WHY ARE PEOPLE EVACUATING?

A QUASI-PANEL ANALYSIS

by

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(Under the Direction of Craig Landry)

ABSTRACT

Hurricane evacuation and the factors that play into why any given individual might choose to not evacuate is an area of coastal household evaluation that needs more research. This study sets out to help answer the question of what factors have a positive or negative effect on evacuation behavior or people living in the United States coastal southeast. Using three variations of a probit model, we found waterfront property, higher rates of expected damage from storms, more severe hurricanes (category 4 relative to category 3), increased number of children, and being male to have a positive effect on evacuation, and previous experience with storm damage and less severe hurricane (category 2 relative to category 3) to have a negative effect on evacuation.

INDEX WORDS: evacuation, quasi-panel data, demographic indicators

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# CHAPTER 1

# INTRODUCTION

If hurricanes are so dangerous, why do people often not evacuate? What factors influence their evacuation behavior? Previous research has found numerous factors that influence evacuation behavior. These include factors like sociodemographic attributes, storm characteristics, and the location of residents. Even though these results have been replicated several times in different locations, most of the surveys are cross-sectional. A cross-sectional survey is a type of observational research that analyzes data across a sample at a specific point in time. Since the data are cross-sectional, analysts have limited methods to address underlying agent heterogeneity. A panel dataset provides support for models that account for this underlying heterogeneity. In the research, a quasi-panel dataset was used to run probit regressions on evacuation intentions using the survey data that includes repeated observations on 483 respondents. Repeated observations allow us to control for unobserved heterogeneity; our survey design also permits the exploration of framing effects on storm intensity. The framing effect is the tendency for people to make distinctive decisions based on the way choices are framed (Tversky & Kahneman, 1981).

# CHAPTER 2

# BACKGROUND

Historically, hurricanes are the costliest natural disasters in terms of money, material, and lives (Halim, et al. 2021, Metaxa-Kakavouli, et al. 2018, Sobanjo, et al. 2013, Gong, J., and A. Maher 2014, and Snaiki, R., et al. 2020). Of the top ten costliest natural disasters since 1980, seven of them are hurricanes (STATISTA 2020). The 1900 Galveston Hurricane was responsible for the death of 8,000 people (Bullard 2008). In 2004, Hurricane Ivan, which was the third costliest disaster in the United States, inflicted $14.2 billion (about $44 per person in the US) in damages and 92 deaths (Franklin et al. 2006). In 2005, one of the costliest hurricanes, Katrina, hit the United States, having a direct impact on New Orleans and south Louisiana with an estimated cost of 151 billion dollars (about $460 per person in the US) in damages and 1833 deaths (Smith et al. 2014). In 2021, Tropical Storms Elsa, Fred, and Ida, and Hurricane Nicholas caused billions of dollars in damage. Tropical Storm Ida had estimated damages totaling 75 billion dollars (about $230 per person in the US), which is the fifth costliest hurricane since 1980 and the most expensive disaster of 2021 (NOAA 2021).

Along the Atlantic Ocean, the higher frequency and intensity of hurricanes coupled with increased population density along the United States coast may cause even greater potential life loss and economic damages (Bowser, G. C., and Cutter, S. L. 2015). In 2019, the Congressional Budget Office predicted $54 billion for hurricane damages which fell short of the 2020 damages of $60-$65 billion (Cegan, J. C., et al. 2022, Congressional Budget Office 2019, and Puleo, M 2021).

The 2021 hurricane season was the third most active year for named storms, and it marks the sixth consecutive year where there was an above-normal Atlantic hurricane season. Additionally, 2020 to 2021 was the first time on record that two consecutive hurricane seasons exhausted the list of 21 storm names. Six storms reached category 5 strength (>157 mph) which is slightly above normal (NOAA 2021). This increase in the frequency and severity of hurricanes has detrimental effects on the economy and people's well-being. Scientists attribute the increased hurricane activity in recent years to the warm phase of the Atlantic Multidecadal Oscillation. It is thought that the Atlantic Multidecadal Oscillation is driven by climate variations over time (NOAA 2021). With the progression of climate change, it is predicted to affect the Atlantic Multidecadal Oscillation which leads to more frequent and more intense hurricanes in the future. It may also move hurricane activity farther inland to communities that have not historically faced hurricanes.

Evacuation is a major way to reduce potential human harm and fatality in the case of hurricanes (Wilmot, C. G., and N. Meduri 2005, Ballard 2007, Mozumder, and Vásquez 2015,2018, Metaxa-Kakavouli, D., et al. 2018, and Meyer, M. A., et al. 2018). In 1960, 47 million lived in coastal counties. (Bureau, U. S. C. 2021). Today 29 percent U.S. population, or 87 million people, live in counties on the coast. Among coastlines, 41 million people are on the Atlantic, 32 million on the Pacific, and 14 million on the Gulf of Mexico. With increased hurricane activity and larger coastal populations, it is increasingly important to understand evacuation behaviors, because it could help prevent deaths from storms.

