evacuate. The first objective establishes that government issued orders can be used as controls in evacuation behavior models. It is a prerequisite to the second objective, which uses a subset of the population (i.e. only those ordered to evacuate) to analyze vulnerable residents' evacuation distances. We address the first objective using a binomial logit model in which the dependent variable is the decision to evacuate (yes or no) and control for the type of home of the resident (site built versus manufactured), the evacuation order (mandatory versus voluntary), the elevation range, the presence of being in an evacuation or flood zone, whether the order was county wide, and the date that the evacuation order was issued. The second objective is addressed using a multinomial log-linear regression in which the dependent variables are the evacuation distance (e.g. did not evacuate, evacuated a short distance, medium, or long distance). This model adds income and density as indicator variables.

FIGURE 1: Evacuation Orders in Florida for Hurricane Irma.

Solid fill in Figure 1 indicates that a mandatory evacuation order was issued, striped indicates a voluntary evacuation order. When the entire county is shaded, the order was issued for that whole county. Otherwise, the order was issued by housing type (MH), road, city/town and/or by evacuation zone.

The remainder of this paper is as follows: First, is a brief overview of the literature. Second is a description our data and sample identification; Then, we provide some descriptive statistics of the data and manufactured or mobile home identification validation; Next, our methodology and variable classification are described; Finally, we discuss our results and policy implications.

2. LITERATURE REVIEW

The vast majority of natural disaster research focusing on hurricanes evacuations uses survey and interview data to estimate evacuation behavior. Thompson et al. (2017) conducted a systematic review of survey-based studies that focused on evacuations from natural disasters. The type of evacuation order is consistently found to be a statistically significant variable in which people are more likely evacuate given a mandatory order compared to a voluntary one. However, the correlation between income and evacuation was inconsistent among the studies [11]. Some studies found that higher income households tend to evacuate at higher rates and further distances after hurricanes [12-14]. Others found an opposite or null relationship between income and evacuation [15, 16]. Many studies have focused on vulnerable populations and natural disasters. Ng et al. (2014; 2015) surveyed the medically fragile population during Hurricane Irene and found that a strong network of family members was key in responsive evacuation behavior [17, 18]. Similarly, Lim et al. (2015) found that families with children and educated individuals were more likely to evacuate [19]. Burger et al. (2019) surveyed minorities following Hurricane Sandy and found that as many as 35% were not going to prepare for an event [20]. Brodie et al. (2006) surveyed individuals affected by Hurricane Katrina and emphasized the need for better plans for emergency communication and evacuation of low-income and disabled individuals [21]. Lazo et al. (2015) specifically analyzed the factors affecting evacuation intentions and found that forecast and receiving an evacuation order were the two largest factors. Moreover, they found that evacuation intentions decrease with age and that evacuation intention based on the evacuation order depended on source of information of individuals [22]. Golshani et al. (2019) used survey data to understand evacuation destination and departure time after no-notice emergency events [23]. Huang et al. (2016) conducted a statistical meta-analysis of hurricane evacuation studies and found that 82% of the 28 studies reported significant positive correlation between mobile home residence and evacuating [24]. Sarwar et al. (2018) analyzed the dynamics of household evacuation decisions during Hurricane Ivan and found that having children, owning at least one vehicle, and being well educated (possibly capturing the effects of high income households) were associated with decision to evacuate [25]. In terms of distance traveled, Ng et al. (2016) modeled two types of evacuations: within the target region and outside that region. They emphasized the importance of examining these two types of evacuations separately [26].

Some recent studies have used big data to analyze evacuation behavior, although so far, they have been limited to the use of social media data [27, 28]. Twitter data, however, typically have a low temporal resolution and demographic bias. LBS data on the other hand, have much higher frequency of location sightings, and a higher penetration rate. Such data offer many opportunities that were not possible before. Vulnerable populations are often understudied, and thus, passively collected data can help understand the behavior and needs of the population without the requirements of time-intensive surveys. Recently, Yabe & Ukkusuri (2020) used mobile phone location data to analyze the effect of income inequality on evacuation during Hurricane Irma. They found that evacuees with higher income were more likely to evacuate regardless of evacuation order [29]. Our study differs from Yabe & Ukkusuri (2020) fundamentally in terms of the methods employed. Specifically, (1) we define evacuation by being a certain distance away from the home location as opposed to being outside the county; (2) we use a discrete choice model to analyze the impacts of several indicators of vulnerability while previous research focuses mainly on income and income inequality. To the best of the authors' knowledge, no previous published natural disaster evacuation study has used passively collected location-based data to analyze evacuation decisions amongst several vulnerable groups.

