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Three Essays Of Assessing The Risk, Adaptation And Resilience To Natural Disasters

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THREE ESSAYS OF ASSESSING THE RISK, ADAPTATION AND RESILIENCE TO NATURAL DISASTERS

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To: Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

This dissertation, written by Mohammad Asif Hasan Khan, and entitled Three Essays of Assessing the Risk, Adaptation and Resilience to Natural Disasters, having been approved in respect to style and intellectual content, is referred to you for judgement.

We have read this dissertation and recommend that it be approved.

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Florida International University, 2020

DEDICATION

This dissertation is dedicated to my parents, my lovely wife, and my entire family for their endless love, support, and encouragement.

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ABSTRACT OF THE DISSERTATION

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Professor Pallab Mozumder, Major Professor

This dissertation consists of three chapters in environmental and natural resource economics. In the first chapter, using survey data, I investigate what factors are important in people's evacuation decisions in the coastal areas of Bangladesh. I examine if temporal spillover is present in their decision making and how significant the spillover effect is. With that objective in mind, I examine the effect of previous evacuation experience on future evacuation decision. I also analyze how network effects influence people's evacuation decisions during a natural disaster.

As the threat of climate change grows, communities around the world are facing the dangers of encountering different kinds of natural hazards with higher frequency and intensity. When people are dealing with multiple hazards, exposure to one hazard can trigger or change their risk perception about the other hazard. In the second chapter, I use data from Lake County in Florida to analyze spillover effects in terms of multiple hazards. I examine if people are exposed to one type of natural hazard, whether their concern for

another type of natural hazard increases or not. To test my hypothesis, in the second chapter, I analyze if exposure to hurricane Irma triggers people's risk perception about their exposure to the risk of sinkhole and how that added risk perception affects the real estate market.

Until 2007, the sinkhole insurance policy coverage in Florida was not very well defined, and it was very broad. In 2011, a new legislature was passed by the Florida Senate, narrowing the scope of qualifying damage and including some other provisions. The new law was made applicable from July 2016. In the third chapter, I attempt to capture the effect of this new insurance law on people's risk perception and how that transformed risk perception is reflected in the housing prices.

The main focus of this dissertation is to gain a better understanding of the dynamics of different types of spillover effects of risk averting behaviors in response to natural hazard risks.

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1.1 Introduction:

The last three and a half decades have witnessed an increase in the number of natural hazards, but the developing countries seem to be bearing the heavier brunt of these events. For example, between 1970 and 2002, out of a total number of 6436 natural disasters, 77% of these events have taken place in the developing world (Strobl, 2012). Due to its unique location, Bangladesh often faces devastating cyclones (Shamsuddoha and Chowdhury, 2007). Coastal Bangladesh is prone to frequent tropical cyclones and associated storm surges during the pre-monsoon (April-May) and post-monsoon (October-November) seasons (Paul and Dutt, 2010). Climate change models predict that the region will be warmer and wetter in the future which will intensify the impacts of tropical cyclones in Bangladesh.

These negative environmental shocks will have long term effects on a developing country and can affect human capital formation in the long run (Mottaleb et al., 2015). More than 1 million people have died in Bangladesh as a result of cyclones since 1877 (Paul and Dutt, 2010). In 1970 and 1991, about 500,000 and 130,000 people lost their lives respectively due to devastating cyclones in Bangladesh (Mushtaque et al., 1993). In the recent past, three major cyclones (Sidr in 2007, Aila in 2009, and Komen in 2015) claimed 3800 lives and damaged thousands of houses with billions of dollars in property damages. Damage and loss from Cyclone Sidr were concentrated on the southwest coast of

Bangladesh. About one million households were severely affected by cyclone Sidr alone (Mendelsohn et al., 2012). The number of deaths caused by Sidr is estimated to be more than 3500 (Mendelsohn et al., 2012). Cyclone Aila hit the west border of Bangladesh on May 25, 2009, affecting an estimated 3.90 million people in 11 districts among 64 districts of Bangladesh. At least 109 people have lost their lives due to cyclone Aila. Cyclone Komen made landfall in Bangladesh on July 30, 2015. At least seven people have lost their lives during the cyclone, and reportedly 30 more people were missing (IFRC, 2016).

After analyzing the cyclone activity of around 234 years, (Haque et al., 2012) showed that there is a trend of around 2.5% decrease in death tolls due to cyclone activity in Bangladesh. They concluded that this downward trend is due to the emergency management efforts made by the government of Bangladesh and by other concerned agencies. The relatively low number of death tolls, especially in the case of cyclone Sidr was attributed to the government's attempt to provide timely weather forecasting and warning systems, and the successful evacuation of people living in the coastal areas (Paul and Dutt, 2010). Disaster preparedness is now a vital component in emergency management plans in many countries, including Bangladesh. In order to minimize losses, people are moved to a safer location on a temporary basis (Sharma et al., 2009). However, making people respond to evacuation orders is still seen as a major challenge for the disaster management agencies (Stein et al., 2013). Aside from advanced warning, several other factors such as gender, income, and other demographic variables may drive the household evacuation decision (Dash and Gladwin, 2007). For example, in countries like Bangladesh, people tend to rely more on radio messages to make their evacuation decision rather than relying on television and newspapers as they are not readily available in the coastal areas (Paul and Dutt, 2010).

In the future, climate change will have severe adverse impacts in coastal areas as rising sea levels are predicted to frequently inundate low-lying coastal landscapes (IPCC, 2018). Furthermore, several models predict that warming sea surface temperatures will lead to an increase in the frequency and severity of storm events (Webster et al., 2005; Bender et al., 2010). Adding context to these considerable risks, coastal population densities are nearly three times higher than inland population densities (Hanson et al., 2011), and the growth of the global population living in the coastal zone is expected to continue. This simultaneous increase in risk and vulnerability underscores the importance of understanding the mechanism that can diminish the exposure and reduce deaths in the face of rising vulnerability.

Evacuation is considered as an effective instrument in saving lives if it can be planned and coordinated effectively. Recently, there have been plenty of studies that focused on factors that influence evacuation behavior (Hasan et al., 2010; Dow and Cutter, 1998; Dash and Gladwin, 2007). The majority of these studies concentrated on developed countries. Only a few studies explored cyclone evacuation in a developing country context. Also, most of these studies ignore the presence of network effect among peers in evacuation decision making by the households and how previous cyclone experience influences evacuation behavior. This paper contributes to the literature by answering these two questions. The analysis presented in this article provides evidence that network effect is indeed present in evacuation decision making by the households, and this effect gets weaker with increased distance between network members. I also show that past evacuation experience is a significant predictor for future evacuation decisions. Alongside these analyses, I also explore other driving factors behind evacuation decisions made by the households, which may provide useful inputs for future evacuation planning by the emergency management agencies.

1.2 Background and Literature Review:

Despite increasing cyclone risks faced by the coastal communities, there is limited social science research addressing evacuation challenges in developing country contexts. Due to the geophysical and topographical conditions, Bangladesh gets hit with frequent natural disasters. Especially, climate-related disasters like floods and cyclones are most common in Bangladesh. Among all disasters, considering the loss of lives, cyclones are the most severe natural disaster in Bangladesh (Parvin et al., 2019). There are several studies that explored Bangladesh's susceptibility to different types of natural disasters (Saha and James, 2017; Parvin et al., 2019; Shamsuddoha and Chowdhury, 2007). Ahsan et al. (2016) investigate the factors that influence people's decision not to evacuate to cyclone shelter.

There is a growing body of research focusing on behavioral response to natural hazards in general. Risk perception is one of the most important determinants of evacuation behavior. (Fischer et al., 1995; Riad and Norris, 2000) found that four categories of variables affect the decision to evacuate: risk perception, preparedness, social influence, and economic resources. Different groups and households respond to climate-related events in distinct socially determined ways. Neef et al. (2018) analyzed a series of field studies in the lower Ba River Catchment on Fiji's main island Viti Levu and found that climate adaptation strategies employed by indigenous Fijian communities and households are influenced by socio-cultural values and access to resources, information, and power.

Mozumder et al. (2008) used survey data from New Mexico to investigate respondents' risk perceptions regarding wildfire risk and their intended evacuation decision in the face of wildfire risk.

Evacuation decisions could also depend on the network of neighbors. Riad et al. (1999) shows that residents with stronger perceived social support were far more likely to evacuate than were residents with weaker perceived social support. They also find that those with strong social networks had greater access to information as well as tangible help. It is difficult to ascertain the factors behind evacuation decisions for a large heterogeneous sample size. Dixon et al. (2017) found no clear correlations between household attributes and evacuation motivators emerge unless the respondents are organized into subpopulations and the stated concerns of survey respondents. Herrera and Konig (2018) Found that social networks have the ability to reduce the costs and risks of migration through the transmission of information and other resources. This analysis can be extended in the context of evacuation decisions and explore the role of social networks as it can reduce the uncertainties regarding their evacuation process.

Experience can also be an influential factor in evacuation decision-making. Because people who have evacuated before having an "evacuation repertoire" in that they know how to act and what to do. However, field-level researches that investigated cyclone-affected people's experiences and decision-making process are not so common (Masuya et al., 2015). And the results are mixed from the literature. Baker (1991) concluded that there is no consistent relationship between evacuation decision and prior experience. Brown et al. (2018) studied the effect of Cyclone Evan on Fijian households' risk attitudes and showed that being struck by an extreme event substantially changes individuals' risk perceptions as well as their beliefs about the frequency and magnitude of future shocks. They also found sharply distinct results for the two ethnicities in their study. One possible reason for the inconsistent findings is that because prior studies have not measured prior disaster experience and prior evacuation separately (Riad et al., 1999).

There is still much that remains to be learned about this important issue, especially in a developing country context. My study analyzes the factors that affected the evacuation decision in a large, heterogeneous sample for three cyclones in Bangladesh and estimates the effect of prior experience on the evacuation decision.

1.3 Sample Selection, Survey Design and Data Collection:

The total area of Bangladesh is divided into eight administrative divisions. Among them, Khulna, Barisal and Chittagong are three administrative divisions that are located in the coastal zones of Bangladesh. Each division is split into several districts and the total number of districts in Bangladesh is 64. The coastal areas of Bangladesh comprise of 19 districts along the Bay of Bengal (Dasgupta et al., 2014). The study sample covers households from nine southwest districts of two coastal divisions (Khulna and Barisal), which have been impacted during the cyclones Aila, Coman and Sidr in Bangladesh. The survey was conducted in 2015 and collected responses from 2035 households in that region of Bangladesh.

On behalf of researchers from Florida International University (FIU), a face to face household survey on coastal vulnerability and livelihood security has been conducted by the Evaluation and Consulting Services (ECONS) Limited in Bangladesh. The focus of the survey was to identify the link between the extent of natural disaster shocks and the dynamics of recovery and resilience. The multi-section survey questionnaire collected information on the nature and extent of environmental shocks faced by the households, their evacuation behavior and their socio-demographic conditions (e.g., education status of the household's head, ownership of housing, land ownership, the value of household's assets, credit, relief and other economic activities of the households, etc.).

In the demographic section, I geocoded the location of the households alongside the cyclone track, which allowed us to see if they are located near or far from the cyclone path in a geo-spatial platform. I showed the location of the households and the cyclone track in Figure 1.1. I also gathered demographic information about the members of the households such as the number of family members, the age of the members of the household, their genders, marital status etc. The three districts show a good deal of variety in their demographic characteristics, and the respondents seem to be generally representative of the region in terms of gender, household size, and the number of children. Respondents were asked two sequential questions about their evacuation behavior, whether or not they evacuated during any of the three previous cyclones that hit in the area in the last 5 years or so. The evacuation related question was asked as: Where were you along with your family during the disaster? 1=Own house, 2= Help center; 3= Relative's house, 4=On the dam, 5= School/College, 6=Other.

This was followed by a similar question for a possible future evacuation, i.e., What would you do if the mentioned disaster appears at your locality this week?

1=Stay at home, 2=Go to your relative's home, 3=Go to a high dam, 4=Tie yourself with a tree, 5=Go to the official help center, 6= others. I refer to these responses to evacuation decision question for the past the future cyclone event as (yes: if they evacuated or (would evacuate) to someplace safe or no: if they stayed home (or would stay home) during the cyclone.) and Evacuate $_{Past}$ and Evacuate $_{Future}$ refer to the past and future evacuation decision questions, respectively.

1.4 Role of Experience in Evacuation Decision:

In addition to sociodemographic and cultural worldviews, people's prior evacuation experience can be an important factor in evacuation decisions (Lazo et al., 2015). Previous studies have produced mixed findings regarding the relationship between past cyclone experience with cyclone and evacuation behaviors. Past experience with a hazard is generally thought to influence one's recognition that a risk exists and increases motivation to protect oneself. Although some studies in the hurricane context have found this positive relationship (Zhang et al., 2007; Morss et al., 2010), other studies have found a negative or no significant relationship between past hurricane experience and evacuation behaviors (Dow et al., 1998; Lindell et al., 2005).

There are two common survey-based approaches that researchers employ to measure past cyclone experience. One approach is with questions that attempt to be all-encompassing by measuring, for example, the existence or amount of experience one has (e.g., “Have you experienced a cyclone?”; “Have you been personally affected by a past cyclone?”; “How many cyclones have you experienced?”) (e.g., Lindell et al., 2005; Peacock et al., 2005; Arlikatti et al., 2006; Lazo et al., 2010; Matyas et al., 2011). We asked similar questions in our survey and I analyzed the responses from people who were living in the cyclone-affected areas.

I also measured experience with several questions that aim to capture different aspects of experience following (Lindell and Hwang, 2008; Trumbo et al., 2011). We asked the respondents about their experiences with evacuating from a hurricane, distance to the nearest cyclone shelter, property damage, and injury. With this approach, I tried to better capture the complexity of people's hurricane experience. I expect that people's past evacuation experience during a cyclone will affect their future evacuation decision and those who have previous evacuation experience will have greater probability of evacuating in future during a cyclone. Thus:

Hypothesis: People who have previous cyclone experience or have evacuated before, will have a greater probability of evacuation for the next cyclone.

To test my hypothesis and to determine what factors influence people's past and future cyclone evacuation decision, I implement multiple probit models by taking past evacuation decision (Evacuate $_{past}$) and future evacuation decision (Evacuate $_{Future}$) as dependent variables. The dependent variables take two values 0 and 1. If the respondent has evacuated before or will evacuate in future, the dependent variable $y_{Past\ evacuate}$ and $y_{Future\ evacuate}$ will be 1 respectively, and otherwise, their values will be 0.

Following (Greene, 2003), the probit models can be described as follows:

$$y_{1i}^{*} = \alpha z_i + \varepsilon_{1i} \dots \dots \dots \dots \dots \dots \dots (1)$$

$$y_{2i}^{*} = \beta x_i + \varepsilon_{2i} \dots \dots \dots \dots \dots \dots \dots (2)$$

Where, y_{1i}^{*} and y_{2i}^{*} are latent variables and $y_{1i}^{*}\,(Past\ Evacuate)$ and $y_{2i}^{*}(Future\ Evacuate)$ are dichotomous variables observed according to the following rule:

$y_{li} = 1\ if\ \ y_{1i}^{*}\ > 0$

$y_{li} = 0 \; if \;\; y_{1i}^{*} \;\leq 0 \; ; \; where, l = 1, 2_{,} \; y_{1i}^{*} \;\leq 0 \; ; \; where, l = 1, 2$

$x_i$and z_i are vectors of exogenous variables including previous cyclone experience and α and β represent conformable vectors of relevant coefficients.

Following (Greene, 2003), I estimate equations (1) and (2) using probit specification.

1.5 Estimation Results:

The distribution of the sample respondents across the nine coastal districts of Bangladesh is presented in Table 1.1. In the survey, the respondents were asked about their past evacuation behavior and the evacuation destination choice following an evacuation during a cyclone event. Their choices of evacuation destinations are presented in Table 1.2. Most of the respondents went to a cyclone shelter or their relative's house or stayed on the dam where the ground level is higher. The definitions and descriptive statistics of the variables used in the analysis are provided in Table 1.3. The sample mean of a positive response (yes) to the past evacuation decision order was 36%. The mean response for future evacuation was 77% (yes response to the question of whether they will evacuate in the future, see Table 1.3).

First, I estimate the likelihood of past evacuation and future evacuation decisions using the probit modeling approach. The probit analysis showing the factors affecting the evacuation decision is reported in Table 1.4. In Models 1 to 4, I find consistent estimates of the factors affecting the household evacuation decision.

The distance of the cyclone path from the household's location (Distance $_{\text{Cyclone}}$) is significant at 1% levels and positively affect the household's evacuation decision. The timing of the cyclone warning (Time $_{\text{Warning}}$) also affects the household's evacuation decision significantly and is significant at 1% levels. So, the earlier the households get the cyclone warning, it is more likely that they would evacuate. The time required to go to the nearest cyclone shelter (Time $_{Shelter}$) has a negative effect on evacuation decision (significant at 1% levels). The closer the cyclone shelter is located, the higher the probability of evacuation.

The structure of the house (Home $_{Brick}$) also plays a significant role in evacuation decision. If the household lives in a brick-built house, then the household is less likely to evacuate (significant at 1% levels). Also, as the distance between the house and the shoreline (Distance $_{Shore}$) increases the probability of evacuation decreases (significant at 1% levels). Also, with increased family members (Family size), the probability of evacuation falls (significant at 1% levels). If the house is located in a low-lying area (which is more likely to be waterlogged during heavy rain) plays a significant role in evacuation decision making (Home $_{Elevation}$ is significant at 10% levels). People who live in these areas have lower probability of evacuation. This is an interesting result as I expect that they would be more willing to evacuate compared to the people who live in higher elevation. Maybe, people who live in these regions are not aware of the risk they face from cyclones and thus, they did not evacuate during the past cyclone. I find evidence for this decision-making process as for future evacuation decision, they have higher probability of evacuation during a cyclone. So, they learned from past cyclone experience and are more aware of their risk for future cyclone events. Also, the presence of an elderly member in the family (Elderly) positively affects the evacuation decision (significant at 5% levels). Among the control variables, family income (Income) positively affects evacuation decision (significant at 5% levels). My results are consistent with earlier findings in a number of similar studies focusing on evacuation. Paul (2011) also found hurricane distance from the home, number of family members and literacy as significant predictors of evacuation decision. Masterson and Horney (2007) also found that the presence of an elderly person negatively affects evacuation decision of a household.

I analyze the factors that might affect the future evacuation decision also by running a probit model. The findings are presented in Table 1.5. One unique aspect of these results is that the predicted values of past evacuation decision (Evacuate $_{\text{Predicted}}$) from probit model reported in Table 1.4 enters into the future evacuation decision equation as an explanatory variable, which is found positive and statistically significant at 1% levels (see Models 4 to 6 in Table 1.5). The finding implies that past evacuation decision positively affects the future evacuation decision. This indicates that people are learning from their past evacuation decision and updating their belief about future evacuation decision. If a household had evacuated previously, they now have more familiarity and experience with the evacuation process and so, they are more comfortable in making the evacuation decision. Among other variables, the distance of cyclone tract from the household location (Distance $_{\text{Cyclone}}$), and the distance of shore from the household location (Distance $_{\text{Shore}}$) affect the evacuation decision negatively (significant at 1% levels). Also, if the households own their house (Home $_{\text{Owner}}$), it affects the evacuation decision negatively (significant at 1% levels). The living environment of the cyclone shelters (Shelter $_{\text{Environment}}$) positively affect the evacuation decision (significant at 5% levels). Among demographic variables, the income of the household (Income) has a negative effect on the future evacuation decision of the household (significant at 1% levels).

Altogether, Tables 1.4 and 1.5 present multiple models to explain past and future evacuation behaviors during cyclones in Bangladesh. Three different models for both past and future evacuation decisions demonstrate the robustness of key findings to alternative specifications that include additional control variables. All these models perform quite well in terms of overall fit (significant at 1% levels for Wald Test Statistics in Tables 1.4 and 1.5), implying strong relevance of the variables used in the analysis.

In Table 1.6, I provide the marginal effects of corresponding coefficients on the probability of past and future evacuation results reported in Tables 1.4 and 1.5. I find that for the people who evacuated during the previous cyclone, the probability of evacuation for a future cyclone is 113% more. This implies that the household's previous evacuation experience is instrumental in future evacuation decision. For both past and future evacuation, the probability of evacuation is 10% to 20% lower for married respondent compared to the unmarried one. If the housing unit is made with brick, that reduced the past evacuation by 7% to 8%. For future evacuation decision, they are 3% more likely to evacuate in future during a cyclone event. So, these households whose homes were built with bricks, they thought they were safe from the effect of cyclone and decided not to evacuate during the past cyclone. Maybe they felt that it was too risky to stay home, and their home may not be strong enough to protect them against cyclone force winds during the past cyclone. So, they are more willing to evacuate during a cyclone in future.

During past evacuation decision, the living environment of the cyclone shelter was not very influential in evacuation decision making. The good living environment of the cyclone shelter increased the probability of past evacuation by 0.3% to 0.5%. For future evacuation decision, good living environment of the cyclone shelter will increase the probability of evacuation by 13%. With an additional family member in the household, the evacuation rate during past cyclone decreases by 0.4% to 2%. For future evacuation, an additional family member reduces evacuation rate by 4%. The presence of an elderly person in the family reduced the past evacuation rate by 9% For future evacuation, it increased the rate by 1%. In a developing country like Bangladesh, transportation is a major obstacle in the rural areas and maybe during the past cyclone, households that have an elderly person in that household thought it would be too difficult to evacuate with an elderly person and so, it negatively affected past evacuation. However, now they might feel that it would be better to evacuate even with an elderly person than to stay home during a cyclone event. So, they are more willing to evacuate during a cyclone in future. The location of the household is in a low-lying region (which is more likely to be waterlogged during a cyclone) decreased that family's past evacuation by 4% but it increases the probability of evacuation by 3% for a future cyclone event. If the household lost some valuables in the previous cyclone, they are 0.6% to 3% more likely to evacuate. If the head of the household is educated, they are 1% to 3% more likely to evacuate. Also, having a child under 5 years reduces the evacuation rate by 1% to 2%. I visually represent the marginal effects of the key variables affecting past and future evacuation decision in Figure 1.7 and Figure 1.8.

1.6 Spatial Analysis:

When the households were deciding whether to evacuate or not during a cyclone or other hazardous situations, one of the main factors that influenced their decision was how their members in their social network members made this key decision at that time (Burnside et al., 2007). Households often think their neighbors are in the same boat as them and often their neighbor's evacuation decision play a significant role in their own evacuation decision. Using spatial correlogram, we can check if the data shows spatial autocorrelation.[1] I present the spatial correlogram of past evacuation decisions in Figure 1.3 to show how the spatial autocorrelation changes with distance. Each blue dot in Figure 1.3 represents the spatial autocorrelation associated with a distance band (in miles). For example, the first blue dot represents autocorrelation of 0.20, for distances between 0-0.3 miles. The intersection between the dashed zero axis (which determines the range of spatial autocorrelation) and the correlogram happens in the midpoint of the second range (0.3 to 0.6 miles). Beyond that range the autocorrelation is first negative and fluctuates below zero. I can see that there is strong positive effect of the neighbor's evacuation on household's own evacuation decision and after a certain distance it becomes zero and then turns negative. So, when a household lives close to another household and has decided to evacuate, it also influences that neighboring household to evacuate. This influence decrease with spatial distance and after a certain distance it becomes zero. Beyond this distance, the effect becomes negative which implies that when a neighbor located far away from a household decides to evacuate, then the household thinks that the cyclone is too far off to strike their home and so they are safe. In that case, their distant neighbor's evacuation decision negatively affects the subject household's evacuation decision. I find evidence of similar network effect on evacuation decision from my spatial analysis.

In order to determine which model would be the most suitable to account for this network effect, I run a probit model using different contiguity-based spatial weights. For

[1] A non-parametric spatial correlogram is an alternate measure of spatial autocorrelation. A local regression is fitted to the covariances or correlations computed for all pairs of observations as a function of the distance between them (Bjornstad et al., 2001).

my analysis, I use queen-based contiguity following Jakobi (2011). The queen criterion determines neighboring units as those that have any point in common, including both common boundaries and common corners. I run my probit model using three neighbors, five neighbors and fifteen neighbors queen contiguity weight matrix. I show my result in Table 1.7. I find that the Moran's I statistic is highly significant, which confirms the presence of spatial autocorrelation in my data. I also find that for all models, both types of Lagrange Multipliers [LM (lag) and LM (error)] are significant. However, the Robust LM (error) is not significant and the Robust LM (lag) is significant. Based on the test statistics, following (Anselin, 2005), I run a spatial lag model to account for spatial autocorrelation in my analysis.

