PREDICTION OF TIME-DEPENDENT POPULATION BEHAVIOR DURING HURRICANE EVACUATIONS

by

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ABSTRACT

The large uncertainty in population behavior with regards to how many people leave, when, from where, and to where, is a key challenge in planning hurricane evacuations. Several empirical and theoretical studies have sought to understand evacuation behavior but few have focused on developing models for predicting population evacuation behavior for future applications. In this study, we improve hurricane evacuation behavior prediction through advances in modeling and data, and offer a comprehensive evaluation of predictive power that other researchers might adopt in evaluating their models. Specifically, we modify and apply a recently introduced dynamic discrete choice framework on survey data collected in a consistent format across four hurricanes. We also take advantage of the dynamic nature of the model and include more hurricane and forecast attributes. The final set of explanatory variables can be obtained at the regional scale; hence our model can be applied in the future for prediction. Through cross validation, out-of-sample predictive power of the model is evaluated across multiple metrics, including prediction of aggregate evacuation rates, individual behavior, and evacuation timing. Cross validation results are also compared with existing statistical models from literature. At the aggregate level across the four hurricanes, the total number of evacuations was predicted with only 1% error. Individual household level results suggest 70% and 72% accurate prediction of evacuees and non-evacuees, respectively. The mean absolute departure time error is approximately only 2 hours across the population. Results across all

evaluation metrics imply our model performs better when compared to existing models in the literature.

Chapter 1

INTRODUCTION

1.1 Hurricane Evacuations

Hurricanes pose massive threats to coastal and inland populations as they are accompanied with strong winds, storm surge, and intense flooding. Destruction is typically in the form of loss of human life, economic loss from physical infrastructure damage, and disruption of social lives. For example, Hurricane Harvey, a category 4 storm made landfall on Texas and Louisiana in 2017, resulting in 103 deaths and about $125 billion in economic losses (Blake & Zelinsky, 2018). Even though these events are inevitable, the huge losses incurred each year can be curtailed through efficient and effective emergency management strategies. Luckily, the National Hurricane Center (NHC) tracks these storms several days prior to landfall and provide real time information (i.e., storm behavior and potential threats) to local emergency units and the general public. Individuals in potential danger zones act on this information to evacuate to safe areas while local emergency units also use this information to implement various disaster management strategies. However, with the vast growth in coastal and inland populations over the decades, thousands to millions of people tend to evacuate each year during these events. Hurricanes Katrina (2005) and Harvey (2017), two of the most dangerous hurricanes in the history of the USA, triggered about 1.5 million and 3.7 million evacuations, respectively (Knabb, Rhome and Brown 2011, Blake and Zelinsky 2018). With these massive evacuations, planning and execution of evacuation strategies become difficult as transportation networks designed to carry normal traffic can become subjected to tremendous congestion and delays.

1.2 Research Motivation

A key challenge in managing hurricane evacuations effectively and efficiently is the large uncertainty in population behavior (e.g., how many people leave, when, from where, and to where). That behavior has major implications for official hurricane preparedness and response decisions, including issuing official evacuation orders, messaging to the public, opening shelters, staging materials and staff, implementing contraflow and other traffic plans, and supporting vehicle-less populations. Recognizing its criticality, there has been a lot of research on the behavior of the population during hurricanes. Investigators have identified factors that influence evacuation behavior; identified typical patterns of movement (e.g., propensity for households to reunify before evacuating (Lindell and Prater 2007); and developed statistical models of evacuation decisions.

Nevertheless, there has been little explicit discussion in the literature of the ability to predict behavior in future hurricanes. The limited evidence suggests it remains difficult to accurately predict population behavior—particularly spatially and temporally disaggregated behavior—for a future hurricane. At the individual level, Deka and Carnegie (2010), for example, report correctly predicting evacuation 72% of the time in what appears to be an in-sample test. Two relatively unusual reports of out-of-sample performance found only 60%-70% correct predictions depending on model type and situation (Wilmot and Mei 2004, Xu et al. 2016). On the plus side, while predicting individual behavior is very difficult, aggregate behavior is somewhat easier, since individual errors of over- and underestimation can cancel each other out.

Predictions aggregated to large geographic regions for three hurricanes using a range of model types resulted in errors of 3 to 16 percentage points on average, depending on the model (Xu et al. 2016). Gudishala and Wilmot (2013) report that their time-dependent sequential logit model overpredicted total evacuation by an average of 36% across nine hypothetical hurricanes.

In this study we contribute to the literature by improving hurricane evacuation behavior prediction through advances in modeling and data, and offering a comprehensive evaluation of predictive power that other researchers might adopt in evaluating their models. First, we apply a recently introduced dynamic discrete choice (DDC) model (Rambha et al. 2020). In the DDC, individuals may choose to evacuate or wait in each time period (say every few hours). In each period, an individual's utility depends on his current choices, present values of influential variables, and discounted expected utilities from future choices should one decide to postpone the evacuation decision. Strengths of this model are that it represents the repeated nature of an individual's decisions over time and includes the effect of information revealed over time (e.g., storm evolution) and perceptions of how attributes change over time.

Second, we use a dataset collected in consistent format across four recent hurricanes that together represent a broad range of conditions and circumstances. Since the focus is on prediction, we limit the study to explanatory variables that are available in advance at a regional scale for applying the model in a predictive mode. Rather than rely on demographic variables, however, which are available but have been shown to have limited ability to predict evacuation behavior (Huang et al. 2016), we take advantage of the dynamic nature of the DDC and include more attributes of the hurricanes and forecasts. While these have been used in the past, they have typically been defined somewhat loosely because static models require a single variable value (e.g., hurricane category), while in reality, those characteristics change dramatically over the course of an event.

Third, we evaluate the predictive power of the DDC model and compare with other methods in literature. We measure the out-of-sample predictive power across multiple metrics, each of which measures different aspects of the fit, including prediction of aggregate evacuation rates, individual behavior, and evacuation timing.

Finally, we conduct two sensitivity analyses on the predictive power of the DDC model by exploring the importance of combining data from multiple hurricanes. Estimating a model on data from different hurricanes creates a low variance or a highly generalized model which can be utilized in any future event. That is, a model trained on multiple hurricanes captures a wide range of possibilities while a model trained on one event may fail to represent diverse possibilities and thus might perform poorly in practice. The base model (DDC1) is trained on data from all four events and predictive power measured via ten-fold cross validation. In the first test, we train another model (DDC2) on just Hurricane Florence and predictive power measured on the other three hurricanes (Michael, Dorian and Barry). Secondly, we examine the importance of having enough variability in our training data by estimating a model (DDC3) on all hurricanes with hurricane indicator variable as an additional predictor. Model results from both tests are compared with the base model.

1.3 Organization of Thesis

In the remainder of this work, we provide details of the processes involved in estimating and computing the predictive power of the dynamic discrete choice framework for population evacuation behavior prediction. In Chapter 2, we summarize the literature with a particular focus on the contributions of this analysis to evacuation modeling. The data is presented in Chapter 3, and the DDC models with evaluation metrics are described in Chapter 4. Chapter 5 includes model results and comparison of predictive power of DDC with existing models in literature. This work concludes in Chapter 6 with discussion of contributions, limitations and suggestions for future work.

Chapter 2

BACKGROUND AND LITERATURE REVIEW

Within the large literature on population behavior during hurricane evacuations, we focus here on quantitative models of behavior, and in particular, the dimensions of key interest in this analysis—predictive power, evacuation timing, and inclusion of hurricane attributes as covariates. Additional aspects of population behavior are summarized well in reviews such as Baker (1991), Dash and Gladwin (2007), Murray-Tuite and Wolshon (2013), Sorensen (2000), Bowser and Cutter (2015), Huang et al. (2016), and Thompson et al. (2017).

2.1 Predictive Power

Two primary approaches have been used to model evacuation demand (i.e., probability of evacuation or number of evacuees)—participation rates or regression-type statistical models (Xu et al. 2016). In the participation rate approach, the state-of-practice, the percentage of people who will evacuate (i.e., participation rate) is assigned for each geographic region, with different values based on a few key features, such as, hurricane intensity and housing type (mobile home or not) (PBS&J 2002). Participation rates are typically based on a subjective combination of conclusions from the literature and empirical data from past storms (Wilmot and Mei 2004). The estimated number of evacuees is determined by multiplying the population in the affected region by the appropriate participation rate.

In the second approach, a sample of survey data is used to fit a statistical model, typically a logit or probit regression, in which the household evacuation decision is the response variable and the set of explanatory variables are attributes of the household, house, and possibly hurricane. Some newer studies have applied different types of models. Mei (2002) used neural networks; Serulle and Cirillo (2017) introduced a dynamic discrete choice model similar to the one herein. The Rambha et al. (2020) approach however differs from Serulle and Cirillo (2017) in the following ways. First, this model defines separate utility functions for stay and wait options while Serulle and Cirillo (2017) assigned the same utilities to both. Also, while the approach in Serulle and Cirillo (2017) utilizes past storms to compute transition probabilities, the dynamic discrete choice model presented in Rambha et al. (2020) relies on storms present in the data to estimate these probabilities. Finally, Serulle and Cirillo (2017) approximated the solution to the dynamic problem while Rambha et al. (2020) solves the complete dynamic problem.

