THESIS

ANALYZING THE IMPACT OF HURRICANE MATTHEW ON THE HOUSING MARKET IN SAVANNAH GEORGIA

Submitted by

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ABSTRACT

ANALYZING THE IMPACT OF HURRICANE MATTHEW
ON THE HOUSING MARKET IN SAVANNAH GEORGIA

This study seeks to shed light on the relationship between destructive hurricanes and public belief in the increasing risk to homeownership from these storms as climate change progresses. We investigate the impact of Hurricane Matthew on transaction prices of properties in the city of Savannah, Georgia because it is an example of a natural disaster which was unique in severity for its era but is characteristic of storms which will become more common with warmer oceans and higher sea levels (IPPC 2021). Hurricane Matthew made landfall in 2016. It was the first category 5 hurricane in the Atlantic since 2007 and occurred late in the season relative to previous hurricanes in the area. We use a hedonic modeling approach to shed light on the perceived risk and vulnerability of owning low elevation real estate by comparing property prices before and after the hurricane. We do this to speculate on whether the impact of a single storm can noticeably change the behavior of market participants in a location.

Within our hedonic modeling framework, we employ several econometric specifications including a difference-in-difference regression, an event study model, and a repeated sales model. Our findings indicate that homebuyers were willing to pay a premium for more protected homes, i.e. higher elevation homes, compared with less protected homes, i.e. lower elevation homes, in the two years after the storm. This changing preference for relatively safer homes within a county, at the expense of the amenities available to the low elevation homes such as

ocean views, is consistent with increased belief in the immediate dangers of climate change following a destructive event.

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CHAPTER 1: INTRODUCTION

Climate change is one of the most significant challenges to humanity of the 21st century. Worldwide, changing temperatures have already begun to affect our societies (IPCC 2021). The warming climate and rising oceans are increasing the size, severity, and frequency of hurricanes. A 2020 PNAS study estimates that since the late 1970's the probability of a tropical storm intensifying to a major hurricane has risen by an average of 8% per decade (Kossin et al. 2020). This poses serious risk to many of the United States' large metropolitan areas such as New York, Miami, New Orleans, and Houston. In the United States, population density as well as growth is higher on average in coastal areas. A 2007 study finds that approximately 23 million people on the U.S. seaboards reside in locations less than 10 meters above sea level, sometimes designated Low Elevation Coastal Zones (LECZs) (McGranahan et al. 2007).

Our goal is to shed light on the effects of a severe hurricane on peoples' risk assessment of living in low-lying homes in increasingly vulnerable coastal areas, as revealed by observed willingness-to-pay. Peoples' perception of risk for natural disasters is captured in housing markets in the form of property premiums and discounts (Ho et al. 2008). We use a hedonic model to calculate the price premiums associated with homes at different elevations. In particular, we are interested in understanding the difference in willingness-to-pay for high and low elevation homes, because this will inform us about the degree to which homeowners are adapting to climate change in this instance. A hedonic model is a revealed preference approach for estimating the marginal willingness to pay for specific property characteristics. We use the hedonic model to analyze changes in the premiums for high and low elevation homes in the period before and after Hurricane Matthew directly hit the southeastern United States in early October 2016. Hurricane

Matthew is chosen because it was unusually powerful for a late-season hurricane and because it reached category 5 intensity at the lowest latitude ever recorded in the Atlantic.

To perform our analysis, we use Geographic Information System (GIS) parcel maps of the area that include real estate transactions, elevation, and proximity to beach or river shoreline. Our main specification is a difference-in-difference model that estimates price changes after the storm for high elevation homes relative to their low-lying neighbors. We also implement an event study specification and a repeat sales model in order to understand the mechanisms driving the effects more clearly and to examine the robustness of our findings to alternative specifications. The results provide clear evidence of an increase in willingness-to-pay for higher elevation homes following the storm, which may indicate a change in beliefs about future storm danger following Hurricane Matthew.