The spatial lag model incorporates the influence of unmeasured independent variables and also stipulates an additional effect of neighboring attribute values, i.e., lagged dependent variables.

The spatial lag model takes the form following (Morenoff, 2003):

$$y = \rho W y + X\beta + \varepsilon \text{ ……………………….. (3)}$$

Where, Wy is an Nx1 vector of spatial lags for the dependent variable (Evacuate $_{\text{past}}$ and Evacuate $_{\text{Future}}$), $\rho(Rho)$ is spatial autoregressive coefficient, $X\beta$ is an NxK matrix of observations on the exogenous explanatory variables multiplied by a Kx1 vector of regression coefficients β for each X, and ε is a Nx1 vector of normally distributed random error terms. In the above equation, ρ (Rho) is a scalar parameter that indicates the effect of the evacuation decision of the neighbors on the evacuation decision of the household.

For the spatial lag model, I run the model considering the neighbors' network of three, five and fifteen nearest neighbors. The objective is to see how the closest neighbor households' (3, 5, or 15) evacuation decision making affects a specific household's own evacuation decision making. I report the results from spatial lag model in Table 1.8. I can check the direction and magnitude of spatial effect from the spatial lag variable (Anselin et. al., 2006). In all three spatial lag models in Table 1.8, I find that neighbors' decisions significantly affect the household's decision making as the lagged evacuation (W-evacuate) variable is highly significant and positive in all three models. For all three spatial weights, I find that the closest three, ten, and fifteen neighbors positively affect the household's decision making. The effect of the neighbor's evacuation decision on the household's evacuation decision decreases as I consider more neighbors, which can be seen from the decreasing value of the coefficient of the spatial lag variable of evacuation (W-evacuate). Among the three models, I can see that model 10 has the smallest AIC, log likelihood and Schwarz criterion. So, model 10, which is analyzing the effect of three nearest neighbors on household evacuation, is the best model fit for my data.

Even after accounting for the spatial correlation among neighbors, my results remain consistent with the previous analysis based on the probit model estimation. After running the spatial lag model, the general model fit has improved as indicated in higher values of R-squared and log likelihood. Also, from the Moran's I scatter plot presented in Figure 1.4 and Figure 1.5, I see that spatial autocorrelation is almost eliminated after running the spatial lag model.

1.7 Discussion and Conclusion:

In this paper, we have presented an analysis of the evacuation decision during cyclone events in Bangladesh. The results show that in addition to variables that capture the level of risk that the cyclone events pose to individuals and to their properties, variables related to the household-they are part of (e.g., its size and presence of children or elderly individuals), as well as their income level, their location from the cyclone path strongly affect the evacuation decisions. My results regarding the importance of demographic variables are consistent with the findings in the literature (Alsnih et al., 2005, McLennan et al., 2012, Parvin et al., 2019)

Based on the cyclone Sidr, Komen, and Aila related experiences, my study analyzes the factors that influence people to make evacuation decisions and select evacuation destinations. My study identified different people's evacuation behavior, risk perception, and selection of evacuation destinations. It identified various factors that guide and influence people to take evacuation decisions and select evacuation destinations. First, one significant contribution of my research is finding support for the influence of previous evacuation experience in future evacuation decision making (Lazo et al., 2015). We found that previous evacuation experience increases future evacuation probability by 113%, and this was the biggest driver of future evacuation decisions.

Second, in my study, we find support for affiliation with familiar faces during emergency evacuation (Kinateder et al., 2018). Specifically, we find that neighbors' evacuation decisions significantly influence people's evacuation decisions. The results thus extend previous findings on Darley and Latané's (1968) bystander effect by demonstrating that the behavior of neighbors influences the decision to evacuate (Kinateder and Warren, 2016). We find the nearest fifteen neighbors' evacuation decision positively affects a household's evacuation decision. Further studies with more neighbors are needed to determine how social influence scales with the number of neighbors.

Finally, studies like this can be replicated in both regional and global contexts by incorporating relevant variables and their influence on the evacuation decision-making processes of people at risk. So, it would be easier to figure out criteria for policy intervention and investments needed to save lives; diminish risks; and shrink economic, structural, and physical damages. Furthermore, by further exploring the influence of network effects on evacuation decisions, different social networking tools can be utilized during a natural disaster to increase the rate of evacuation and save more lives.

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TABLES

Table 1.1: Distribution of survey respondents (%) across regions.

Name of the District	Frequency	Percentage
Bagerhat	558	27.68
Khulna	402	19.94
Satkhira	322	15.97
Bhola	243	12.05
Patuakhali	125	6.20
Barguna	124	6.15
Barisal	63	3.13
Perojpur	56	2.78
Jhalokathi	25	1.24
Others	98	4.86
Total	2016	100

Table 1.2: Destination choices made by the households following an evacuation.

Evacuation destination	Number of observations	Percentage	Cumulative percentage
Did not evacuate	917	64.40	64.40
Shelter	206	14.47	78.86
Relatives house	65	4.56	83.43
On the dam	157	11.03	94.45
School/college	42	2.95	97.40
Other	37	2.6	100
Total	1424	100	

Note: The total number of observations is less than the sample size as all respondents did not answer the question.

Table 1.3: Descriptive statistics of survey responses and variables of interest.

Variable	Description	N	Mean	Standard deviation
Evacuate $_{Past}$	1 if respondent had evacuated before the cyclone, 0 otherwise	1435	0.36	0.48
Evacuate $_{Future}$	1 if respondent said that they will evacuate in case of future cyclones, 0 otherwise	1435	0.77	0.56
Literacy	1 if respondent can read or write, 0 otherwise	1424	1.85	1.50
Time $_{Warning}$	The estimated time of the warning the respondent got before the cyclone	1424	412.3	641
Time $_{Shelter}$	How much time is required to go to the nearest shelter	1435	15.4	28.1
Home $_{Brick}$	1 if the respondent's home is built with bricks, 0 otherwise	1603	0.18	0.39
Home $_{Owner}$	1 if the respondent is the owner of the home, 0 otherwise	1433	0.958	0.2
Employed	1 if the respondent was employed during the cyclone, 0 otherwise	2016	0.64	0.48
Loss	1 if the respondent lost anything in previous cyclone, 0 otherwise	1596	0.360	0.480
Distance $_{Shore}$	Average distance of respondent's house from the shoreline	1435	20996	16223.95
Family size	Number of family members of the respondent's household	1435	5.26	2.464
Distance $_{Cyclone}$	Distance between the respondent's home and the cyclone track	1414	54655	22495
Home $_{Elevation}$	1 if home is in low lying areas, 0 otherwise	1434	0.645	0.48
Children	1 if the household has a child less than 5-year-old, 0 otherwise	1,431	0.358	0.48
Elderly	1 if the household has a person older than 75-year-old, 0 otherwise	1,435	0.0878049	0.2831096
Income	Households income in the last month	1,435	2704.564	3685.929
Married	1 if the respondent is married, 0 otherwise	1435	0.4966469	0.5000874
Shelter $_{Environment}$	1 if the respondent is satisfied with the environment of the cyclone shelter, 0 otherwise	1,383	0.9696312	0.1716619
Evacuate $_{Predicted}$	Predicted values of past evacuation decision from probit equation	1366	0.3469	0.2715845

(W-evacuate)	Lagged evacuation variable

Table 1.4: Estimated probability of past evacuation (probit model).

	Model 1	Model 2	Model 3
Distance $_{Cyclone}$	0.011*** (0.000002)	0.011 *** (0.000002)	0.011 ***(0.0001)
Married	-0.07 (0.08)	-0.062 (0.08)	
Income	0.00002 ** (0.00001)	0.00002 * (0.00001)	
Time $_{Warning}$	-0.0008 ***(.0001)	-0.0008 *** (0.0001)	-0.00089* (.00040)
Time $_{Shelter}$	-.008 *** (0.002)	-0.008 ** (0.002)	
Home $_{Brick}$	0.29 ** (0.10)	0.30** (0.10)	0.51*** (.18)
Shelter $_{Environment}$	0.01 (0.29)	0.01 (0.30)	0.66 (.55)
Home $_{Owner}$	0.10 (0.23)	0.11 (0.23)	0.387 (.366)
Family size	-0.07 *** (.02)	-0.07 ***(0.02)	-0.184*** (.036)
Elderly	0.34 ** (0.17)	-0.33* (0.16)	-0.506*** (.275)
Home $_{Elevation}$	-0.17 * (0.09)	-0.16* (0.08)	-0.134 (.121)
Distance $_{Shore}$	-.00005 *** (4.26e-06)	-0.00005 ***(4.24e-06)	-0.00005 ***(4.24e-06)
Loss	0.13 (0.08)	0.13 (0.08)	
Literacy	0.11 (.0.08)	0.10 (0.08)	
Child	-0.07 (0.09)		
Constant	-0.70* (-0.40)	0.72* (0.40)	0.77*(0.40)
N	1313	1316	1316
Pseudo R2	0.31	0.30	0.30

LR chi2 $(\chi^2)(\chi^2)$	525.92(0.00) ***	524.62(0.00) ***	521.95(0.00) ***
Log likelihood	-590.46	-593.62	-594.95

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are robust standard errors.

Table 1.5: Estimated probability of future evacuation (probit model).

	Model 4	Model 5	Model 6
Evacuate $_{Predicted}$	5.29 ***(0.57)	5.29 ***(0.56)	5.36 ***(0.55)
Distance $_{Cyclone}$	-0.00002***(2.4e-06)	-0.00002 ***(2.4e-06)	-0.00002 ***(2.36e-06)
Married	-0.09 (0.09)	-0.09 (0.09)	-0.09(0.09)
Income	-0.00006*** (0.00001)	-0.00006*** (0.00001)	- 0.00006(0.00001)
Time $_{Warning}$	0.0009 ***(.0001)	0.0008*** (0.0001)	0.0009*** (0.0001)
Time $_{Shelter}$	-0.004 ** (0.002)	-0.004 ** (0.002)	-0.004**(0.002)
Home $_{Brick}$	-0.14 (0.14)	-0.14 (0.14)	-0.14 (0.13)
Shelter $_{Environment}$	0.61** (0.24)	0.62** (0.24)	0.62** (0.24)
Home $_{Owner}$	-0.79 *** (0.24)	-0.78** (0.24)	-0.77** (0.24)
Family size	-0.02 (.02)	-0.02 (0.02)	-0.02 (0.02)
Elderly	0.05 (0.15)	0.05* (0.14)	0.05 (0.14)
Home $_{Elevation}$	0.14 * (0.10)	0.14 (0.1)	0.14 (0.1)
Distance $_{Shore}$	-.00005*** (7.59e-06)	-0.00004 ***(7.57e-06)	-0.00005 ***(7.45e-06)
Loss	0.03 (0.09)	0.03 (0.09)	
Literacy	0.06 (.0.09)	0.06 (0.09)	
Child	-0.05 (0.09)		

Constant	-0.45 (0.53)	0.72* (0.40)	-0.51(0.52)
N	1313	1316	1316
Pseudo R2	0.27	0.30	0.27
LR chi2 $(\chi^2)(\chi^2)$	383.38(0.00) ***	384.31(0.00) ***	383.69(0.00) ***
Log likelihood	-506.58	-506.88	-507.19

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are robust standard errors.

Table 1.6: Marginal effects of estimated probit models for past and future evacuation.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Past evacuation equation			Future evacuation equation		
Evacuate $_{Predicted}$				1.13	1.13	1.15
Distance $_{Cyclone}$	0.000002	0.000002	0.000002	-0.000005	-0.000005	-0.000005
Married*	-0.02	-0.01	-0.01	-0.02	-0.02	-0.02
Income	0.000006	0.000006	0.000006	-0.00001	-0.00001	-0.00001
Time $_{Warning}$	-0.0002	-0.0002	-0.0002	0.0001	0.0002	0.0001
Time $_{Shelter}$	-0.002	-0.002	-0.002	-0.0009	-0.0009	-0.0009
Home $_{Brick}$ *	0.07	0.08	0.07	-0.03	-0.03	-0.03
Shelter $_{Environment}$	0.003	0.003	0.005	0.13	0.13	0.13
Home $_{Owner}$ *	0.03	0.03	0.032	-0.17	-0.17	-0.17
Family size	-0.02	-0.02	-0.02	-0.004	-0.004	-0.004
Elderly*	-0.09	-0.09	-0.09	0.01	0.01	0.01
Home $_{Elevation}$ *	-0.04	-0.04	-0.04	0.03	0.03	0.03
Distance $_{Shore}$	-0.00001	-0.00001	-0.00001	0.00001	0.00001	0.00001
Loss *	0.03	0.03	0.03	0.006	0.007	
Literacy *	0.03	0.03		0.01	0.01	
Child*	-0.02			-0.01		

Notes: Marginal effects represent % changes in probability of evacuation decision given a unitary increase in a variable (or change from 0 to 1 in the case of binary variables marked with *).

Table 1.7: Ordinary least squares (OLS) regression results with spatial weights.

	Model 7	Model 8	Model 9
Distance $_{Cyclone}$	0.0000003 (4.92e-007)	0.0000003 (4.91e-007)	0.0000004 (4.86e-007)
Married	-0.007 (0.021)	-0.007 (0.021)	-0.007 (0.021)
Income	3.66e-006 (2.95e-006)	3.60e-006 (2.94e-006)	3.63e-006 (2.94e-006)
Time $_{Warning}$	-0.0001*** (1.74e-005)	-0.0001*** (1.74e-005)	-0.0001*** (1.74e-005)
Time $_{Shelter}$	-0.0004 (0.0005)	-0.0004 (0.0004)	-0.0004 (0.0004)
Home $_{Brick}$	0.10 *** (0.02)	0.10 *** (0.02)	0.10 *** (0.02)
Shelter $_{Environment}$	0.12 ** (0.05)	0.12 ** (0.05)	0.12 ** (0.05)
Home $_{Owner}$	-0.04 (0.05)	-0.04 (0.05)	-0.04 (0.05)
Family size	-0.02 *** (0.004)	-0.02 *** (0.004)	-0.02 *** (0.004)
Elderly	-0.15 ** (0.07)	-0.15 ** (0.07)	-0.15 ** (0.07)
Home $_{Elevation}$	-0.06** (0.02)	-0.06** (0.02)	-0.06** (0.02)
Distance $_{Shore}$	-1.14e-005 *** (7.44e-007)	-1.14e-005 *** (7.44e-007)	-1.14e-005 *** (7.44e-007)
Loss	0.05 ** (0.02)	0.05 ** (0.02)	0.05 ** (0.02)
Literacy	0.02 (0.02)	0.02 (0.02)	
Child	-0.007 (0.02)		
Constant	0.67*** (0.08)	0.67*** (0.08)	0.68*** (0.08)
N	1313	1316	1316
R2	0.30	0.25	0.25
F statistic	39.93	42.81	46.01
Log likelihood	-731.07	-731.13	-731.69
AIC	1494.16	1492.26	1491.38
Schwarz criterion	1578.46	1571.29	1565.14
Moran's I(error)	25.92 ***	25.92 ***	25.98 ***
Lagrange Multiplier(lag)	739.10 ***	739.25 ***	741.25 ***
Robust LM (lag)	91.38 ***	91.38 ***	89.54 ***

Lagrange multiplier(error)	649.06 ***	649.27 ***	652.85 ***
Robust LM (error)	1.34	1.33	1.14

Notes: $***$, $**$, $*$ imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are robust standard errors.

Table 1.8: Estimated probability of evacuation (spatial lag model).

	Model 10 (3 neighbors)	Model 11 (10 neighbors)	Model 12 (15 neighbors)
W-evacuate	0.63 ***(0.02)	0.49 ***(0.11)	0.15 ***(0.04)
Distance $_{Cyclone}$	$9.84e^{-008}$($3.94 e^{-007}$)	$3.95e^{-007}$($4.84 e^{-007}$)	$2.70e^{-007}$($4.89 e^{-007}$)
Married	-0.01(0.01)	-0.009(0.02)	-0.007(0.02)
Income	$2.55e^{-006}$($2.36e^{-006}$)	$3.25e^{-006}$($2.90e^{-006}$)	$3.83e^{-006}$($2.92e^{-006}$)
Time $_{Warning}$	$-7.2e^{-005}$ ***($1.4e^{-005}$)	-0.0001 ***($1.72e^{-005}$)	-0.0001 ***($1.72e^{-005}$)
Time $_{Shelter}$	-0.0005(0.0003)	-0.0001(0.0004)	-0.0002(0.0004)
Home $_{Brick}$	0.06 **(0.02)	0.09 **(0.02)	0.10 ***(0.02)
Shelter $_{Environment}$	0.11 **(0.04)	0.09 **(0.05)	0.13 **(0.05)
Home $_{Owner}$	-0.07(0.04)	-0.05(0.05)	-0.03(0.05)
Family size	-0.01**(0.003)	-0.02**(0.004)	-0.02***(0.004)
Elderly	-0.10(0.05)	-0.15 **(0.07)	-0.15 **(0.07)
Home $_{Elevation}$	-0.04 **(0.01)	-0.04 **(0.01)	-0.06 **(0.02)
Distance $_{Shore}$	$-3.54e^{-006}$($6.73e^{-007}$)	$-9.05e^{-006}$($9.38e^{-007}$)	$-1.03e^{-006}$ ***($7.52e^{-007}$)
Loss	0.02(0.01)	0.04 **(0.02)	0.04 **(0.02)
Literacy	0.007(0.01)	0.02(0.02)	0.02(0.02)
Child	0.01(0.01)	-0.005(0.02)	-0.0007(0.02)
Constant	0.24(0.02)	0.24(0.02)	0.66 **(0.04)
N	1313	1313	1313
R^2	0.54	0.31	0.30
Log likelihood	-518.46	-715.92	-724.74
AIC	1070.92	1465.85	1483.5
Schwarz criterion	1160.49	1555.42	1573.07
Likelihood ratio test	425.24 ***	30.31 ***	12.65 ***
Rho	0.64	0.49	0. 15

FIGURES

Figure 1.1: Distribution of survey respondents (as % of total respondents).

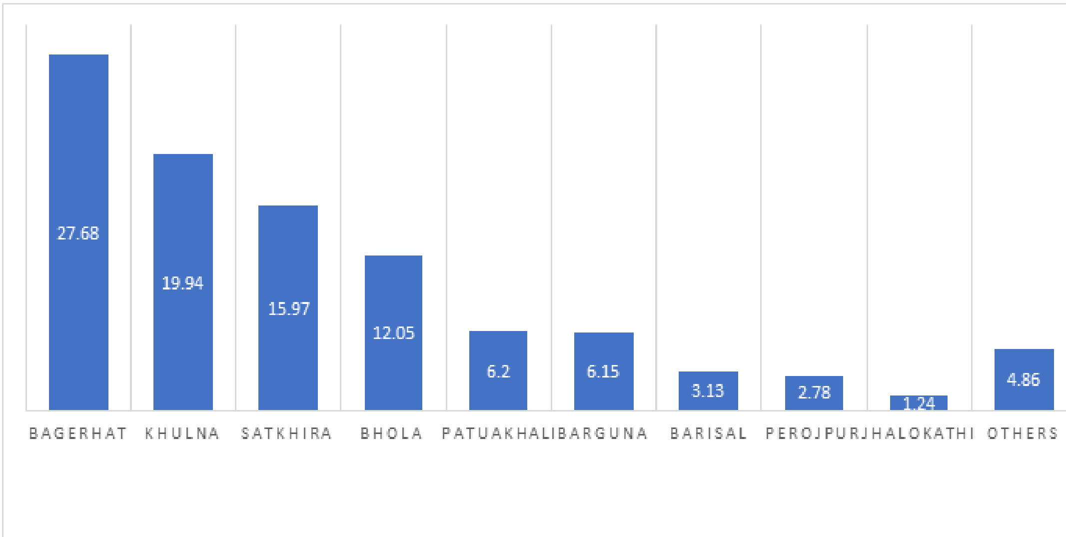


Figure 1.2: Evacuation destination choices (as % total respondents) made by the households.

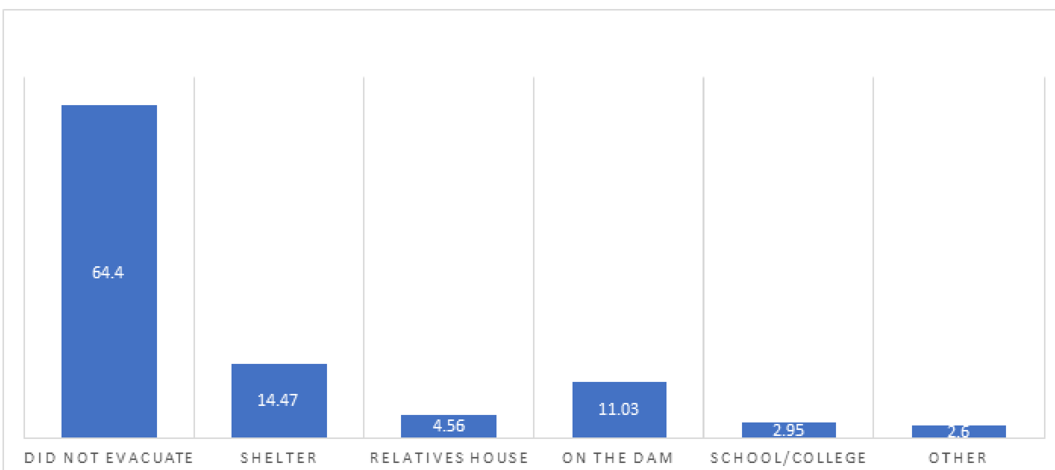
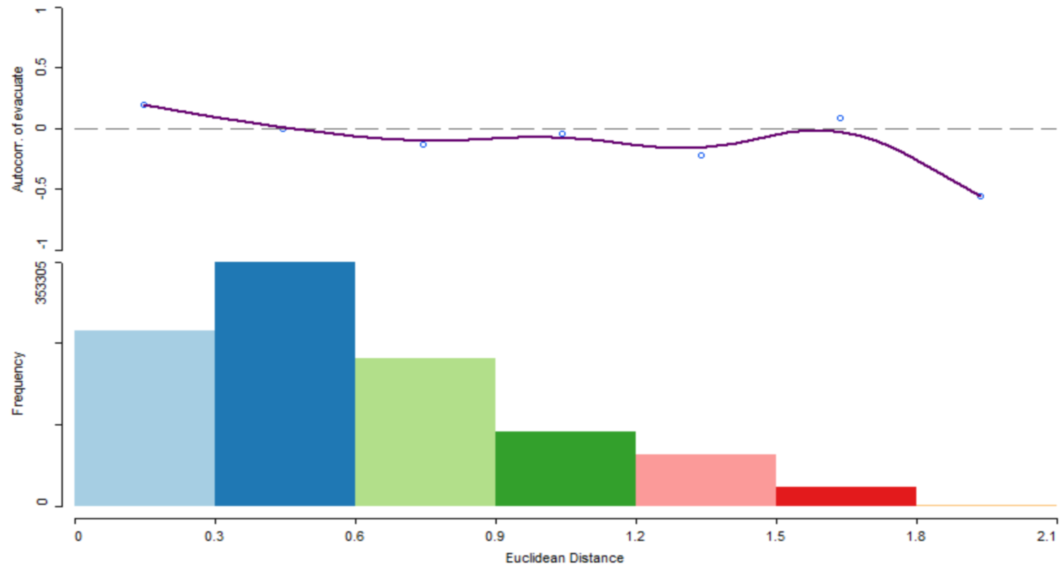


Figure 1.3: Spatial correlogram of evacuation decision.



Note: Figure 3 shows how the spatial autocorrelation changes with distance between neighbors; for example, the first blue dot represents autocorrelation of 0.20, for distances between 0-0.3 miles. Spatial autocorrelation decreases to 0 when distance between neighbors is 0.3-0.6 miles. The spatial autocorrelation moves up and down until it becomes 0 again when the distance between the neighbors is 1.5-1.8 miles. If the distance between the neighbors increases more, then the spatial autocorrelation becomes negative and increases with distance.