As discussed in Xu et al. (2016), few previous papers—even those that include quantitative models—report the models' predictive power or discuss the issue of prediction at all. They mostly have aimed to identify variables related to evacuation decisions, not develop models for purposes of prediction in future hurricanes. While some models likely could be used for prediction if desired, some could not because they include explanatory variables that are not available at a regional scale. Some exceptions briefly report prediction errors using in-sample prediction (e.g., Solis et al. 2010, Cheng et al. 2008). Serulle and Cirillo (2017) and Wilmot and colleagues used holdout validation with 15% or 20% of the data omitted from the model fitting and used to determine predictive accuracy (Wilmot and Mei 2004; Fu and Wilmot 2006;

Fu et al. 2007; Gudishala and Wilmot 2012, 2013). With a central focus on predictive power, the current project extends those efforts by using only explanatory variables that are available at a regional scale, and by conducting repeated cross validation and using a suite of prediction error metrics to fully describe the dimensions of out-of-sample predictive ability.

2.2 Evacuation Timing

The literature provides several general findings about evacuation timing, including that relatively few evacuees (15% to 20%) depart before official evacuation orders are issued, and that more evacuees leave in daytime, but they will leave at night if they believe that their departures cannot safely be delayed until morning (Huang et al. 2017, Fu et al. 2007). In terms of modeling evacuation departures, the most common way to estimate evacuation trips is in two steps, first computing the total number of evacuees, then distributing their departures over time (Murray-Tuite and Wolshon 2013). In this process, the second step is typically represented by an S-shaped departure curve of percentage evacuees who have left vs. time (relative to issuance of orders or perhaps landfall) (Lindell and Prater 2007). Often developed based on a combination of empirical evidence and judgment, a few versions of such curves are often specified to capture, for example, slow, medium, or fast overall response, as in the North Carolina Hurricane Evacuation Study, which is currently used in practice (USACE 2016).

In reality, individuals likely do not first make the decision about whether to evacuate and then select a departure time. Instead, they repeatedly decide whether to evacuate or wait, and the decision changes over time as social and environmental cues, official actions, and other circumstances change. To more directly represent that repeated decision-making, in the less commonly used one-step approach, a single model simultaneously determines the number of evacuees and their departure times. These models estimate time-dependent evacuation demand (i.e., probability a household evacuates in time interval t) (e.g., Wilmot and Mei 2004; Fu and Wilmot 2006; Fu et al. 2007; Hasan et al. 2011; Gudishala and Wilmot 2012, 2013; Sarwar et al. 2018). Sadri et al. (2013) presents a model of mobilization time, i.e., time elapsed from the evacuation decision to the actual evacuation. In this paper, we develop a one-step DDC model.

2.3 Hurricane Attributes

The characteristics of the hurricane itself, the hazard conditions it creates (e.g., flooding, strong winds), as well as its forecast future behavior, as represented for example by National Hurricane Center (NHC) cones of uncertainty, are all potentially related to an individual's decision to evacuate or not. Nevertheless, many predictive hurricane evacuation population behavior models do not include them, perhaps due to at least three issues. First, the characteristics, such as hurricane location, hurricane intensity, forecast landfall location, can all change dramatically over the duration of a hurricane event. Some previous models have included one or more of these variables, but as a static quantity. Whitehead et al. (2000) and Xu et al. (2016), for example, include hurricane category as an explanatory variable, but do not specify the time at which it is measured, leaving its interpretation ambiguous. The structure of the time-dependent evacuation demand models allows them to accommodate time-varying explanatory variables, and thus those few models do include hurricane characteristics that vary with time. Fu and Wilmot (2006), for example, includes distance from the individual to the hurricane at each six-hour time interval. Second, hurricane characteristics can be captured as perceived by survey respondents or as measured by the NHC or other scientists. Huang et al. (2017), for example, includes perceptions of hurricane characteristics such as likelihood of nearby landfall as explanatory variables. For prediction in future hurricanes, values of perception variables are not available, however, whereas measured values are. Third, including variables that describe attributes of hurricane, hazards, and forecasts, requires enough variability in the values that coefficients can be estimated which, in turn, requires data from multiple hurricanes. Many studies fit models based on one or two past hurricanes. In this study, we aim to explore the use of time-varying hurricane-, hazard-, and forecast-related variables fully.

Chapter 3

DATA

This chapter provides a detailed description of the data used in the study. The characteristics (i.e., formation, and landfall information) of the four hurricanes—Florence (2018), Michael (2018), Dorian (2019) and Barry (2019)—are described in Section 3.1. Data collection process for both socio-demographic and hurricane attributes is explained in Section 3.2. Data on household evacuation decisions and socio-demographic attributes were obtained through web surveys deployed on Facebook and Reddit after each event, whereas hurricane attributes were sourced from GIS data provided by the NHC. The chapter concludes in Section 3.3, with a summary of final variables used for analysis.

3.1 Hurricanes

The data used in this analysis are related to four hurricanes from 2018-2019: Florence, Michael, Barry, and Dorian. They extend to multiple geographic areas along the coasts of the United States and represent various storm intensities, timings, and characteristics (Table 1). While both Hurricane Michael (2018) and Hurricane Barry (2019) formed in the Gulf of Mexico, Hurricane Florence (2018) and Hurricane Dorian (2019) impacted the Atlantic coast (Figure 1). Inclusion of the four events aims to ensure sufficient variability in the hurricane attributes to capture their effects on evacuation behavior. With sufficient variability in data, we aim to produce a model which can generalize well on future events. Data from a single hurricane might not capture the different possibilities and distributions of hurricane and forecast attributes.

Table 1: Summary of hurricanes in study

Attributes	Florence	Michael	Barry	Dorian
Formation date	31-Aug-18	7-Oct-18	11-Jul-19	24-Aug-19
Landfall date	14-Sep-18	10-Oct-18	13-Jul-19	6-Sep-19
Dissipation date	18-Sep-18	15-Oct-18	15-Jul-19	10-Sep-19
Landfall location	Southeastern NC	FL Panhandle	South-central LA	Cape Hatteras, NC
Max. category	Cat. 4	Cat. 5	Cat. 1	Cat. 5
Category at landfall	Cat. 1	Cat. 5	Cat. 1	Cat. 1
Damage (in U.S.)	$24 billion	$25 billion	$600 million	$1.6 billion
Fatalities (in U.S.)	22 + 30 indirect	16 + 43 indirect	0	10
Power outages (in U.S.)	1.1 million	"widespread"	300,000	190,000 in NC

Sources. Florence: Stewart and Berg (2019). Michael: Beven et al. (2019). Barry: Cangialosi et al. (2019). Dorian: NCEI (2020) for damage and fatalities, Breslin (2018) for power outages, and NWS (2019) for all else.

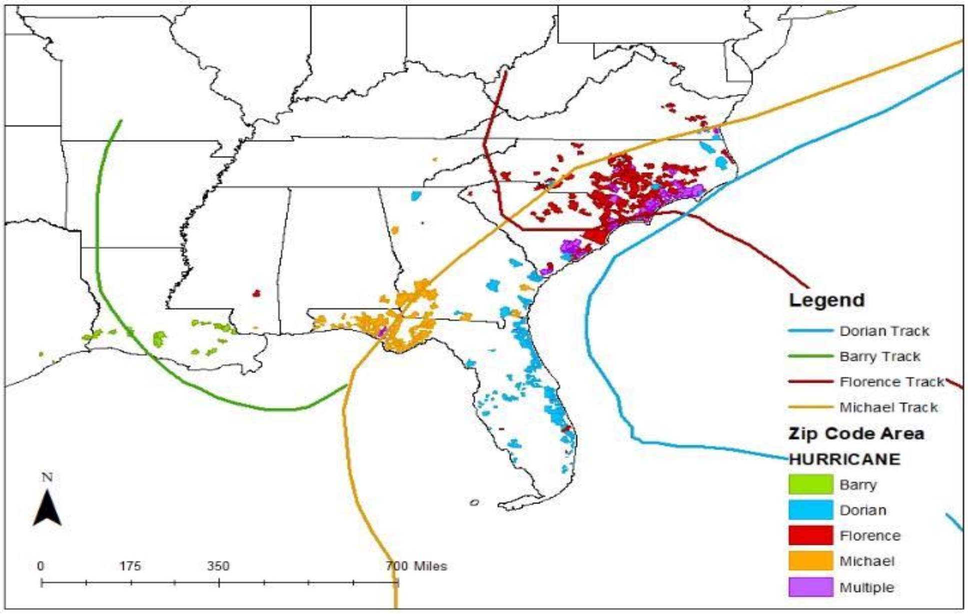

Figure 1: Hurricane tracks and respondent locations (Multiple indicates responses for >1 hurricane)

3.2 Survey Deployment

The first part of the data used in this study was collected through a web-based survey of individuals affected by one of the four hurricanes (Mongold et al. 2020). The survey, which was the same across hurricanes, includes questions related to: (1) respondent location at the time of the event; (2) evacuation behavior, including if the respondent evacuated, and if so, destination location and type, route, and timing; (3) reasons for evacuation decisions; and (4) household attributes. Complete survey questions are attached in the Appendix section (QUESTIONNAIRE SURVEY).

The survey was created in Qualtrics and deployed on Facebook and Reddit using the method described in Farmer and DeYoung (2019) and DeYoung et al. (2019). The groups in which surveys were posted were specifically related to hurricanes and/or were connected to affected areas for the events. Survey groups for hurricanes were predominantly located in North Carolina, South Carolina, Louisiana, Florida and Virginia. Examples for Hurricane Florence included the Facebook page *Hurricane Florence Wilmington NC* and Reddit pages *South Carolina* and *New Bern*. In the process of distributing the surveys, members of the research team had to join groups on Facebook and Reddit. While some of the pages were public and members could easily join, others were private and required approval from group moderators. With access to the groups and permission from moderators, members posted a link to the survey with an explanation of the study on each page. The link was sharable once deployed. One to two weeks after the initial posting, the survey was boosted by commenting on the initial post to draw attention of potential respondents and remind them of survey closing date. Table 2 summarizes the numbers of groups to which the survey was posted and the numbers of members of those groups. After data cleaning and preprocessing, there were 1274, 330, 39, and 438 useable responses for Hurricanes Florence, Michael, Barry, and Dorian, respectively, for a total of 2081 observations. With the survey requiring an average completion time of 5.6 minutes, 95% of respondents finished in 15 minutes. Institutional review board approval was obtained at the University of Delaware. A copy of the approval letter is attached in Appendix B.