Relevant literature to this research includes papers analyzing other large hurricanes with hedonic models as well as papers employing hedonic models for other purposes in Savannah and on the East Coast. Ortega and Taspinar 2018 find that Hurricane Sandy's landfall in New York in 2012 reduced unaffected home prices in the flood zone by 9% overall. The authors conclude that the storm may have increased the perceived risk of major flood events in the area and that their results may provide evidence for a learning mechanism. Beck and Lin 2020 is a similar hedonic study of the Savannah housing market that focuses on the risk assessment of future permanent flooding, or inundation. Using data from 2007 to 2016 the authors find a 3.1% price discount for homes at risk of inundation with sea-level rise of less than three feet, which provides evidence that the market is accounting for increased future risk due to climate change. They also find that the discount is 3.4% for the period 2007-2011, and 4% for the period 2012-2016, indicating a changing effect over time. Our study builds on prior work such as Ortega and Taspinar 2018 by analyzing the effects of a specific hurricane as in previous papers, but taking the further step of differentiating properties based on their vulnerability to coastal storms through the use of elevation data.

This study is the first hedonic analysis of risk assessment changes due to a major storm on the Georgia coast, as well as the first hedonic case study of Hurricane Matthew in general that we are aware of. Our findings are relevant to policymakers who wish to forecast future conditions in coastal housing markets or predict public support for coastal storm mitigation investments. Lastly, when paired with previous hedonic work in the region that finds that home buyers are pricing in future permanent flooding from sea level rise, a clearer picture of the Savannah housing market's adaptation to climate change begins to form. Case studies such as this also form the foundation for future comparative work which could begin to give a picture of macro-trends in climate change risk assessment following unusually large natural disasters which are indicative of future natural disaster severity. Our framework can also be extended to other anthropogenically influenced natural disasters such as the wildfires or heat waves which have battered the American west in recent years.

The paper proceeds as follows. Chapter 2 provides background on Hurricane Matthew that illustrates how it impacted the areas where it made landfall. Chapter 3 summarizes the relevant literature related to climate change risk assessment and hedonic modelling in environmental attribute valuation. We describe our data and present summary statistics in Chapter 4 for the property transactions, parcel geographic and elevation data, and explain our approach for merging the data. We then present the empirical models in Chapter 5 before providing the empirical results in Chapter 6. Finally, in Chapter 7 we discuss and summarize the findings, and provide thoughts on future research.

CHAPTER 2: HURRICANE MATTHEW

We focus on Hurricane Matthew due to its severity, lateness in the season, and the fact that it is one of several major hurricanes in recent years which are thought to have been fueled in part by a warmer climate. This makes it a useful case study to examine how housing markets respond to climate-change fueled hurricanes. It was the first category 5 storm in the Atlantic in nearly a decade but was followed by at least one category 5 hurricane in 2017, 2018, and 2019. Hurricane Matthew is also representative of the more severe natural disasters, including wildfires and floods, which have become and will continue to become more common as anthropogenic climate change progresses (McGranahan 2007) (IPPC 2021). The most recent IPPC (Intergovernmental Panel on Climate Change) report in August 2021, stated that hurricanes in the Atlantic will increase in number, severity, and in length of season over the course of the next century concurrent with the rising global temperatures. This section will illustrate the importance of this specific storm and describe its impacts.