Figure 1.4: Spatial autocorrelation from the probit model

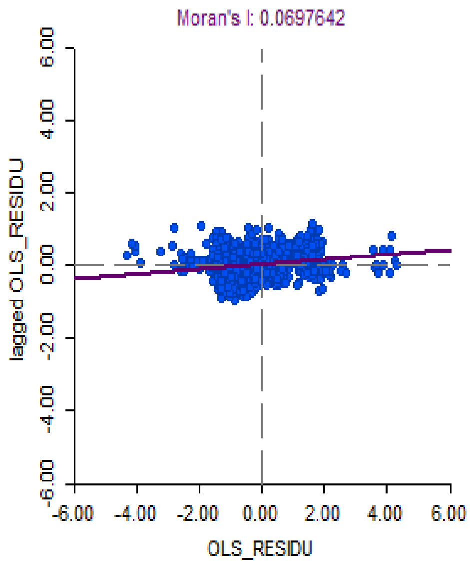


Figure 1.5: Spatial autocorrelation from the spatial lag model.

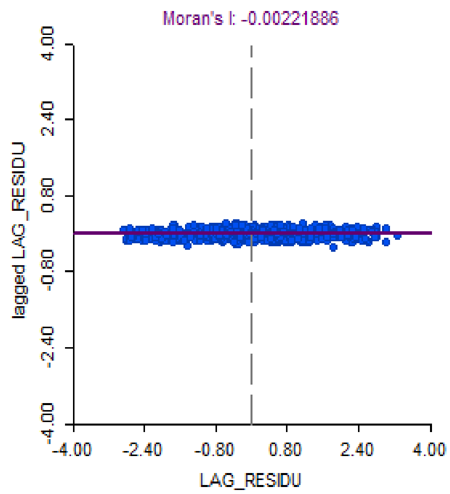


Figure 1.6: Locations of households and the path of three recent cyclones (Aila, Komen and Sidr).

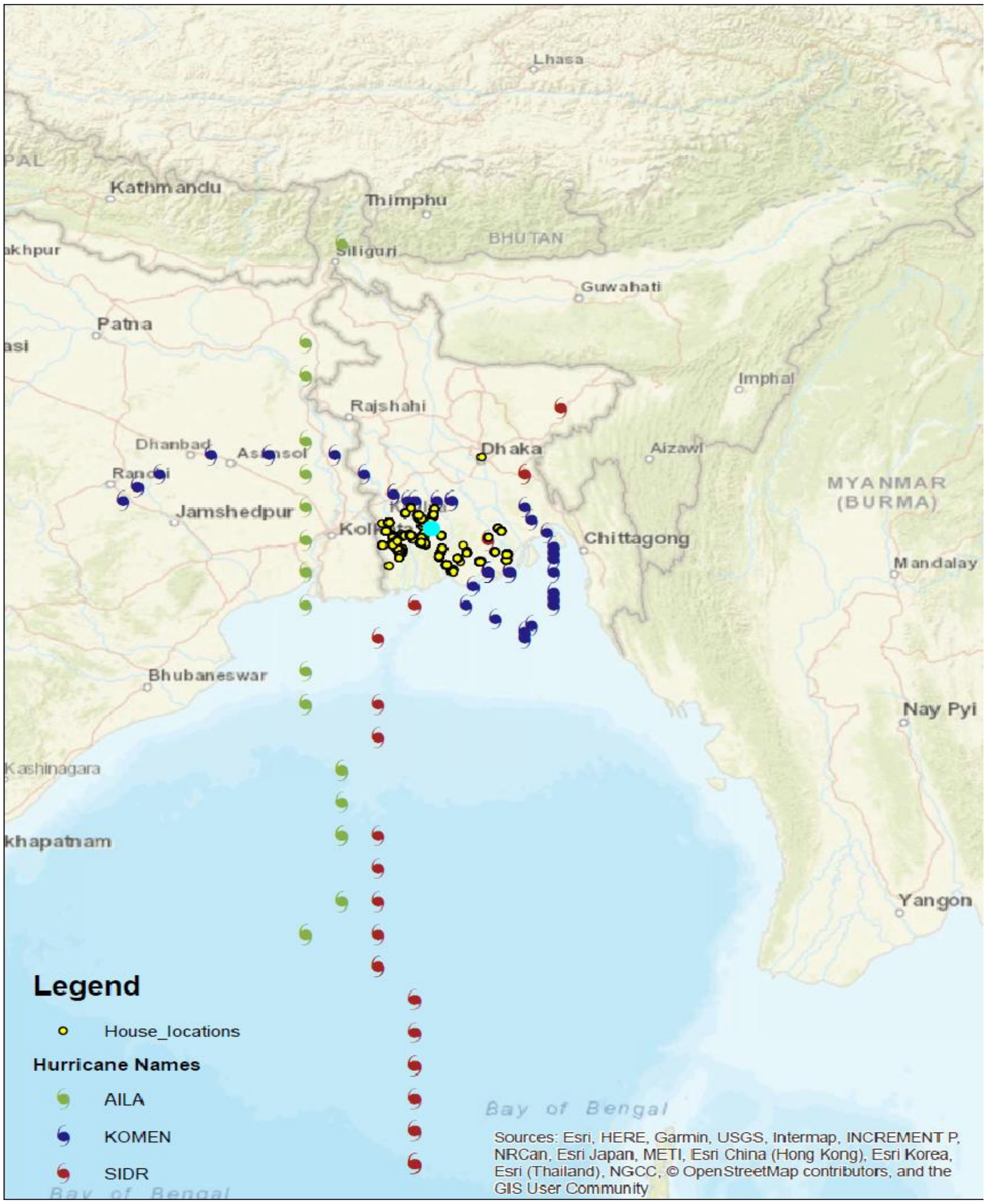


Figure 1.7: Average marginal effects for past evacuation decision.

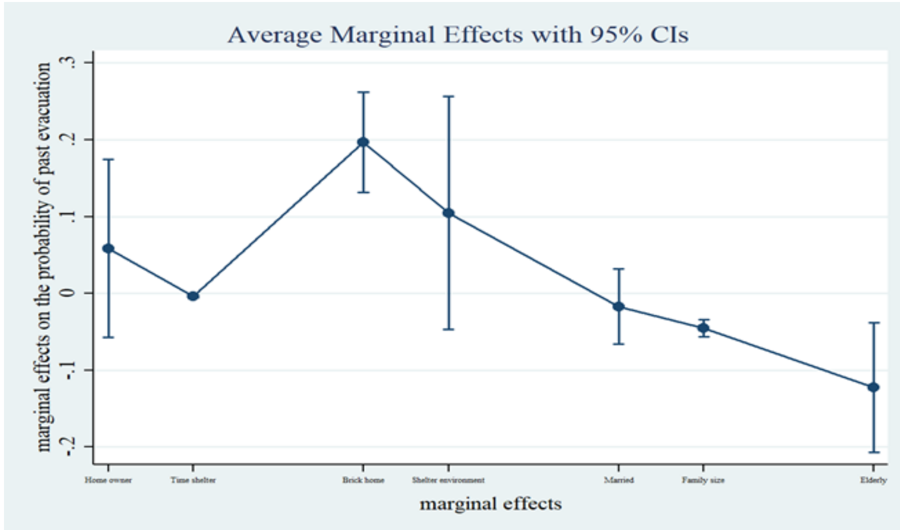
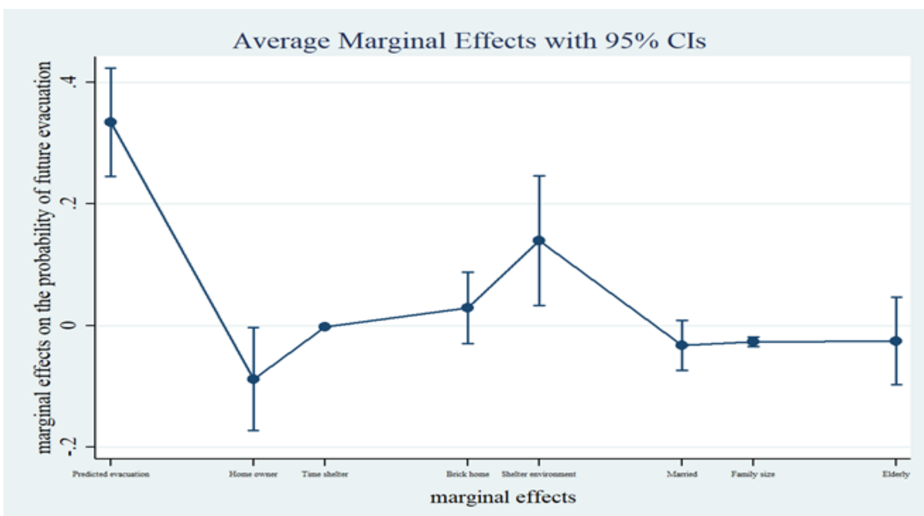


Figure 1.8: Average marginal effects for future evacuation decision.



1.8 Appendix:

1.8.1 OLS Model

I use the following OLS regression to identify the factors behind future evacuation decision:

$$Evacuate_{Future} = \beta_1 X' + \gamma_1 Evacuate_{Past} + \varepsilon_1 \text{ ……………. (1.1)}$$

Where X is a vector of individual-level, family-level, and community-level observables. $Evacuate_{Past}$ is past evacuation decision by the respondent. The estimate of γ_1 will only be an unbiased estimate of the effect of past evacuation on future evacuation if there are no unobservable individual, geographical, socio economic or family-level characteristics correlated with both past evacuation and future evacuation; That is if this identification assumption is violated, for example, if there is endogeneity or heterogeneity bias, then the OLS estimator will be biased in this study.

1.8.2 IV model:

The widely used method of addressing the endogeneity bias is by using instrumental variables (IV). The IV estimation can control for any reverse causality (Sabia, 2007). The IV estimation requires finding characteristics that provide exogenous variation in past evacuation decision that are uncorrelated with future evacuation decision except through past evacuation decision. The two-stage least squares model jointly estimates the future evacuation decision in Equation 1 and a past evacuation equation:

$$Evacuate_{Past} = \beta_2 X' + \varepsilon_2 \text{ ……………. (1.2)}$$

The classic IV identification assumption requires setting one or more elements in $\beta_1 = 0$. This implies that a subset of X will serve as exclusion restrictions (Z) to identify the model (Sabia, 2007). The exclusion restrictions the are chosen for identification of the standard IV model: distance of the past two cyclones (Sidr and Aila) from the respondent's home. The identification assumption of the IV model requires that the distance of the previous cyclone from the respondent's home to be strongly correlated to/with past evacuation decision. This is expected to be the case because recent studies have found that evacuation decision is strongly correlated with the proximity of cyclone from the households (Dow and Cutter, 1998; Meyer et al., 2018; Cohn et al., 2006).

The identification of the model also requires that the distance of the previous cyclone from the respondent's home not be correlated with unmeasured determinants of future evacuation decision. This assumption should be valid as when people are making their future evacuation decision, the previous cyclone track should not influence that decision. The results of the IV regression are given in Table 1.10. The past evacuation decision is found as a significant predictor of future evacuation decision in the regression. So, households learning from experience plays a significant role in future evacuation decision.

1.8.3 Lewbel (2006) method:

Given concerns about the validity of the instrument described above, a second IV model is needed that does not need the assumption that distance to the nearest shelter is uncorrelated with future evacuation decision. Several recent papers used the identification strategy used by Lewbel such as King et al. (1994), Rigobon (2002), and Klein (2003)

1.8.4 Lewbel IV Estimates:

Lewbel IV estimates are very similar to standard IV estimates in magnitude and direction. The magnitudes of the Lewbel estimates appear more plausible and. in some specifications, suggest that reverse causality may not be a sufficient explanation for the negative relationship between past evacuation experience and future evacuation decision.

TABLES

Table 1.9: Estimated probability of future evacuation, OLS model.

	Model 1	Model 2	Model 3
Evacuate $_{past}$	5.29 ***(0.57)	5.29 ***(0.56)	5.36 ***(0.55)
Distance $_{Cyclone}$	-0.00002***(2.4e-06)	-0.00002 ***(2.4e-06)	-0.00002 ***(2.36e-06)
Income	-0.00006*** (0.00001)	-0.00006 *** (0.00001)	-0.00006(0.00001)
Time $_{Warning}$	0.0009 ***(.0001)	0.0008 *** (0.0001)	0.0009*** (0.0001)
Time $_{Shelter}$	-0.004 ** (0.002)	-0.004 ** (0.002)	-0.004**(0.002)
Home $_{Brick}$	-0.14 (0.14)	-0.14 (0.14)	-0.14 (0.13)
Shelter $_{Environment}$	0.61** (0.24)	0.62** (0.24)	0.62** (0.24)
Home $_{Owner}$	-0.79 *** (0.24)	-0.78** (0.24)	-0.77** (0.24)
Family size	-0.02 (.02)	-0.02 (0.02)	-0.02 (0.02)
Elderly	0.05 (0.15)	0.05* (0.14)	0.05 (0.14)

Home $_{Elevation}$	0.14 * (0.10)	0.14 (0.1)	0.14 (0.1)
Distance $_{Shore}$	-.00005 *** (7.59e-06)	-0.00004 ***(7.57e-06)	-0.00005 ***(7.45e-06)
Literacy	0.06 (.0.09)	0.06 (0.09)	
Constant	-0.45 (0.53)	0.72* (0.40)	-0.51(0.52)
N	1313	1316	1316

Notes: ∗∗∗, ∗∗, ∗ imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are robust standard errors.

Table 1.10: Estimated probability of future evacuation, standard IV model:

	First Stage for Evacuate $_{past}$	Second Stage For Evacuate $_{Future}$
Evacuate $_{past}$		0.83 *** (0.29)
Distance $_{Sidr}$	9.70e^{-07} ** (5.15e^{-07})	
Distance $_{Aila}$	-0.0000118 *** (7.91e^{-07})	
Income	6.82e $^{-06}$ (3.34^{-06})	-0.00007 *** (0.00001)
Home $_{Brick}$	0.10 *** (0.03)	0.61** (0.22)
Home $_{Owner}$	0.08 (0.06)	0.43 (0.37)
Family size	-0.02 *** (.004)	-0.13 *** (0.03
Elderly	-0.07 ** (0.039)	-1.57 ** (0.49)
Home $_{Elevation}$	-0.04 *** (0.02)	0.18 (0.15)
Constant	0.68 *** (0.09)	1.25 *** (0.34)
N	1313	1313

Notes: ***, **, * imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are robust standard errors.

Table 1.11: Estimated probability of future evacuation, Lewbel IV model:

	First Stage for Evacuate $_{past}$	Second Stage For Evacuate $_{Future}$
Evacuate $_{past}$		-3.89 (0.69)
Distance $_{shelter}$	-4.72 ***(0.54) ***	
Distance $_{Hurricane}$	2.82e^{-08} (5.47e^{-07})	-0.00001 (3.31e^{-06})
Income	0.00001** (3.49^{-06})	-0.000026 (0.00002)
Time $_{Warning}$	-0.0001 ***(.00001)	0.0005** (0.0002)
Home $_{Brick}$	0.15 (0.03)	0.61** (0.22)
Shelter $_{Environment}$	0.09** (0.06)	1.20** (0.43)
Home $_{Owner}$	-0.05 *** (0.06)	0.43 (0.37)
Family size	-0.38 (.004)	-0.27*** (0.03)
Elderly	-0.17 (0.79)	-1.57*** (0.49)

Home $_{Elevation}$	-0.038 * (0.24)	0.18 (0.15)
Constant	0.52*** (0.10)	3.75*** (0.69)
N	1316	1316

Notes: ∗∗∗, ∗∗, ∗ imply significance at 1%, 5%, and 10% levels respectively; numbers in parentheses are robust standard errors.

Chapter 2

The Deadly Connection between Hurricanes and Sinkholes: Analyzing Market Responses to Multiple Environmental Risks

2.1 Introduction:

Natural disasters are becoming more frequent and severe with climate change (Nakicenovic & Swart, 2000; Pachauri et al., 2014). People's perceptions of risk from hazards and their relationship to the adoption of protective adjustments have long been issues of theoretical (Perry et al., 1990) and analytical (Leone et al., 1999) importance. The same aspects of risk perception were studied for different natural hazards (Bin et al.,2006; Harrison et al., 2001; Ewing et al.,2007) and technological hazards (Burton et al., 1993; Lindell et al., 2007).

Most of the frameworks that link hazard perceptions and other variables with people's protective behaviors are applied to single hazards. This study examines citizen risk perceptions and threat adjustments in a hazard environment composed of hurricanes and sinkholes. I use data from Lake County in Florida to analyze how sinkhole and hurricane interact with each other to change the risk perception of homeowners and how that changed risk perception affects the real estate market.

Sinkholes can be both a property characteristic and a negative externality (Dumn et al., 2018). Hurricanes negatively affect housing prices in the affected areas. Both events can adversely affect the property prices in the impacted and surrounding areas. Florida ranks highest in the USA as the sinkhole risk area (Florida Geological Survey, 2018) and suffers tropical storms almost every hurricane season. Sinkholes open in areas where there are some specific types of rock, such as limestone, carbonate rock, and salt beds that are dissolved by water flow. So, the probability of sinkhole opening may increase after a hurricane as increased rainwater could be one of the reasons for the occurrence of sinkholes as there will be more groundwater after increased rainfall during a hurricane (Florida Geological Survey, 2017).

In this study, I explore if the risk perception of the homeowners regarding sinkhole risk changes following a hurricane event, especially homeowners who live close to sinkholes. If the homeowners are aware of the increased probability of sinkhole opening following a hurricane, the real estate market should reflect this modified risk perception. In this paper, I use a hedonic property price function to estimate the price discount of the houses located near known sinkhole locations following Hurricane Irma.

To the best of my knowledge, there has been no prior attempt to evaluate the combined effect of multiple hazards on property prices. My results show that Hurricane Irma changed the risk perception of the homeowners who live close to known sinkhole locations, and I observe a price discount for those houses after the hurricane, reflecting that changed risk perception. This significant combined effect of multiple hazards on the real estate market is a novel finding in the literature. However, the price discount depends on the proximity of the house to a known sinkhole location. The negative effect decreases with increased distance from a sinkhole, and after a specific range, the effect disappears.

2.2 Background:

There is considerable research on the effects of natural (Harrison et al., 2001; Ewing et al., 2007) and technological hazards (Adeola, 2000; Lee et al., 2008) on real estate pricing. However, the conclusions from these studies were inconsistent as some of them found a negative effect on property prices, some found no effect, and some of them even found a positive impact on property prices from these hazards. Compared to some of these studies, such as Bin et al. (2008), my dataset is much larger, and I find a significant negative effect of natural hazards in my study, and the results are robust to different specifications.

There is little evidence showing the effect of sinkholes on housing prices. And the findings from these studies are not consistent. Yoo and Frederick (2017) examined the price discount suffered by the residential properties due to earth fissures in Maricopa County, Arizona. Using a quantile regression, they analyzed 82,716 arms-length property sales between 2004 and 2010 and they found that properties suffer significant price discounts due to earth fissures. Fleury (2007) studied the effect of sinkholes on housing prices using census data from 1990. He used data from Tampa Bay and used OLS and probit models to see the impact of sinkhole proximity/density on median home prices by census block. The author found no significant effect of sinkholes on home values and concluded that maybe the homebuyers are not aware of the risk that sinkholes pose to their houses. Another explanation might be, according to Dumm et al. (2018), is that using census level data, such as median home value by census block, obscures the true price variation across properties that are affected by sinkholes and those are not. Since I am using individual property transaction price data in my study, I don't have that issue.

My analysis is particularly related to two recent studies. Dumm et al. (2018) studied property data from 2010 to 2014 of Hernando county in Florida and sinkhole data from Florida Geological Services (FGS) to examine the effect of sinkhole presence, proximity, and density on the housing sale price. Using a spatial regression model, they show that sinkhole proximity and exposure create a negative externality, and both have a significant adverse effect on housing prices. In my study, I not only analyze the effect of sinkholes on property prices but also explore the added impact of Hurricane Irma and on properties that are located near the sinkhole.

There can be many factors that might amplify or attenuate people's risk perception regarding environmental risk when they are making a real estate purchase decision (Kasperson et al., 1988; Perry et al., 2008). Recent experience with a natural disaster such as flooding or hurricane or a sinkhole opening nearby raises the discount rate of living in the disaster-prone areas. Donnelly (1991) found that location within a floodplain lowers property value between 4% to 12%. They hypothesize that there is a change in risk premium after a natural hazard in the affected area. So, the buyer's and seller's risk perceptions were changing with the prevalence of hazard events, and the home buyers are unaware of flood risks and insurance requirements when bidding on properties. I also assume that the price differential of the properties following a hurricane event can be rationalized through a model of changing risk perception, responding to a rare, extreme event.

Several hedonic studies analyze the value that the homeowners attach to the reduction of the probability of loss from a natural hazard (self- protection). Brookshire et al. (1985)

studied the effect of living in an earthquake zone. Similar to my analysis, they also used real estate transaction data from San Francisco and Los Angeles and found that homes that are in earthquake risk zones suffer price discounts compared to houses that are outside the earthquake risk zone.

Finally, most of the studies that have studied the effect of a natural hazard on property prices tried to examine the impact of a single natural hazard. Few studies investigated the effect of multiple natural hazards on property prices and how one hazard can trigger or increase risk perception about another hazard. Perry et al. (2008) gathered data from two northern California (USA) communities that are exposed to wildfires, earthquakes, and volcanic activity, and they found that risk perception was not a statistically significant predictor of the number of adjustments for any of the three hazards. They also don't consider the effect of the three hazards together for their analysis.

In contrast to the research described previously, my study examines two natural hazards together and how two different kinds of environmental risks can combine and affect the real estate market. In this study, I analyze how two different types of natural hazards like hurricanes and sinkholes interact with each other and affect the real estate prices that face the dual threat of sinkhole damage and hurricane event.

2.3 Sinkhole Risk

2.3.1 What is sinkhole?

Sinkhole is a ground depression through which water cannot escape (FGS, 2019). Natural events like excessive rainfall or flood after a dry season can lead to sinkhole outbreak in an area that is rich with rocks such as salt beds and domes, gypsum, limestone, and other carbonate rocks (Florida Geological Survey, 2018).

2.3.2 Sinkhole Risk in Florida

Sinkhole damages over the last 15 years cost on average at least $300 million per year (US geological Survey, 2018). Since there is no national tracking of sinkhole damage costs, this estimate is probably much lower than the actual number, according to the United States Geological Survey (US geological Survey, 2018).

Central Florida was in a severe drought at the beginning of 2017, followed by the intense rainfall of Hurricane Irma that hit many parts of Florida in September, and “a deluge after a drought is the optimal condition for a sinkhole outbreak” (Florida Geological Survey, 2018). A proof of this mechanism was evident in 2017 when at least 400 new sinkholes were reported after Hurricane Irma (FGS).

2.4 Data and Study area

Hurricane Irma, one of the most devastating and powerful hurricanes in recent memory, hit the state of Florida on September 10, 2017. The storm, which came ashore south of Tampa, veered east, landing a direct blow on Lake County in the early morning hours on September 11 (National Oceanic and Atmospheric Administration, 2017). By that time, the eye of the once-Category five storm had eroded, and the winds had significantly diminished, although not enough to head off significant tree damage there. Some roads were rendered impassable when large oaks were uprooted or splintered from sustained winds that reached as high as 76 mph (FEMA, 2017). Irma was the fifth most expensive tropical cyclone to hit the USA, and the estimated damage from Hurricane Irma in Lake County was at least $36 million (FEMA, 2019). As Lake County is one of the major counties that have sinkhole risk, there was a high chance of new sinkholes opening in lake county after the hurricane. I capture the homebuyers and home sellers' modified risk perception about sinkhole risk after the hurricane event from their real estate purchase decision.

Multiple data sources were used for the study. Property parcel data, GIS data of the parcels, and the real estate purchase records were collected from the property appraiser's office. The data contains relevant property characteristics such as the number of bedrooms, number of bathrooms, the presence of amenities such as fireplace, pool etc. I also collected the geocoded data of natural amenities such as the locations of nearby lakes, schools, airports etc. and connected them with the real estate data to identify their influence of property price.

I also collected the sinkhole location data from the Florida Geological Survey website. GIS spatial queries were performed to calculate sinkhole proximity and density within different distance bands such as ¼ mile, ½ mile, ¾ mile, 1 mile, and 2 miles.

This study uses a total of 35000 single-family residential homes from Lake county, Florida, that were sold between 2014 and 2018. Lake County is approximately 1157 square miles, with a population of roughly 3,46,017 and a population density of 369/sq. miles.