3. Materials/Methods

3.1 DATA PROCESSING AND SAMPLE IDENTIFICATION

The authors utilized LBS data from August 1st, 2017 to September 30th, 2017 in Florida. This dataset was provided by Cuebiq, a location intelligence and measurement company which provides access to an LBS dataset of anonymized smartphone devices from users who actively opted-in to share their location data. Using passively collected LBS data has many benefits over traditional surveys. Above all, it allows researchers to conduct analysis using a significant portion of the population at a very fine temporal scale. Additionally, it is not prone to bias or errors associated with self-reported data. Nonetheless, the data

do not supply any socio-demographic information on the users themselves and since LBS data come from location enabled cell phones, we hypothesized that some bias towards wealthier and younger individuals was possible. We first conducted a correlation test for the population in a census tract and the sample proportion of devices within a tract and found a very weak negative correlation ($< |0.1|$). We then tested the correlation between the device penetration rate and the median income per census tract and found a positive but weak correlation. We tested the device penetration rate and the population older than 65 per census tract and found a much weaker correlation. The correlation is weak enough (< 0.30) that all groups are still well represented.

The main objective of this study is to analyze how different vulnerable populations made decisions depending on the evacuation order. Because one common evacuation order type is by home structure type, home locations needed to be estimated [30]. The home locations were estimated using a DBSCAN clustering algorithm of all points between 11pm and 7am during the month of August 2017. The minimum number of points per cluster was 30 (i.e. equivalently at least one sighting per day) and distance threshold was 50 meters. Additionally, a device had to have at least two clusters (or at least one cluster and one “cluster” of outliers) to ensure that the devices were not static (i.e. tablets or desktop computers that remain in one location). The median coordinate was used to calculate the center of the cluster with the most points. This method was validated using the open source 2017 Florida Statewide Parcel Data and the authors found that around 80% of the home locations were correctly identified as residential.

Correctly identified residential locations were spatially assigned a home structure type [31], elevation [31], census block group (CBG) [4, 5], and evacuation zone [32] using publicly available data. The data were then joined by CBG to include built environment attributes [33], by census tract to include socio-economic characteristics [4], and by county to control for the path of the hurricane [34]. Residents were considered to be within Hurricane Irma’s path if they lived in a county whose centroid was within 50 miles of the path.

To identify whether people evacuated, we first calculated the nearest sighting to each home for each day in September 2017. Second, we removed any record that did not have a sighting within 300 meters of the home. This likely meant that the home location was not correctly identified (and instead, a vacation location was identified). Third we used a minimum distance to identify whether a user had evacuated. A device was considered “evacuated” if its nearest sighting between September 10th and September 11th, 2017 was at least 1 mile away. This signified that a device was not in its “home location” during the entire 48-hour period that the storm hit. The data preparation flow chart is shown by **Figure 2**. Data preparation for this study followed the steps described in [30].

FIGURE 2: Data Preparation Flow Chart. Major input and outputs are colored in red; data verification is in blue and in between steps are colored green.

We classified the evacuation Euclidean distances by short, medium, or long: 1-10 miles, 10-50 miles and 50 miles or longer. Based on an initial spatial join, around 38% of the devices in our dataset were in areas that received evacuation orders (**Table 3**). This is in line with the actual estimated proportion of people who were ordered to evacuate during Hurricane Irma (6-7 million people). Ultimately, our final usable dataset contained a sample of 454,117 residents in Florida, of which 171,536 were in counties or evacuation zones that received evacuation orders. The data structure is displayed in **Table 1**. Notice that there are three evacuation order types: evacuation order by zone or by county (if county-wide), evacuation order by home structure (Mobile or Manufactured home residents), and evacuation order by elevation (low-lying areas). Mandatory, voluntary, and no order are represented by a 2, 1 and 0, respectively. The authors populated the evacuation order category based on different news and media sources [35].