Table 2: Survey deployment summary

Hurricane	Land-fall	First post	Date closed	Days open	Num. groups	Num. members in groups				Num. obs.	Num. evacuees
						Min	Mean	Max	Total		
Florence	9/14	9/19	10/15	26	38	199	30,721	589,930	1,136,695	1274	723
Michael	10/10	10/17	11/27	41	50	46	13,665	419,801	669,561	330	161
Barry	7/13	7/17	8/27	41	18	46	10,178	40,300	174,140	39	5
Dorian	9/6	9/7	10/7	30	19	229	39,105	482,784	725,322	438	72
Total	---	---	---	---	125	---	---	---	2,705,718	2,081	961

In order to accurately capture individual experiences with regards to details on the event, timing of evacuation decisions and official orders, surveys were deployed within a week of landfall (Table 2). For each event, the survey was available to the groups for nearly one month which was deemed a sufficient time to collect enough data for analysis. The distribution of respondents across time, however, differs for each event. For the events Florence, Michael, Barry, and Dorian, respectively, 32%, 0%, 49%, and 100% of responses were collected within one week of landfall, and 84%, 42%, 100%, and 100% were collected within two weeks.

This comparatively new deployment technique has benefits and drawbacks. It provides fast deployment which helps maximize the accuracy of recollections from individuals about their decisions and timing during the event. It is much less costly to deploy and analyze than conventional mail or telephone surveys, however the ensuing pattern is not random.

We compared demographic data for the sample to that for the population from which it was drawn to examine how representative it is. With county-level data from the U.S. census (U.S. Census 2020), population demographics were estimated by assigning weights to counties based on the number of observations they contribute to the sample. Comparing the sample to the population revealed the sample is reasonably similar to the population, with only a couple of exceptions. The sample is less African American/Black (1% in sample vs. 17% in the population), higher income ($81,600 sample average vs. $64,900 population), less likely to be in mobile homes (6% in sample vs. 13% in population), but equally likely to be employed (81% in sample and population), and have children (39% in sample vs. 40% in population). As a web-based survey, it does not include those without internet access. Distributing through many hurricane-related Facebook and Reddit pages also raises a question about whether the sample might be more engaged in hurricanes than the general population. While it is important to keep these issues in mind in the interpretation, the data nevertheless are sufficient quality to provide useful information.

3.3 Data Summary

Tables 3 and 4 provide summary of variables used in this study—all hurricanes combined and individual events. The variables were selected based on the literature, in particular the meta-analysis in Huang et al. (2016). From a longer list of possible explanatory variables, however, only those that are available for regional prediction were included (not, for example, risk perception). The utility functions defined in the DDC use three different variable types (Tables 3 and 4). All socio-demographic variables treated as static variables; they do not change over the duration of a hurricane. *Official orders* (x_o), *Hurricane category* (x_{cat}), *Distance to forecast landfall location*(x_{fdist}), *Forecast P(Wind>74 mph)* (x_w) (i.e., probability of experiencing wind speed greater than 74mph (category 1 hurricane) in the next 5 days) and *Forecast surge flooding* (x_{ss}) (i.e., projected flood level in the next 5 days) are treated as *Dynamic, static in future*, which means their values can change over time, but we treat their future realizations as constant. That is, at any time t, we assume the individual believes the variable value (say, *Hurricane category* (x_{cat})) will remain at its value at time t for the remaining time steps (t+1…, T). Finally, for only *Distance from household to hurricane* (x_{dist}), we assume those future values are dynamic. That is, we assume that not only can the value of x_{dist} change over time, but in addition we specify the values that the individual believes that it will take on in the remaining time steps, and they may differ from the value at t.

Ideally, all dynamic attributes in the model should have forecast values or future realizations. While forecast data is readily available on NHC website for *Distance from household to hurricane* (x_{dist}), forecast information on the other hurricane attributes is not available. We therefore assume their future realizations or forecast stay the same as the value in each time step.

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Table 3: Data summary for categorical variables across all hurricanes and individual hurricanes

	Variable	Levels	Hyp[a]	Num. and % observations										Variable type
				All		Florence		Michael		Dorian		Barry		
y	Evacuation	0 Did not Evacuate	n/a	1120	54%	551	43%	169	51%	366	84%	34	87%	Dynamic
		1 Evacuated		961	46%	723	57%	161	49%	72	16%	5	13%	
x_{o1}, x_{o2}	Official order	0 None	+	471	23%	221	17%	122	37%	112	25%	26	67%	Dynamic, static in future
		1 Voluntary		851	41%	715	56%	12	4%	113	26%	11	28%	
		2 Mandatory		759	36%	348	27%	196	59%	213	49%	2	5%	
x_{mh}	Mobile home	0 No	+	1951	94%	1198	94%	302	92%	415	95%	36	92%	Static
		1 Yes		130	6%	76	6%	28	8%	23	5%	3	8%	
x_{ho}	Homeownership	0 Home you own	+	1291	62%	782	61%	205	62%	273	62%	31	79%	Static
		1 Rental for primary, other		790	38%	492	39%	125	38%	165	38%	8	21%	

Table 3 continued.

	Variable	Levels	Hyp[a]	Num and % observations										Variable type
				All		Florence		Michael		Dorian		Barry		
x_v	Vehicle access	0 No	+	22	1%	12	1%	7	2%	3	1%	0	0%	Static
		1 Yes		2059	99%	1262	99%	23	98%	435	99%	39	100%	
x_{ch}	Have children	0 No	+	1226	59%	696	55%	207	63%	296	68%	27	69%	Static
		1 Yes		855	41%	578	45%	123	37%	142	32%	12	31%	
x_{em}	Employed	0 No	n/a	391	19%	284	22%	86	26%	19	4%	2	5%	Static
		1 Yes		1690	81%	990	78%	244	74%	419	96%	37	95%	
x_{ind}	Hurricane Indicator	0 Barry	n/a	39	2%									Static
		1 Michael		330	16%									
		2 Dorian		438	21%									
		3 Florence		1274	61%									

[a] Positive means a higher value is associated with increased likelihood of evacuation

[b] For *Official order*, x_o, Level 0 corresponds to x_{o1}=0 and x_{o2}=0, Level 1 corresponds to x_{o1}=1 and x_{o2}=0, and Level 2 corresponds to x_{o1}=0 and x_{o2}=1.

Table 4: Data summary for continuous variables across all hurricanes and individual hurricanes

Variable		Hyp[a]	Mean and standard deviation										Variable type
			All		Florence		Michael		Dorian		Barry		
			Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	
x_{cat}	Hurricane category	+	2.24	1.52	2.42	1.41	1.04	1.41	2.83	1.34	0.04	0.20	Dynamic, static in future
x_{dist}	Distance household-to-hurricane, km (10^2)	–	10.45	7.62	12.04	8.72	8.62	4.38	7.69	4.34	5.11	3.77	Dynamic, dynamic in future
${x_{dist}}^2$	Distance household-to-hurricane squared, $km^2(10^3)$	–	16.73	19.42	22.11	22.42	9.35	7.47	7.80	7.70	4.03	10.05	Dynamic, dynamic in future

Table 4 continued.

Variable		Hyp[a]	Mean and standard deviation										Variable type
			All		Florence		Michael		Dorian		Barry		
			Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	
x_{fdist}	Distance to forecast landfall location, km	–	2.83	3.58	1.32	1.10	4.20	5.30	6.07	4.03	4.04	4.07	Dynamic, static in future
x_w	Forecast P(Wind>74 mph)	+	0.30	0.24	0.38	0.22	0.22	0.25	0.16	0.19	0.01	0.03	Dynamic, static in future
x_{ss}	Forecast surge flooding, ft	+	2.26	2.69	2.01	1.94	1.21	1.94	3.69	4.08	3.36	2.72	Dynamic, static in future

[a] Positive means a higher value is associated with increased likelihood of evacuation.
[b] Summary statistics does not consider forecast values for all hurricane attributes

Official order (x_o), which denotes whether official evacuation orders were issued in respondents' location, was derived from overlay of official order maps on respondent zip location using the overlay tool in GIS. For Hurricane Barry, data on affected areas where evacuation orders were issued was gathered from news sources (Advocate Staff 2019, Nowak 2019); for the other hurricanes, they were sourced from state emergency management agencies upon request. All other variables in Table 3 were obtained from the survey. *Homeownership* (x_{ho}) was derived from the question "Which best describes your location as Hurricane *X* approached?" The children question (x_{ch}) asked if the respondent had children with them at the time of the hurricane. The *Hurricane category* (x_{cat}) was obtained directly from the NHC website. For distance from household locations to the hurricane center at time *t* (x_{dist}), we computed distances at each time *t* as well as future realizations or forecast. The NHC provides shapefiles for hurricane track at each time *t* (every 6-hour interval), and this consist of current location of hurricane and its forecast locations for the next few days. In our case, we utilized the five-day cone which has the exact location of the hurricane at time *t* and also projects the hurricane location for the next 5 days. Since our application involves 24 six-hour time intervals, we had to interpolate and, in some cases, extrapolate forecasts locations for each event. With the shapefile fully processed, the distances between center of household zip code locations and hurricane eye and its forecast locations were computed with the nearest neighbor tool in GIS. *Distance to forecast landfall location* (x_{fdist}) was also computed in GIS by projecting the same hurricane track at each time *t* to the coastline and measuring its distance to household zip locations. The two forecast hazard attributes—*Forecast Probability of wind great than 74 mph* (x_w) (probability of experiencing wind speed greater than 74mph in the next five days) and *Forecast storm surge flooding* (x_{ss}) (potential flood level in the next five days) —were also obtained from NHC (2020) in the form of GIS shapefiles for each time period. With the help of the overlay and spatial join tools in GIS, we calculated the *Forecast Probability of wind great than 74 mph* (x_w), for each respondent. The GIS data files on *Forecast storm surge flooding* (x_{ss}), were raster files which required the zonal statistic tool in GIS. The zonal statistic tool analyzed flood level values within each zip area and extracted the maximum value.