# CHAPTER 3

## LITERATURE REVIEW

Research has been conducted to study the hurricane evacuation decisions of people in the United States and what may influence evacuation decisions. These studies focus on different coastal parts of the United States and have produced varying results. The surveys tend to focus on two regions of the United States.  Mid-Atlantic/ Northeastern coastal states consisting of New Jersey, New York, Connecticut, Maryland, Massachusetts, Virginia, West Virginia, Delaware, Pennsylvania, and Rhode Island, and the states bordering the Gulf of Mexico including Texas, Louisiana, Alabama, Mississippi, and Florida (Halim, N., 2021, Vásquez, W. F., et al. 2016, and Mozumder, P., and Vásquez, W. F. 2018).

Geographic location plays a key role in evacuation decision-making. Living in a flood zone has been shown to have a positive effect on the likelihood of an individual evacuating (Daniel, S., et al. 2010, Vásquez, W. F., et al. 2016, and Jiang, F., et al. 2021). Both living in a mobile home (Daniel, S., et al. 2010, Tanim, S. H., et al. 2022, Huang, S. K., et al. 2016, Baker, E.J. 1991, Samiul Hasan et al. 2011, Morss, R.E., et al. 2016, Meyer, M. A., et al. 2018, and Whitehead et al. 2000) and living in a coast area (Lindell et al. 2005, Huang, S. K., et al. 2012, Meyer, M. A., et al. 2018, and Mongold, E., et al. 2021) have also been shown to increase the probability of evacuation.  In some cases, the longer someone has lived in an area, the less likely they are to evacuate (Lazo, J. K., et al. 2010, Daniel, S., et al. 2010, Huang et al. 2016, Morss, R.E., et al. 2016). However, others found it to be insignificant (Petrolia, D. R., et al. 2013, Huang, S. K., et al. 2016, Samiul Hasan et al. 2011, and Lindell M.K., et al 2005). Finally, hazard proximity can play a role. When one is closer to a hazard, such as a hazardous agent or risky area, they are often more aware of their surroundings. In many cases, individuals located near risky areas are positively correlated with evacuation (Huang et al. 2016 and Meyer, M. A., et al. 2018).

Storm characteristics are also an indicator of hurricane evacuation behavior. Storms predicted to have higher wind damage have higher evacuation rates. (Tanim, S. H. et al. 2022 Lazo, J. K., et al. 2015). Literature also indicates that increases in potential flood damage also increase the likelihood of evacuation (E.J. Baker 1991, Lazo, J. K., et al. 2010, Tanim, S. H., et al. 2022). Wind damage and flooding contribute to the overall risk perception of a storm which has been correlated to evacuation behavior as well (Burnside, 2006 and Horney et al., 2010). The size of the storm surge has also been shown to have an influence on evacuation behavior. Often the greater the storm surge the more likely people will leave (Tanim, S. H., et al. 2022 and Mozumder, P., & Vásquez, W. F. 2018). Some of the strongest indicators of evacuation decisions are the severity of a storm and the perceived danger of the storm. (Lazo et al., 2010; Smith & McCarty, 2009). Unsurprisingly, individuals or households that face a storm Category 3 and above on the Saffir-Simpson Hurricane Wind Scale display a higher probability of evacuation compared to less severe storms like Category 1 or 2 (Daniel, S., l. 2010, Whitehead J. Edwards B, et al. 2000, Huang, S. K., et al. 2016, Morrow B. and Gladwin H. 2006, and DeYoung, et al., 2016).

Having previous experience with a hurricane can be a main determinant of evacuation (Dow and Cutter 2000, Daniel, S., et al. 2010, Dash 2002, Lindell et al. 2011). In many cases, prior experience with a hurricane increases evacuation likelihood; this is due to previous evacuation being deemed necessary and successful, or because individuals do not evacuate and regret it. On the other hand, there are cases where individuals did not evacuate, and the impending hurricane missed them, or its impact was less severe than predicted, which leads them to believe not evacuating was the right decision and thus decreasing their desire to evacuate for future hurricanes (Lazo, J. K., et al. 2010). In a similar fashion, previous evacuation decisions are correlated with intentions for the future (Meyer, M. A., et.al. 2018).

Actions by authority figures such as the government, friends, or family have been found to have an influence on evacuation behavior. Attributes associated with forecasting, warning, and evacuation orders for hurricanes performed by the government have been shown to affect individuals' decisions to leave. Government warnings and evacuation orders have been shown to be effective in increasing the likelihood of people leaving before a hurricane (Huang, S. K., et al. 2016, Tanim, S. H., et al. 2022,). If people do not think the forecast is accurate, however, the probability of evacuation decreases (Lazo, J. K., et al. 2015). People are more likely to evacuate when the evacuation order is mandatory (as opposed to voluntary) (Tanim, S. H., et al. 2022, Meyer, M. A.,2018, Mozumder, P., & Vásquez, W. F. 2018, and Whitehead J. Edwards B, et al. 2000).