TABLE 1: Data Structure

Device ID	Elevation range (m)	CBG (and SLD vars)	County	Evacuation Zone	Evacuation Order for Zone or County	Evacuation Date	MHP Dummy	Evacuation Order for MHP	Evac Order for Low-lying areas
ID123	4-11		Pasco	A	1	9/7/2017	1	2	0
ID456	< 1		Monroe	B	2	9/6/2017	0	0	0

3.2 DESCRIPTIVE STATISTICS

The descriptive statistics are based on an evacuation distance of at least 1 mi (1.609 km) – meaning they were not seen within 1 mi of their home for an entire 24-hour period. Devices that were not observed at all were counted as non-evacuees to avoid including false positives. **Table 2** displays the percentage of people who evacuated at least 1 mi, broken down by resident type and by evacuation order. Those who were given a mandatory evacuation order consistently evacuated more often than those who received either a voluntary or no evacuation order. Residents in low-lying areas (5 meters or less) evacuated with highest frequency, followed by evacuation zone residents and finally by MH residents. We found the initial finding that MH residents did not evacuate at the same scale as other vulnerable populations intriguing. However, it should be noted that MH units are rather spatially skewed in the north of Florida, in which the hurricane had considerably weakened by the time it had reached those areas (**Figure S1**).

TABLE 2: Percentage of population who evacuated at least 1 mile depending on the evacuation order. N = the share of the population.

	None	Voluntary	Mandatory
Low Lying residents (N = 207,953)	35.49% (N = 96,890)	37.22% (N = 33,978)	53.63% (N = 77,085)
MH residents (N = 13,594)	23.60% (N = 1,326)	27.32% (N = 2,269)	38.70% (N = 9,999)
Evacuation Zone residents (N = 151,761)	34.94% (N = 63,227)	35.00% (N = 12,294)	51.56% (N = 76,240)
Total (N = 454,888)	30.98% (N = 281,317)	32.33% (N = 75,192)	46.61% (N = 113,335)

Within each county, evacuations are higher on average among MH residents than among non-MH populations (35.5% and 32.8%, respectively). For instance, 50.8% of Hendry County non-MH residents evacuated at least 1 mi. during Hurricane Irma while 64.8% of MH residents evacuated at least that same distance. In Glades County, the proportion was of 51.1% and 63.4% for non-MH residents and MH residents, respectively. To exemplify a northern Florida county, the proportion of Dixie non-MH residents that evacuated was of 32.8%, compared to 36.1% for Dixie MH residents. Overall, within county, MH residents are indeed more likely to evacuate than the overall population which is in line with the literature. Moreover, these findings enhance the validity of the data processing method using LBS data and parcel data.

Given the descriptive statistics from **Table 2**, an apparent association between the evacuation order and the home location is observed. The next section uses a binary logit model to analyze evacuation decisions depending on the order type, controlling for home type, evacuation zone, and elevation. **Table 3** shows the indicator variables used in this study. We use three different evacuation distance criteria (based on Euclidean distance), four types of orders for two populations (non-MH and MH residents), the date that the order was issued, elevation, income, and density. Once the LBS data are combined with census and Environmental Protection Agency (EPA) data sources, the resulting number of individuals who received an evacuation order is 171,536. Due to missing data from too-low populated CBGs or census tracts, about 9% of the data is removed. Similarly, the total number of individuals in Florida is reduced from 454,888 to 454,117 after records are removed due to having a missing elevation from raster data.