2.5 Theory of hedonic property prices, hazards, and insurance:

Bin and Landry (2012) showed the relationship between marginal implicit hedonic prices, incremental option value, and insurance costs. I adjust their theory to explicitly account for the sinkhole effect and how that effect interacts with a hurricane event. I assume the homebuyers are buying sinkhole insurance because the location of the houses is in a sinkhole risk zone and the expected utility for the homebuyers is given by:

$$EU = p(i)\int_0^S V_1(a, y - R(a, p(i)) - I(p, C) - L + C)f(L)dL + (1 - P(i))V_0(a, y - R(a, p(i) - I(p, C)) \;\ldots\ldots\ldots\ldots\ldots(1)$$

Where, C ϵ (0, S) is the insurance cover on the property, and I (p, C) is the insurance premium. If I assume that full insurance is purchased, Eq. (1) simplifies to

$$EU = p(i)V_1(a, y - R(a, p(i)) - I(p, C) + (1 - p(i))V_0(a, y - R(a, p(i)) - I(p, C) \ldots\ldots\ldots(2)$$

And for the homeowners who do not buy sinkhole insurance, their expected utility is given by:

$$EU = p(i)\int_0^S V_1(a, y - R(a, p(i) - L)f(L)dL + (1 - p(i))V_0(a, y - R(a, p(i)) \;\ldots\ldots\ldots\ldots(3)$$

In my framework, incremental option value (OV) is defined as the maximum amount an individual is prepared to make to avoid a certain adverse situation. It can be defined as:

$$[p(i) - \sigma]V_1(a, \hat{y} - OV) + [1 - p(i) + \sigma]V_0(a, \hat{y} - OV)$$
$$= EU \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

When the homeowner has full insurance cover:

$$\frac{dOV}{d\sigma} = \frac{V_0(a,\hat{y}-OV)-V_1(a,\hat{y}-OV)}{[1-p(i)+\sigma]\frac{\partial V_0}{\partial y}+[p(i)-\sigma]\frac{\partial V_1}{\partial y}} \ldots\ldots\ldots\ldots\ldots (5)$$

A similar case can be derived for no insurance scenario. Macdonald et al. (1987) show that the maximization of EU in (2) implies the following equality in equilibrium:

$$\frac{\partial R}{\partial P} = \frac{V_1(a,\hat{y}- V_0(a,\hat{y})}{[1-p(i)]\frac{\partial V_0}{\partial y}+[p(i)]\frac{\partial V_1}{\partial y}} - \frac{\partial I(p)}{\partial P} = -\frac{dOV}{dp} - \frac{dI(p)}{dp} < 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

I assume, with the occurrence of a hurricane event, the risk factor of a sinkhole event happening will increase for the homebuyers who are buying or selling homes in a sinkhole risk zone, and we will see the reflection of that changed risk factor in the marginal implicit hedonic price in (6).

Finally, a change in the information set [i] could affect marginal implicit prices. Assume $\frac{\partial p(i)}{\partial i} > 0$, so that information conveyed by a hurricane event heightens the subjective perception of risk because now the probability of a sinkhole opening is higher.

Differentiating (6) with respect to i shows that the implicit price of risk factors is decreasing in information that heightens perception in risk (i.e. becomes more negative) if $\frac{\partial V_0}{\partial y} > \frac{\partial V_1}{\partial y}$, while the effect is indeterminate if $\frac{\partial V_1}{\partial y} > \frac{\partial V_0}{\partial y}$. Here I use occurrence and non-occurrence of hurricane events to test for such effects in marginal implicit housing prices. So, after a hurricane, people who live close to a sinkhole location update their risk perception, and the sinkhole risk gets triggered by hurricane risk, and there would be a price discount for such properties.

2.6 Empirical Strategy

2.6.1 Empirical Model

A popular method for measuring the effect of different property characteristics and other relevant factors in the Hedonic method. Sirmans (2005) reviewed around 125 studies on the real estate market and analyzed the influence of different factors on real estate pricing. He found that different property characteristics such as the number of bedrooms, number of bathrooms, existence of a fireplace and pool have the most prominent effect on real estate prices. This study includes these variables with the influence of sinkhole and, additionally, the changing effect of these sinkholes after a natural hazard event such as a hurricane that might be correlated with a new sinkhole opening nearby.

According to Sirmans (2005), the most commonly used form of the hedonic pricing model is:

$$P_i = f(X_j, L_j, E_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

where P_i is the log of the transaction price of house i, X_j is a vector of j structural housing characteristics, L_j is vector of location variables, and E_i is a vector of externalities affecting the transaction price.

My first model estimates the effect of the presence and proximity of sinkhole on housing value using the log of the sales price of the houses as the dependent variable. I use binary variables for quarters between 2014 to 2018, using the first quarter of 2014 as the base quarter. With these additional variables, my first model can be written as:

$$log\ (price)_{i,t} = \alpha_0 + \beta_i\, X_{ij} + \ \varphi_i\ \ sinkhole_i + \mu_i\, Distance_{sinkhole\ ij} + \theta_i\ time_i + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where $price_i$ is the selling price of the house, i, X_{ij} is the matrix of explanatory variables j for the house i, $Sinkhole_i$ is a binary variable for house i with a value of one if a sinkhole is located within a specific distance band and zero otherwise.

$Distance_{sinkhole\ ij}$ capture the proximity of the nearest sinkhole to house i. $Time_i$ is a vector of binary variables indicating the quarter that property i was sold and ε_i is the error term.

To estimate the combined effect of hurricane and sinkhole on the property value, I use a difference-in-differences (DID) framework with a hurricane event. I compare the price differentials of the houses located near sinkholes with price differentials of the houses that are not close to sinkholes from a sample of housing sales data. I use the log of the sales price of the houses as dependent variable to estimate my model:

$$log(price_i) = \alpha_1 + \beta_i\, X_{ij} + \ \varphi_i\ \ sinkhole_i + \ \gamma_t\ irma_t + \delta_{irma}\ (sinkhole_i * irma_t) + \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where $price_i$ is the selling price of the house, i, X_{ij} is the matrix of explanatory variables j for the house i, $sinkhole_i$ is a binary variable for house i with a value of one if sinkhole is located within a certain distance band for the sold property and zero, if it is located further than the distance band. $irma$ is a binary variable taking the value of one if the house is sold after Hurricane Irma and zero if the house is sold before hurricane Irma. δ_{irma} represents the effect of hurricane Irma on the value of the houses that are close to known sinkhole locations. From δ_{irma} I can estimate the changing risk perception of the homebuyers and sellers due to hurricane Irma.

Model (8) is designed to test two hypotheses. First, the presence of a sinkhole near a property has a negative effect on the selling price of the property. According to this hypothesis, the φ_i on the sinkhole would be negative. I will try to prove this hypothesis using different distance bands such as ½ mile, 2/3-mile, 1 mile and 2 miles.

The second hypothesis is that sinkhole proximity has a negative effect on selling price (i.e., the closer the sinkhole, the lower the selling price) and I will try to prove this hypothesis for the continuous case. So, the μ_i for the $Distance_{sinkhole\ ij}$ would be negative.

Model (9) is designed to test the third hypothesis: After hurricane Irma, the negative effect of close sinkhole proximity to the property will be exacerbated and I will see more price discounts for the houses that are located close to known sinkhole locations. So, my δ_{irma} will be negative.

2.7 Estimation Results

2.7.1 Baseline Estimates

The definitions and the descriptive statistics of the variables that I have estimated are given in Table 2.1. As shown in Table 2.1, the average price of the houses sold between 2014 and 2018 is $227118.3, the average age of the sold houses is 22.3 years, and the average lot size is 0.66 acres. There are 3.02 bedrooms per house on average, and almost all the houses have central heating. Regarding the distance of the nearest sinkhole from the sold houses, 18% of the houses have the nearest sinkhole within ½ mile, 27% of the houses have the nearest sinkhole within 3/4 mile, 50% of the houses have the nearest sinkhole within 1.5 miles and 70% of the houses have the nearest sinkhole within 2 miles.

I collected the geographic location data for all the houses in the data set as well as the location data for the sinkholes in Lake County from the Florida Geological Survey (FGS) website. Using *ArcGIS*, I calculated the shortest distance between each house and nearest known sinkhole location using their geocoded location. In Figure 2.2, I have shown the locations of the geocoded houses in Lake County and known sinkhole locations in Florida. In Figures 2.3, 2.4 and 2.5, I have shown the price trend of the houses that have a sinkhole within ½ mile, and 1 mile and 2 miles respectively and observed that the houses that are located close to the sinkholes have a negative price premium compared to the houses that are not close to sinkholes. It can also be seen that the price discount increases after Hurricane Irma. This indicates the risk perception of the homebuyers who are buying houses near sinkhole locations changes following a hurricane event.

The focus of this study is to analyze two primary effects: (1) the price effect of being within proximity of a sinkhole, and (2) the change in risk perception about sinkhole risk following a hurricane event and the effect of that changed risk perception on the real estate market. These effects are measured by analyzing both sinkhole and non-sinkhole properties.

2.7.2 Effect of sinkhole on housing price

I estimate the Ordinary Least Squares (OLS) regression model to calculate the effect of sinkholes on housing prices. As there can be some spatial effect present in the data, I also estimate the spatial error regression model to account for the spatial autocorrelation among the houses that are located close to each other. I use the log of the sales price as the dependent variable in all of my regression models.

I report the result for the OLS regression in Table 2.2, where I estimate the percentage change in prices for the houses that are located close to sinkhole locations. I find that sinkholes have a significant effect on housing prices from my OLS regression. I run the regression using different dummy variables covering the distance of sinkholes as well as continuous distance variables from the nearest sinkhole location. I also control for time trend by using quarterly dummy variables from the 1st quarter of 2014 to the last quarter of 2018, using the 1st quarter of 2014 as the base quarter. In the OLS regression, all the structural variables such as the number of bedrooms (Bedrooms), number of bathrooms (Bathrooms), land size of the house (Acres), and age of the house ($House_{Age}$) have expected signs and are significant at 1% level. Amenities such as pools (Pool), fireplace (Fireplace), and having central air-conditioning (Central air) also significantly affect the housing values, and they are also significant at 1% level. I find a significant price discount for the houses due to proximity to sinkhole locations. I find that houses that are within ½ mile of a known sinkhole location suffer an 8.2 % price discount compared to other houses, and it is significant at 5% level. The price discount falls to 7% when the house is within ¾ mile of a known sinkhole location, and it is significant at 1% level. I find that the price discount remains 7% for the properties that have a known sinkhole location within 1 mile and this negative premium is significant at 1% level. When the house is located further than that, for example, when the house is 2 miles away from a sinkhole location, the price discount falls to 5%, and this discount is also significant at 1% level.

As the houses are sometimes clustered together in my sample, and sinkhole exposure may show spatial trend, I run different spatial error models to explore the effect of sinkholes on housing prices further. My estimation results from the spatial error model are given in Table 2.3. In Table 2.3, I show the effect of structural and neighborhood variables such as the number of bedrooms (Bedrooms), number of bathrooms (Bathrooms), land size (Acres), pools (Pool), fireplaces (Fireplace), etc. on sales values. The coefficients of the structural variables all have expected signs and are statistically significant at 1% level. In the spatial error model, the price discount is even higher for different distance bands compared to the OLS model. Here, after controlling for spatial autocorrelation, houses that are within ½ mile of a known sinkhole location suffer a 6% price discount compared to other houses, and it is significant at 1% level.

The price discount increases to 8% when the house is within ¾ mile of a known sinkhole location and this discount is also significant at 1% level. When a house has a known sinkhole location within 1 mile, the price discount increases to 8.9%, and it is significant at 5% level. After controlling for spatial autocorrelation, even when the house is 2 miles away from a sinkhole location, there is a 2.3% price discount due to sinkhole proximity, and it is significant at 1% level. Overall, there is a significant price discount if the house is located close to a known sinkhole location and from different estimated models. The price discount for being in proximity to a known sinkhole location varies from 8.9% to 2.3% and almost all of these negative price premiums are significant at 1% level.

2.7.3 Effect of Hurricane Irma on houses close to known sinkhole locations

To analyze the effect of a hurricane event on housing prices that are located close to sinkholes, I estimate the difference in differences (DID) model. Hurricane Irma is used as a natural experiment to capture how the risk from Hurricane Irma triggers the risk from sinkholes among the homebuyers and homeowners who live close to sinkhole locations. The natural experiment happened on September 10, 2017, when Hurricane Irma passed over Lake County. This hurricane event made homeowners of the hurricane-affected areas aware of the hurricane risk, and it had an added effect for the homeowners who lived near a known sinkhole location and made them aware of the increased possible risk of a sinkhole in the near future. The homeowners who live far away from any known sinkhole location, are exempt from this added effect. I have established them as the control group and applied a difference in difference estimator (DID) to quantify the added risk for living near a sinkhole location. The results of the difference in difference estimation are reported in Tables 2.4 and 2.5.

I use the log of the sales price as the dependent variable in Tables 2.4 and 2.5. I control for household characteristics (e.g., number of bedrooms (Bedrooms), number of bathrooms (Bathrooms), land size (Acres), etc.) along with quarter fixed effects. I also use the squared value of the number of bedrooms (Bedrooms Sq.) and bathrooms (Bathrooms Sq.) as control variables following Bin and Polasky (2004). I find that there is an additional price discount for the houses that are located close to sinkholes after Hurricane Irma. I calculate the effect of Hurricane Irma for houses that are located within different distance bands from known sinkhole locations. I find an additional price discount when the houses are located within ½ mile, ¾ mile, and 1 mile of a known sinkhole location. When the house has a known sinkhole location within ½ mile distance, that house faces an extra 2% price discount compared to the houses that are not that close to sinkholes, and it is significant at 10% significance level. When the house is located ¾ mile away from the nearest sinkhole location, that house suffers a 3% extra price discount, and it is significant at 5% level. If the nearest sinkhole is located within 1 mile of the house, I again find a 2% price discount compared to other houses, and it is significant at 5% level. Like before, the effect disappears when the distance increases to 2 miles. So, people who are buying houses that are at least 2 miles away from the nearest sinkhole location, their perception of sinkhole risk after a hurricane is unlikely to change.

I find convincing evidence that a hurricane event is likely to change people's risk perception about sinkholes. People have increased risk perception of sinkholes after a hurricane event, and due to that increased risk perception, the houses located close to sinkhole suffer a price discount of around 2% to 3% compared to similar houses that are not close to sinkholes. As seen from Tables 2.4 and 2.5, buyers will count the fact that after a hurricane, there is an increased risk of a sinkhole opening nearby due to the presence of an already open sinkhole and that increased risk factor is represented in their purchase decision. There can also be a supply-side effect present in the increased price discount for sinkholes after a hurricane event. People who are already living in a house that is close to a sinkhole, might also think about this increased risk of a new sinkhole opening, and they will try to move to some other place where the risk is lower. So, the supply of housing units that are available for sale will increase, and this increased supply will further reduce the prices of the houses, exacerbating the price discount. So, the overall price discount observed in Tables 2.4 and 2.5 can be considered as the combined effect of demand-side and supply-side responses to increased risk perception for sinkholes after a hurricane event.

I show the treatment effect of Hurricane Irma in figures 2.6, 2.7 and 2.8. I observe that following the hurricane, the houses that are within 0.25-mile face a significant price discount as they think that they are in danger of increased activity due to the hurricane. When the distance increases to 0.50 mile, I again observe a significant price discount for the houses that are within 0.50 mile of a sinkhole. When the distance increase to 2 miles, the price discount diminishes, as people who live this far from a sinkhole might think that they are not in increased danger of suffering sinkhole damage due to the hurricane as they are far away from any sinkhole activity and so, Hurricane Irma doesn't affect their risk perception.

2.7.4 Quantile Regression Analysis:

After Hurricane Irma, the additional price discount to the properties that are near known sinkhole locations might differ according to the property values. Owners of the more expensive properties might react to the increased sinkhole risk differently compared to the owners of the relatively less expensive properties. To explore the possible differences in price discounts to the properties based on their valuation, I run a quantile regression analysis for properties within different distance bands from a known sinkhole location. The results from the quantile regression specification are presented in Tables 2.6, 2.7, 2.8, and 2.9.

The 75th quantile regression will show the added effect of Hurricane Irma on the most expensive properties in my sample. For the properties in the 75th percentile, these properties suffer a 1% price discount following Hurricane Irma if there is a known sinkhole within ¾ mile of the property, and that discount is significant at 5% level. These properties also suffer a 1% further price discount due to Hurricane Irma if a sinkhole is present with 1 mile of the property, and this discount is also significant at 5% level. The properties that are further than 1 mile of a known sinkhole location doesn’t suffer further price discounts following Hurricane Irma.

The 50th quantile regression will show the added effect of Hurricane Irma on the moderately expensive properties. For properties in the 50th percentile, they suffer a 2% price discount following Hurricane Irma if they have a sinkhole within ½ mile, and this discount is significant at 5% level. If a sinkhole is present with ¾ mile of the properties, they suffer a further 3% price discount following Hurricane Irma, and this discount is significant at 1% level. The properties that have a sinkhole with 1 mile suffer a further 2% price discount, and this discount is significant at 5% level.

The 25th quantile regression will show the added effect of Hurricane Irma on the least expensive properties in the sample. The properties in the 25th percentile, suffer a 3% price discount following Hurricane Irma if there is a sinkhole with ¾ mile of the property and this discount is significant at 1% level. If the property has a sinkhole within 1 mile, then that property will suffer a 1% price discount following Hurricane Irma, and this discount is significant at 5% level.

After Hurricane Irma, the sinkhole discount increases similarly for the properties that are in the 25th and 50th percentile, but the price discount is relatively low for the 75th percentile or the properties that are most expensive in the sample. So, homeowners of the relatively expensive properties are less concerned about the added sinkhole risk caused by Hurricane Irma compared to the other homeowners. Even though the differences in price discount are very small, this is an interesting finding as the owners of the more expensive properties are expected to be more concerned about the risks to their properties as they are more valuable. Although the difference in the price discount is very low, and the price discounts for these properties are still statistically significant and substantial in terms of total reduced value.

2.7.5 Event study of the effect of hurricane on houses close to sinkholes

When trying to identify the effect of a reform or an event, it is imperative to differentiate the effect of interest from other irrelevant effects (Olsson, 2008). In an ideal situation, one would prefer to estimate the outcome for an individual or for one unit of the variable of interest that is both treated and untreated at the same point in time. Unfortunately, that is not possible. So, the closest to the ideal situation one researcher can come to is to find a feasible control group that, in the absence of treatment, is on average the same as the treatment group, and that way, the average treatment effect can be correctly estimated. All of the time effects should thereby be common across the two groups, that is, the average outcome for the two groups should be parallel over time in the absence of treatment (Greene, 2009). I can assume that this assumption is fulfilled if I can establish that the parallel trend assumption is fulfilled.

In Figures 2.3, 2.4 and 2.5 below, I presented a visual analysis of the effect of Irma on the selling price of the houses that are located within ½ mile,1 mile, and 2 miles respectively to known sinkhole locations. These figures also visually present the parallel price trend for houses that are close to the sinkholes and the houses that are not. This trend comparison is crucial and is helpful to visually inspect the parallel trend assumption for the difference in differences model reported in Tables 2.4 and 2.5. We can see that parallel trend assumption is fulfilled for the houses that are located closer than 2 miles within a sinkhole. However, if the distance increases to 2 miles, the price trends are not parallel.

These diagrams also help to show the change in price trends following Hurricane Irma on housing prices that were close to sinkholes. From Figures 2.3 and 2.4, we can see that there is a price discount for houses that are located close to sinkholes compared to the houses that are far away from known sinkhole locations.

After Hurricane Irma, we can see that there is an increase in price discounts for houses that are close to sinkholes due to the changed risk perception. In Figure 2.5, we see that the price trend of the houses that are located more than 2 miles away from the nearest sinkhole location does not show the price discount.

2.7.6 Can we trust the estimated treatment effect?

Are the treatment effects estimated in Tables 2.4 and 2.5 unique and attributable to the effect of Hurricane Irma? One frequently used method of testing the robustness of an estimated treatment effect is to estimate placebo effects at different points in time. If any of these placebo effects turn out to be significant, it can cast doubt on the treatment effect. Table 2.6 shows that all the estimated treatment effects for the placebo regression models are insignificant and that the only DID estimator that is significant is that for 2016 and 2017. The significant placebo effect of 2016 is because of an insurance policy change with respect to sinkhole coverage. The significant results in 2017, the actual year of the treatment, Hurricane Irma, indicates that the effect that occurred in 2017 is not random.

A common objection against the use of a difference in differences model for an event is that if individuals anticipate the event and begin to behave in a certain way before the event is implemented, it will bias the treatment effect. For this case, as the shock is a hurricane event, the chance of people anticipating it ahead of time and adjusting their behavior is very low, and so, that possibility can be ruled out.

2.8 Regression Discontinuity Specification:

This study also uses a regression-discontinuity design, namely, I explore how price discount due to sinkhole presence for the properties changes discontinuously at different distance bands following Hurricane Irma, which may produce "near" experimental causal estimates of the effect of sinkhole presence on property prices following the two events.

2.8.1 Effect of Hurricane Irma:

To estimate the discontinuously changed effect of the presence of sinkhole on property price after Hurricane Irma, I estimate the following log-linear RD model:

$$\begin{aligned} log(Saleprice) \\ &= \alpha + \beta_1\, irma + \beta_2(irma\ *\ sinkhole_{distance}) + \tau_1\, sinkhole_{distance} \\ &+ \epsilon_i \ldots\ldots\ldots (10) \end{aligned}$$

Where $log(Saleprice)$ refers to the log of sales price of the houses. $sinkhole_{distance}$ refers to the cutoff point (i.e., if the house is located outside the sinkhole distance band), $irma$ is a binary variable. $irma$ is 1 if the house was sold after hurricane Irma and 0 otherwise. The coefficient τ is my variable of interest and represents the local average treatment effect.

The results from the regression discontinuity specification is presented in Table 2.7. The RD treatment effect is showing the changed local average treatment effect of sinkhole presence on housing price after Hurricane Irma. The presence of sinkhole presence within ¼ mile of a house causes a 5% price discount to that house and that discount is significant at 5% level. If the sinkhole is within ¾ mile of a house, it causes a 3% price discount to that house and this discount is significant at 5%. I find no significant price discount after Hurricane Irma if the house is located further that this from a known sinkhole location.

2.9 Conclusion:

Climate change-induced hydro-meteorological hazards are projected to become more frequent and intense and they are likely to cause immense socioeconomic impacts. Against this backdrop, there is a growing interest among policymakers and research communities in understanding the potential impacts of these natural hazards on the real estate market. Real estate is a major asset for most of the households, and an adverse impact to the real estate market can cause a substantial negative shock to the economy. In this study, I estimate the effects of sinkhole location on residential property values using the hedonic pricing approach. I analyze the effects of sinkhole proximity on residential property values before and after Hurricane Irma, which swept through Florida in September 2017.

The estimation results from this study indicate that the price of a residential property located close to a known sinkhole is lower than an otherwise similar property. Proximity to a known sinkhole location lowers estimated sales value for an average home by 2.3% to 8.9% of the average sales price. This price discount, which ranges from $4,309 to $23,702, is found to have gradual decaying with distance from the nearest sinkhole location.

My analysis has shown that after Hurricane Irma, home values located close to sinkholes have suffered a further 2% - 3% price discount compared to the homes that are located further away from known sinkhole areas, which is approximately $4309 to $6464. This result indicates that hurricane risk perception triggers people's risk perception of sinkholes. Homebuyers and sellers are aware of the increased risk of sinkhole occurrence following Hurricane Irma, and their increased risk perception is reflected in the housing prices. This price discount allows us to observe how one hydrological hazard like a hurricane interacts with a geological hazard like a sinkhole and how that combined effect is reflected in the real estate market.

The evolution of the risk premium may be contingent upon various factors such as severity and frequency of hurricane events and sinkhole incidences and the occurrence of similar events in other places that receive extensive news coverage. I observed the increased risk premium due to Hurricane Irma even after one year. Further research is needed to see if the risk premium persists over a longer period, or it gets eroded shortly after one year. Also, the evolution of this risk premium with time is not clear, and people's reaction to the dual risk of sinkhole and hurricane might change as the memory of a major Hurricane recedes. This evolution of risk perception can be an important topic for future research.

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TABLES

Table 2.1: Descriptive statistics.