Friends and family also influence evacuation decisions; social networks, information transfer, and the role of norms can play a role in evacuation behavior. The location of these people also plays a role because if they are located outside the evacuation zone it provides an opportunity for shelter if one decided to evacuate, while if all of one’s network is concentrated in the hurricane-prone area, they may be less inclined to evacuate because they want to help, protect, or be close to their network. (E.J. Baker 1991, Lindell M et al. 2005, Lazo, J. K., et al. 2010, Morss RE, et al. 2010, Bateman, J. M., & Edwards, B. (2002), Stein, R. M., et al. 2010)

When it comes to sociodemographic/household factors, gender, income, age, number of children, and pet ownership have been shown to have a significant effect on evacuation behavior. In some cases, larger household sizes have been shown to be negatively related to evacuation. (Huang, S. K., et al. 2016 and Metaxa-Kakavouli, D., et al. 2018, Gladwin and Peacock (1997), Dash and Gladwin 2007). In some analyses, however, family size did not have a significant effect (Solís, D., et al. 2010). When people have children, it increases the probability of evacuation (Gladwin and Peacock 1997, Dash and Gladwin 2007, Lindell et al. 2005, Daniel, S., et al. 2010, Stein et al., 2010; Van Willigen et al., 2005, Tanim, S. H., et al 2022). It is estimated that one additional child in the household increases the probability of evacuating by approximately 4% (Daniel, S., et al. 2010). On the opposite end, many studies found that the presence of elderly is negatively correlated with evacuation (Gladwin et al. 2001, Stein et al., 2010; Van Willigen et al., 2005, Tanim, S. H., et al 2022). This could be caused by the fact that the elderly often need assistance evacuating and may not be willing to leave the place they have been for a while. This means that increased age is negatively correlated to evacuation.

Income has shown mixed results in the literature; studies have found that evacuation likelihood increases with income, (Bateman JM and Edwards B. 2002, Peacock W. et al. 2011) decreases with income, (Trumbo C. et al. 2014) or is insensitive to income. (Whitehead J. et al. 2000, Huang S. et al. 2012, Smith S and McCarty C. 2009, Burnside R. 2006, Smith K. 1999). It is often assumed that people with more income would be more likely to evacuate because they have the funds to so, but the contradictory result could be explained by the fact that people with larger incomes on average own more capital goods so they may prefer to stay in their house to protect their belongings from post-storm looting (Daniel, S., et al. 2010). Another explanation could be that high-income families live in bigger or safer houses, giving them a sense of security (Daniel, S., et al. 2010). It has been found that income was negatively correlated with evacuation intentions for Category 1–2 storms with no accompanying instructions or recommended evacuation, but income was found to be positively correlated with evacuation from Hurricane Katrina (a stronger storm with mandatory evacuation orders for many parts of Louisiana).

Pet ownership is negatively correlated with evacuation because people do not want to abandon their pets and are frequently concerned about accommodations for pets at evacuee receiving locations (Vásquez, W. F., et al 2016, Tanim, S. H., et al 2022). Some studies have found that race is associated with evacuation choice (Dash and Gladwin 2007, Bateman and Edwards 2002, Whitehead et al. 2000, and Smith 1999), and others have found no association (Dow and Cutter 1998, Baker 1991, Huang S. et al 2012, Bateman and Edwards 2002, Horney J. et al 2011, and Stein R. et al 2010). Huang et al. (2016) found that being non-Hispanic black has negative effects on evacuation likelihood, and a few studies have found that white and/or Latino individuals were more likely to evacuate (Whitehead J. Edwards B, et al. 2000, Whitehead J.C. 2005). Finally, household ownership is shown to be negatively correlated with evacuation decisions (Hasan et al., 2012; Smith & McCarty, 2009, Tanim, S. H., 2022). The longer somebody has lived in an area the less likely they will evacuate (Dash and Gladwin 2007 Lazo, J. K., et al. 2010, Tanim, S. H., et al 2022, Morss R.E. et al 2016).