The impact of *Distance household-to-hurricane, km* (x_{dist}) on the probability of evacuation is not expected to be linear. Rather, we assume that when the hurricane is very far off the coast, households are least likely to evacuate but as the hurricane approaches the coast, the probability of evacuation increases and finally when the hurricane is very close to making landfall, it becomes dangerous to evacuate, hence a decrease in the probability of evacuation. To capture this non-linear relationship, we added the *Distance household-to-hurricane squared* (x_{dist}^2), as a square transform of the *Distance household-to-hurricane* (x_{dist}).

In summary, at each time *t*, we computed, *Distance household to hurricane center* (x_{dist}) and its future expected values but for the *Distance to forecast landfall location* (x_{fdist}), *Forecast Probability of wind great than 74 mph* (Cat. 1) (x_w), *Hurricane category* (x_{cat}), *Forecast storm surge flooding* (x_{ss}), and *Official order* (x_o) variables, forecast values at each time *t* are assumed to be the same as values in the current time.

Chapter 4

MODEL AND EVALUATION

In this chapter, we describe the dynamic discrete choice framework introduced in Rambha et al. (2020) and the modifications made to accommodate our problem definition. The DDC model formulation, described in Section 4.1, closely represents the evacuation decision making process in reality. In the DDC, individuals may choose to evacuate or wait in each time period (say every few hours). In each period, an individual's utility depends on his current choices, present values of influential variables, and discounted expected utilities from future choices should one decide to postpone the evacuation decision. Strengths of this model are that it represents the repeated nature of an individual’s decisions over time and includes the effect of information revealed over time (e.g., storm evolution) and perceptions of how attributes change over time. In Section 4.2 we discuss the changes made to the original algorithm in order to fit our problem definition. The chapter concludes in Section 4.3 with a description of evaluation metrics used to measure the out-of-sample predictive power of the models with regards to aggregate evacuation rates, individual behavior, and evacuating timing.

4.1 Dynamic Discrete Choice Model (DDC)

The evacuation decisions of each individual potentially affected by a hurricane are represented by a finite-horizon dynamic discrete choice (DDC) model. Specifically, we apply the partial information DDC model with forecasts described in detail in Rambha et al. (2020) with some modifications to the problem formulation and data. Unlike more common static discrete choice models, it captures the reality that people make evacuation decision repeatedly during a hurricane. When an individual first becomes aware of a hurricane, they decide to evacuate or wait. If they wait, then they often revisit the decision at some later time *t*, and again decide to evacuate or wait, considering any new information that becomes available in the intervening period. This continues repeatedly until the last time period, then person decides to evacuate or stay for good (Figure 2). At each time *t*, the decision is based on the alternatives available to the individual at *t*, the values of the influential variables at *t*, and the discounted expected utilities from future choices.

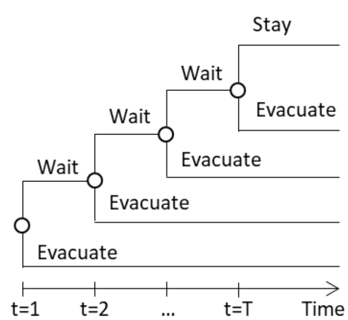

Figure 2: An individual's decisions during a hurricane

Formally, the time horizon is divided into intervals $t = 1, 2, \ldots, T$. The start time, end time, and time intervals should be defined in a way that is interpretable in a consistent manner across hurricanes, and that includes the full period during which people evacuate. At each time *t*, the individual chooses an action a_t from a set of possible actions A_t after observing a state vector $(\vec{x}_t, \vec{\epsilon}_t)$, where $\vec{x}_t$ includes observable individual- and alternative-specific attributes and $\vec{\epsilon}_t$ includes one error term for each action and represents the latent attributes that influence the decision-making process. In this analysis, the set of possible actions are $A_t \in \{Evacuate, Wait\}$ for $t = 1, 2, \dots, T-1$ and $A_T \in \{Evacuate, Stay\}$ (Figure. 2). As in static discrete choice models, if we assume the errors are independent across alternatives and identically distributed according to extreme value type I distribution, then the probability of choosing action a_t in time t is:

$$P(a_t|\vec{x}_t) = \frac{\exp(v_t(\vec{x}_t, a_t))}{\sum_{a'_t \in A_t} \exp(v_t(\vec{x}_t, a'_t))} \quad (1)$$

where $v_t(\vec{x}_t, a_t)$ is the conditional value function, a measure of the utility of choosing a_t in time period t and behaving "optimally" thereafter. Unlike in a static model, in this case $v_t(\vec{y}_t, a_t)$ cannot be expressed in closed form; rather they require solving a dynamic program to determine the policy that maximizes utility of the future decisions. Rambha et al. (2020) describes a backward recursive algorithm to solve for the conditional value functions. It assumes ϵ_t values are i.i.d over time periods; the observable component of the state vector, $\vec{x}$, is Markovian and satisfies conditional independence so that it has a probability density function of $f(\vec{x}_{t+1}|\vec{x}_t, a_t)$; and that the utilities of future actions are discounted by a factor $0 \leq \alpha \leq 1$, where $\alpha = 0$ implies future utilities have no importance and $\alpha = 1$ implies future and current utilities are equally important.

Within the recursive algorithm, the $v_t(\vec{x}_t, a_t)$ are functions of one-step utilities, $u(\vec{x}_t, a_t) + \epsilon_t(\ a_t)$, where the first term is the observable component, which we assume is linearly dependent on the covariates. Allowing the impact of variables on the one-step utilities of evacuating and waiting to differ and normalizing the one-step utility of *Stay* to zero to avoid identification issues since the state vector in this case does not include alternative-specific variables, we define the one-step utilities as $u(\vec{x}_t, Evacuate) = \vec{\beta}^T \vec{x}_t$, $u(\vec{x}_t, Wait) = \vec{\psi}^T \vec{x}_t$, and $u(\vec{x}_t, Stay) = 0$. The parameters $\vec{\beta}$ and $\vec{\psi}$ are obtained from the panel data using maximum likelihood estimation with a gradient descent optimization algorithm adopted.

4.2 Modifications to Dynamic Discrete Choice Framework

The DDC algorithm was originally implemented in C++ as detailed in Rambha et al. (2020). In our application, we modified the source code to integrate novel changes related to (1) integration of multiple hurricanes, (2) definition of time steps, and (3) inclusion of additional hurricane and forecast attributes. First, the model presented in Rambha et al. (2020) is fitted to data from a single hurricane (Hurricane Gustav), so we had to modify the source code to accommodate multiple events. With multiple hurricanes, each of which has a different time horizon (i.e., different formation and landfall dates) (Table 1), we had to define time steps consistently across each event. Ideally, the first- and last-time steps should coincide with the timing of the first and last forecasts from NHC, respectively, however, doing so might: (1) generate different number time steps across hurricanes and/or (2) create long sequence data with probably no evacuations in early time steps. The algorithm requires the same number of time steps for each individual in the data. Numerical issues may arise when long sequence data with no evacuation in several time steps is modelled with the

DDC. To address these issues, we defined 24 six-hour time steps across each hurricane where the first-time step corresponds to the first evacuation time observed in the data. The last time step, across each event is at least 18 hours after landfall. We also lined up time-of-day for all events and could not use it as an explanatory variable. Finally, the algorithm in Rambha et al. (2020), used only *Distance from household to hurricane* (x_{dist}) and *Hurricane category* (x_{cat}) as hurricane attributes but in our application, we added *Distance to forecast landfall location* (x_{fdist}), *Forecast Probability of wind great than 74 mph* (Cat. 1) (x_w), and *Forecast storm surge flooding* (x_{ss}).

4.3 Model Evaluation

To evaluate the out-of-sample predictive power of the DDC model and compare it to methods in literature, we implemented ten-fold cross validation (CV). The dataset was partitioned into ten randomly sampled folds. In the partitioning process, we employed a stratified sampling technique to ensure proportionate distribution of observations across hurricanes. For each fold, the 90% of observations not in the fold made up a training set used to fit the models, which were then applied to predict the values for each of the 10% of observations in the fold—the validation set. In this way, CV estimates the expected prediction error over all training sets, rather than for a specific one. That is, it compares the methods rather than specific models with specific coefficient values. While holdout validation could be used to compare specific models, it can lead to high variance depending on the particular holdout data used. To minimize variability due to the fold sampling, we repeated the cross-validation 10 times, each with a different set of randomly generated folds and averaged the resulting 10 estimates of each error metric.