Hurricane Matthew began forming in late September of 2016, moved across the Atlantic over the next several weeks, and made landfall on the east coast of the United States in early October. It was the largest Atlantic hurricane since 2007 and was notably more powerful than usual October hurricanes. Another unusually severe October hurricane which is more widely known is Hurricane Sandy in 2012. Although Sandy caused significant damages and gained media attention due to its impact on New York City, it was actually only a category 3 storm. The official death count from Hurricane Matthew is 585, primarily in Haiti where the storm had a direct impact. It was the deadliest Atlantic storm since Hurricane Stan during the 2005 hurricane season. The storm was unusually powerful for so late in the season and was noted to have reached category 5 intensity at the lowest latitude ever recorded in the Atlantic. The storm made a direct hit on the barrier islands of the southeastern United States, including Georgia, Florida, South Carolina, and North Carolina. 96 mile per hour winds were recorded on Tybee Island, the barrier island next to Savannah. The maximum storm surge (temporary flooding) from the event on the mainland U.S. was a 7.70 ft surge measured at Fort Pulaski in Savannah, Georgia (NOAA 2017). Homes in the middle of Tybee Island were noted to have high-water marks up to 3 feet. Savannah was one of, if not the most, impacted areas by the hurricane in the United States in terms of physical storm intensity (NOAA 2017).

On the mainland United States, 34 deaths occurred due to the storm: 25 in North Carolina, 2 in Florida, 2 in Georgia, 4 in South Carolina, and 1 in Virginia. The storm caused widespread damage to structures as well as downed trees and power lines which caused massive power outages. Approximately 3.5 million people from Virginia to Florida were left without power. The storm surge is estimated to have inundated and damaged 1 million structures in the southeastern coastal states. Thousands of businesses were closed. The estimated monetary damages calculated by NOAA is $10.0 billion with a 90% confidence interval of +- $2 billion (Stewart 2017). It was the 10th most damaging hurricane to be recorded in the United States by total damages at that time. In Chatham County, where Savannah is located, inundation was severe and reached several blocks inland in many places. Homes, restaurants, and hotels were inundated with up to 3 feet of saltwater. 300,000 people were left without power along the Georgia coast, primarily in Chatham County. Tybee Island, Savannah's barrier island, experienced near total inundation, as shown in the two NOAA storm surge simulation maps in Figure 1. The left panel of Figure 1 shows a regular satellite image of Tybee Island and the marshland it protects, while the right panel shows a simulation of the 7.7-foot sea rise and resulting inundation of the island during Hurricane

Matthew. Only the very highest points of the island escaped major flooding. The inundation level for Tybee is significant because it is where the highest storm surge of the hurricane on the entire east coast was observed. Because this storm is indicative of the stronger hurricanes to come as climate change progresses, complete inundation of the island could become a more regular occurrence for residents and business-owners.

Figure 1: Tybee Island Simulated Storm Surge from Hurricane Matthew. On the left is a normal satellite image of Tybee Island, Savannah's barrier island, while on the right is Hurricane Matthew's storm surge of 7.7 feet as modeled using a NOAA inundation program (NOAA, IPCC).

CHAPTER 3: LITERATURE REVIEW

In this chapter we detail relevant studies related to climate change risk assessment, environmental attribute valuation with hedonic models, more general climate change related hedonic studies, and finally some studies from the physical sciences which provide necessary scientific background on climate change's effects on coastlines.

3.1: Environmental Attribute Valuation Using Hedonics

Hurricane risk is just one of many environmental attributes that can be captured using hedonic modeling. The hedonic method has been widely used to value non-market environmental conditions. It assumes that the value of a property consists of structural, neighborhood, and environmental attributes. The buyers are assumed to have "well-behaved preferences" for housing and are constrained by their income and prices (Bin et al 2008). Buyers make home purchasing decisions that maximize their individual utility functions. Using these assumptions and this framework, property transaction data can be used to estimate average marginal willingness-to-pay for various housing attributes. The hedonic method has been used to value an assortment of non-market environmental attributes, ranging from proximity to woodlands (Willis 1991), to views of harbors versus mountains (Jim and Chen 2009), and to beach quality, flood risk, and erosion risk (Bin et al. 2008). Here we use a hedonic framework to estimate willingness-to-pay for characteristics that are associated with hurricane risk.