# CHAPTER 4

## SURVEY

In 2014, a dual method/ mixed model survey was conducted in Mobile Bay, Alabama, and Pensacola Bay, Florida on 583 coastal residents. Out of the 583 coastal residents, 400 were inland and 183 were on the waterfront. Qualtrics was used to gain the sample of 400 inland residents. The panel sample was proportioned to the public and randomized before the survey was deployed (Qualtrics 2014). The waterfront properties were randomly selected using Google Earth Pro and county tax assessor websites. If the property was listed or sold within the previous year the property was excluded. The waterfront property participants were recruited for the survey using a modified Dillman method (Dillman, 2011). Participants were mailed postcards and then sent follow-up reminder postcards. Twenty percent of online participants were mailed the survey and provided to individuals upon request. The online survey was hosted and administered using Qualtrics Research Suite. The survey had an adjusted response rate of 21%, a mean completion rate of 83%, and a mean completion time of 20 minutes for the online version.

The survey consisted of 67 questions and was given to coastal residents. The survey included questions on social/psychological constructs; ecological beliefs and concerns; and flooding and storm experiences. To assess hazard perceptions and behavior, the survey systematically varied hurricane severity, with one group shown a Category 2 storm scenario followed by a Category 3 scenario, whereas the other group was shown a Category 3 storm scenario followed by a Category 4 scenario. For each scenario, subjects we asked to assess the likelihood (relative frequency) and consequences (expected monetary damage) associated with the storm and their evacuation intentions. The latter was multiple choice: 1) My entire household would evacuate, 2) My entire household would remain home and not evacuate, or 3) Part of part household would evacuate while others would remain home, (with a follow-up "Please indicate how many people would stay"). The survey also collected data on socio-demographic characteristics on gender, age, annual household income, education, environmental dependence, years at current residence, and years lived on coastal waters.

Table 1- Variable Descriptions

| **Variable** | **Description** |
|---|---|
| Baldwin | currently live in Baldwin County, AL: Yes-1, No-0 |
| Mobile | currently live in Mobile County, AL: Yes-1, No-0 |
| Escambia | currently live in Escambia County, FL: Yes-1, No-0 |
| Santa Rosa | currently live in Santa Rosa County, FL: Yes-1, No-0 |
| Inc | Total household income (coded at mid-point; top-coded via Pareto Distribution) |
| Age | Age of participant |
| White | Race or ethnicity is white: Yes-1, No-0 |
| h_edu | completed a form of higher education (bachelors, masters, PHD): Yes-1, No-0 |
| Male | Identify as male: Yes-1, No-0 |
| SFH | current home is a single-family home: Yes-1, No-0 |
| Waterfront | term waterfront apply to your home: Yes-1, No-0 |
| Cat23 | the participant given the evacuation scenario of Category 2 and Category 3 |
| Hh_num | Number of people that lived in your household in 2013 including dependents |
| Cat2 | indicators for those Category 2 strength |
| Cat3 | indicators for those Category 3 strength |
| Cat4 | indicators for those Category 4 strength |
| Exp_dam | percentage of home value expected to be damaged under various hurricane strengths |
| Evacuate | contingent behavior evacuation indicator |
| Storm_exp | dummy variable indicating previous experience with storm damage |
| Children | Number of children under the age of 18 |

Table 2: Descriptive Statistic Table

| *Variable* | *Observations* | *Mean* | *Std. dev.* | *Min* | *Max* |
|---|---|---|---|---|---|
| *Male (y/n)* | 1,156 | .462 | .499 | 0 | 1 |
| *Baldwin (y/n)* | 1,166 | .293 | .455 | 0 | 1 |
| *Mobile (y/n)* | 1,166 | .201 | .401 | 0 | 1 |
| *Escambia (y/n)* | 1,166 | .274 | .446 | 0 | 1 |
| *Santa Rosa (y/n)* | 1,166 | .230 | .421 | 0 | 1 |
| *Income* | 1,152 | 109.057 | 226.467 | 19.604 | 499 |
| *Age* | 1,094 | 52.687 | 17.406 | 18 | 94 |
| *White (y/n)* | 1,166 | .879 | .325 | 0 | 1 |
| *Higher education* | 1,166 | .549 | .498 | 0 | 1 |
| *Single family home* | 1,166 | .792 | .406 | 0 | 1 |
| *Waterfront* | 1,166 | .310 | .463 | 0 | 1 |
| *Cat23* | 1,166 | .449 | .498 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| *Household number* | 1,148 | 2.580 | 1.586 | 1 | 20 |
| *Cat2* | 1,166 | .225 | .418 | 0 | 1 |
| *Cat4* | 1,166 | .238 | .426 | 0 | 1 |
| *Percentage of home value expected to be damaged* | 1,012 | 42.864 | 26.187 | 0 | 100 |
| *Previous experience with storm damage* | 1,166 | .798 | .402 | 0 | 1 |
| *Children* | 1,110 | .431 | .828 | 0 | 4 |

Information on household characteristics is presented in Table 2. In the data, 88% of the respondents are white and 46% male. According to the 2020 U.S. Census, 75% of the population are percent white and 49.5% male. The average household size is 2.58 which is comparable to the U.S. average of 2.6 (US Census Bureau 2021). In our sample, education with a bachelor's degree or greater educational attainment mean was 54.9% while the U.S. is 33.7% (US Census 2020). The median income in the U.S. is 69,021 ours is 62,500 (the mean is 109,000). Our sample is more white and more educated than the U.S. population on average.