TABLE 3 Description of Variables

	N	Interpretation	%
<i>Dependent Variables</i>			
Did not evacuate	108,939	Residents who did not evacuate more than 1 mile	63.51%
Evacuated (1-10] mi	20,282	Evacuated more than 1 mile but less than 10 miles	11.82%
Evacuated (10-50] mi	10,200	Evacuated more than 10 miles but less than 50 miles	5.95%
Evacuated >50 mi	32,115	Evacuated more than 50 miles	18.72%
<i>Discrete Variables</i>			
<i>Mandatory Order</i>	89,383	Residents who received a mandatory order, others received a voluntary order.	52.11%
<i>Order Type</i>			
County Wide ONLY	9,618	Non-MH residents issued a county-wide evacuation order	5.61%
Ezone ONLY	117,388	Non-MH Residents issued an evacuation order for their Evacuation Zone	68.4%
Low Lying Area ONLY	27,666	Non-MH Residents living below 11 meters above sea level issued an evacuation order for “Low Lying Areas”	16.1%
<i>Mobile/Manufactured Home Residents Orders</i>	12,464	Proportion of residents ordered to evacuate who also live in MHs	
Mobile/Manufactured Home ONLY	7,295	MH Residents who were issued an order to evacuate only for MHs	4.25%
Mobile/Manufactured Home and another order	5,169	MH residents who were issued an MH evacuation order AND another type of evacuation order	3.01%
<i>Date Ordered</i>			
	Date that the evacuation order was issued		
9/6/2017	7,107		4.14%
9/7/2017	40,993		23.90%
9/8/2017	45,874		26.74%
9/9/2017	70,634		41.17%
9/10/2017	6,928		4.04%
<i>In Hurricane Irma’s Path [34]</i>			
	Residents living in a County whose centroid is within 50 miles of Hurricane Irma’s Path		
Not in path	89,181		51.99%
In Hurricane’s Path	71,894		41.91%

In Tropical Storm's Path	10,471			6.10%
<i>Continuous Variables</i>	<i>Geographic Scale</i>	<i>Range</i>	<i>Average</i>	<i>Standard Deviation</i>
Elevation (meters) [31]	Raster (5-meter pixel)	(-1,96)	10.19	14.44
Median Household Income (USD) [4, 5]	Census Tract (2017)	(8804, 232778)	56,892	22,808
Residential Density (Housing Units/Acre) [33]	Census Block Group (2010)	(0.002, 286)	3.55	8.32
Employment Density (Jobs/Acre) [33]	Census Block Group (2010)	(0, 527.8)	2.44	13.04
Auto-oriented intersection density per square mile [33]	Census Block Group (2010)	(0, 72.84)	0.96	2.79

3.3 MODEL SPECIFICATION

This study seeks to understand how vulnerable populations respond to evacuation orders. The focus is on residents who were issued a government order to evacuate (either voluntarily or mandatorily). However, there is still interest in understanding how people evacuate regardless of whether they received an evacuation order. Hence, we perform a discrete choice binomial logit model on the Floridian population (N = 454,117) (minus western pan-handle counties who were not impacted by the hurricane) and then perform a more detailed multinomial logit model on those who were ordered to evacuate (N = 171,536) to understand how different populations decide to evacuate. Correlation tests on the selected variables for both models are found in the Supplementary Material (**Tables S1 and S2**).

4. RESULTS

4.1 Binomial Logit Model

Table 4 displays the results of the binomial model for the entire population. The dependent variable is the decision to evacuate at least 1 mile during the hurricane period. We control for three evacuation order types: evacuation for county or evacuation zone, evacuation for mobile and manufactured homes, and evacuations for low lying areas. These orders are not exclusive. In fact, many orders were given for both mobile or manufactured homes and evacuation zones. The reference in the model is not being issued an evacuation order. We control for elevation range with the highest elevation being the reference and within the path of the hurricane, with the reference not being in the direct path. A note on the path of the hurricane is that many people evacuated prior to knowing the true path of the hurricane, particularly on the Atlantic coast of the state.

Issuing a mandatory order is a significant and positively associated with evacuating. On the other hand, a voluntary order does not appear to prompt evacuations more so than not issuing an evacuation order. Voluntary orders are often prompted as curfews, indicating that people should remain off the roads, thus, the decision not to evacuate is in line with the evacuation order. Elevation, which is strongly related to coastal areas, has an expected negative relationship with evacuation: as elevation increases, decision to evacuate decreases.