Variable	Observations (N)	Mean	Min	Max	Variable definitions	Standard deviation
Price	37,788	227118.3	50000	3500000	Sale price of the house.	153004.2
House $_{Age}$	37,788	22.34	0	159	Number of years since the house was built.	19.74
Bedrooms	37,788	3.02	1	6	Number of bedrooms in the house.	0.81
Acres	37,788	0.66	0	517.1	Lot size of the house.	4.78
Bathrooms	37,788	2.07	0	6	Number of bathrooms in the house.	0.57
Fireplace	37,788	0.121	0	1	1, If the house has a fireplace and 0 otherwise.	0.350

Pool	37,788	0.142	0	1	1, If the house has a pool and 0 otherwise.	0.349
Central air	31,901	0.974	0	1	1, If the house has central air and 0 otherwise.	0.156
Distance Airport	37,788	2.65	0.08	15.13	Distance of the nearest airport from the house.	1.54
Distance Lake	37,788	0.18	0.003	1.22	Distance of the nearest lake from the house.	0.12
Distance Flood zone	37,788	0.32	0.001	1.30	Nearest distance of the flood zone from the house.	0.18
Distance Library	37,788	2.92	0.37	12.21	Distance of the nearest library from the house.	1.66
Distance Sinkhole	37,788	1.30	0.001	16.86	Distance of the nearest sinkhole from the house.	1.35

Irma	37,788	0.41	0	1	1, If the house was sold after Hurricane Irma and 0 otherwise.	0.49
Log (price)	37,788	12.02	8.51	18.07	Log of the sale price of the house.	0.76
Sinkhole 1/2 mile	37,788	0.18	0	1	1, if the house is located within ½ mile of a known sinkhole location and 0 otherwise.	0.38
Sinkhole 3/4 mile	37,788	0.27	0	1	1, if the house is located within 3/4 mile of a known sinkhole location and 0 otherwise.	0.44
Sinkhole 1 mile	37,788	0.50	0	1	1, if the house is located within 1 mile of a known	0.49

					sinkhole location and 0 otherwise.	
Sinkhole 2 miles	37,788	0.70	0	1	1, if the house is located within 2 miles of a known sinkhole location and 0 otherwise.	0.45
Q1-2014	37,788	.0081	0	1	1 if the house was sold in quarter 1, 2014 and 0 otherwise.	0.09
Q2-2014	37,788	.0083	0	1	1 if the house was sold in quarter 2, 2014 and 0 otherwise.	0.09
Q3-2014	37,788	.0084	0	1	1 if the house was sold in quarter 3, 2014 and 0 otherwise.	0.09

Q4-2014	37,788	0.045	0	1	1 if the house was sold in quarter 4, 2014 and 0 otherwise.	0.09
Q1-2015	37,788	0.051	0	1	1 if the house was sold in quarter 1, 2015 and 0 otherwise.	0.20
Q2-2015	37,788	0.051	0	1	1 if the house was sold in quarter 2, 2015 and 0 otherwise.	0.22
Q3-2015	37,788	0.048	0	1	1 if the house was sold in quarter 3, 2015 and 0 otherwise.	0.21
Q4-2015	37,788	0.04	0	1	1 if the house was sold in quarter 4, 2015 and 0 otherwise.	0.19
Q1-2016	37,788	0.051	0	1	1 if the house was sold in	0.22

					quarter 1, 2016 and 0 otherwise.	
Q2-2016	37,788	0.059	0	1	1 if the house was sold in quarter 2, 2016 and 0 otherwise.	0.23
Q3-2016	37,788	0.06	0	1	1 if the house was sold in quarter 3, 2016 and 0 otherwise.	0.23
Q4-2016	37,788	0.051	0	1	1 if the house was sold in quarter 4, 2016 and 0 otherwise.	0.22
Q1-2017	37,788	0.068	0	1	1 if the house was sold in quarter 1, 2017 and 0 otherwise.	0.25
Q2-2017	37,788	0.075	0	1	1 if the house was sold in quarter 2, 2017 and 0 otherwise.	0.26

Q3-2017	37,788	0.063	0	1	1 if the house was sold in quarter 3, 2017 and 0 otherwise.	0.24
Q4-2017	37,788	0.061	0	1	1 if the house was sold in quarter 4, 2017 and 0 otherwise.	0.24
Q1-2018	37,788	0.07	0	1	1 if the house was sold in quarter 1, 2018 and 0 otherwise.	0.25
Q2-2018	37,788	0.08	0	1	1 if the house was sold in quarter 2, 2018 and 0 otherwise.	0.27
Q3-2018	37,788	0.07	0	1	1 if the house was sold in quarter 3, 2018 and 0 otherwise.	0.25
Q4-2018	37,788	0.06	0	1	1 if the house was sold in	0.24

	quarter 4, 2018 and 0 otherwise.

Table 2.2: Effect of sinkholes on housing prices. Ordinary Least Squares (OLS) regression.

	Model 1	Model 2	Model 3	Model 4
House $_{Age}$	0.01 ***	-0.01 ***	-0.01 ***	-0.01***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Bedrooms	0.14 ***	0.08 ***	0.08 ***	0.08 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Acres	0.015 ***	0.03 ***	0.03 ***	0.03 ***
	(0.0006)	(0.001)	(0.001)	(0.001)
Bathrooms	0.24 ***	0.23 ***	0.23 ***	0.23 ***
	(0.006)	(0.006)	(0.006)	(0.006)
Fireplace (=1)	0.32 ***	0.23 ***	0.23 ***	0.23***
	(0.009)	(0.008)	(0.008)	(0.008)
Pool (=1)	0.25 ***	0.2 ***	0.19 ***	0.19 ***
	(0.009)	(0.008)	(0.007)	(0.007)
Central air	0.48 ***	0.48 ***	0.48 ***	0.48 ***
	(0.02)	(0.02)	(0.02)	(0.02)
Distance $_{Park}$	-0.02 ***	-0.016 ***	-0.02 ***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Distance $_{Library}$	-0.005 ***	-0.004 ***	-0.005 **	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Distance $_{Sinkhole}$	0.02 ***	0.015 ***	0.01 ***	0.01 ***
	(0.002)	(0.003)	(0.003)	(0.003)

Distance $_{Airport}$	-0.02 ***	-0.01 ***	-0.016 ***	-0.018 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Sinkhole $_{1/2\ mile}$	-0.082 ***			
	(0.008)			
Sinkhole $_{3/4\ mile}$		-0.07 ***		
		(0.007)		
Sinkhole $_{1\ mile}$			-0.07 **	
			(0.006)	
Sinkhole $_{2\ miles}$				-0.05 ***
				(0.008)
Constant	11.00 ***	10.93 ***	10.95 ***	11.00 ***
	(0.04)	(0.04)	(0.04)	(0.04)
N	31,901	31,901	31,901	31,901
R^2	0.40	0.40	0.40	0.40

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 2.3: The effect of sinkhole location on housing prices. Spatial error regression.

	Model 5	Model 6	Model 7	Model 8
House $_{Age}$	-0.01 ***	-0.01 ***	-0.02 ***	-0.01***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Bedrooms	0.07 ***	0.07 ***	0.07 ***	0.05 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Acres	0.03 ***	0.03 ***	0.029 ***	0.03 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Bathrooms	0.18 ***	0.17 ***	0.18 ***	0.22 ***
	(0.005)	(0.006)	(0.006)	(0.006)
Fireplace (=1)	0.15 ***	0.16 ***	0.15 ***	0.21***
	(0.007)	(0.008)	(0.008)	(0.008)
Pool (=1)	0.18 ***	0.20 ***	0.18 ***	0.18 ***
	(0.007)	(0.007)	(0.007)	(0.007)
Central air	0.43 ***	0.42 ***	0.43 ***	0.48 ***
	(0.01)	(0.02)	(0.01)	(0.02)
Distance $_{Park}$	-0.02 ***	-0.006 ***	-0.012 ***	-0.02***
	(0.001)	(0.002)	(0.001)	(0.001)
Distance $_{Library}$	0.002	0.002	0.003	-0.01***
	(0.01)	(0.002)	(0.016)	(0.002)
Distance $_{Flood\ zone}$	0.025		0.03	-0.014 ***
	(0.01)		(0.02)	(0.009)

Distance $_{Sinkhole}$	0.01 ***	0.01 **	-0.003	-0.001 ***
	(0.003)	(0.004)	(0.003)	(0.10)
Distance $_{Airport}$	-0.01 ***	-0.003 **	-0.01 ***	-0.014
	(0.02)	(0.003)	(0.002)	(0.003)
Sinkhole $_{1/2\ mile}$	-0.06 ***			
	(0.02)			
Sinkhole $_{3/4\ mile}$		-0.08 ***		
		(0.01)		
Sinkhole $_{1\ mile}$			-0.089 **	
			(0.010)	
Sinkhole $_{2\ miles}$				-0.023 ***
				(0.008)
Constant	11.10 ***	11.32 ***	11.13 ***	11.36 ***
	(0.04)	(0.02)	(0.04)	(0.10)
R^2	0.51	0.49	0.49	0.46
Lamda	0.48 ***	0.47 ***	0.62 ***	0.61 ***
	(0.006)	(0.006)	(0.005)	(0.006)
AIC	39984	41419.3	39925	39938.3
Schwarz	40277	41544.9	40217.9	40231.2
Likelihood ratio	4709.19***	4618.41 ***	4697.32***	4691.8***

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.4: The effect of Hurricane Irma on the sale price of houses that are close to sinkholes.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11

	(0.11)	(0.12)	(0.10)	(0.12)
Sinkhole $_{½\ mile}$	-0.03 *** (0.009)			
Sinkhole $_{¾\ mile}$		-0.01 (0.009)		
Sinkhole $_{1\ mile}$			-0.01 (0.008)	
Sinkhole $_{2\ miles}$				-.02 * (0.030)
Sinkhole $_{1/2\ mile}$* Irma	-0.02 ** (0.01)			
Sinkhole $_{3/4\ mile}$ * Irma		-0.03 ** (0.013)		
Sinkhole $_{1\ mile}$ * Irma			- 0.02 ** (0.01)	
Sinkhole $_{2\ miles}$ * Irma				-0.01 (0.01)
R^2	44	43	44	42
N	31,901	31,901	31,901	31,901

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.5: Difference in differences estimates for Hurricane effect on different sinkhole locations.

Distance to nearest sinkhole location	Hurricane Irma	Sinkhole	Diff-in-diffs estimation	Quarter fixed effects	Number of observations
½ mile	0.033 (0.12)	-0.03 (0.009)	-0.02 ** (0.01)	Yes	31,901
¾ mile	-0.10 (0.11)	-0.01 (0.009)	-0.03 ** (0.013)	Yes	31,901
1 mile	-0.11 (0.10)	-0.01 (0.008)	- 0.02 ** (0.01)	Yes	31,901
2 miles	-0.11 (0.12)	-.02 * (0.030)	-0.01 (0.01)	Yes	31,901

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%. All models include control variables for housing characteristics and quarter dummies.

Table 2.6: Effect of Hurricane Irma on the 75th quantile properties.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11
	(0.11)	(0.12)	(0.10)	(0.12)

Sinkhole $_{½\ mile}$	0.01 (0.007)			
Sinkhole $_{¾\ mile}$		0.02 ** (0.009)		
Sinkhole $_{1\ mile}$			0.003 (0.006)	
Sinkhole $_{2\ miles}$				-.02 * (0.030)
Sinkhole $_{1/2\ mile}$* Irma	-0.01 (0.01)			
Sinkhole $_{3/4\ mile}$ * Irma		-0.01 ** (0.009)		
Sinkhole $_{1\ mile}$ * Irma			-0.01 ** (0.008)	
Sinkhole $_{2\ miles}$ * Irma				-0.01 (0.01)
R^2	44	43	44	42
N	30,675	30,675	30,675	30,675

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 2.7: Effect of Hurricane Irma on the 50th quantile properties.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11
	(0.11)	(0.12)	(0.10)	(0.12)
Sinkhole $_{½\ mile}$	-0.03 ***			

	(0.009)			
Sinkhole $_{¾\ mile}$		-0.03 *** (0.009)		
Sinkhole $_{1\ mile}$			-0.01 (0.008)	
Sinkhole $_{2\ miles}$				-.02 * (0.030)
Sinkhole $_{1/2\ mile}$* Irma	- 0.02 ** (0.01)			
Sinkhole $_{3/4\ mile}$ * Irma		-0.03 *** (0.008)		
Sinkhole $_{1\ mile}$ * Irma			- 0.02 ** (0.007)	
Sinkhole $_{2\ miles}$ * Irma				-0.008 (0.001)
R^2	33.8	33.8	33.9	33.8
N	30,675	30,675	30,675	30,675

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 2.8: Effect of Hurricane Irma on the 25th quantile properties.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11
	(0.11)	(0.12)	(0.10)	(0.12)
Sinkhole $_{½\ mile}$	-0.03 ***			

	(0.009)			
Sinkhole $_{¾ \text{ mile}}$		-0.03 *** (0.009)		
Sinkhole $_{1 \text{ mile}}$			-0.01 (0.008)	
Sinkhole $_{2 \text{ miles}}$				-.02 * (0.030)
Sinkhole $_{1/2 \text{ mile}}$* Irma	-0.03 *** (0.01)			
Sinkhole $_{3/4 \text{ mile}}$ * Irma		-0.03 *** (0.009)		
Sinkhole $_{1 \text{ mile}}$ * Irma			- 0.01 ** (0.008)	
Sinkhole $_{2 \text{ miles}}$ * Irma				-0.005 (0.01)
R^2	35.6	36.8	35.6	35.6
N	30,675	30,675	30,675	30,675

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 2.9: Summary results from quantile regression

Quantiles	Distance Bands			
	½ mile	¾ mile	1 mile	2 miles
75th	-0.01	-0.01 **	-0.01 **	-0.01
	(0.01)	(0.009)	(0.008)	(0.01)
50th	- 0.02 **	-0.03 ***	- 0.02 **	-0.008
	(0.01)	(0.008)	(0.007)	(0.001)
25th	-0.03 ***	-0.03 ***	- 0.01 **	-0.005
	(0.01)	(0.009)	(0.008)	(0.01)

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 2.10: Robustness test with placebo regressions

	Coefficients	Std. error
DID14	-0.07	(0.04)
DID15	-0.003	(0.019)
DID16	-0.03 *	(0.02)
DID17	-0.03 *	(0.014)
DID18	0.025	(0.021)
Treatment	0.08	(0.04)
Constant	0.025	(0.06)
R^2	0.41	
N	31,901	

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.11: Regression discontinuity to estimate the effect of Hurricane Irma on the houses close to sinkhole locations.

	Nearest sinkhole within ¼ mile	Nearest sinkhole within ¾ mile	Nearest sinkhole within 1mile	Nearest sinkhole within 2 miles
RD treatment effect	-0.05 **	-0.03 **	0.02	0.02
	(0.03)	(0.01)	(.01)	(.02)
Control for housing characteristics	No	No	No	No
Time fixed effects	No	No	No	No
County fixed effects	No	No	No	No
N	34,708	34,708	34,708	34,708

Note: Dependent variable is the log of sales price. Robust standard errors are presented at the parenthesis. $*$ significant at 10%; $**$ significant at 5%; $***$ significant at 1%.

FIGURES

Figure 2.1: Sinkhole locations in Florida counties.

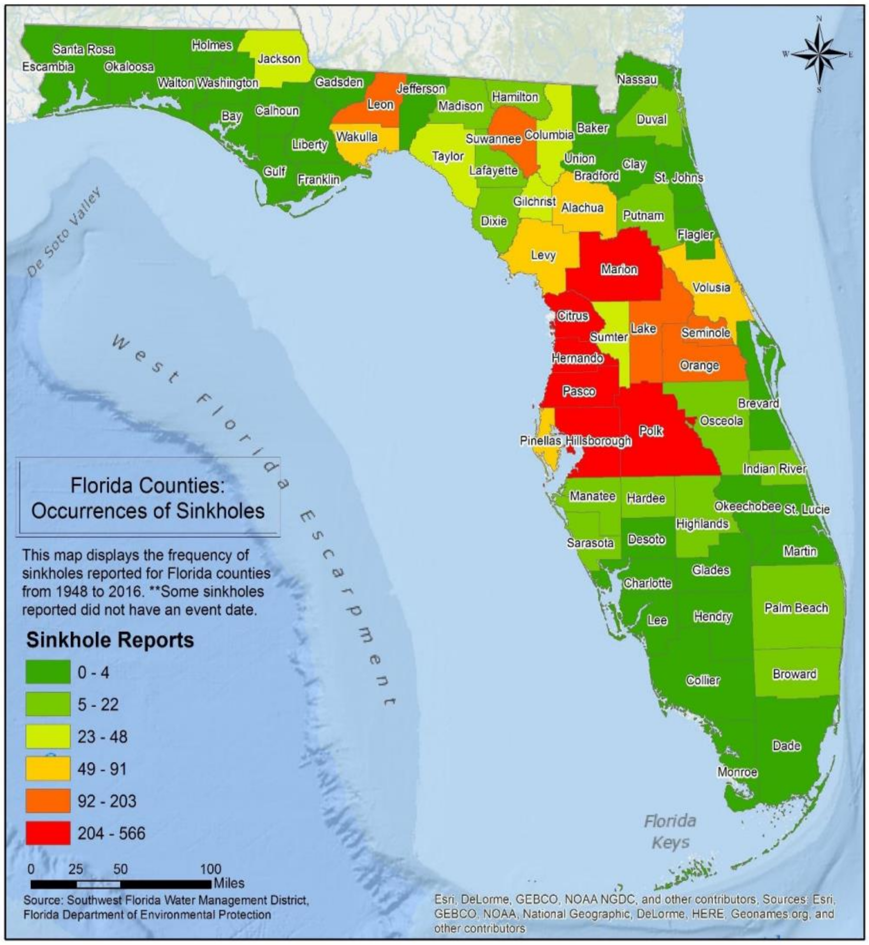


Figure 2.2: Locations of the known sinkholes in Florida and sold houses in Lake county.

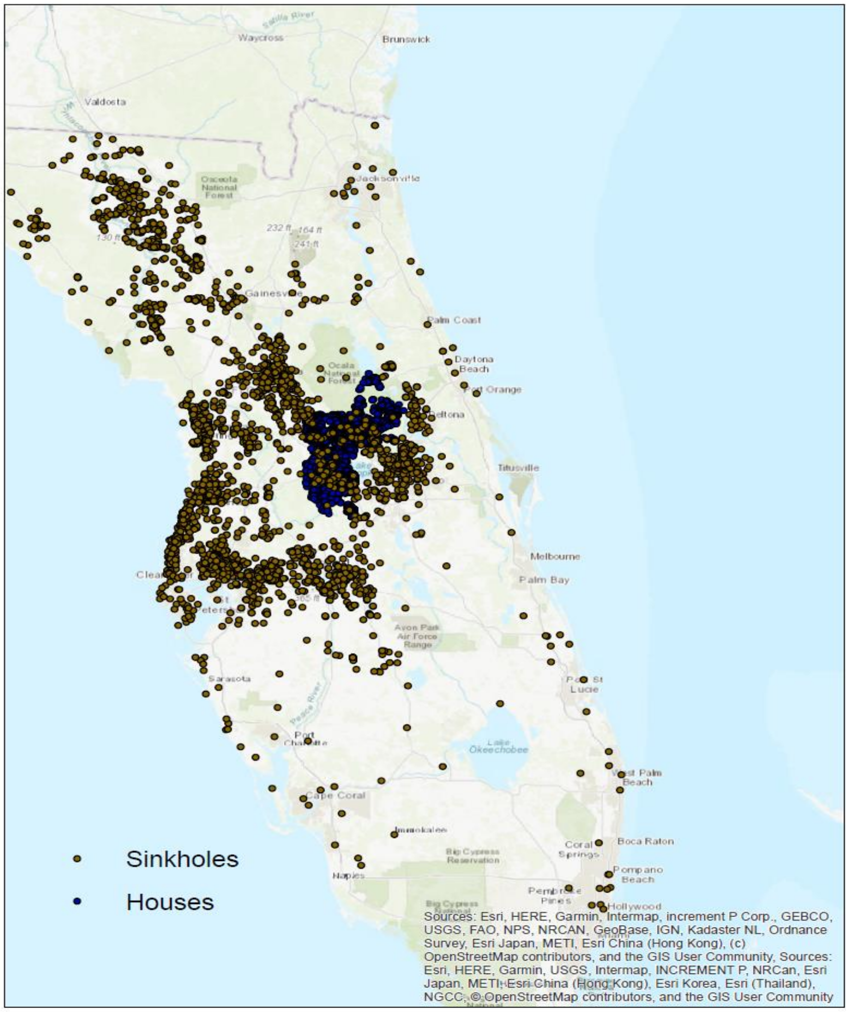
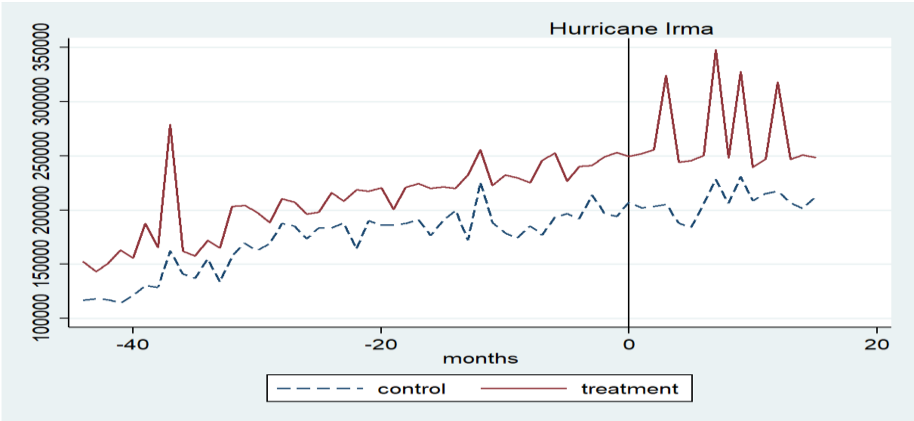
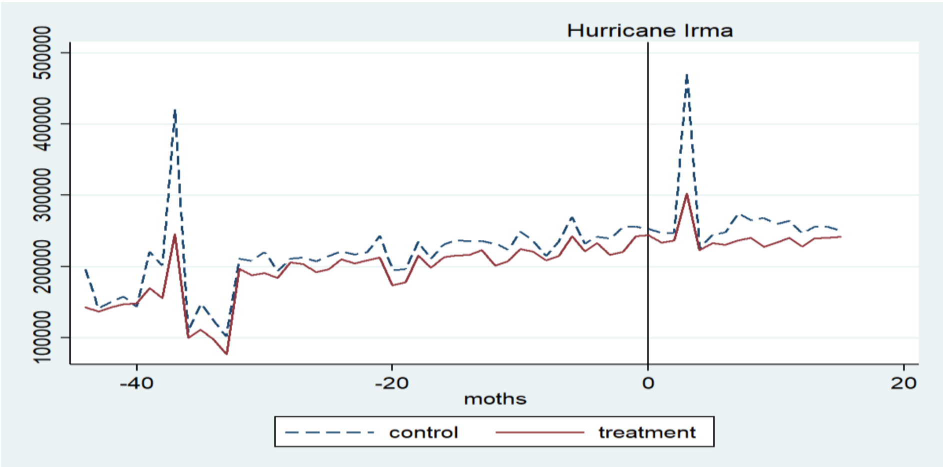


Figure 2.3: Price trend of houses sold within 1/2 mile of a known sinkhole location between 2014 and 2018.



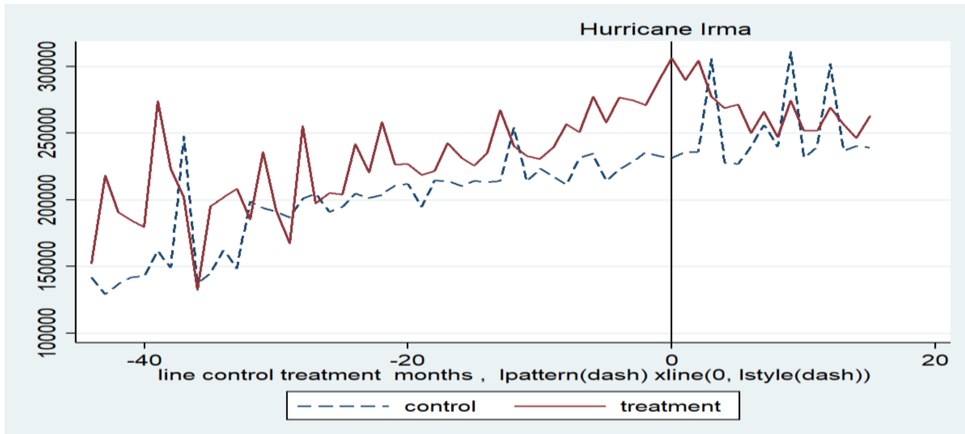
Notes: This figure depicts price trends before and after Hurricane Irma for properties located within ½ miles of a sinkhole (treatment) and properties located beyond this distance from a sinkhole (control).