# CHAPTER 5

## CONCEPTUAL FRAMEWORK

According to microeconomic theory, in the face of uncertainty and risk a person will make a decision that provides the greatest expected outcome, but describing that expectation depends on the underlying model formulation. Human behavior under environmental risks, such as hurricanes and tropical storm landings, may hinge on this principle where people make decisions for environmental risks based on maximizing some version of expected utilities, including the disutility of costs (Lazo et al., 2010, Burton et al. 1993, and Viscusi 1995). In practice, this can look like sacrificing wealth to reduce environmental threats. From an empirical standpoint, individuals, or households subject to the risk of a hurricane strike face a dichotomous decision: to stay at home or evacuate to a safer area. The way in which the individual derives utility can be tied to many decision attributes. A combination and weighting of these attributes is presumably what ultimately causes the decision to leave or not. Based on previous literature, we expect the framing effect to be significant in determining evacuation decisions.

The framing effect is the tendency for people to make distinctive decisions based on the way choices are framed (Tversky & Kahneman, 1981). The choices are logically equivalent, but the key attribute affecting responses concerns the phenomenon of the frame is positive or negative Linville et al., 1993). This may be a result of “risky choice framing (i.e., how framing options with different levels of risk influences one’s risk preference)” or “attribute framing (i.e., how framing a characteristic of an object or event may influence one’s overall evaluation of the item)”

(Hasselldine and Hite, 2003; Levin and Gaeth, 1988). In our study, positive framing occurs when a participant is shown scenario category 3 and 4 because it may cause category 3 to seem less severe and dangerous. The negative framing occurs when a participant is shown scenario categories 2 and 3 because it frames the category 3 hurricane as riskier. In both cases, we are looking at respondents' answers to category 3.

We predict the negative framing would increase the probability of evacuation of category 3 hurricanes. In the literature, the current research found negative outcome framing was more effective than a positive framed outcome in affecting general attitudes towards their own earthquake preparation; the negatively framed outcome led to higher judgments of risk, intentions to prepare, and the importance of earthquake preparation (McClure et al. 2009). We predict this to be the same phenomenon with hurricanes. It has important implications for disaster agencies aiming to promote preparedness and is likely to apply to other domains where agencies wish to increase actions that reduce risk.

# CHAPTER 6

# METHODS

We focus our attention on the evacuation intentions of respondents in our study counties. While we only have a single cross-section of data, we have multiple evacuation responses (and risk perception measures) associated with different levels of hurricane strength, which provides a quasi-panel of respondent data accounting for unobserved heterogeneity, which could help better identify preferences for evacuation decisions (Landry and Lui 2009). It is a quasi-panel, and not a true panel, because previous values of variables were not directly measured at time t – 1 (Cao et al. 2007).

The quasi-panel dataset was created by stacking contingent behavior responses to storm strike scenarios: "Suppose that a Category 2 hurricane was projected to directly impact your community, would your household evacuate to a safer place or stay home?" The Cat23 version followed up questions about Category 2 Hurricanes (subjective likelihood, expected damage, evacuation intentions) with a similar set of questions about Category 3, while the Cat34 version started with Category 3, then focused on Category 4. All the participants were asked whether they would evacuate the Category 3 hurricane, so the constant/base response and additional responses for Category 2 or 4 varied systematically with treatment.

Once the panel data was created, a random-effects probit model was used. A probit model was used because the outcome of interest is a binary response, evacuate or not evacuate. The random effects model is used to estimate the effect of individual-specific characteristics inherently unmeasurable. It was chosen for this model because unobserved individual-specific characteristics that are unmeasurable causing evacuation is of interest in the regression.

The Random Effects Probit Model is given by:

$$y_{it}^{*} = x_{it}'\beta + \alpha_i + u_{it} \tag{1}$$

where $y_{it}^{*}$ is the latent dependent variable ($i = 1, \ldots, N$ ; $t = 1, 2$), $x_{it}$ is a vector of exogenous explanatory variables, $\alpha_i$ are (unobserved) individual-specific random effects, and the $u_{it}$ are assumed to be distributed N(0, $\sigma^2$). The observed binary outcome variable is defined as:

$$y_{it} = \begin{cases} 1 \; if \; y_{it}^{*} \geq 0 \\ 0 \; otherwise \end{cases} \tag{2}$$