TABLE 4 Regression Results for Entire Population

	<i>Dependent variable:</i>
	Evacuated at least 1mi
Evacuation (County wide or zone): Voluntary	0.051*** (0.010)
Evacuation (County wide or zone): Mandatory	0.608*** (0.010)

Evacuation (Mobile/Manufactured Home): Voluntary	-0.008
	(0.048)
Evacuation (Mobile/Manufactured Home): Mandatory	0.173***
	(0.021)
Evacuation (Low-lying): Voluntary	0.016
	(0.021)
Evacuation (Low-lying): Mandatory	0.182***
	(0.011)
Elevation Low (Reference: High elevation)	0.905***
	(0.016)
Elevation Low Mid	0.627***
	(0.013)
Elevation Mid	0.476***
	(0.012)
Elevation Mid High	0.141***
	(0.013)
In Tropical Storm Path (Reference: Not in Hurricane Path)	-0.044*
	(0.024)
In Hurricane Path	0.267***
	(0.007)
Constant	-1.252***
	(0.012)
Observations	454,117
Log Likelihood	-285,545.700
Akaike Inf. Crit.	571,117.400
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01 Number in parenthesis is the standard error

4.2 Multinomial Log-Linear Model

While evacuating is an important factor in reducing casualties in a natural disaster, it is of further importance to understand how far people choose to evacuate. A multinomial log-linear model is now fitted on those ordered to evacuate, either voluntarily or mandatorily [36]. As described in Table 3, four choices are estimated: Not evacuating, evacuating a short distance (1-10 miles), a medium distance (10-50 miles) or a long distance (more than 50 miles). We control for the evacuation type, elevation and hurricane path to understand the impacts of income, home structure type, and density on decision to evacuate and distance of evacuation. (**Table 5**).

TABLE 5 Multinomial Log-Linear Model Results for Residents issued Evacuation orders

	<i>Dependent variable: (Reference: Did not evacuate)</i>		
	Evacuated 1-10 mile	Evacuated 10-50 mile	Evacuated >50 mi
	(1)	(2)	(3)
<i>In Hurricane Path (Reference: Not in Hurricane Path)</i>			
In Tropical Storm Path	0.148***	0.192***	0.323***
	(0.042)	(0.059)	(0.043)
In Hurricane Path	0.459***	0.442***	0.726***
	(0.021)	(0.027)	(0.017)

Mandatory (reference= Voluntary order)	0.370***	0.740***	0.443***
	(0.023)	(0.033)	(0.020)
Living in a government designated flood or hurricane zone (Reference = Not in a designated flood zone)	-0.222***	0.089***	-0.062***
	(0.022)	(0.032)	(0.019)
Elevation (meters) (Continuous)	-0.019***	-0.010***	-0.036***
	(0.001)	(0.001)	(0.001)
Living in a Manufactured Home (Reference = in a site-built home)	-0.018	0.160***	-0.191***
	(0.032)	(0.042)	(0.031)
Date evacuation order issued (Reference: 9/6/2017)			
9/7/2017	-0.327***	-0.373***	-0.596***
	(0.041)	(0.048)	(0.031)
9/8/2017	-0.447***	-0.685***	-0.734***
	(0.042)	(0.050)	(0.032)
9/9/2017	-0.372***	-0.483***	-0.767***
	(0.042)	(0.050)	(0.032)
9/10/2017	-1.059***	-1.144***	-0.955***
	(0.068)	(0.093)	(0.052)
Median Household Income (in 1000s USD) (Continuous)	-0.002***	-0.002***	0.004***
	(0.0004)	(0.0005)	(0.0003)
Population Density in CBG (Continuous)	-0.002	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
Employment Density in CBG (Continuous)	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.0005)
Road Network Density in CBG (Continuous)	0.025***	0.007*	0.008***
	(0.003)	(0.004)	(0.002)
Constant	-1.295***	-2.395***	-1.047***
	(0.049)	(0.062)	(0.039)
Akaike Inf. Crit.	336,718.800		
McFadden R2	0.04		
Note:	*p<0.1; **p<0.05; ***p<0.01 Number in parenthesis is the standard error		

The coefficients for continuous variables can be interpreted as the change in log odds of evacuating (a certain distance) versus not evacuating (the baseline). The coefficients of discrete variables are interpreted as the change in the log odds of evacuating versus not evacuating if changing categories (e.g. issuing an order on 9/6/17 to issuing the order on 9/7/17). The evacuation order, date, hurricane path, and elevation are all significant controls for evacuation behavior, regardless of the distance. Results appear alarming for residents living in lower income communities, manufactured homes, and rural or low-density areas. Residents living in lower income census tracts are associated with being more likely to evacuate short and medium distances (< 50 mi) but are more likely to not evacuate at all than to evacuate a long distance. This indicates that people in lower income communities may be reluctant to travel long distances or may simply not have the means to do so. Evacuating a short distance for manufactured or mobile home residents was not statistically significant from site-built home residents. Manufactured home residents, however, were more likely to evacuate a medium distance but less likely to evacuate a long distance than site-built home residents. Increasing population, employment and road density is positively associated with the odd of evacuating a medium and long distance (>10 miles).