Figure 2.4: Price trend of houses sold within 1 mile of a known sinkhole location between 2014 and 2018.



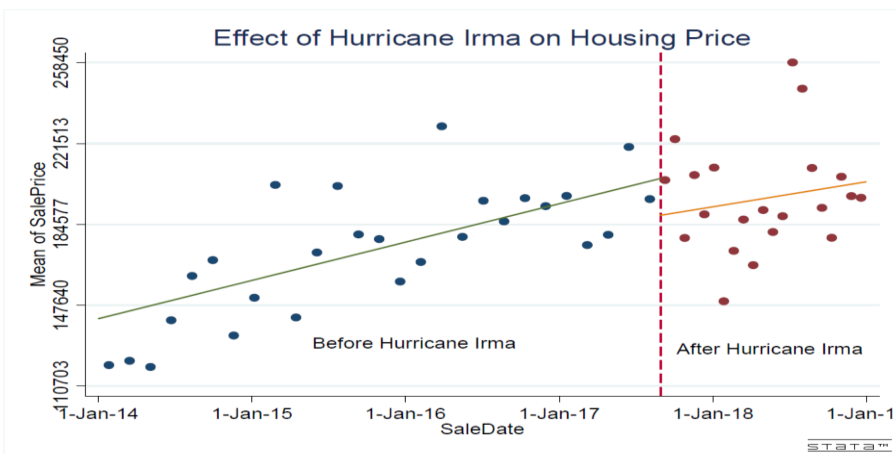
Notes: This figure depicts price trends before and after Hurricane Irma for properties located within 1 mile of a sinkhole (treatment) and properties located beyond this distance from a sinkhole (control).

Figure 2.5: Price trend of houses sold within 2 miles of a known sinkhole location between 2014 and 2018.



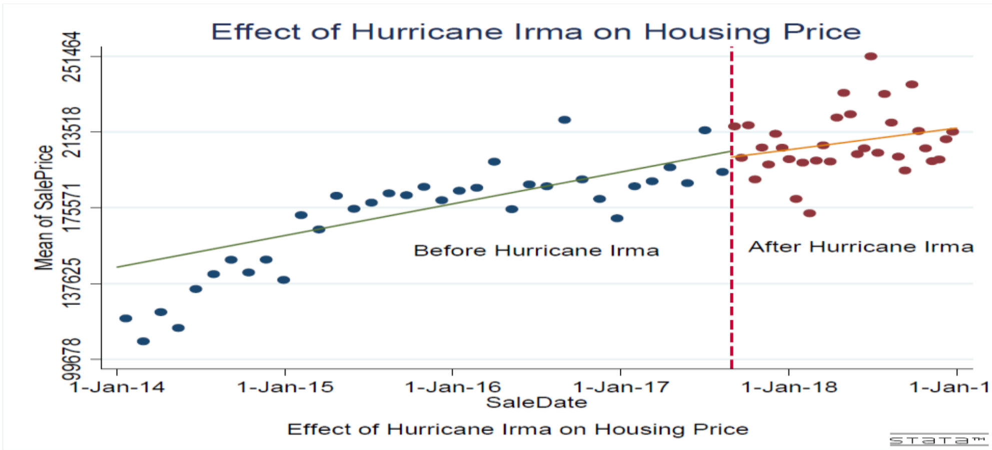
Notes: This figure depicts price trends before and after Hurricane Irma for properties located within 2 miles of a sinkhole (treatment) and properties located beyond this distance from a sinkhole (control).

Figure 2.6: Effect of Irma on houses within 0.25 mile of a sinkhole



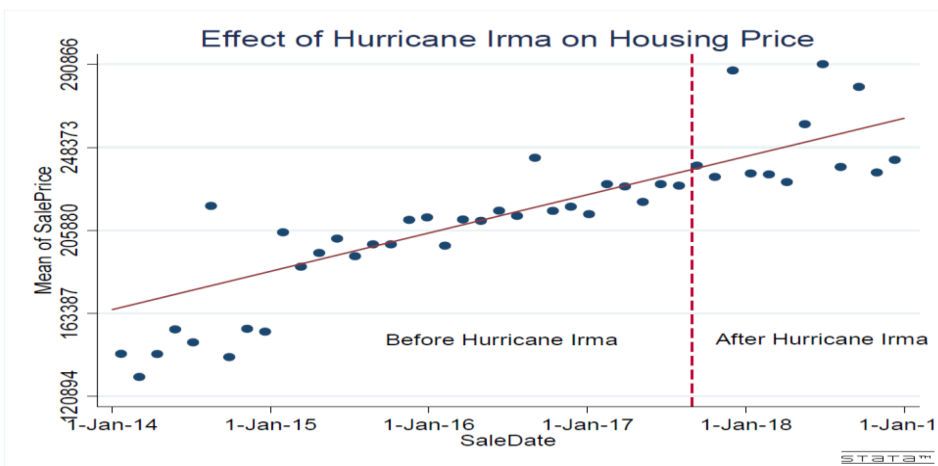
Note: This figure depicts the treatment effect of Hurricane Irma on the prices of the properties that are located within 0.25 mile of a sinkhole and compares the treatment effect with the same property prices before Hurricane Irma.

Figure 2.7: Effect of Irma on houses within 0.50 mile of a sinkhole



Note: This figure depicts the treatment effect of Hurricane Irma on the prices of the properties that are located within 0.50 mile of a sinkhole and compares the treatment effect with the same property prices before Hurricane Irma.

Figure 2.8: Effect of Irma on houses within 2 miles of a sinkhole



Note: This figure depicts the treatment effect of Hurricane Irma on the prices of the properties that are located within 2 miles of a sinkhole and compares the treatment effect with the same property prices before Hurricane Irma.

Chapter 3

Real Estate Market Response to Hydro-geological Hazard Risk: The Role of Insurance Policy Change

3.1 Introduction:

Property prices in hazard risk areas reflect the incremental option value for differences in real property risk and a properly specified hedonic model can reveal that price differential (Smith, 1985). Property prices are also affected when information is released regarding the risk faced by a property (Gayer et al., 2000). This risk information can be released by a natural hazard shock or a policy change that can affect the risk faced by the homeowners. The recent rise in natural disasters due to climate change around the world points to an increasing need for research on efficient public policy in areas where a significant possibility of natural disaster exists (MacDonald et al., 1987). I study the effect of a new sinkhole insurance law in Florida that increased the amount of risk homeowners face from sinkholes. By using a difference in differences framework, I attempt to capture the effect of this new insurance law indicating an increase in risk regarding sinkholes, explicitly allowing for temporal variation in the risk premium. Although there is some existing literature that explores the effects of insurance price regulation (Grabowski et al.,1989; Cummins et al., 2001), the effects of insurance law change are less well documented.

In my study, using property sales transaction data, I analyze the effect of the new sinkhole insurance law in Florida that was effective from July 1, 2016. This law drastically reduced the sinkhole damage coverage offered to the homeowners by the insurance companies. For this change in insurance law, the risk homeowners face from sinkhole related hazards has increased as the proximity of a sinkhole to the property would make them less likely to receive compensation from the insurance companies for structural damages.

Studies like this one can have implications regarding important policy questions. What would be the potential effect of a policy change in financial terms? How much people are willing to pay to prevent the policy change or enforce the change? Another important role of such research on the role of natural hazard impacts and policy change in the urban real estate market is important as such research allows us to test consumer behavior when they are facing these risks (Brookshire et al., 1985; MacDonald et al., 1987).

This study contributes to the literature by extending the research on insurance regulation. This study also contributes to the empirical literature on the insurance market by analyzing the effect of the new sinkhole insurance law for the first time. This chapter proceeds as follows. In the next section, I describe the existing research that explores insurance regulation on the real estate market. After that I describe the sinkhole insurance law in Florida, and the requirements according to the new sinkhole insurance law. Based on these institutional details, I then develop testable hypotheses about the impact of policy change regarding sinkhole insurance. This is followed by a description of the data and methodology used to empirically test my hypotheses, and a section containing my results. The final section concludes.

3.2 Literature Review:

The effect of insurance price regulation on insurance price is well explored in the literature, although the findings are not consistent. For instance, Harrington (2002) collected data for different states in the U.S. from 1972 to 1998 and found no significant effect of regulation on insurance price. On the other hand, Cummins et al. (2001) found that price regulation has different effects in different states.

Using real estate transaction data, Brookshire et al. (1985) showed that consumer's behavior is consistent with the expected utility model when they are buying properties in potential earthquake zones such as San Francisco. Using real estate sales data from Baton Rouge, Louisiana, Shilling et al. (1985) showed that the properties located in a flood-prone area suffer significant price discounts. All of these studies use residential property values to study consumer behavior with respect to probabilistic events that cause losses in utility (MacDonald et al., 1987). In a similar manner, I am also using real estate transaction data to explore the behavioral response of the homebuyers following a new insurance policy that significantly amplified the risk from a natural hazard, sinkhole.

There are few studies that explore the effect of a change in insurance law on the real estate market. Butler (2002) explored the health insurance policy change in Australia using a difference in differences framework, where the Australian government decided to provide subsidies for purchasing health insurance and impose fines for not having health insurance from 1997. He did not find any significant long-run effect due to the change in policy. An extensive body of literature covers insurance rate regulation. Grabowski et al. (1989) analyzed the effect of insurance regulation on take-up rate and insurance rate using data from 30 states using a difference in differences framework and found that strict regulation decreases take-up rate and increases insurance rate. Bin and Landry (2012) assumed that following a flood insurance policy amendment in North Carolina, the implicit flood risk premiums would decrease. They did not find any support for their assumption from their analysis.

The results from studies exploring the effect of insurance on the real estate market are inconsistent. Bin and Landry (2012) used real estate transaction data from Pitt County, North Carolina, and explored homebuyer's knowledge about flood insurance requirements before buying a property. Using a difference in differences method, they found that homebuyers are unaware of insurance cost during bidding for a property. On the other hand, Bakkensen and Barrage (2018) used survey data from Rhode Island to analyze the effect of different flood insurance rates. Using simulations, they found that flood insurance policy change will have a significant effect on the housing prices in the long run.

Although there are many studies that explore the effect of insurance requirements on the real estate market, very few studies explore the effect of insurance policy change. I try to fill that gap by examining the new sinkhole insurance law in Florida. My study is also the first one to explore the effect of the new sinkhole insurance law on housing prices. As accurate policies regarding hazard risk mitigation are essential for markets to incentivize efficient adaptation measures, understanding the effect of different policies on the housing market is thus important not only for this emerging literature but also for public policy.

3.3 Sinkhole Insurance in Florida:

Central to the fear factor for sinkholes is how unpredictable they are. Most of the time, sinkholes form without warning. Ground-penetrating radar (GPR), is the best way to detect cavities that cause sinkholes in the ground. According to Florida law, it is not required to use GPR before selling or buying a property, and due to the high cost of using GPR, people are not interested in using it. Even after using GPR, there is no certainty that sinkholes will not form in near future. So, one of the few ways homeowners can have peace of mind about sinkhole risk is by buying insurance.

Due to high sinkhole risk, Florida law used to require insurers to include sinkhole activity coverage in homeowners' insurance policies until 2007 (Florida Office of Insurance Regulation, 2010). Sinkhole insurance coverage in Florida was very broad. In 2007, a new legislature passed, which required insurance companies to provide all homeowners with coverage for catastrophic ground cover collapse. There were no clearly defined parameters for coverage. So, property owners were filing for sinkhole damage even when the damage was not related to sinkholes. So, insurance companies faced significant losses.

In Florida, sinkhole insurance claims increased from 2,360 in 2006 to 6,694 in 2010 (Office of Insurance Regulations (OIR), 2011). The approximate dollar amount of these claims was $1.4 billion (OIR, 2011). In 2011, the Florida Senate passed a new legislature, narrowing the scope of qualifying damage and includes other provisions. The new law was applicable from July 2016. This law states that the insurance companies may require an inspection before extending coverage and they can decline coverage for a property if sinkhole activity is present on the property or within a certain distance of the property to be insured. According to this law, homeowner's insurance only covers 'catastrophic ground collapse' when a sinkhole makes a home uninhabitable. Any damage just short of that must be covered by sinkhole insurance, whose deductible is very high in Florida and is typically 10 percent of the home's value. So, it is relatively costly for the homeowners to have sinkhole insurance. And even when they buy sinkhole insurance, in the event of sinkhole damage, they must pay a large portion of repair cost.

3.4 Data and Study area

I used housing sales data from Lake County in Florida to capture the effect of the sinkhole insurance law on the real estate market. Lake county is one of the major sinkhole prone counties in Florida. This study uses a total of 35000 single-family residential homes from Lake county, Florida, that were sold between 2014 and 2018. Lake County is approximately 1157 square miles, with a population of roughly 3,46,017 and a population density of 369/sq. miles.

Multiple data sources were used for the study. Property parcel data, GIS data of the parcels, and the real estate purchase records were collected from the property appraiser's office. The data include structural characteristics such as the age of the property, number of bedrooms, and area size. Additional characteristics such as if the property has a fireplace, if there is a swimming pool in property, and presence of central air conditioning were also collected. I converted some of these to binary variables with a value of one to indicate the existence of the specific characteristic and zero otherwise. I linked the structural characteristics of the property with the sales database using parcel identifiers. All sales in my data are qualified sales or arm's length transactions. I used binary variables to represent the quarters from 2014 to 2018, with the first quarter of 2014 as the base quarter. I also tried to establish the effect of various amenities such as lakes, libraries, and hospitals. I calculated the distance of the nearest known amenity from the sold house and determined its effect on the price of the house. Then these data sets were combined with unique parcel id.

Additionally, I obtained the location data of all known sinkholes from Florida Geological Survey (FGS) website. The FGS is the premier sinkhole research institution in Florida. I utilized GIS to identify properties that contain reported sinkhole activity and to calculate the proximity of properties without sinkholes to the nearest property with a sinkhole.

GIS spatial queries were performed to calculate sinkhole proximity and density within different distance bands such as ¼ mile, ½ mile, ¾ mile, 1 mile, and 2 miles.

3.5 Theory of hedonic property prices and insurance:

Bin and Landry (2012) showed the relationship between marginal implicit hedonic prices and insurance costs. I add a minor alteration to their theory to explicitly account for the effect of the new sinkhole insurance law on housing prices.

If I assume the homebuyers are buying sinkhole insurance because the location of the houses is in a sinkhole risk zone, the expected utility for the homebuyers is given by:

$$EU = p(i)\int_0^S V_1(a, y - R(a, p(i)) - I(p, C) - L + C)f(L)dL + (1 - P(i))V_0(a, y - R(a, p(i) - I(p, C)) \ldots\ldots\ldots\ldots\ldots(1)$$

Where, C ϵ (0, S) is the insurance cover on the property, and I (p, C) is the insurance premium. If I assume that full insurance is purchased, Eq. (1) simplifies to:

$$EU = p(i)V_1(a, y - R(a, p(i)) - I(p, C) + (1 - p(i))V_0(a, y - R(a, p(i)) - I(p, C) \ldots\ldots\ldots (2)$$

And for the homeowners who do not buy sinkhole insurance, their expected utility is given by:

$$EU = p(i)\int_0^S V_1(a, y - R(a, p(i) - L) f(L) dL + (1 - p(i)) V_0(a, y - R(a, p(i)) \text{ ....} (3)$$

In my framework, incremental option value (OV) is defined as the maximum amount an individual is prepared to make to avoid a certain adverse situation. It can be defined as:

$$[p(i) - \sigma] V_1(a, \hat{y} - OV) + [1 - p(i) + \sigma] V_0(a, \hat{y} - OV) = EU \text{ ....} (4)$$

When the homeowner has full insurance cover:

$$\frac{dOV}{d\sigma} = \frac{V_0(a,\hat{y}-OV) - V_1(a,\hat{y}-OV)}{[1-p(i)+\sigma]\frac{\partial V_0}{\partial y} + [p(i)-\sigma]\frac{\partial V_1}{\partial y}} \text{ ....} (5)$$

A similar case can be derived for no insurance scenario. Macdonald et al. (1987) show that the maximization of EU in (2) implies the following equality in equilibrium:

$$\frac{\partial R}{\partial P} = \frac{V_1(a,\hat{y} - V_0(a,\hat{y})}{[1-p(i)]\frac{\partial V_0}{\partial y} + [p(i)]\frac{\partial V_1}{\partial y}} - \frac{\partial I(p)}{\partial P} = -\frac{dOV}{dp} - \frac{dI(p)}{dp} < 0 \text{ ....} (6)$$

Differentiating (6) with respect to i shows that the implicit price of risk factors is decreasing in information that heightens perception in risk (i.e. becomes more negative) if $\frac{\partial V_0}{\partial y} > \frac{\partial V_1}{\partial y}$, while the effect is indeterminate if $\frac{\partial V_1}{\partial y} > \frac{\partial V_0}{\partial y}$. So, if there is an increase in insurance cost, the cost of living in the area will increase, and this will increase marginal implicit price in (6), which will cause a negative price premium for such properties.

3.6 Empirical Strategy

3.6.1 Empirical Model

The hedonic method is a widely used method for measuring the effect of different property characteristics and other relevant factors in their market price. Sirmans (2005) reviewed around 125 studies on the real estate market and analyzed the influence of different factors on real estate pricing. He found that different property characteristics such as the number of bedrooms, number of bathrooms, existence of a fireplace and pool have the most prominent effect on real estate prices. This study includes these variables with the influence of sinkhole and, additionally, the changing effect of these sinkholes after a natural hazard event such as a hurricane that might be correlated with a new sinkhole opening nearby.

The general form of the hedonic pricing model is:

$$P_i = f(X_j, L_j, E_i)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

where P_i is the log of the transaction price of house i, X_j is a vector of j structural housing characteristics, L_j is vector of location variables, and E_i is a vector of externalities affecting the transaction price. The method typically used to measure the marginal effect of the explanatory variables on the house price is OLS regression which minimizes the sum of squared residuals (Sirman et al., 2005).

3.6.2 Baseline Estimates

The definitions and the descriptive statistics of the variables that I have estimated are given in Table 3.1. As shown in Table 3.1, the average price of the houses sold between 2014 and 2018 is $227118.3, the average age of the sold houses is 22.3 years, and the average lot size is 0.66 acres. There are 3.02 bedrooms per house on average, and almost all the houses have central heating. Regarding the distance of the nearest sinkhole from the sold houses, 18% of the houses have the nearest sinkhole within ½ mile, 27% of the houses have the nearest sinkhole within 3/4 mile, 50% of the houses have the nearest sinkhole within 1.5 miles and 70% of the houses have the nearest sinkhole within 2 miles.

I collected the geographic location data for all the houses in the data set as well as the location data for the sinkholes in Lake County from the Florida Geological Survey (FGS) website. Using *ArcGIS*, I calculated the shortest distance between each house and nearest known sinkhole location using their geocoded location. In Figure 3.2, I have shown the locations of the geocoded houses in Lake County and known sinkhole locations in Florida. In Figures 3.3, 3.4 and 3.5, I have shown the price trend of the houses that have a sinkhole within ½ mile, and 1 mile and 2 miles respectively and observed that the houses that are located close to the sinkholes have a negative price premium compared to the houses that are not close to sinkholes. It can also be seen that the price discount increases after the new insurance law. This indicates the risk perception of the homebuyers who are buying houses near sinkhole locations changes following the sinkhole insurance law.

3.6.3 Effect of the new sinkhole insurance law on housing prices

To analyze the effect of the new insurance law (effective from June 1, 2016) on housing prices that are located close to sinkholes, I estimate the difference in differences (DID) model. Here, I utilize the new insurance law as a natural experiment. This new insurance law may influence the homeowners who live close to a known sinkhole location as this new rule will increase their insurance cost, and the more limited sinkhole coverage will increase the risk of living in a sinkhole prone area. The homeowners who live far away from any known sinkhole location, are exempt from this effect. I establish them as the control group and apply a difference in differences estimator (DID) to quantify the added risk for living near a sinkhole location. I compare the price differentials of the houses located near sinkholes with price differentials of the houses that are not close to sinkholes from my sample of housing sales data.

I use the log of the sales price of the houses [log (price)] as the dependent variable to estimate my model (10):

$$log\ (price)_{i,t} = \alpha_2 + \beta_i X_{ij} + \varphi_i\ Sinkhole_i + \gamma_t\ insurance_t + \delta_{insurance}\ (sinkhole_i * insurance_t) + \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Where $price_{i,t}$ is the selling price of the house, $i\ at\ time\ t$, X_{ij} is the matrix of explanatory variables j for the house i, $Sinkhole_i$ is a binary variable for house i with a value of one if the sinkhole is located within a certain distance band for the sold property and zero, if it is located further than the distance band. $insurance$ is a binary variable taking the value of one if the house is sold after June 1, 2016, and zero if the house is sold before June 1, 2016. $\delta_{insurance}$ represents the effect of the new insurance law on the value of the houses that are close to known sinkhole locations. From δ, I can estimate the changing risk perception of the homebuyers and sellers due to insurance policy change.

I analyze the effect of the new insurance policy for the houses located within different distances from the nearest known sinkhole location to explore the spatial nature of the effect as well as to check the robustness of my analysis. To isolate the effect of the new insurance law from the potential hurricane effect, I used sales data of the properties that were sold before hurricane Irma. So, I use data from January 1, 2014, to September 1, 2017, for my analysis. My results are presented in Tables 3.4 and 3.5. I estimate the effect of the new insurance law on houses that are within ½ mile, ¾ mile, 1 mile, and 2 miles of a known sinkhole location.

When the house has a known sinkhole location within ½ mile distance, I find that following the new insurance law, the houses that are within ½ mile of a sinkhole suffer a 2% price discount, and this is significant at 10%. When the property is located ¾ mile away from the nearest sinkhole location, that house suffers a 4% extra price discount after the new insurance law, and it is significant at 1% level. If the nearest sinkhole is located within 1 mile of the house, I find a 3.2% price discount compared to other houses, and it is significant at 1% level. When the distance of the property is increased to 2 miles from the nearest sinkhole location, there is still a significant price discount of 3% compared to the properties that are located further than that.

I also observe that the change in insurance law doesn't have any significant effect on housing prices by themselves. Only when the new insurance law interacts with sinkhole presence, then the new insurance law has a significant impact on housing prices. So, after the change in insurance law, only people who live close to sinkholes react to the new law and their risk perception regarding sinkholes increases due to their increased exposure to sinkhole damage as they have less protection by insurance now. And that increased risk perception is reflected in property price.

Also, properties that are located at least 2 miles away from a sinkhole don't face price discounts due to sinkhole presence. Only after the change in insurance law, these properties face a 3% price discount due to sinkhole presence. Maybe because, with more protection from the previous insurance policy, they didn't care about sinkhole risk. After the new insurance law was passed, which offered less protection from sinkhole damage, they became more aware of sinkhole risk, and that change in risk perception is reflected in property price.

I show the treatment effect of this new insurance law in Figures 3.6, 3.7 and 3.8. I observe that following the new insurance law, the houses that are within 0.25-mile face a small but significant price discount. When the distance increases to 0.50 mile, I observe a significant price discount for the houses that are within 0.50 mile of a sinkhole. When the distance increases to 2 miles, the price discount diminishes greatly but I still observe some price discount following the new insurance policy.

3.6.4 Quantile Regression Analysis:

After the sinkhole law was passed, the additional price discount to the properties that are near known sinkhole locations might differ according to the property values. Owners of the more expensive properties might react to the increased sinkhole risk due to less insurance coverage differently compared to the owners of the relatively less expensive properties. To explore the possible differences in price discounts to the properties based on their valuation, I run a quantile regression analysis for properties within different distance bands from a known sinkhole location. The results from the quantile regression specification are presented in Tables 3.6, 3.7, 3.8, and 3.9.