We used ten evaluation metrics to measure the models' ability to achieve the desired performance along four dimensions of interest—the ability to predict the (1) total number of evacuees, (2) approximate spatial distribution of evacuees, (3) approximate timing of evacuations, and (4) behavior of individuals (Table 5). Error and percentage error in the expected total number of evacuees for the region (*TE* and *TEP*, respectively) evaluate the ability to capture the overall magnitude of the evacuation, without concern for the spatial distribution or timing. To assess the ability of the models to predict the approximate spatial distribution of evacuees correctly, we compute percentage of counties with absolute error greater than 2 and also the median absolute percentage error across counties (*PCAE* and *MPCE*). Since the DDC model computes not just who evacuates but at what time, we can evaluate its ability to estimate the timing as well. The metrics mean and absolute departure time errors (*MDTE* and *ADTE*) are computed by creating departure curves (percentage of evacuees who have evacuated vs. time) using the observed and predicted times, then averaging the horizontal differences and absolute differences.

Finally, although for practical emergency management purposes it is not as important to predict individual behavior as to behavior at the county level, for completeness, we examine a few individual level metrics as well, distinguishing between false positive and false negative errors. The three-threshold metrics—SN, SP, TSS—require comparing the predicted evacuation probability, $\hat{p}_i$, for each individual *i* to a threshold (we use 0.5), and classifying the person as an evacuee if $\hat{p}_i > 0.5$. The sensitivity (*SN*) and specificity (*SP*) then identify the percentage of evacuees correctly classified and percentage of non-evacuees correctly classified, respectively. True skill statistic (*TSS*) is a newer threshold metric that corrects the overall accuracy by the accuracy expected to occur by chance. Also known as the Hanssen-Kuipers discriminant, $-1 \leq TSS \leq 1$, with +1 indicating perfect agreement and zero indicating no better than chance (Allouche et al. 2006).

Table 5: Evaluation metrics

Dimension of performance	Metric	Equation[a]
Total number of evacuees	Error in total num. of evacuees	$TE = \sum_i y_i - \sum_i \hat{p}_i$
	Percentage error in total num. of evacuees	$TEP = TE / \sum_i y_i$
Spatial distribution of evacuees	Percentage of counties with absolute error >2	$PCAE = \sum_i n_c \left\lvert \sum_{i \in n_C} y_i - \sum_{i \in n_C} \hat{p}_i \right\rvert > 2 / \sum_i n_c$
	Median percentage county error	$MPCE$=Median of $\left\lvert \sum_{i \in n_C} y_i - \sum_{i \in n_C} \hat{p}_i \right\rvert / \sum_{i \in n_C} y_i$
Departure timing	Mean departure time error	$MDTE = \int_0^T \{F_o(t) - F_p(t)\}\, dt$
	Absolute departure time error	$ADTE = \int_0^T \lvert F_o(t) - F_p(t) \rvert\, dt$
Individual evacuation decisions	Sensitivity	$SN = tp/(tp + fn)$
	Specificity	$SP = tn/(tn + fp)$
	True skill statistic	$TSS = SN + SP - 1$
	Area under the ROC plot	AUC = area under ROC plot

[a] y_i=observed evacuation for individual *i* (1/0 if evacuated/did not); $\hat{p}_i$ = estimated probability of evacuating for individual *i*; n_C = number of individuals in county *C*; $F_o(t)$ and $F_p(t)$ are the observed and predicted cumulative % of evacuees who had departed by time *t*; *tp* = num. true positive; *fp* = num. false positive; *tn* = num. true negative; *fn* = num. false negative.

Finally, the AUC is an individual prediction metric that is not dependent on the choice of threshold. A receiver operating characteristic (ROC) plot is a graph of *SN* vs. (1-*SP*), where each point corresponds to a possible threshold value (Fielding and Bell 1997). The area under a ROC plot (AUC) is a ranking metric so it assesses the correctness of the ordering of the probabilities but does not distinguish if they range from 0 to 1, for example, or from 0.40 to 0.42. The AUC, which varies from 0.5 (worthless) to 1.0 (perfect), can be interpreted as the probability the model will rank a randomly selected evacuee as more likely to evacuate than a randomly selected non-evacuee.

Chapter 5

RESULTS

This chapter presents model estimation and prediction results. Three different models are presented—base model (DDC1) and test models (DDC2 and DDC3). The base model (DDC1) and DDC3 were estimated on full data (2081 observations) across all four hurricanes with DDC3 having hurricane indicator as an additional explanatory variable (Tables 2,3 and 4). Predictive power on both models was measured through ten-fold cross validation. Test model, DDC2 was however, estimated on Hurricane Florence and predictive power measured on the other three hurricanes. Model estimation results are presented in Section 5.1 while Section 5.2 presents the prediction results.

5.1 Final Fitted Models

Table 6 describes estimation results for the three DDC models, including estimated coefficients and p-values for each variable. While DDC1 and DDC3 were estimated on data across all 4 hurricanes, DDC2 was estimated on only Hurricane Florence data. Also, DDC1 and DDC2 include the full set of covariates for prediction while DDC3 includes an extra hurricane indicator variable. DDC1 is the base model for future application with all predictors fully available at the regional scale. DDC2 was included to investigate the importance of combining data from diverse hurricanes as it is believed model trained on a single hurricane data will not have a good predictive power as a model trained on multiple events.

Table 6: Estimation results for DDC models

Discount factor, α = 1		DDC1 (All hurricanes)				DDC2 (Florence)				DDC3(All hurricanes with indicators)			
	Variable	Evac. utility		Wait utility		Evac. utility		Wait utility		Evac. utility		Wait utility	
		coef.	p-val.	coef.	p-val.	coef.	p-val.	coef.	p-val.	coef.	p-val.	coef.	p-val.
k	Intercept	-11.488*	0.001	-0.825*	0.001	-15.422*	0.001	-1.816*	0.001	-11.373*	0.001	-0.938*	0.001
x_{ho}	Homeownership	0.013	0.963	-0.045‡	0.015	0.112	0.769	-0.071‡	0.011	0.030	0.921	-0.044‡	0.035
x_{mh}	Mobile home	1.418*	0.001	0.069 †	0.050	1.521‡	0.029	0.067	0.214	1.356‡	0.016	0.075 †	0.071
x_v	Vehicle access	4.041 †	0.052	0.188	0.179	4.475	0.129	0.207	0.243	4.577‡	0.037	0.234	0.113
x_{ch}	Have children	0.342	0.246	0.013	0.524	0.177	0.649	-0.006	0.834	0.440	0.151	0.022	0.326
x_{em}	Employed	0.456	0.232	0.071*	0.001	1.038‡	0.020	0.134*	0.001	0.717 †	0.079	0.085*	0.001
x_{man}	Mandatory official order	0.263	0.555	-0.067‡	0.015	1.170	0.176	-0.034	0.572	0.045	0.930	-0.082‡	0.016
x_{vol}	Voluntary official order	-0.384	0.398	-0.075‡	0.014	2.435*	0.001	0.096‡	0 .041	0.227	0.649	-0.023	0.513
x_{dist}	Distance to hurricane, km	0.248*	0.001	0.028‡	0.010	0.859*	0.001	0.279*	0.001	0.146	0.115	0.024‡	0.024
x_{dist}^2	Distance to hurricane squared, km^2	-0.010‡	0.029	-0.001‡	0.039	-0.010	0.229	-0.009*	0.001	-0.011‡	0.039	-0.001	0.386

Table 6 continued

Discount factor, α = 1		DDC1 (All hurricanes)				DDC2 (Florence)				DDC3(All hurricanes with indicators)			
Variable		Evac. utility		Wait utility		Evac. utility		Wait utility		Evac. utility		Wait utility	
		coef.	p-val.	coef.	p-val.	coef.	p-val.	coef.	p-val.	coef.	p-val.	coef.	p-val.
x_{fdist}	Distance to forecast landfall location, km	0.040	0.447	0.025*	0.001	0.046	0.392	0.044‡	0.021	-0.075	0.332	0.008 †	0.081
x_{cat}	Hurricane category	0.887*	0.001	-0.011	0.319	0.333	0.411	-0.052	0.042	0.583‡	0.031	-0.010	0.519
x_{ss}	Forecast surge flooding, ft	-0.387*	0.001	-0.041*	0.001	-0.950*	0.001	-0.082*	0.001	-0.298‡	0.021	-0.035*	0.001
x_w	Forecast P(Wind>74 mph)	1.667	0.050	0.045	0.466	0.997	0.541	0.442*	0.001	1.086	0.272	0.030	0.663
x_{flo}	Florence									-2.023	0.434	-0.265	0.141
x_{mich}	Michael									2.391	0.362	0.142	0.401
x_{dor}	Dorian									0.024	0.992	0.059	0.722
	Log-Likelihood	-3549.178				-2479.671				-3509.23			

[a] The symbols †, ‡, * denote significant levels of 0.1,0.05, and 0.01, respectively

The addition of DDC3 is to investigate whether the difference in behavior across the four hurricanes in the dataset is fully captured by the hurricane and forecast attributes included as explanatory variables.