5. DISCUSSION

LBS data allowed the authors to analyze the evacuation patterns of over 170,000 people. The results of this analysis were in line with previous survey-based research, making LBS data a promising source for evacuation research. One of the main benefits of using such data is the time and cost savings associated with deploying a survey. LBS data allows us to cover a very large part of the population. In our case, we limited our analysis to the state of Florida. However, future analysis can conduct such studies on the entire U.S. While we chose Hurricane Irma from 2017, it is possible to conduct this analysis in near real-time which is another advantage of LBS data. Limitations to LBS data compared to survey data come down to the lack of individual level socio-demographic information. For instance, we could only use the data to analyze people who live in low-income census tracts; this does not necessarily mean that all of these people are low-income themselves. LBS data also lack the possibility of asking questions with regards to perception of natural disasters. It is very possible that some of the people who evacuated would have evacuated regardless of the evacuation order. For the purpose of our analysis, LBS data were deemed more useful than not in that it provided insights for an entire state and allowed for comparison between counties.

Several important findings emerged from this analysis. As expected, those who received a mandatory evacuation order were more likely to evacuate any distance than those who received a voluntary order. This makes sense since voluntary orders tend to be ambiguous about whether one should stay or evacuate. Elevation, which tends to be closely tied to coastal areas, also showed to be a significant indicator of evacuation behavior. Living in a government designated flood and evacuation zones was generally associated with evacuating medium to long distances, compared to not living in an evacuation zone. Many counties have evacuation zones in place to make it easier for residents to know when to evacuate. Counties that do not have such zones in place gave more general orders such as “county wide” or “low-lying areas”. Order date was a significant variable. Giving the earliest notice (4 days) to evacuate, was associated with the highest probability of evacuating. Evacuees given only one day to evacuate were significantly less likely to evacuate compared to issuing the order two to four days earlier. The authors recommend that at least a 48-hour notice to evacuate be given.

Vulnerable residents, namely those living in manufactured homes, in low-income communities, or in less dense areas were more likely not to evacuate at all than to evacuate a long distance. They were also less likely to evacuate long distances than less vulnerable communities (higher income and site-built home residents). Previous studies found that manufactured and mobile home residents were more likely to evacuate in general [24]. Our study found this to be true for medium distances (not significantly different for short distances) but found contradictory results for longer distances. Likewise, low-income communities were found less likely to evacuate longer distances. This is of practical significance for policy makers because policies aiming at evacuating residents for their safety may not actually keep vulnerable populations safe if they are not evacuating as far as they should. In the context of hurricanes, the diameter of the storm can span over 80 miles and require evacuating potentially long distances. We recommend focusing on the destination choice of vulnerable residents, since many of them appear to choose destinations that distance-wise, are not reasonably far away from a storm. Public shelters and sturdy structures (such as family members living in site-built homes) are likely to be short distance destination choices that can be safer than their current location. Research on destination choice will be analyzed in future research to further understand evacuation behavior and safety aspects of evacuating shorter distances.

Living in a census block group with smaller population, employment and road density were associated with a lesser probability of evacuating. Road network density is important to consider when advising residents on evacuation routes, particularly in less dense areas. People who live in rural areas are already less likely to have access to resources than urban residents, and thus, it is especially important that they be prepared for the effects of a natural disaster. Not evacuating during a mandatory evacuation not only places residents at risk, but it also puts rescue workers in potentially dangerous situations. Thus, it is important that information about evacuating reaches all parts of a county, particularly less densely populated areas.