The 75th quantile regression will show the added effect of the sinkhole insurance law on the most expensive properties in my sample. For the properties in the 75th percentile, these properties suffer least amount of price discount compared to the less expensive properties. If properties in the 75^{th} percentile have a sinkhole within ¾ mile, they don’t suffer significant price discount following the new insurance law. This is probably because if these homeowners are buying expensive properties near sinkholes, they are prepared to pay higher price for insurance. The properties that are located within 1 mile of a sinkhole, they suffer 2% price discount, and this is significant at 10% level. Interestingly, properties that are located within 2 miles of a sinkhole location suffer 7% price discount and this discount is significant at 1% level. This is maybe beacuase when homeowners who are buying properties far from a sinkhole location are not prepared to pay high sinkhole insurance premiums.

The 50th quantile regression will show the added effect of the new insurance law on the moderately expensive properties. For properties in the 50th percentile, they suffer a 2% price discount following the new insurance law if they have a sinkhole within ½ mile, and this discount is significant at 5% level. If a sinkhole is present with ¾ mile of the properties, they suffer a further 3% price discount following the insurance law, and this discount is significant at 1% level. The properties that have a sinkhole with 1 mile suffer a further 3% price discount, and this discount is significant at 1% level. Properties that are located 2 miles within a sinkhole location suffer 4% price discount and this discount is significant at 1% level.

The 25th quantile regression will show the added effect of new insurance law on the least expensive properties in the sample. For properties in the 25^{th} percentile, they suffer a 3% price discount following the new insurance law if they have a sinkhole within ½ mile, and this discount is significant at 1% level. Properties suffer a 3% price discount following the insurance law if there is a sinkhole with ¾ mile of the property and this discount is significant at 1% level. If the property has a sinkhole within 1 mile, the price discount is again 3%, and this discount is significant at 1% level. If the property has a sinkhole within 2 miles, then that property suffers a 2% price discount and this discount is significant at 10% level.

After the new insurance law, the sinkhole discount increases similarly for the properties that are in the 25th and 50th percentile, but the price discount is relatively low for the 75th percentile or the properties that are most expensive in the sample. So, homeowners of the relatively expensive properties are less concerned about the added sinkhole risk caused by the insurance law compared to the other homeowners. This difference in price discount is observed maybe because the owners of the more expensive properties are financially more well off compared to the other homeowners and they care less about the increase in insurance cost compared to the homeowners of the less expensive properties.

3.6.5 Event study of the new insurance law on houses close to sinkholes

When trying to identify the effect of a reform or an event, it is imperative to differentiate the effect of interest from other irrelevant effects (Olsson, 2008). In an ideal situation, one would prefer to estimate the outcome for an individual or for one unit of the variable of interest that is both treated and untreated at the same point in time. Unfortunately, that is not possible. So, the closest to the ideal situation one researcher can come to is to find a feasible control group that, in the absence of treatment, is on average the same as the treatment group, and that way, the average treatment effect can be correctly estimated. All of the time effects should thereby be common across the two groups, that is, the average outcome for the two groups should be parallel over time in the absence of treatment (Greene, 2009). I can assume that this assumption is fulfilled if I can establish that the parallel trend assumption is fulfilled.

In Figures 3.3, 3.4 and 3.5 below, I presented a visual analysis of the effect of the new insurance law on the selling price of the houses that are located within ½ mile,1 mile, and 2 miles respectively to known sinkhole locations. These figures also visually present the parallel price trend for houses that are close to the sinkholes and the houses that are not. This trend comparison is crucial and is helpful to visually inspect the parallel trend assumption for the difference in differences model reported in Tables 3.4 and 3.5. I can see that parallel trend assumption is fulfilled for the houses that are located closer than 2 miles within a sinkhole. When the distance increases to 2 miles, the price trends are not parallel.

We can see the change in price trends following the new insurance law in Figures 3.3, 3.4, and 3.5. We observe a price discount following the new insurance rule for houses that are located within ½ mile and 1 mile of a known sinkhole location. When the distance increases to 2 miles within a sinkhole location, I don't observe any price discount for the properties.

3.6.6 Can we trust the estimated treatment effect?

Are the treatment effects estimated in Tables 3.4 and 3.5 unique and attributable to the effect of the new insurance law? An easy and straightforward way of testing the robustness of an estimated treatment effect is to estimate placebo effects at different points in time. If any of these placebo effects turn out to be significant, it can cast doubt on the treatment effect.

Table 3.6 shows that all the estimated treatment effects for the placebo regression models are insignificant and that the only DID estimator that is significant is that for 2016 and 2017. I assume that the significant placebo effect of 2017 is because of the shock of Hurricane Irma.

The significant results in 2016, the actual year of my treatment, insurance policy change with respect to sinkhole coverage, indicates that the effect that occurred in 2016 is not random.

For the new insurance law, as the effective date of the implementation of the new rule was announced about a year before, we can assume that people expected the change and had time to adapt to the new rule. As I am attempting to capture the behavioral effect of the new rule, this change in behavior shouldn't affect my analysis.

3.6.7 Regression Discontinuity Specification:

This study also uses a regression-discontinuity design. Specifically, I explore how price of the properties due to sinkhole proximity changes discontinuously at different distance bands following the new sinkhole insurance law. The policy change is likely to produce "near" experimental causal estimates of the effect of sinkhole proximity on property prices following the two events.

3.6.8 Effect of the new insurance law:

To estimate the discontinuously changed effect of the presence of sinkhole on property price after the new insurance law, I estimate the following log-linear RD model:

$$log(Saleprice)$$
$$= \alpha + \beta_3\ insurance + \beta_4(insurance\ *\ sinkhole_{distance})$$
$$+ \tau_2\ sinkhole_{distance}\ + \epsilon_i \ldots\ldots\ldots (11)$$

Where $log(Saleprice)$ refers to the log of sales price of the houses. $sinkhole_{distance}$ refers to the cutoff point (i.e., if the house is located outside the sinkhole distance band), $insurance$ is a binary variable. insurance is 1 if the house was sold after the new insurance law was effective and 0 otherwise. The coefficient τ is my variable of interest and represents the local average treatment effect.

I present results from the regression discontinuity specification in Table 3.7. The RD treatment effect is showing the changed local average treatment effect of sinkhole presence on housing price after the new insurance law. The presence of sinkholes within ¼ mile of a house causes a 3% price discount to that house and that discount is significant at 5% level. The presence of sinkholes within ¾ mile of a house causes a 3% price discount to that house and that discount is significant at 5% level. If the sinkhole is within 1 mile of a house, it causes a 3% price discount to that house and this discount is significant at 5%. I find no significant price discount if the house is located further than this from a known sinkhole location.

3.7 Conclusion:

This study offers quasi-experimental evidence of the effect of new sinkhole insurance law on property values in Lake County, Florida. The analysis contributes to the literature by examining the effect of the new sinkhole insurance law on property prices, and I find that this new insurance law had a negative effect on the real estate market and caused a 2% to 5% price discount to the houses located close to a sinkhole.

Another interesting finding from this study is that I observe price discounts due to the new insurance law that is very similar to the price discount due to Hurricane Irma that I found in the second chapter. This discovery that the spillover effect in terms of direction and magnitude due to this new law was very similar to the spillover effect due to Hurricane that I found in my second chapter is very exciting as hurricane is a completely random natural shock, and this is a planned and an institutional change.

I compared the effect of Hurricane Irma and the new sinkhole insurance law on properties close to sinkholes in Table 3.10. Both of the effects are similar to the properties according to percentiles. The more expensive properties are less affected by the events. Most probably the homeowners of the more expensive properties are less concerned about the possible increased cost due to increased risk and that is why these properties are showing less sensitivity to the shocks. For the other distance bands, the effects of the Hurricane and the new insurance law are similar. So, the homeowners of similarly priced properties behave similarly to the different shocks. This is another interesting finding from the study.

Government policies are meant to be targeted towards stabilizing the real estate market, but in this case, the new law has resulted in reducing the protection from sinkhole damage.

This reduced protection has caused price discounts for the houses that are located close to sinkholes. The insight from this analysis can be helpful for the policymakers when they are considering policy changes regarding the real estate market and insurance regulation in the future. For future research, it can be explored how the insurance requirements set by the lending institutions are influencing homeowner's insurance purchase decision. It will be very interesting to explore if there is collusion between the lending institutions and the insurance companies to influence the insurance market in this multi-hazard context.

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TABLES

Table 3.1: Descriptive statistics.

Variable	Observations (N)	Mean	Min	Max	Variable definitions	Standard deviation
Price	37,788	227118.3	50000	3500000	Sale price of the house.	153004.2
House $_{Age}$	37,788	22.34	0	159	Number of years since the house was built.	19.74
Bedrooms	37,788	3.02	1	6	Number of bedrooms in the house.	0.81
Acres	37,788	0.66	0	517.1	Lot size of the house.	4.78
Bathrooms	37,788	2.07	0	6	Number of bathrooms in the house.	0.57
Fireplace	37,788	0.121	0	1	1, If the house has a fireplace and 0 otherwise.	0.350

Pool	37,788	0.142	0	1	1, If the house has a pool and 0 otherwise.	0.349
Central air	31,901	0.974	0	1	1, If the house has central air and 0 otherwise.	0.156
Distance Airport	37,788	2.65	0.08	15.13	Distance of the nearest airport from the house.	1.54
Distance Lake	37,788	0.18	0.003	1.22	Distance of the nearest lake from the house.	0.12
Distance Flood zone	37,788	0.32	0.001	1.30	Nearest distance of the flood zone from the house.	0.18

Distance Library	37,788	2.92	0.37	12.21	Distance of the nearest library from the house.	1.66
Distance Sinkhole	37,788	1.30	0.001	16.86	Distance of the nearest sinkhole from the house.	1.35
Insurance	37,788	0.66	0	1	1, If the house was sold after June 1, 2016 and 0 otherwise.	0.47
Log (price)	37,788	12.02	8.51	18.07	Log of the sale price of the house.	0.76
Sinkhole 1/2 mile	37,788	0.18	0	1	1, if the house is located within ½ mile of a known	0.38

					sinkhole location and 0 otherwise.	
Sinkhole 3/4 mile	37,788	0.27	0	1	1, if the house is located within 3/4 mile of a known sinkhole location and 0 otherwise.	0.44
Sinkhole 1 mile	37,788	0.50	0	1	1, if the house is located within 1 mile of a known sinkhole location and 0 otherwise.	0.49
Sinkhole 2 miles	37,788	0.70	0	1	1, if the house is located within 2 miles of a	0.45

					known sinkhole location and 0 otherwise.	
Q1-2014	37,788	.0081	0	1	1 if the house was sold in quarter 1, 2014 and 0 otherwise.	0.09
Q2-2014	37,788	.0083	0	1	1 if the house was sold in quarter 2, 2014 and 0 otherwise.	0.09
Q3-2014	37,788	.0084	0	1	1 if the house was sold in quarter 3, 2014 and 0 otherwise.	0.09
Q4-2014	37,788	0.045	0	1	1 if the house was sold in quarter 4,	0.09

					2014 and 0 otherwise.	
Q1-2015	37,788	0.051	0	1	1 if the house was sold in quarter 1, 2015 and 0 otherwise.	0.20
Q2-2015	37,788	0.051	0	1	1 if the house was sold in quarter 2, 2015 and 0 otherwise.	0.22
Q3-2015	37,788	0.048	0	1	1 if the house was sold in quarter 3, 2015 and 0 otherwise.	0.21
Q4-2015	37,788	0.04	0	1	1 if the house was sold in quarter 4, 2015 and 0 otherwise.	0.19

Q1-2016	37,788	0.051	0	1	1 if the house was sold in quarter 1, 2016 and 0 otherwise.	0.22
Q2-2016	37,788	0.059	0	1	1 if the house was sold in quarter 2, 2016 and 0 otherwise.	0.23
Q3-2016	37,788	0.06	0	1	1 if the house was sold in quarter 3, 2016 and 0 otherwise.	0.23
Q4-2016	37,788	0.051	0	1	1 if the house was sold in quarter 4, 2016 and 0 otherwise.	0.22
Q1-2017	37,788	0.068	0	1	1 if the house was sold in	0.25

					quarter 1, 2017 and 0 otherwise.	
Q2-2017	37,788	0.075	0	1	1 if the house was sold in quarter 2, 2017 and 0 otherwise.	0.26
Q3-2017	37,788	0.063	0	1	1 if the house was sold in quarter 3, 2017 and 0 otherwise.	0.24
Q4-2017	37,788	0.061	0	1	1 if the house was sold in quarter 4, 2017 and 0 otherwise.	0.24
Q1-2018	37,788	0.07	0	1	1 if the house was sold in quarter 1,	0.25

					2018 and 0 otherwise.	
Q2-2018	37,788	0.08	0	1	1 if the house was sold in quarter 2, 2018 and 0 otherwise.	0.27
Q3-2018	37,788	0.07	0	1	1 if the house was sold in quarter 3, 2018 and 0 otherwise.	0.25
Q4-2018	37,788	0.06	0	1	1 if the house was sold in quarter 4, 2018 and 0 otherwise.	0.24

Table 3.2: Effect of sinkholes on housing prices. Ordinary Least Squares (OLS) regression.

	Model 1	Model 2	Model 3	Model 4
House $_{Age}$	0.01 ***	-0.01 ***	-0.01 ***	-0.01***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Bedrooms	0.14 ***	0.08 ***	0.08 ***	0.08 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Acres	0.015 ***	0.03 ***	0.03 ***	0.03 ***
	(0.0006)	(0.001)	(0.001)	(0.001)
Bathrooms	0.24 ***	0.23 ***	0.23 ***	0.23 ***
	(0.006)	(0.006)	(0.006)	(0.006)
Fireplace (=1)	0.32 ***	0.23 ***	0.23 ***	0.23***
	(0.009)	(0.008)	(0.008)	(0.008)
Pool (=1)	0.25 ***	0.2 ***	0.19 ***	0.19 ***
	(0.009)	(0.008)	(0.007)	(0.007)
Central air	0.48 ***	0.48 ***	0.48 ***	0.48 ***
	(0.02)	(0.02)	(0.02)	(0.02)
Distance $_{Park}$	-0.02 ***	-0.016 ***	-0.02 ***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Distance $_{Library}$	-0.005 ***	-0.004 ***	-0.005 **	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Distance $_{Sinkhole}$	0.02 ***	0.015 ***	0.01 ***	0.01 ***

	(0.002)	(0.003)	(0.003)	(0.003)
Distance $_{Airport}$	-0.02 ***	-0.01 ***	-0.016 ***	-0.018 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Sinkhole $_{1/2\ mile}$	-0.082 ***			
	(0.008)			
Sinkhole $_{3/4\ mile}$		-0.07 ***		
		(0.007)		
Sinkhole $_{1\ mile}$			-0.07 **	
			(0.006)	
Sinkhole $_{2\ miles}$				-0.05 ***
				(0.008)
Constant	11.00 ***	10.93 ***	10.95 ***	11.00 ***
	(0.04)	(0.04)	(0.04)	(0.04)
N	31,901	31,901	31,901	31,901
R^2	0.40	0.40	0.40	0.40

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3.3: The effect of sinkhole location on housing prices. Spatial error regression.

	Model 5	Model 6	Model 7	Model 8
House $_{Age}$	-0.01 ***	-0.01 ***	-0.02 ***	-0.01***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Bedrooms	0.07 ***	0.07 ***	0.07 ***	0.05 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Acres	0.03 ***	0.03 ***	0.029 ***	0.03 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Bathrooms	0.18 ***	0.17 ***	0.18 ***	0.22 ***
	(0.005)	(0.006)	(0.006)	(0.006)
Fireplace (=1)	0.15 ***	0.16 ***	0.15 ***	0.21***
	(0.007)	(0.008)	(0.008)	(0.008)
Pool (=1)	0.18 ***	0.20 ***	0.18 ***	0.18 ***
	(0.007)	(0.007)	(0.007)	(0.007)
Central air	0.43 ***	0.42 ***	0.43 ***	0.48 ***
	(0.01)	(0.02)	(0.01)	(0.02)
Distance $_{Park}$	-0.02 ***	-0.006 ***	-0.012 ***	-0.02***
	(0.001)	(0.002)	(0.001)	(0.001)
Distance $_{Library}$	0.002	0.002	0.003	-0.01***
	(0.01)	(0.002)	(0.016)	(0.002)
Distance $_{Flood\ zone}$	0.025		0.03	-0.014 ***
	(0.01)		(0.02)	(0.009)

Distance $_{Sinkhole}$	0.01 ***	0.01 **	-0.003	-0.001 ***
	(0.003)	(0.004)	(0.003)	(0.10)
Distance $_{Airport}$	-0.01 ***	-0.003 **	-0.01 ***	-0.014
	(0.02)	(0.003)	(0.002)	(0.003)
Sinkhole $_{1/2\ mile}$	-0.06 ***			
	(0.02)			
Sinkhole $_{3/4\ mile}$		-0.08 ***		
		(0.01)		
Sinkhole $_{1\ mile}$			-0.089 **	
			(0.010)	
Sinkhole $_{2\ miles}$				-0.023 ***
				(0.008)
Constant	11.10 ***	11.32 ***	11.13 ***	11.36 ***
	(0.04)	(0.02)	(0.04)	(0.10)
R^2	0.51	0.49	0.49	0.46
Lamda	0.48 ***	0.47 ***	0.62 ***	0.61 ***
	(0.006)	(0.006)	(0.005)	(0.006)
AIC	39984	41419.3	39925	39938.3
Schwarz	40277	41544.9	40217.9	40231.2
Likelihood ratio	4709.19***	4618.41***	4697.32***	4691.8***

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 3.4: The effect of the new insurance law on the sale price of houses that are close to sinkholes.

	Model 13	Model 14	Model 15	Model 16
Bedrooms	0.08 *** (0.02)	0.08 *** (0.02)	0.08*** (0.02)	0.08 *** (0.01)
Acres	0.02 *** (0.001)	0.02 *** (0.001)	0.03 *** (0.001)	0.02 *** (0.001)
Bathrooms	0.29 *** (0.01)	0.29 *** (0.01)	0.30 *** (0.01)	0.30 *** (0.01)
House Age	-0.02 *** (0.0003)	-0.02 *** (0.0004)	-0.02 *** (0.0004)	-0.02 *** (0.0003)
Bathrooms $_{Sq.}$	-0.01 *** (0.001)	-0.01 *** (0.001)	-0.01 (0.002)	-0.01 *** (0.001)
Bedrooms $_{Sq.}$	-0.006 ** (0.002)	-0.006 *** (0.002)	-0.006 (0.003)	-0.006 ** (0.002)
Fireplace	0.21 *** (0.007)	0.21 *** (0.007)	0.21 *** (0.008)	0.21 *** (0.007)
Pool	0.23 *** (0.007)	0.23 *** (0.007)	0.23 *** (0.007)	0.23 *** (0.007)
Distance $_{Sinkhole}$	0.00003 (01.54e-06)	0.00003 *** (1.73e-06)	2.92E-05 *** (1.85E-06)	0.00002 (1.93e-06)
Distance $_{Lake}$	0.0001 *** (0.00001)	0.0001 *** (0.00001)	0.00014 *** (1.25E-05)	0.0001 *** (0.00001)
Central air	0.11 *** (0.02)	0.10 *** (0.02)	0.10 *** (0.02)	0.10 *** (0.02)
Sinkhole $_{½ \text{ mile}}$	-0.0003 (0.009)			

Sinkhole $_{3/4\ mile}$		0.03 *** (0.008)		
Sinkhole $_{1\ mile}$			0.02 *** (0.008)	
Sinkhole $_{2\ miles}$				0.007 (0.01)
Insurance	0.05 (0.06)	0.06 (0.06)	0.06 (0.07)	0.90 (0.07)
Sinkhole $_{1/2\ mile}$ # Insurance	-0.02 ** (0.01)			
Sinkhole $_{3/4\ mile}$ # Insurance		-0.04 *** (0.01)		
Sinkhole $_{1\ mile}$ # Insurance			-0.032 *** (0.01)	
Sinkhole $_{2\ miles}$ # Insurance				0.03 *** (0.01)
Constant	11.29 *** (0.05)	11.27 *** (0.04)	11.27 *** (0.05)	11.30 *** (0.05)
R^2	0.50	0.50	0.50	0.50
N	18,933	18,933	18,933	18,933

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 3.5: Difference in differences estimates for the effect of new insurance law on different sinkhole locations.

Distance to nearest sinkhole location	Insurance	Sinkhole	Diff-in-diffs estimation	Quarter fixed effects	Number of observations
½ mile	0.05	-0.0003	-0.02 **	Yes	18,933
	(0.06)	(0.009)	(0.01)		
¾ mile	0.06	0.03 ***	-0.04 ***	Yes	18,933
	(0.06)	(0.008)	(0.01)		
1 mile	0.06	0.02 ***	-0.032 ***	Yes	18,933
	(0.07)	(0.008)	(0.01)		
2 miles	0.90	0.007	0.03 ***	Yes	18,933
	(0.07)	(0.01)	(0.01)		

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%. All models include control variables for housing characteristics and quarter dummies.

Table 3.6: Effect of the new insurance law on the 75th quantile properties.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11
	(0.11)	(0.12)	(0.10)	(0.12)

Sinkhole $_{½\ mile}$	0.01 (0.007)			
Sinkhole $_{¾\ mile}$		0.02 ** (0.009)		
Sinkhole $_{1\ mile}$			0.003 (0.006)	
Sinkhole $_{2\ miles}$				-.02 * (0.030)
Sinkhole $_{1/2\ mile}$* Insurance	0.004 (0.11)			
Sinkhole $_{3/4\ mile}$ * Insurance		-0.01 (0.01)		
Sinkhole $_{1\ mile}$ * Insurance			-0.02 ** (0.009)	
Sinkhole $_{2\ miles}$ * Insurance				-0.07*** (0.01)
R^2	44	43	44	42
N	30,675	30,675	30,675	30,675

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3.7: Effect of the new insurance law on the 50th quantile properties.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11
	(0.11)	(0.12)	(0.10)	(0.12)
Sinkhole $_{½\ mile}$	-0.03 ***			

	(0.009)			
Sinkhole $_{¾ \text{ mile}}$		-0.03 ***		
		(0.009)		
Sinkhole $_{1 \text{ mile}}$			-0.01	
			(0.008)	
Sinkhole $_{2 \text{ miles}}$				-.02 *
				(0.030)
Sinkhole $_{1/2 \text{ mile}}$* Insurance	- 0.02 **			
	(0.01)			
Sinkhole $_{3/4 \text{ mile}}$ * Insurance		-0.03 ***		
		(0.009)		
Sinkhole $_{1 \text{ mile}}$ * Insurance			- 0.03 ***	
			(0.008)	
Sinkhole $_{2 \text{ miles}}$ * Insurance				-0.04***
				(0.01)
R^2	33.8	33.8	33.9	33.8
N	30,675	30,675	30,675	30,675

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3.8: Effect of the new insurance law on the 25th quantile properties.