Model coefficients were estimated using the popular maximum likelihood estimator with the Berndt–Hall–Hall–Hausman algorithm (BHHH) (Berndt, Hall, & Hall, 1974) as the optimization algorithm. The convergence threshold for each of model was set to $1\text{E}-5$. The *discount factor* (α) which denotes how households weigh future utilities in the present was fixed to 1. This means households in each time step value current and future utilities equally with the justification that the time steps defined are only 6-hour intervals. With separate utility functions defined for evacuate and wait options, the algorithm estimates different parameters for each option as in Table 6. In dynamic models such as the one presented here, we are not able to relate the likelihood of evacuation to signs of model parameters since the utility functions are time-dependent (i.e., utility functions have both static and dynamic components) and signs of parameters are likely to change over time (Rambha et al. 2020). The estimated coefficients in Table 6 capture only the static component of the utility functions defined and thus cannot fully explain the impact of each variable on the probability of evacuation. To understand why, consider, the partial derivative of the probability of evacuation with respect to *Distance from household to hurricane* (x_{dist}), given by

$$\frac{\partial \mathrm{P}(\text{evacuate}|\vec{x}_{nt})}{\partial x_{dist}} = \beta_{x_{dist}} + \varphi_{x_{dist}} - \alpha \frac{\partial}{\partial x_{dist}} \bar{V}_{nt,t+1}(\vec{x}_{n,t+1}) \qquad (2)$$

where $(\beta_{x_{dist}} + \varphi_{x_{dist}})$ represents the static component, which stays constant over the entire time horizon (except for last time step which has a 'stay' option) with $\beta_{x_{dist}}$ and $\varphi_{x_{dist}}$ denoting the estimated coefficient of x_{dist}, for evacuate and wait utilities, respectively, as in Table 6. The second term $(\alpha \frac{\partial}{\partial x_{dist}} \bar{V}_{nt,t+1}(\vec{x}_{n,t+1}))$, with $\bar{V}_{nt,t+1}$ representing future realization of utilities, is the dynamic component which depends on other variables which are time-dependent. Equation 2, therefore fails to capture the isolated effect of a single variable on the probability of evacuation as it is heavily influenced by the presence of other variables.

To this end, we focus on prediction and kept all variables in the model independent of their p-values. In Section 5.2, results on the predictive performance of the DDC models are presented.

5.2 Prediction

Table 7 presents results for the three DDC models using the evaluation metrics described in Table 5. In DDC1 and DDC3, 10-fold cross validation with 10 iterations was conducted to estimate the out-of-sample predictive power while in DDC2, the model was trained on Hurricane Florence and tested on the other three hurricanes (Michael, Barry and Dorian). As already stated, DDC1 is the base model which will be applied for future predictions. DDC2 and DDC3 were added to examine the importance of having multiple hurricanes (i.e., sufficient variability) in the data for modelling.

Table 7: Prediction results for DDC models

Model	Hurricane	Total region		County		Timing		Individual			
		TE	TEP (%)	PCAE (%)	MPCE (%)	MDTE	ADTE	SN (%)	SP (%)	TSS	AUC
DDC1	All	13.43	1.39	14.28	35.67	-0.33	2.14	70.24	71.54	0.42	0.70
	Florence	7.78	1.07	16.91	38.41	0.81	2.11	76.41	52.14	0.29	0.64
	Michael	23	14.34	13.79	38.95	-6.79	7.03	65.04	75.23	0.40	0.70
	Barry	3.64	72.92	5.88	84.09	19.3	22.07	0.00	100	0.00	0.50
	Dorian	-21	-29.09	8.77	23.09	4.49	6.47	13.25	95.04	0.08	0.54
DDC2	Michael	-49.46	-30.72	17.24	33.89	21.71	23.85	85.71	46.75	0.32	0.66
	Barry	-14.92	-298.4	5.88	113.78	-10.99	26.67	80.00	52.94	0.32	0.66
	Dorian	-125.09	-173.73	38.59	91.27	8.98	14.00	44.44	59.56	0.04	0.52
DDC3	All	10.76	1.12	12.14	37.15	-0.41	1.98	70.86	69.82	0.41	0.70
	Florence	1.84	0.25	14.08	39.32	-0.01	1.87	77.59	50.82	0.28	0.64
	Michael	10.58	6.57	10.34	42.09	-1.95	4.61	73.91	66.27	0.40	0.70
	Barry	0.36	7.14	0.00	47.82	0.45	12.94	0.00	97.06	-0.03	0.49
	Dorian	-2.02	-2.81	10.53	31.87	0.85	5.11	1.00	97.54	-0.01	0.49

[a] Table 5 presents the definition for each metric.

5.2.1 Aggregate Level Predictions

At the aggregate (total region) level for all hurricanes, the base model, DDC1 performed reasonably well with an absolute TEP value of 1.39% (Table 7). Practically, there are approximately a million people living along the coast of North Carolina. Considering half were under an evacuation order, applying the DDC would mean an over- or underestimation of 7000 people. Xu et al. (2016) also reported out-of-sample prediction errors of 4%, 5%, 10%, and 21% across two ordered probit models, a participation rate model and a logit model which was adapted from Wilmot and Mei (2004). It is evident that our model, based on this metric and per the current application, outperforms all models reported in Xu et al. 2016. The TEP for individual hurricanes seemed reasonable for Florence and Michael with relatively high errors reported for Barry and Dorian (72.92% and 29.09%, respectively). The high TEP values for Dorian and Barry could attributed to the fact that there is not enough variability in the training set, thus the model could not generalize well on some data points.

At the aggregate county level, we also computed the spatial distribution of errors for the DDC. The county level predictions are of prime importance since in practice, evacuations are planned and carried out at the county level. As shown in the *County* column of Table 7, with PCAE, the percentage of counties with absolute error greater than 2, and MPCE which is the median percentage county error, DDC1 performs reasonably well, both across all hurricanes and individual events (PCAE and MPCE of 14.28% and 35.67% across all hurricanes, respectively).

5.2.2 Individual Level Predictions

Although for emergency management purposes it is not as important to predict individual behavior as to behavior at the aggregate county level, for completeness, we computed individual evaluation metrics for DDC1 and compared with models in literature. From the Individual metrics section of Table 7, DDC1 across all hurricanes correctly classifies evacuees and non-evacuees approximately 70% and 72% of the time, respectively. Xu et al. 2016 also evaluated two ordered probit models at the individual level and reported approximately 70% accurate prediction of household behavior.

5.2.3 Timing Prediction

As shown in the *Timing* column of model results in Table 7, we also measured the timing performance of DDC1 using timing metrics defined in Table 5. The metrics, mean and absolute departure time errors (*MDTE* and *ADTE*, respectively) were computed by creating departure curves (percentage of evacuees who have evacuated vs. time) from the observed and predicted times as shown in Figure 3, and averaging the horizontal differences and absolute horizontal differences. As already stated, each interval on the horizontal axis is a 6-hour period. For all hurricanes and individual events, DDC1 provides a good timing performance. MDTE values range from -0.33hrs to 19.30hrs across all hurricanes while ADTE values are in the range of 2.11hrs to 22.07hrs.

Figure 3 compares the percentage cumulative evacuation over time for DDC1 and the observed data. It is presented in terms of predictions across all hurricanes in Figure 3a and in terms of individual events in Figures 3b, c, and d for Florence, Michael and Dorian, respectively. Barry was omitted due to its small sample size. In each plot, DDC1, over-estimates cumulative evacuations in some time steps and under-estimates in other time steps. Figure 3a represents data from all four hurricanes and thus, does not have actual dates along its horizontal axis. For individual hurricanes, we can relate predictions over time with the actual dates along the time horizon. Actual dates help in explaining model performance with reference to critical points such as landfall date. Landfall dates correspond to 21st, 18th and 21st time steps as indicated in the grayscale vertical lines for Florence, Michael and Dorian, respectively. It is observed that about 98% of evacuations were recorded prior to landfall and our model does well in capturing this trend across individual hurricanes. Also, 3 days prior to landfall seemed the most critical time when most evacuations occur and it is promising to see our model with good predictions within this period.

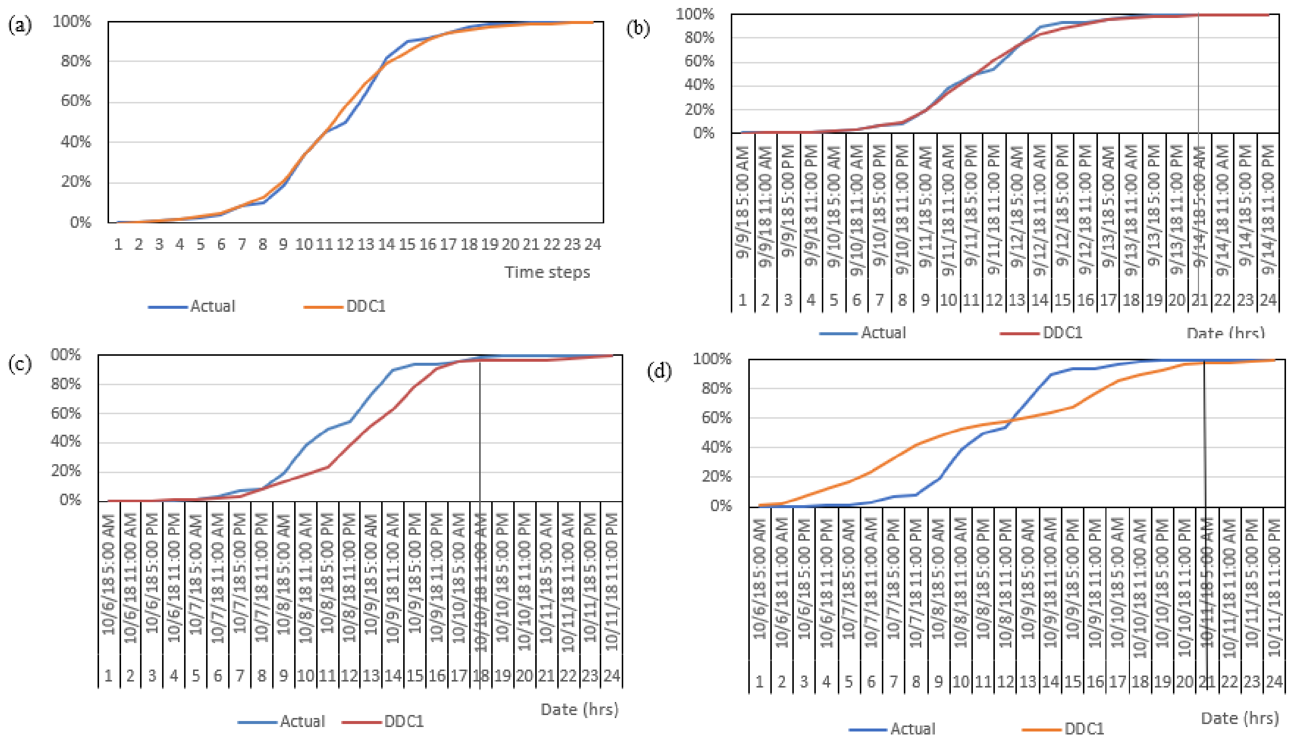

Figure 3: Cumulative percentage of evacuees over time for actual and DDC1 on (a) All hurricanes, (b) Florence, (c) Michael, (d) Dorian

Specifically, for Florence in Figure 3b, DDC1 barely over- or under-estimated evacuations in time steps within three days prior to landfall. However, for Michael and Dorian, DDC1 over- and under-predicted evacuations in some time steps but at the aggregate scale over the three days, they cancelled out to give a good overall performance.