3.2: Risk Assessment Following Major Hurricanes

A large body of work has examined the ways hurricanes impact housing markets. Initial studies which look at older hurricanes tend to find a price reduction in the short-run followed by a complete disappearance of the effect within 4-8 years. An example is Hallstrom and Smith 2005 which analyzes the impact of Hurricane Andrew in 1992. They evaluate the housing market in a county that was barely missed by the storm and found that, even in the absence of direct damage, property values fell at least 19 percent. Studies that find short term price discounts in similar situations include Atreya and Ferreira (2013) as well as Bin and Landry (2013).

More recently published is Ortega and Taspinar (2018), which looks at the risk premiums in the New York City Housing market following Hurricane Sandy in 2018. Using FEMA data that details specific damage to each parcel from the storm, they find robust evidence of a persistent price discount for flood-zone properties. This includes properties that were not directly damaged but that are in the flood zone. They find an initial drop in prices of 17-22% for damaged properties that slowly rebounds, showing signs of partial recovery in the market. This price discount converges on roughly 8% by 2017, equal to the discount for non-damaged homes in the flood zone. This provides evidence of a persistent price suppression in all homes in the flood plain that is consistent with a learning mechanism. The authors argue that their findings reflect increased perceptions of risk from severe flooding episodes following Hurricane Sandy.

A similar study of the Miami housing market in 2018 finds that the increasing flooding risk due to climate change has a statistically significant discounting effect on home prices (McAlpine and Porter 2018). A somewhat new direction for the field is the inclusion of quantified climate change belief data in coastal flooding risk assessments. One such paper is Bakkensen and Barrage (2017), which finds that lower climate-change belief levels in an area can lead to significantly lower risk premiums from flood risk.

3.3: Sea-Level Rise Risk Hedonic Studies

An adjacent topic to this study is the effect of expected future sea-level rise on coastal housing markets. The science regarding sea level rise and resulting permanent flooding or inundation has improved to the point that individual property-owners can view their homes in a sea level rise projection tool from the NOAA and get reasonably accurate information about whether their land will experience permanent flooding in the future, how much, and the timeline. The development and dispersion of this information to property owners has allowed for future inundation risk to be priced in the market similarly to hurricane risk. Similar to mapping the risk of hurricane flooding to property transaction data, one can integrate future inundation maps from NOAA with property transaction data.

Estimates of risk premiums associated with expected sea-level rise vary, and yet it is unclear how much of the disparities in results have to do with the heterogeneity of housing markets, differing levels of local belief in climate change, or other unknown factors. There was a sea-level rise risk assessment study done in Savannah, GA, in 2020 which found a 3.1 percent price discount for homes that would be inundated with an increase in sea-level of 0-3 feet, relative to homes that would only be inundated with greater than a 6 foot rise (Beck and Lin 2020). Additionally, they find that the discount is larger in magnitude during the period 2012-2016 than in the period from 2007-2011. This is consistent with an increased demand for more protected coastal homes as sea-level rise projections become more robust and accessible. Beck and Lin (2020) is also additional evidence, when paired with this study, of the Savannah housing market in particular responding to changing knowledge of climate risk. For the Chesapeake Bay, Walsh et al. (2019) finds a discount for parcels at risk of sea-rise inundation and also that coastal protective structures can not only offset the risk discount but increase the values of the properties they protect by up to 21 percent. In a nationwide study of the United States, Bernstein et al. (2019), finds that vulnerable properties were associated with a 7 percent discount during the period of 2007-2016.

CHAPTER 4: DATA DESCRIPTION AND SUMMARY STATISTICS

Data for the empirical analysis are collected from three primary sources and combined to create one final dataset, which includes spatial attributes. These data consist of individual property sales data from the Chatham County Tax Assessors website, which administers property sales in the City of Savannah; spatial parcel maps for the area from the City of Savannah Open GIS website; and elevation data from the US Geological Survey. [1,2,3]

4.1 Primary Data

Property transaction data come from the Chatham County Tax Assessor website. The raw transaction dataset contains 363,987 unique property transactions, ranging from January 1980 to December 2018. Shapefile data of property parcels come from the City of Savannah Open GIS Website and reflect 2018 parcel boundaries, to match the ending year of the property transaction data. 117,126 parcels are represented in the raw parcel GIS data. Each parcel has a unique PIN identifier which we use when merging to the other data sources. Each parcel that is in a neighborhood also has a numerical identifier for that neighborhood. There are 746 unique neighborhood identifiers represented in the data. Several variables are included for each parcel, including acreage of the parcel as well as the assessed value of the house in 2018.