The binary outcome being evacuating (1) or not evacuating (0). When we analyze the data as a cross section, we cannot identify $\alpha_i$, so we specify $v_{it} = \alpha_i + u_{it}$. For quasi-panel data, the individual-specific random effects specification adopted implies equi-correlation between the $u_{it}$ across the panel dimension:

$$\lambda = corr(u_{i1}, u_{i2}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2} \tag{3}$$

The random effects probit model assumes that $u_{it}$ is normally distributed:

$$= \Pr\left[y_{ig} = 1 \middle| \alpha_g, x_{ig}\right] = \Omega(x_{ig}'\beta + \alpha_g) \tag{4}$$

where Ω is the normal cumulative density function. The joint density is derived by integrating the unknown $\alpha_g$ out of the c.d.f., and the likelihood function is created by taking a natural logarithm. We specify two versions of the random effects model, one with robust (sandwich) standard errors and the other with standard errors clustered at the county level. In addition, we present a population-average model.

Population average models typically use a generalized estimating equation (GEE) approach. The GEE describes changes in the population mean given changes in covariates. At the same time, it accounts for within-county nonindependence of observations when deriving the variability estimates of these coefficients. The GEE approach does not require distributional assumptions because the estimation of the population-average model depends only on correctly specifying a few aspects of the observed data-generating distribution (Hubbard et al., 2010).

# CHAPTER 7

# RESULTS

Table 3 presents three-panel probit regressions with the same independent and dependent variables with slight variations. Each model takes a different approach to address the model not being independently and identically distributed. Model one is a random effects model that clusters the standard errors at the county level. The second model uses the robust sandwich estimator approach, and finally, the third model uses the population average model. Each model produces similar significant results. However, model one is the best-fitting model (based on information criteria).

The average marginal effects for model one was calculated to determine the variables' influence. The average marginal effects (AME) were calculated to assess the effect each variable contributes. The average marginal effects show the average change in probability when x increases by one unit with x being the independent variable. The effect of x on the probability of evacuation.

Several variables were found to have a positive and significant effect on evacuation intentions. A household that expected a higher percentage of home value to be damaged under a hurricane was more likely to evacuate. As indicated by the marginal effects, households with higher perceived home damage were 4.9% more likely to evacuate. However, people who have previous experience with storm damage are less likely to evacuate. The marginal effects signify if a participant has previous experience with storm damage, there is a 13% decrease in the probability of evacuation.

Demographic factors such as the number of children and gender are shown to be significant in increasing the probability of leaving. With each additional child, the marginal effects show that evacuation probability increases by 4.2%. When the participants identified as male, the evacuation likelihood increases by 8.9%. A household that occupies waterfront property has an increased evacuation probability of 21%.

The marginal effects indicate that participants given the scenario of a category 2 hurricane are 16% less likely to evacuate compared to a category 3 hurricane. On the other hand, a more severe storm, a category 4 hurricane, increases the probability of leaving by 9.4% compared to a category 3 hurricane. It should be noted that respondents were only shown either the category 2 or category 4 hurricane in comparison to the category 3 hurricane. No respondents were shown both 2 and 4. Participants that were given the category 3 and 2 scenarios were found to significantly decrease the probability of evacuation by 29.7%. This reflects the average difference in risk across treatments not a reflection of evacuation behavior.

The county variables, Mobile, Baldwin, and Escambia, are significant in the model (this differs from models 2 and 3). Santa Rosa County is the baseline county meaning that participants that live in Escambia are more likely to evacuate at a rate of 2.1% (marginal effects). People living in Mobile and Baldwin County have a lower probability of evacuation than people living in Santa Rosa. Indicated by marginal effects, the probability of people evacuating in Mobile is 4.6% lower than Santa Rosa and Baldwin is 1.5%. However, these are less relevant because it only controls for unobserved differences across space.