	Model 9	Model 10	Model 11	Model 12
House $_{Age}$	-0.02 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Bedrooms	0.18 ***	0.64 ***	0.18 ***	0.64 ***
	(0.02)	(0.02)	(0.02)	(0.019)
Bedrooms $_{Sq.}$	-.011 ***	-.011 ***	-.011 ***	-.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Acres	0.03 ***	0.016 ***	0.03 ***	0.017 ***
	(0.001)	(0.0006)	(0.001)	(0.0006)
Bathrooms	0.37 ***	0.48 ***	0.37 ***	0.48
	(0.02)	(0.014)	(0.01)	(0.014)
Bathrooms $_{Sq.}$	-0.023 ***	-0.03 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.0025)	(0.002)	(0.002)
Distance $_{Airport}$	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance $_{Flood\ zone}$	-0.04 ***	-0.04 ***	-0.005	-0.007
	(0.014)	(0.01)	(0.01)	(0.014)
Distance $_{Sinkhole}$	0.05 ***	0.05 ***	0.06 ***	0.06 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Hurricane	-0.10	0.033	-0.11	-0.11
	(0.11)	(0.12)	(0.10)	(0.12)
Sinkhole $_{½\ mile}$	-0.03 ***			

	(0.009)			
Sinkhole $_{¾\ mile}$		-0.03 *** (0.009)		
Sinkhole $_{1\ mile}$			-0.01 (0.008)	
Sinkhole $_{2\ miles}$				-.02 * (0.030)
Sinkhole $_{1/2\ mile}$* Insurance	-0.03 ** (0.01)			
Sinkhole $_{3/4\ mile}$ * Insurance		-0.03 *** (0.01)		
Sinkhole $_{1\ mile}$ * Insurance			- 0.03 *** (0.008)	
Sinkhole $_{2\ miles}$ * Insurance				-0.02* (0.01)
R^2	35.6	36.8	35.6	35.6
N	30,675	30,675	30,675	30,675

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3.9: Summary results from quantile regression: Effect of the new insurance law

Quantiles		Distance Bands		
	½ mile	¾ mile	1 mile	2 miles
75^{th}	0.004	-0.01	-0.02 **	-0.07 ***
	(0.11)	(0.01)	(0.009)	(0.01)
50^{th}	- 0.02 **	-0.03 ***	- 0.03 ***	-0.04***
	(0.01)	(0.009)	(0.008)	(0.01)
25^{th}	-0.03 **	-0.03 ***	- 0.03 ***	-0.02*
	(0.01)	(0.01)	(0.008)	(0.01)

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3.10: Summary results from quantile regression: Effect of Hurricane Irma and new insurance law

Quantiles	Distance Bands							
	½ mile		¾ mile		1 mile		2 miles	
	Insurance	Irma	Insurance	Irma	Insurance	Irma	Insurance	Irma
75th	0.004	-0.01	-0.01	-0.01	-0.02 **	-0.01	-0.07 ***	-0.01
	(0.11)	(0.01)	(0.01)	**	(0.009)	**	(0.01)	(0.01)
				(0.009)		(0.008)		
0.50th	- 0.02 **	- 0.02	-0.03 ***	-0.03	- 0.03 ***	- 0.02	-0.04***	-0.008
	(0.01)	**	(0.009)	***	(0.008)	**	(0.01)	(0.001)
		(0.01)		(0.008)		(0.007)		
0.25th	-0.03 **	-0.03	-0.03 ***	-0.03	- 0.03 ***	- 0.01	-0.02*	-0.005
	(0.01)	***	(0.01)	***	(0.008)	**	(0.01)	(0.01)
		(0.01)		(0.009)		(0.008)		

Note: Dependent variable is the log of sales price. All models are estimated with quarterly dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 3.11: Robustness test with placebo regressions

	Coefficients	Std. error
DID14	-0.07	(0.04)
DID15	-0.003	(0.019)
DID16	-0.03 *	(0.02)
DID17	-0.03 *	(0.014)
DID18	0.025	(0.021)
Treatment	0.08	(0.04)
Constant	0.025	(0.06)
R^2	0.41	
N	31,901	

Note: dependent variable is the log of sales price. All models are estimated with time dummy variables. Robust standard errors are reported in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 3.12: Regression discontinuity to estimate the effect of the new insurance law on the houses close to sinkhole locations.

	Nearest sinkhole within ¼ mile	Nearest sinkhole within ¾ mile	Nearest sinkhole within 1mile	Nearest sinkhole within 2 miles
RD treatment effect	-0.05 **	-0.03 **	-0.03 **	0.02
	(0.03)	(0.01)	(.01)	(.02)
Control for housing characteristics	No	No	No	No
Time fixed effects	No	No	No	No
County fixed effects	No	No	No	No
N	34,708	34,708	34,708	34,708

Note: Dependent variable is the log of sales price. Robust standard errors are presented at the parenthesis. ∗ significant at 10%; ∗∗ significant at 5%; ∗∗∗ significant at 1%.

FIGURES

Figure 3.1: Sinkhole locations in Florida counties.

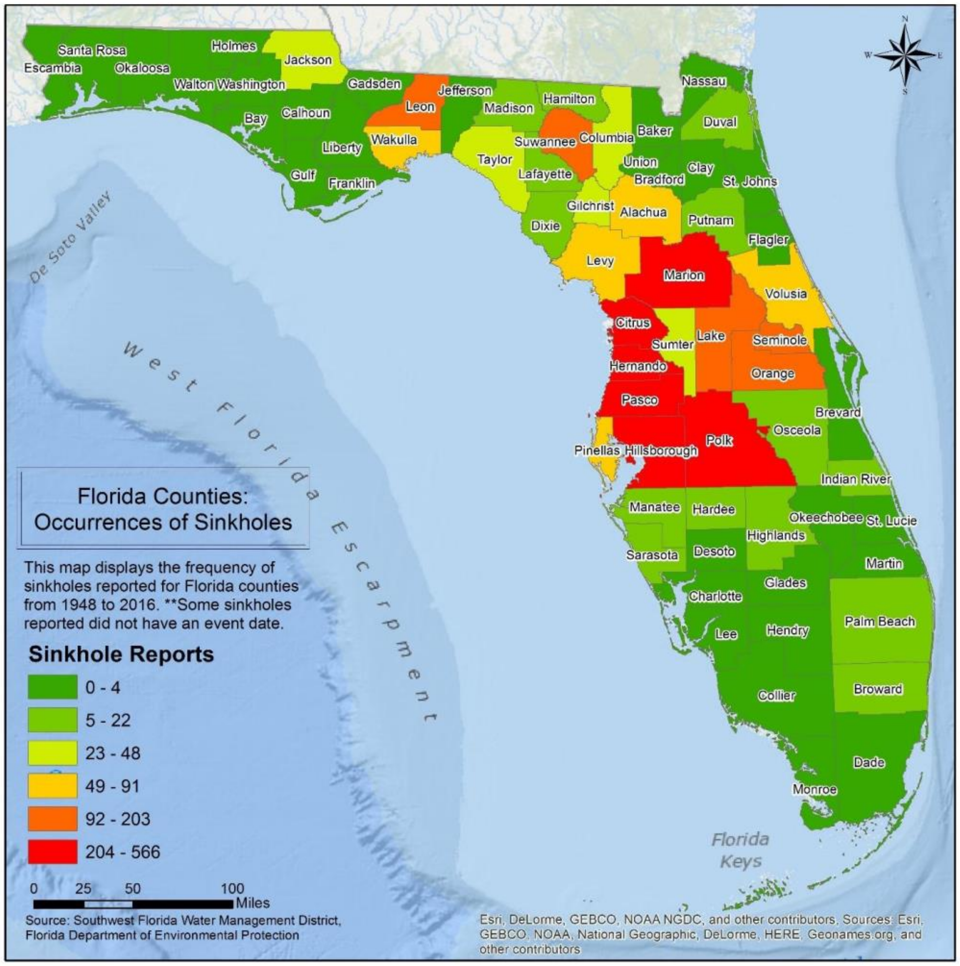


Figure 3.2: Locations of the known sinkholes in Florida and sold houses in Lake county.

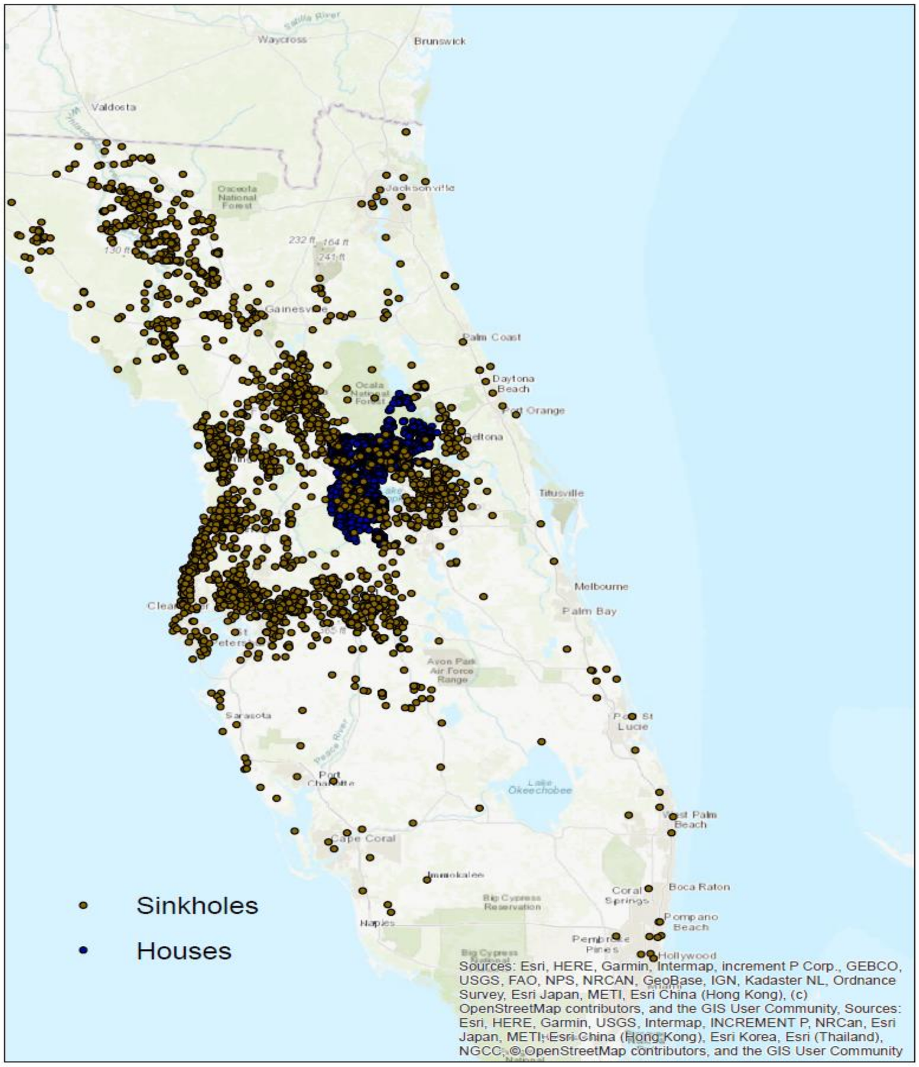
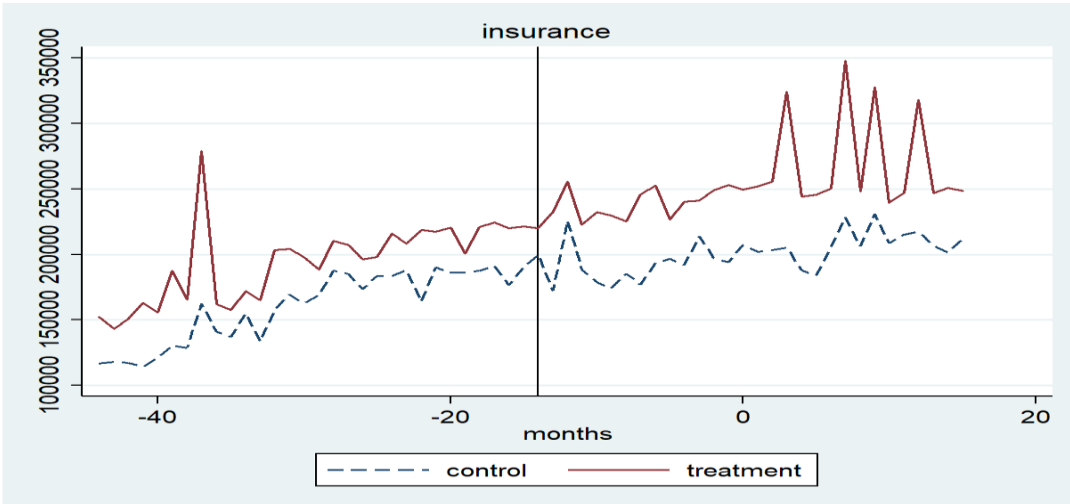
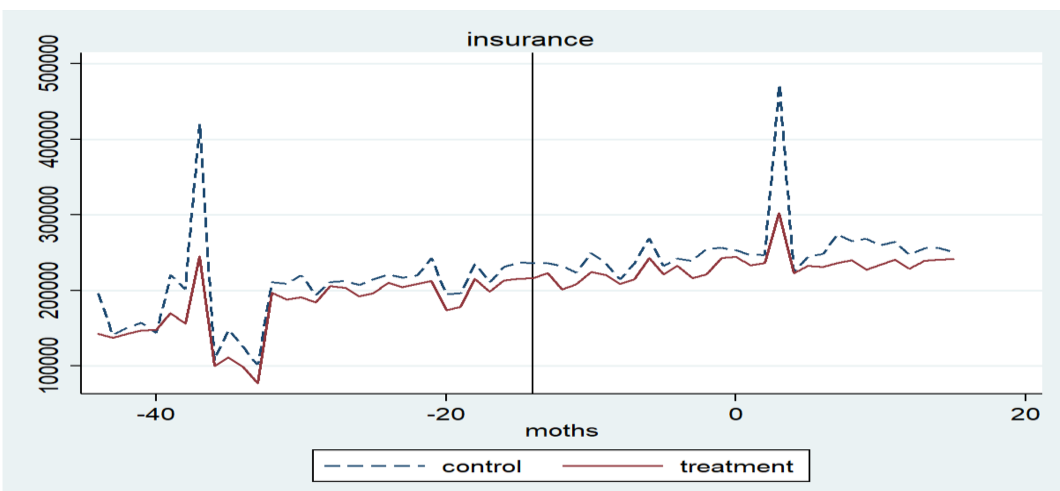


Figure 3.3: Price trend of houses sold within 1/2 mile of a known sinkhole location between 2014 and 2018.



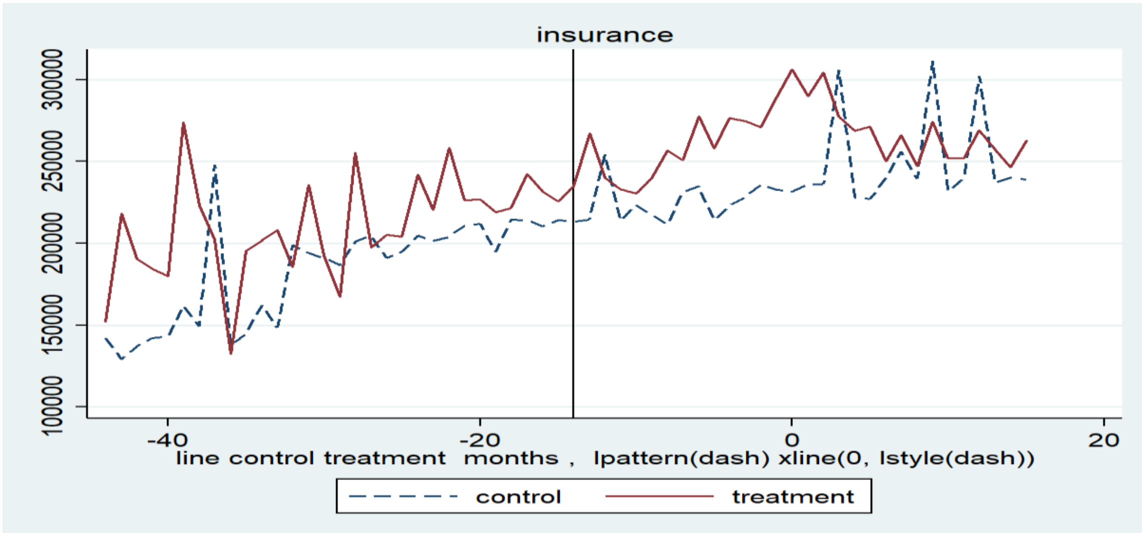
Notes: This figure depicts price trends before and after the new insurance law was effective for properties located within ½ miles of a sinkhole (treatment) and properties located beyond this distance from a sinkhole (control).

Figure 3.4: Price trend of houses sold within 1 mile of a known sinkhole location between 2014 and 2018.



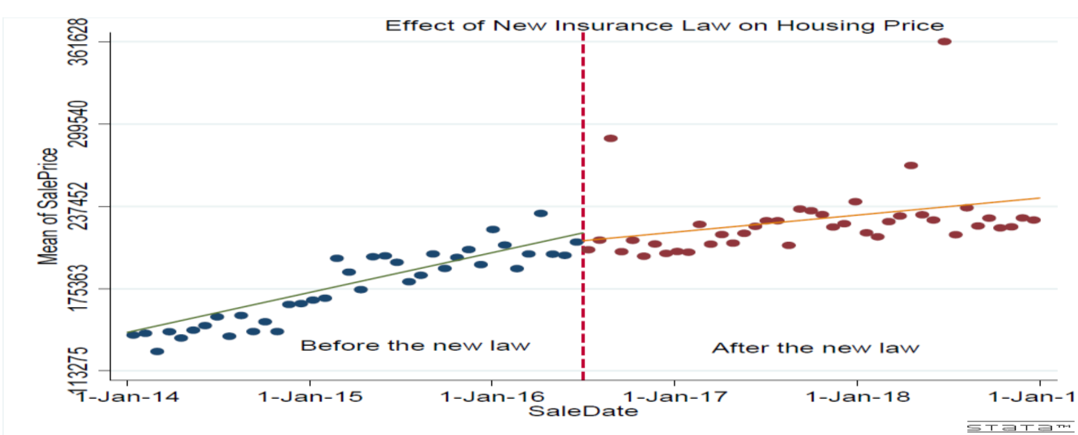
Notes: This figure depicts price trends before and after the new insurance law was effective for properties located within 1 mile of a sinkhole (treatment) and properties located beyond this distance from a sinkhole (control).

Figure 3.5: Price trend of houses sold within 2 miles of a known sinkhole location between 2014 and 2018.



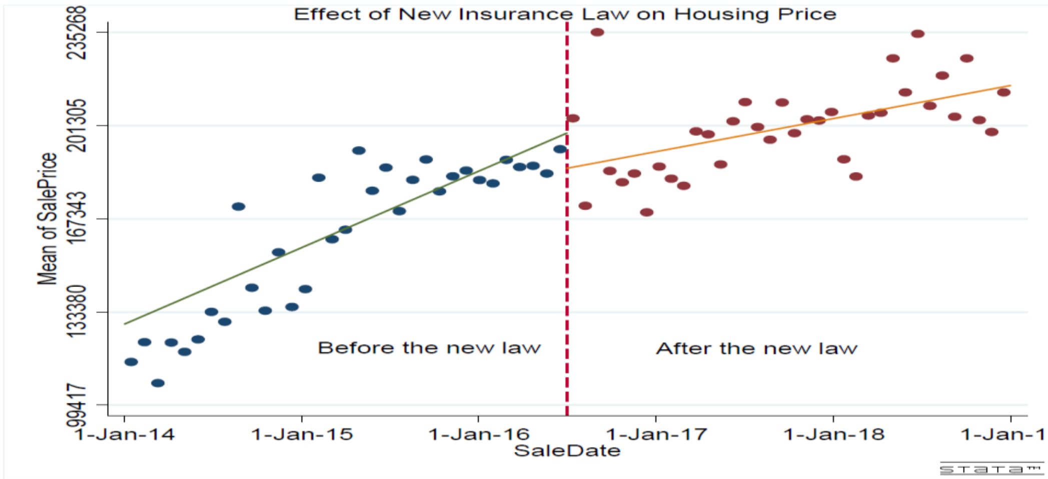
Notes: This figure depicts price trends before and after the new insurance law was effective for properties located within 2 miles of a sinkhole (treatment) and properties located beyond this distance from a sinkhole (control).

Figure 3.6: Effect of new insurance law on houses within 0.25 mile of a sinkhole



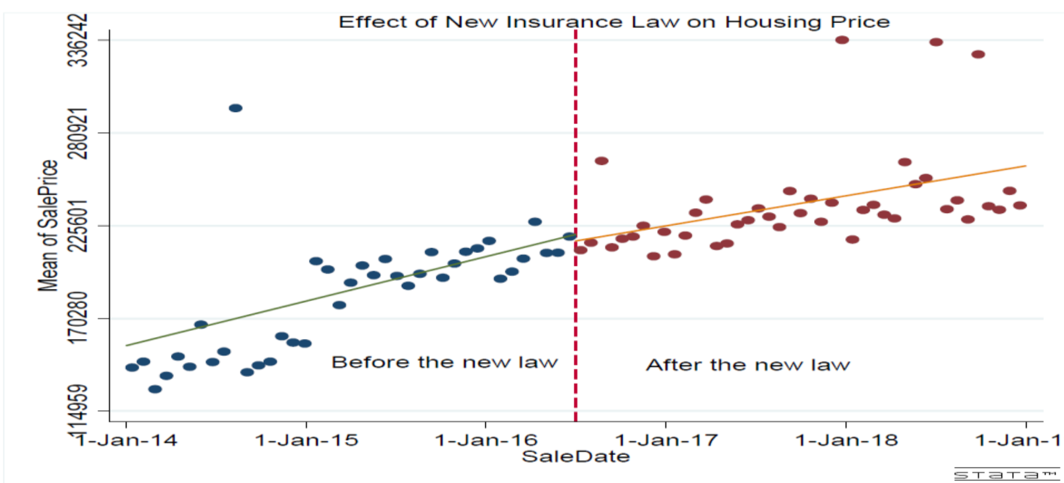
Note: This figure depicts the treatment effect of the new insurance law on the prices of the properties that are located within 0.25 mile of a sinkhole and compares the treatment effect with the same property prices before the new law was in effect.

Figure 3.7: Effect of new insurance law on houses within 0.50 mile of a sinkhole



Note: This figure depicts the treatment effect of the new insurance law on the prices of the properties that are located within 0.50 mile of a sinkhole and compares the treatment effect with the same property prices before the new law was in effect.

Figure 3.8: Effect of new insurance law on houses within 2 miles of a sinkhole



Note: This figure depicts the treatment effect of the new insurance law on the prices of the properties that are located within 2 miles of a sinkhole and compares the treatment effect with the same property prices before the new law was in effect.

CHAPTER 4

CONCLUSION

4.1 Summary and Contribution of This Dissertation

Natural hazards are becoming more frequent and intense and are affecting a larger segment of population over time. They are causing severe property damages and claiming thousands of lives every year. If we can understand better how people react to different types of hazards and how they behave to mitigate risks from these disasters, it would be easier to formulate effective disaster risk reduction policies.

Against this backdrop, this dissertation focuses on people's risk averting behaviors in different contexts. Even though they share the common theme of risk aversion, the three chapters in this dissertation are diverse in terms of its scope, the study area, data, and methodology. I used data from both developing and developed countries, which included both primary and secondary data. I studied the effect of different natural hazards and institutional changes and used various econometric and spatial methods to answer different questions.

In Chapter 1, using survey data from Bangladesh, I analyzed the factors influencing a major risk averting behavior, evacuation decisions during cyclone events. I also examined the presence of temporal and spatial spillover effects in evacuation decisions, which are often missing in evacuation literature. The results support the evacuation literature in terms of a number of sociodemographic factors (e.g., age, sex, income level, etc.) as the primary set of determinants of evacuation decisions. The findings also reveal that past evacuation experience and the evacuation decision by nearest neighbors significantly increase the evacuation rate. This research provides useful information for facilitating evacuation responses by the emergency management agencies and community planners in developing countries.

Florida is one of the most vulnerable states in the USA in terms of exposure to hurricanes. Florida is also one of most sinkhole prone areas in the world. Both hurricanes and sinkholes affect property values in the real estate market. In chapter 2, using real estate sales data from Florida, I studied the effect of sinkhole presence and proximity on property prices and found a significant price discount due to the proximity of sinkholes. More importantly, I explored spillover effect in a multi-hazard context, and analyzed how exposure to one hazard change homeowners risk perception about another hazard and found that even though hurricane is a hydrometeorological hazard and sinkhole is a geological hazard, a hurricane event increases people's concern about the danger of sinkhole and causes further price discount to the houses that are located closer to known sinkhole locations.

Due to high sinkhole risk in Florida, it is required by the insurance companies to provide certain kinds of coverage for the earth's movement. This insurance law was changed in 2011, offering less coverage and thus increasing sinkhole risk exposure for the homeowners. In my third essay, I studied the possible effect of this change in insurance law on housing prices that are located close to sinkholes. Here, I examined how people's risk aversion changes following an institutional change in insurance policy. My findings were quite insightful. I found that the spillover effect in terms of direction and magnitude due to this new law was very similar to the spillover effect caused due to the Hurricane. In my second chapter, I found that even though a hurricane is a random natural shock, this has an impact in the housing market similar to a planned institutional change in the insurance policy.

4.2 Conclusion and Scope for Future Research

As highlighted before, the dissertation covers diverse areas from both developed and developing countries and uses both primary and secondary data to analyze a number of issues that influence people's risk-averting behavior. My findings suggest that temporal spillover is present in significant lifesaving decisions such as evacuation decisions. Moreover, I also found that homeowners react to natural and institutional shocks to some extent in a similar fashion, and the spillover effects in terms of direction and magnitude are also comparable.

The findings may be helpful in forming effective evacuation strategies, risk management, and policy design. There is also room for further analysis of whether the same factors affect the evacuation behavior in all regions similarly or not. If the influence of different factors in different regions can be determined, it will be possible to manage evacuation for specific regions more effectively. Future research can also be done on learning how to formulate effective insurance policies that will not have a distorting effect on the market.

VITA

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