5.2.4 Sensitivity Analysis

An evacuation model for prediction should be able to generalize well on any future event. Training data utilized should therefore comprise data from multiple and diverse events. Data used in our analysis includes observations from four different hurricanes and based on the predictive performance of DDC1, we can say the data has a reasonable level of variability. To further demonstrate the need for including data from multiple events, we estimated the predictive power of a model (DDC2), fitted on a single hurricane and compared its predictive power to the base model. DDC2 was trained on only Hurricane Florence and predictive power measured on Michael, Dorian, and Barry as hold-out set. Comparing model results in Table 7 for DDC1 and the test model, DDC2, indicates, DDC1 highly outperforms DDC2. For instance, in terms of regional level predictions, DDC1 achieved TEP values of approximately 14%, 73%, and -29% while DDC2 recorded -30%, -298% and -174% for Michael, Barry and Dorian, respectively.

To further investigate the effect of using data from multiple hurricanes in fitting evacuation models, a hurricane indicator variable was added as a predictor to the original set of explanatory variables. DDC3 was then estimated with this new set of covariates and its predictive power measured with a ten-fold cross validation as in DDC1. To minimize sampling variability for fair comparison of models, we maintained the same folds as utilized in DDC1. Although the hurricane indicators are not statistically significant (Table 6), comparing cross validation results (Table 7) for DDC3 to our original DDC1, shows a substantial improvement in predictive performance, especially for timing and regional metrics. Specifically, the absolute TEP values for DDC1 range from 1.07% to 72.92% with an average of 29.36% across the four hurricanes while DDC3's absolute TEP values range from 0.25% to 7.14% with an average of 3.58%. These results suggest, even though the data used in this analysis comes from four different hurricanes, the hurricane-specific attributes (*Distance to hurricane* x_{dist}, *Distance to forecast landfall location* x_{fdist}, *Forecast Probability of wind great than 74 mph* x_w, *Hurricane category* x_{ca}), and *Forecast storm surge flooding* x_{ss}) do not fully capture the difference between observations from different events. This can be explained from the significant differences in the summary statistic of these hurricane-specific attributes as detailed in Table 4. Further advancement in predictive power, will require capturing these differences by building a large database from diverse hurricanes in the future.

Chapter 6

CONCLUSIONS, LIMITATIONS AND FUTURE PROPOSALS

6.1 Conclusions

In this work, we made significant contributions to the literature on population evacuation behavior prediction during hurricanes through advances in modeling and data. We also defined novel evaluation metrics which researchers might utilize in evaluating their models in the future. First, we modified and applied the dynamic discrete choice (DDC) model introduced in Rambha et al. (2020). Second, our data was sourced from four diverse hurricanes which ensured sufficient variability for analysis. With the main focus on prediction, we limited model covariates to variables that will be available in the future at a regional scale. Rather than rely on only demographic variables as in most previous studies, we took advantage of the dynamic nature of the DDC and added more hurricane dynamic and forecast variables. Third, through cross validation, we evaluated and compared the predictive power of the DDC model, and the methods literature. Finally, we conducted two tests to understand the importance of combining data from multiple hurricanes.

Analysis of model out-of-sample predictive power measured through cross validation at the aggregate level across the four hurricanes suggests approximately 99% (TEP of 1.39%) of total evacuation demand will be predicted. In terms of prediction at the individual household level, the DDC will correctly predict evacuees and non-evacuees 70% and 72% of the time, respectively. This shows errors will be somewhat equally distributed between false positives and false negatives for individual predictions, which will enhance aggregate level estimates. Finally, the DDC model with an extra advantage of estimating time- dependent evacuation demand, when applied in the future, will only give an absolute departure time error of 2.14hrs across the entire population. Also, the DDC model compares better with models for prediction in literature, across multiple metrics, including prediction of aggregate evacuation rates, individual behavior, and evacuation timing. Finally, results from the sensitivity tests conducted suggest, a model trained on data from multiple events will perform better in the future as compared to a model trained on a single hurricane data. Predictive power of evacuation models, can therefore be improved by training models on data from diverse set of hurricanes.

It is imperative to understand that, while human behavior during hurricane evacuations is very difficult to predict, building models based on good data and assumptions to capture reality can go a long way to assist emergency managers and transportation officials. These models, at the end of the day can inform good decision-making at every stage of the evacuation planning process. With the DDC especially providing time-dependent predictions, decision makers can plan into the future and minimize traffic congestions while saving lives.

6.2 Limitations and Future Work

Finally, this study makes proposals with regards to new directions for future works. In application of the dynamic discrete choice framework, a few assumptions were made with reference to definition of time steps and forecast attributes. Ideally, the decision-making process should start when the National Hurricane Center releases the first advisory but doing so increases the number of time steps as landfall date is hardly known ahead of time. Modelling such long sequences with no evacuations in early time steps, creates numerical problems such as non-convergence of objective function. To avoid such problems, we shortened the number of time steps to only 24 six-hour time intervals across each hurricane with the start time being the date when the first evacuation was observed in each hurricane data. Time-of-day will be an important variable to capture peaks and trends in the evacuation process as people are more likely to evacuate during the day than at night. However, we could not integrate time-of-day as an explanatory variable since time steps were aligned across all hurricanes (i.e., the same values for all households). Another limitation of our analysis is the lack of forecast data for some hurricane attributes. While forecast data is readily available on NHC website for *Distance from household to hurricane* (x_{dist}), forecast information on the other hurricane attributes (*Forecast Probability of wind great than 74 mph* x_w, *Hurricane category* x_{cat}), and *Forecast storm surge flooding* x_{ss}) is not available. We therefore assumed their future realizations or forecast stay constant. Future work should extend the DDC approach to capture the entire time horizon as reported by NHC and integrate time-of-day as an explanatory variable. Furthermore, due to the complex nature of evacuation behavior and hurricanes, with each event being different, sourcing data from multiple diverse events will go a long way to enhance out-of- sample predictive power of evacuation models as they become capable of explaining more variability in population evacuation behavior.

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Appendix A

QUESTIONNAIRE SURVEY

The survey presented here is the version deployed after Hurricane Florence. For the other three hurricanes, slight changes were made to a couple of questions (Q1, Q2, Q3, Q8 and Q13) to reflect the specifics of each event. Otherwise, the survey instrument was the same across all hurricanes.

STATEMENT OF INFORMED CONSENT

Decision-Making and Evacuation for Hurricane Florence

You are invited to participate in a survey about how people make decisions about evacuation from a hurricane. This is part of a study conducted by the University of Delaware and funded by the National Science Foundation. You must be 18 years old or older to participate. There are no anticipated risks associated with this study. The survey will last approximately 5-10 minutes, but may last longer if you wish to write more. There is no compensation for your participation. The information collected will be used for research and educational purposes. Your participation in this study is voluntary. If you wish to withdraw from the study, you may do so at any time during the survey. You cannot withdraw once you have completed the survey. We will ask you to recollect your experiences during disaster events and evacuations. We will not ask your name or associate your identity with the information you provide. We will not use your name in reports or publications. Data will be kept at the Disaster Research Center indefinitely on a secure server and may be shared in the future with permission of the director of the Disaster Research Center. If you have any questions or concerns, you may contact the study's Principal Investigator, Dr. Rachel Davidson, at the Disaster Research Center, University of Delaware at rdavidso@udel.edu (302-831-6618). Alternatively, if you have any questions about your rights as a participant in this study, you may contact the University of Delaware's Chairperson of the Institutional Review Board (302-831-2137).

By continuing with this form, you acknowledge to the researcher that that you understand your rights as a research subject, have read this form, and voluntarily consent to participate in this study. *(Name of hurricane different for each survey)*

○ Yes, I agree to proceed and participate.

○ No, I do not wish to take this survey.

Skip To: End of Survey If STATEMENT OF INFORMED CONSENT   Decision-Making and Evacuation for Hurricane Florence   You are i... = No, I do not wish to take this survey.

Q1 Where were you located as Hurricane Florence approached the U.S.? Please provide the state, city, and 5-digit zip code if possible.

○ State ____

○ City____

○ Zip code ____

Q2 Did you evacuate for Hurricane Florence, any related storm activity (including inland flooding), or any impact after the storm had started (like secondary flooding or trees falling)?