Table 3: Panel Data Evacuation Likelihood Regressions

| | *Std.err. clustered at County Level* | | *sandwich estimator* | | *population average* | |
|---|---|---|---|---|---|---|
| | Evacuate | | Evacuate | | Evacuate | |
| *Main* | | | | | | |
| *exp_dam* | 0.0543*** | -0.0089 | 0.0543*** | -0.012 | 0.0171*** | -0.0025 |
| *cat2* | -1.7868*** | -0.2646 | -1.7868*** | -0.3678 | -0.5780*** | -0.0936 |
| *cat4* | 1.0539*** | -0.1317 | 1.0539*** | -0.3433 | 0.3127*** | -0.1004 |
| *Inc* | -0.0015 | -0.002 | -0.0015 | -0.0011 | -0.0005** | -0.0002 |
| *Waterfront* | 2.4516** | -1.0992 | 2.4516*** | -0.664 | 0.7982*** | -0.1509 |
| *storm_exp* | -1.4360*** | -0.3681 | -1.4360** | -0.5742 | -0.4654*** | -0.1643 |
| *Male* | 0.9935* | -0.517 | 0.9935** | -0.4152 | 0.3049** | -0.13 |
| *White* | -0.3091 | -0.8105 | -0.3091 | -0.6167 | -0.0749 | -0.2096 |
| *h_edu* | 0.1065 | -0.6376 | 0.1065 | -0.3786 | 0.0422 | -0.125 |
| *Hh_num* | -0.0058 | -0.1978 | -0.0058 | -0.1381 | -0.0096 | -0.0441 |
| *Children* | 0.4793** | -0.215 | 0.4793 | -0.2946 | 0.1593* | -0.0938 |
| *Age* | -0.0012 | -0.0161 | -0.0012 | -0.014 | -0.0003 | -0.0047 |
| *Sfh* | -0.4299 | -0.7566 | -0.4299 | -0.5186 | -0.1599 | -0.1646 |
| *Mobile* | -0.5123*** | -0.1249 | -0.5123 | -0.5734 | -0.1669 | -0.1827 |
| *Baldwin* | -0.1724*** | -0.0455 | -0.1724 | -0.5326 | -0.0471 | -0.1767 |
| *Escambia* | 0.2398* | -0.1454 | 0.2398 | -0.5242 | 0.0894 | -0.1726 |
| *cat23* | -0.9409*** | -0.3638 | -0.9409** | -0.4758 | -0.2966** | -0.131 |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Constant* | 0.5261 | -1.5413 | 0.5261 | -1.2341 | 0.184 | -0.399 |
| *lnsig2u* | 2.1904*** | -0.348 | 2.1904*** | -0.3847 | | |
| *Observations* | 891 | | 891 | | 891 | |
| | *p<.10 | | ** p<0.05 | | ***p<0.01 | |

Table 4: Average Marginal Effects of Random Probit Model with Standards Errors Clustered at the County Level

| *Variable* | *dy/dx* | *Std. err.* | *P > \|z\|* |
|---|---|---|---|
| *Exp_dam* | .0048633 | .0002695 | 0.000 |
| *cat2* | -.1600901 | .0138754 | 0.000 |
| *cat4* | .0944249 | .0094515 | 0.000 |
| *Inc* | -.0001317 | .0001621 | 0.416 |
| *waterfront* | .2196569 | .0618519 | 0.000 |
| *Storm_exp* | -.1286632 | .0182276 | 0.000 |
| *Male* | .0890187 | .0467562 | 0.057 |
| *White* | -.0276947 | .0709065 | 0.696 |
| *H_edu* | .009546 | .058335 | 0.870 |
| *Hh_num* | -.0005185 | .0178002 | 0.977 |
| *children* | .0429402 | .0219344 | 0.050 |
| *Age* | -.0001109 | .001454 | 0.939 |

| | | | |
|---|---|---|---|
| *Sfh* | -.0385149 | .0622192 | 0.536 |
| *Mobile* | -.0459011 | .007504 | 0.000 |
| *Baldwin* | -.015448 | .0032998 | 0.000 |
| *escambia* | .0214893 | .0124649 | 0.085 |
| *cat23* | -.0842979 | .025335 | 0.001 |

# CHAPTER 8

# DISCUSSION

Determining attributes that influence or are attributed to higher rates of evacuation is important to know because evacuation is the main way to reduce injuries, deaths, and costs in the face of hurricanes. The research found several factors that contribute to evacuation decision-making.

The attributes associated with location play a factor in evacuation decisions. The literature finds people who live on the coast have a higher probability of evacuating compared to inland residents meaning the closer to the water the higher rates of evacuation (Lindell et al. 2005, Huang, S. K., et al. 2012, Meyer, M. A., et al. 2018, and Mongold, E., et al. 2021). Our research finds a similar conclusion by having an increased probability of evacuation due to a property being on the waterfront. A possible reason behind the higher probability of evacuation due to properties closer to the water is a resident is closer to the water a hurricane poses a larger risk. A home directly on the water gets the full impact of the storm which brings higher rates of danger.

Storm characteristics and how they are perceived play a significant role in determining whether to stay or go as well. The ranking of hurricanes on the Saffir-Simpson Hurricane Wind Scale has been shown in our research and previous literature to affect evacuation intentions. In our regression, a participant facing a scenario of a category 4 hurricane (compared to a category