One shortcoming of these data is that we do not observe information on physical attributes of these homes, for example the number of bedrooms or square footage. To address this challenge, we use the total value of the house as a proxy for these characteristics, with the assumption that

[1] Chatham County Tax Assessor Website: https://www.chathamtax.org
[2] https://www.sagis.org
[3] https://www.usgs.gov/the-national-map-data-delivery/gis-data-download

the value of the house encompasses the value of physical attributes while not capturing the nonmarket attributes of the property that we are interested in. Panel A of Figure 2 shows the map of all parcels used in this study, which is all parcels in Chatham County, GA. The high-density area of parcels in the center of the map is Savannah, and the high-density area on the northeast end of the map is Tybee Island, a popular tourist beach. Panel B of Figure 2 shows zoomed in maps of these areas to illustrate the proximity of heavily developed areas to the coast and to the Savannah River.

Finally, our elevation data come from the US Geological Survey website as a raster layer ".tif" file. We accessed these data for a section of the east coast and then cropped them to the range of Chatham County, using a shapefile of the county boundary from Savannah Open GIS. Each pixel indicates the average elevation of the pixel, which is 1000 by 1000 meters (30 arc-seconds). The elevation at the center of each parcel is made into a variable. The maximum elevation in the dataset is 14 meters above sea level and the minimum is -2 meters. In our analysis later we break the data into high and low elevation parcels using a cutoff of 7 meters and later explain our rationale for doing so. Figure 3 shows the elevation data for Chatham County. Panel A displays the county elevation as a gradient (-2 to 14 meters), while Panel B displays the same data divided into above and below 7 meters. Several higher elevation areas exist in the county, most notably in the county center where the original settlement was located and where part of modern-day downtown Savannah resides. It is important to note that while there seems to be a correlation between a higher density of structures and these high elevation areas, structures are also widespread in the low-lying areas of the county.