6. CONCLUSIONS

1 With the growing threat of climate change and more frequent storms, there is importance in
2 understanding how people respond to such storms. This study sought to explore evacuation patterns among
3 vulnerable populations using big data in the state of Florida during Hurricane Irma. The results of the data
4 are very much in line with previous analyses using survey data, which provides a promising opportunity
5 for using big data for assessing risk in future studies. Using big data has significant advantages over surveys
6 in that the data processing requires a fraction of the time of that of surveys; data can be retrieved in near
7 real-time, making results available that cover a much quicker for rescue organizations and policy makers;
8 and LBS data provide results that cover a far larger area. This study covers the majority of the state of
9 Florida and future studies can use similar methods to cover even wider areas.

10 The evacuation patterns of over 170,000 individual devices were analyzed in this study to provide
11 insight on the evacuation behavior of vulnerable residents in Florida. We found that mobile and
12 manufactured home residents appeared to be more responsive to evacuation orders than non-mobile home
13 residents for short distances. For longer distances, the relationship appeared reversed; site-built home
14 residents were more likely to evacuate.

15 Income was positively associated with evacuation distance. People living in higher income census
16 tracts were more likely to evacuate at least 50 miles than those in lower income census tracts. Those living
17 in lower income communities were, however, more likely to evacuate short distances. This has important
18 implications for addressing the success of evacuations in low income communities. A short distance may
19 not be more effective than not evacuating at all. Because we do not control for perceived threat of the
20 disaster, more research is needed to confirm whether a lack of resources in lower income census tracts is
21 the cause for decision not to evacuate or if it is due to other factors. Population, employment and road
22 density within a census block group were positively associated with decision to evacuate. This indicates
23 that people in urban areas are more likely to evacuate than those in less dense or rural areas. This has
24 important implications for policies as it may suggest a couple of things: less densely populated areas may
25 not have as many resources to evacuate (public shelters, evacuation routes) and communication and news
26 may not reach those areas as well as urban areas (knowledge of threat). Policies should pay particular
27 attention to less densely populated areas.

28 Conclusions with respect to the type of evacuation orders are not clear until more research is done
29 to control for the threat of the storm in each county and to control for spatial variations. Nonetheless, based
30 on the results of the analysis, the authors recommend the following to policy makers: a greater focus must
31 be placed on low income areas and less densely populated areas. Both of these indicated a lesser willingness
32 to evacuate, and particularly evacuate longer distances. Lower income and rural areas could be particularly
33 vulnerable to the effects of natural disasters and may have less resources to cope with its aftermath.

34 35 **7. LIMITATIONS AND FUTURE RESEARCH OPPORTUNITIES**

36 This study acknowledges several limitations. Passively collected LBS data do not have any
37 demographic or socio-economic information attached to it and thus either requires further data collection
38 or assumptions at more aggregate levels. Using the census block group and census tract level allowed us to
39 control for some of the more general effects of living in a particular area, but no conclusions can be made
40 with respect to someone's individual income (or age, education level, etc.) and their evacuation decisions.
41 The forecasted hurricane path changed several times, initially aimed at the eastern portion of Florida. This
42 initial path (and the perceived threat and risk) of the hurricane was not included in this study. Future analysis
43 will control for these effects in hope to improve the interpretation of the impact of policies on evacuation
44 decisions. Furthermore, we acknowledge the limitation of possible spatial dependence. One's evacuation
45 decision is not simply based on the order itself; many decisions are influenced by the decisions of those
46 around them. Future research will include spatial dependencies using for instance, a spatially lagged
47 discrete choice model. Additionally, order types were generally classified as county-wide, low-lying,
48 evacuation zone, or manufactured home. However, some orders were given based on other factors such as
49 year of building (e.g. Glades), nursing homes (e.g. Flagler), and islands or specific cities/towns. A few
50 counties also upgraded from voluntary to mandatory once the storm approached, and the implications of
51 changing orders are not analyzed, but should be in further studies (only the final order and date was

1 accounted for). Because they were rather isolated examples, they could not be used in the analysis
2 effectively. Future work could address these limitations by using several case studies and to confirm the
3 results of the present one. Finally, the authors plan to analyze destination choice to further understand how
4 far and where people evacuate during evacuations to understand how resources are utilized.

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