○ Yes

○ No

○ I was rescued

Skip To: Q10 If Did you evacuate for Hurricane Florence, any related storm activity (including inland flooding),... = No
Skip To: Q10 If Did you evacuate for Hurricane Florence, any related storm activity (including inland flooding) ... = I was rescued

Q3 On what date did you evacuate? For reference, the hurricane made landfall Friday, September 14 at 7:30am. *(Changed for each survey)*

○ Friday, September 7

○ Saturday, September 8

- Sunday, September 9
- Monday, September 10
- Tuesday, September 11
- Wednesday, September 12
- Thursday, September 13
- Friday, September 14
- Saturday, September 15
- Sunday, September 16
- Monday, September 17
- Tuesday, September 18
- Wednesday, September 19
- Thursday, September 20
- Friday, September 21
- Saturday, September 22
- Sunday, September 23
- Monday, September 24
- Tuesday, September 25
- Wednesday, September 26
- Thursday, September 27

○ Friday, September 28

○ Saturday, September 29

○ Sunday, September 30

○ Monday, October 1

○ Tuesday, October 2

○ Wednesday, October 3

○ Thursday, October 4

○ Friday, October 5

○ Saturday, October 6

○ Sunday, October 7

○ Monday, October 8

Q4 On that day, approximately what time did you evacuate?

○ midnight

○ 1:00 am

○ 2:00 am

○ 3:00 am

○ 4:00 am

○ 5:00 am

○ 6:00 am

○ 7:00 am

○ 8:00 am

○ 9:00 am

○ 10:00 am

○ 11:00 am

○ 12 noon

○ 1:00 pm

○ 2:00 pm

○ 3:00 pm

○ 4:00 pm

○ 5:00 pm

○ 6:00 pm

○ 7:00 pm

○ 8:00 pm

○ 9:00 pm

○ 10:00 pm

○ 11:00 pm

Q5 Where was your final destination? Please provide the state, city, and 5-digit zip code if possible.

○ State ____

○ City ____

○ Zip Code ____

Q6 What was your final destination?

○ Family or friend's home

○ American Red Cross public shelter

○ Other public shelter

○ Others (Please specify)

____

Q7a What was the primary route you took to get to your final destination? Please list the main interstates, highways, and/or other roads you used to evacuate. The map is available for reference. *(Map of affected area included with the question and changed for each survey)*

____

Q7b Did you change your path at any point to take an alternative route from the one you started out on?

○ Yes

○ No

○ Not sure

Q8 On what date did you arrive at your final destination? (Landfall was on Friday, September 14 at 7:30am)

- ○ Friday, September 7
- ○ Saturday, September 8
- ○ Sunday, September 9
- ○ Monday, September 10
- ○ Tuesday, September 11
- ○ Wednesday, September 12
- ○ Thursday, September 13
- ○ Friday, September 14
- ○ Saturday, September 15
- ○ Sunday, September 16
- ○ Monday, September 17
- ○ Tuesday, September 18
- ○ Wednesday, September 19
- ○ Thursday, September 20
- ○ Friday, September 21
- ○ Saturday, September 22
- ○ Sunday, September 23
- ○ Monday, September 24

○ Tuesday, September 25

○ Wednesday, September 26

○ Thursday, September 27

○ Friday, September 28

○ Saturday, September 29

○ Sunday, September 30

○ Monday, October 1

○ Tuesday, October 2

○ Wednesday, October 3

○ Thursday, October 4

○ Friday, October 5

○ Saturday, October 6

○ Sunday, October 7

○ Monday, October 8

Q9 On that day, approximately what time did you arrive at your final destination?

○ midnight

○ 1:00 am

○ 2:00 am

○ 3:00 am

○ 4:00 am

○ 5:00 am

○ 6:00 am

○ 7:00 am

○ 8:00 am

○ 9:00 am

○ 10:00 am

○ 11:00 am

○ 12 noon

○ 1:00 pm

○ 2:00 pm

○ 3:00 pm

○ 4:00 pm

○ 5:00 pm

○ 6:00 pm

○ 7:00 pm

○ 8:00 pm

○ 9:00 pm

○ 10:00 pm

○ 11:00 pm

Q10 What were the major determining factors that lead to your decision to ultimately evacuate? (Choose no more than five)

- ☐ Mandatory evacuation order issued
- ☐ Voluntary evacuation order issued
- ☐ Determination others in household were at risk
- ☐ Determination pets were at risk
- ☐ Storm's impact in other areas
- ☐ Urging of friend or family member
- ☐ Seeing the storm effects first hand (e.g., flooding, rough seas, strong winds)
- ☐ Expected loss of power or other utilities
- ☐ Prior experience with evacuating for a hurricane
- ☐ Prior experience with staying for a hurricane
- ☐ Urging from news media/meteorologists
- ☐ Urging from public officials

- [ ] Urging from community leaders
- [ ] Saw others leaving
- [ ] Others (Please specify)

____

Q11 Which, if any, of the following were major factors in causing delays or preventing you from evacuating? (Choose no more than five)

- [ ] No official evacuation orders
- [ ] Did not think your location would be impacted
- [ ] Did not understand information about the storm's severity
- [ ] Did not trust information about the storm's severity
- [ ] Saw others staying in place
- [ ] Access to transportation
- [ ] Concern about traffic
- [ ] Lack of evacuation destination
- [ ] Concerns about shelter safety
- [ ] Work obligation
- [ ] Caring for dependents (children, elderly, medically fragile, other)
- [ ] Caring for pets or other animals

- [ ] Caring for others in the impacted area who did not/could not evacuate
- [ ] Expected expense of the evacuation
- [ ] Protecting property
- [ ] Prior experience with evacuation
- [ ] Other (Please Specify ____

Q12 To your knowledge, did your location receive an official evacuation order before the storm hit?

- ○ Yes
- ○ No
- ○ Do not know

Skip To: Q15 If To your knowledge, did your location receive an official evacuation order before the storm hit? ! = Yes

Q13 On what date did you become aware of the official evacuation order for your location? (Landfall was on Friday, September 14 at 7:30am) *(Changed for each survey)*

- ○ Friday, September 7
- ○ Saturday, September 8
- ○ Sunday, September 9
- ○ Monday, September 10

○ Tuesday, September 11

○ Wednesday, September 12

○ Thursday, September 13

○ Friday, September 14

○ Saturday, September 15

○ Sunday, September 16

○ Monday, September 17

○ Tuesday, September 18

○ Wednesday, September 19

○ Thursday, September 20

○ Friday, September 21

○ Saturday, September 22

○ Sunday, September 23

○ Monday, September 24

○ Tuesday, September 25

○ Wednesday, September 26

○ Thursday, September 27

○ Friday, September 28

○ Saturday, September 29

- Sunday, September 30
- Monday, October 1
- Tuesday, October 2
- Wednesday, October 3
- Thursday, October 4
- Friday, October 5
- Saturday, October 6
- Sunday, October 7
- Monday, October 8

Q14 On that day, approximately what time did you become aware of the official evacuation order for your location?

- midnight
- 1:00 am
- 2:00 am
- 3:00 am
- 4:00 am
- 5:00 am
- 6:00 am
- 7:00 am
- 8:00 am

- 9:00 am
- 10:00 am
- 11:00 am
- 12 noon
- 1:00 pm
- 2:00 pm
- 3:00 pm
- 4:00 pm
- 5:00 pm
- 6:00 pm
- 7:00 pm
- 8:00 pm
- 9:00 pm
- 10:00 pm
- 11:00 pm

Q15 How many of your family, friends, neighbors, and acquaintances evacuated?

- Almost none
- Some
- Many

○ Almost all

○ I do not know

Q16 Which best describes your location as Hurricane Florence approached?

○ In a home you own

○ In a home you rented as your primary residence

○ In a home you rented for a vacation or other short period of use (e.g., week or two)

○ Other (Please explain)
____

Q17 Were you in a mobile home?

○ Yes

○ No

Q18 Were you in a low-lying area, or in an area near a beach, river, or other body of water that might be prone to flooding?

○ Yes

○ No

○ Do not know

Q19 Did you have a vehicle or access to a vehicle to evacuate?

○ Yes

○ No

Q20 Did you have any children with you?

- ○ Yes
- ○ No

Q21 Did you have pets, livestock, or other animals with you?

- ○ Yes
- ○ No

Q22a Are you employed?

- ○ Yes
- ○ No

Skip To: Q23 If Are you employed? != Yes

Q22b What is your job?

____

Q23 Which category best describes your race?

- ○ Caucasian/White
- ○ African American/Black
- ○ Asian
- ○ American Indian

- Pacific Islander
- Multi-racial

Q24 What is the primary language you speak at home?

- English
- Spanish
- Arabic
- Chinese
- Farsi
- German
- Hebrew
- Hindi
- Japanese
- Korean
- Vietnamese
- Other (Please specify) ____________________

Q25 Please mark the income range that best describes your annual household income from all sources. This is before taxes and other deductions.

- $0-$14,999
- $15,000-$34,999

- $35,000-$49,999
- $50,000-$74,999
- $75,000-$99,999
- $100,000-$149,999
- $150,000-$249,999
- $250,000+

Q26 Did you have enough time to evacuate? Why or why not?

____

Q27 How did you find out about this survey?

- Facebook
- Twitter
- Reddit
- Other (please specify) ____

Q28 Is there anything else you would like to share?

____

Appendix B

INSTITUTIONAL REVIEW BOARD APPROVAL LETTER

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	October 17, 2018
TO:	Rachel Davidson, PhD
FROM:	University of Delaware IRB
STUDY TITLE:	[1323864-2] Decision-making and evacuation for [insert name of disaster]
SUBMISSION TYPE:	Amendment/Modification
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	October 17, 2018
REVIEW CATEGORY:	Exemption category 2

Thank you for your submission of Amendment/Modification materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Maria Palazuelos at (302) 831-8619 or mariapj@udel.edu. Please include your study title and reference number in all correspondence with this office.