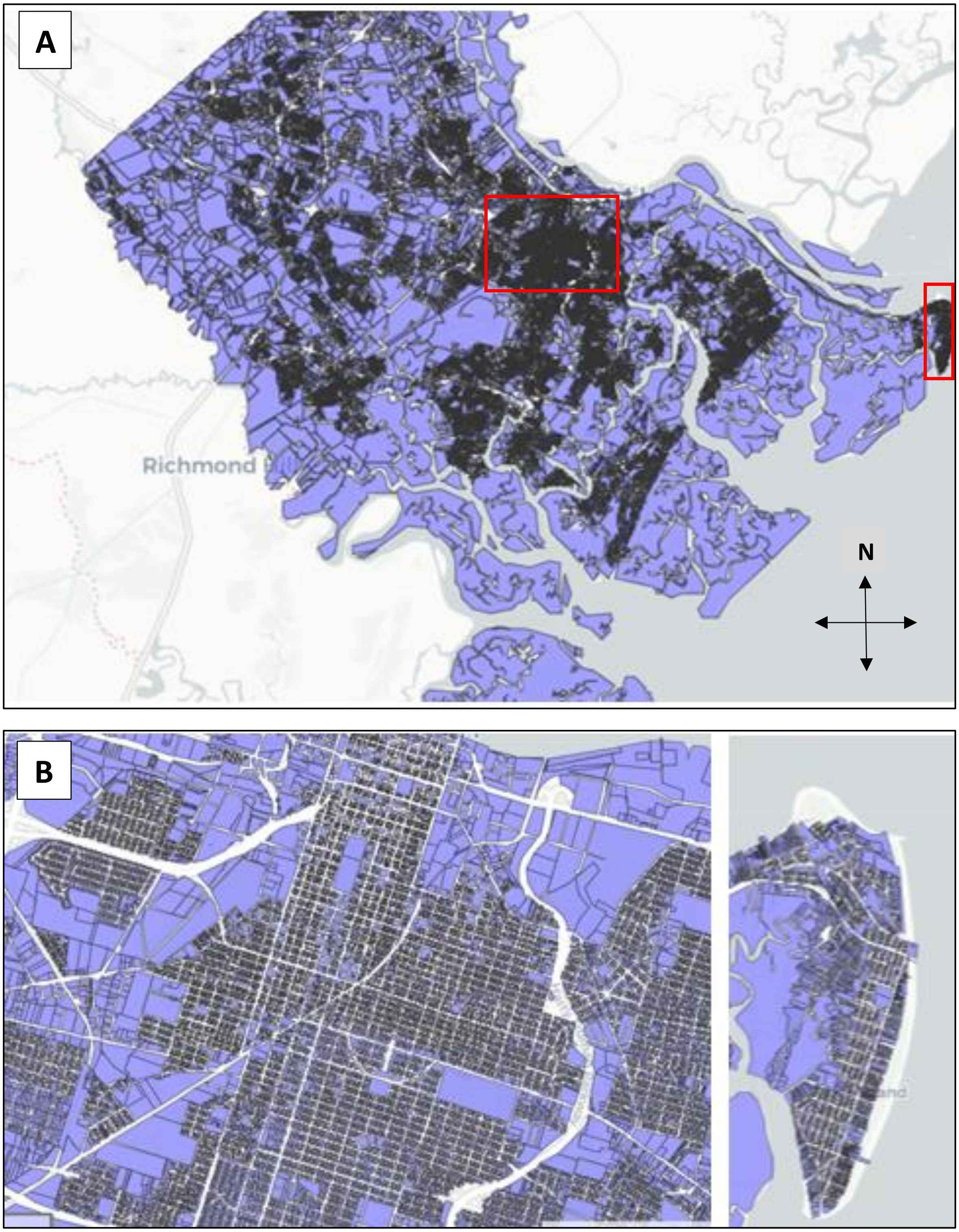

Figure 2: Savannah Parcel Map. This figure shows GIS parcel data, retrieved from the City of Savannah Open GIS Data website. It is displayed using the "Map View" package in R. Panel A shows the entirety of Chatham County, while Panel B shows detail of the two red boxes in Panel A- Downtown Savannah and Tybee Island.