3) has an increased probability of evacuation. On the other hand, a participant asked about evacuating Category 2 decreased the probability of evacuation (compared to Category 3). These findings align with previous research that has found that the more severe the hurricane the higher probability of evacuation. This is intuitive because the more severe a storm the more risk it poses which is the underlying force behind evacuation. (Daniel, S., l. 2010, Whitehead J. Edwards B, et al. 2000, Huang, S. K., et al. 2016, Morrow B. and Gladwin H. 2006, and DeYoung, et al., 2016). Another aspect of a storm is the damage it can do. Our data indicates people who had previous experience with storm damage are less likely to evacuate during a hurricane. This could be due to multiple reasons. One case could be where individuals did not evacuate, and the impending hurricane missed them, or its impact was less severe than predicted leading them to believe not evacuating was the right decision and thus decreasing their desire to evacuate for future hurricanes as found in Lazo, J. K., et al. 2010. The amount of storm damage a person perceives also plays a crucial role in decision making. Our research finds participants who expected a larger percentage of home value damaged under various hurricane strengths have higher probabilities of evacuation. Similarly, the literature finds when people predict more damages the increases probability of evacuation (Lazo et al., 2010; Smith & McCarty, 2009). People who perceived more damage also perceive more risk to themselves which prompts them to evacuate. However, this variable may have the potential for endogeneity. With the quasi-panel specification, we do not rule out that risk perceptions can be correlated with unobserved random effects.

Several socioeconomic factors affect one's decision to evacuate. In the analysis, the number of children increases the probability of evacuation. The reasoning is that residents with children are likely to perceive higher risks (Karaye, et al., 2019). In our regression people who identify as male increased the probability of evacuation. This is different than most of the literature that finds women tend to evacuate more (Huang et al., 2016). However, this could be because the survey asks about household evacuation whereas many surveys focus on individual behavior. Since the decision-making is based on the individual's household, men may perceive heightened risk. In this case, men are more likely to evacuate than women with comparable risk exposure and perception (Bateman and Edwards 2002).

It was hypothesized that the framing effect may have influenced the decision to evacuate a category 3 hurricane. The framing effect is the tendency for people to make varying decisions based on the way choices are framed (Tversky & Kahneman, 1981). Hurricane strength is an indicator of destructive force and risk of death and thus should influence evacuation decisions. In assessing behavioral intentions, however, survey respondents sometimes are not able to fully comprehend the magnitude and complexity of the decision environment and may thus rely on simplified heuristics that can be prone to error (introducing potential bias into their responses). (Hensher et al. 2015 and Penn & Hu 2018). Within the survey, half of the participants were asked about evacuating Category 2 whereas the other half were asked about Category 4, because of this the category the participant saw could affect how they answer the Category 3 evacuations. To test this a non-panel probit analysis was performed. The framing effect was not significant. We construe this as evidence of internal validity, which bolsters confidence in the accuracy of our contingent behavior data.

Evacuation is an important strategy to reduce the adverse effects of hurricane damage. Our findings add to the body of literature on determinants of evacuation decision-making. By determining attributes, policymakers can help and encourage these households to develop an evacuation plan. The significant factors can act as a baseline to develop hurricane education and risk communication efforts. Even with this policy applicability, more research can be done to gain more detailed information on risk perception and action taken due to risk.

Since our model evaluated hurricane evacuation at the household level where evacuation is defined as at least one person evacuated in the house, our research could look more in-depth at the household. A multinomial model with 3 choices; no evacuate, partial, full household, could be run. For future research where cases of partial evacuation occur, information on the details of who evacuates and who does not would be interesting.

Risk plays a crucial role in evacuation decisions. Risk is a factor that is difficult to observe and can create variations. Attributes that can demonstrate people's risk such as insurance and reinforcing a home to withstand storms are interesting because they demonstrate risk adaptations and can contribute to policy. However, endogeneity poses a threat to these variables, so they need to be addressed. Risk perception is a determinant that underlies all decision making but how to quantify it in hurricane research has not been done. Testing for risk preferences can be performed. Further research with this variable may be able to explain somewhat of the unexplained model.

Previous experience with storm damage was found to be significant. Storm damage is one of the main risks associated with hurricanes so further investigation into why it would decrease the probability of evacuation could be insightful. It is hypothesized that this is due to previous hurricane experience which is not addressed in the survey. Future research assessing previous hurricane experience. A limitation in our study is the hypothetical nature of the storm (revealed versus stated preference).

# CHAPTER 9

# CONCLUSION

Hurricanes and the dangers associated with them are an inevitable occurrence for people living on or near the coast. Evacuation is the most reliable method of avoiding the physical harm hurricanes and tropical storms, and thus discovering the reasons behind why people may choose not to evacuate a hurricane is an especially important matter of public safety, natural disaster preparation, and public policy. This study has served to further our scientific understanding of hurricane evacuation and the factors affecting evacuation likelihood.

This study finds residents with waterfront property, higher rates of expected damage from storms, more several categories (category 4), increased number of children, and being male increased evacuation likelihood. It was also found that previous experience with storm damage and less severe hurricane (category 2) decreased evacuation likelihood. With this information policy can focus on groups or attributes that are associated with low evacuation and help create and encourage plans for evacuation. Follow-up research on previous experience, risk preference, and individual behaviors can provide more detailed information and further explain evacuation behavior.

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