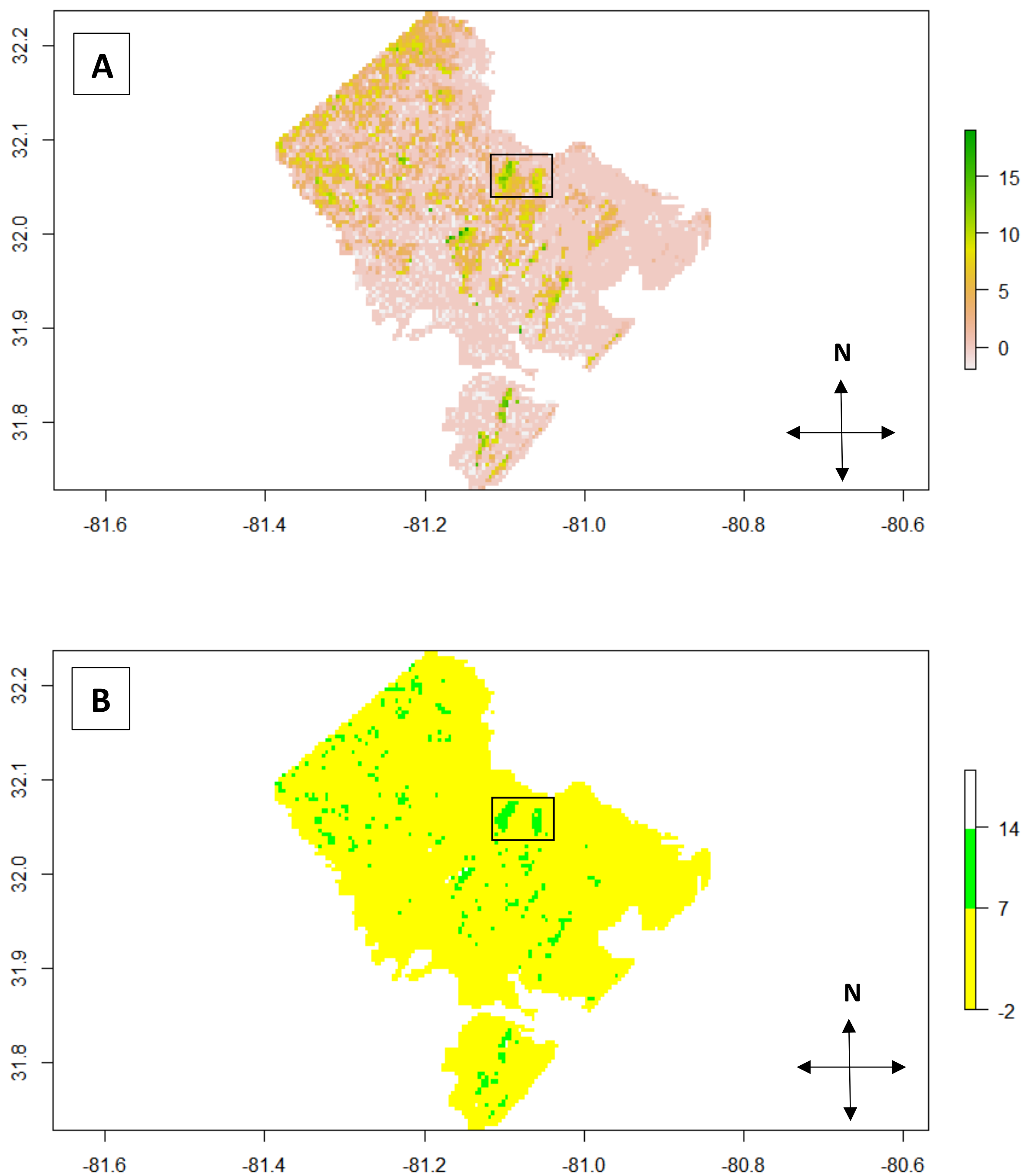

Figure 3: Chatham County Elevation Data. This figure shows elevation raster data accessed from the United States Geological Survey cropped to the boundary of Chatham County, Georgia, using a shapefile of the county boundary available on the City of Savannah Open GIS Website. A variety of higher elevation areas exist in the county, interspaced by lower lying areas and wetlands. Downtown Savannah is located in the center of the county, denoted with a box. Panel A shows elevation as a range, while Panel B shows elevation as a binary (above or below 7 meters).

4.2 Merging Approach and Data Cleaning

We merge the previously mentioned datasets in order to perform our analysis. Using the unique parcel identifier number that is included in both the property transaction data and the parcel shapefile, we combine the datasets to give a single shapefile of the county. This combined shapefile has each parcel viewable by its ID with the Mapview Package in R, with either one or multiple transactions per parcel. Elevation is mapped to each parcel before merging using the elevation at the centroid of each parcel. This provides us with an elevation variable ranging from -2 to 14 meters. A binary elevation variable is created from this elevation range variable that denotes 7 meters and above as high elevation, and below 7 meters as low elevation. 7 meters is chosen as a cutoff for two reasons. First, this is roughly in the middle of the range of elevations in the sample. And second, because robustness testing confirmed that the effect was robust to different choices of cutoff. (Appendix 1). We further confirm in Appendix 5 that there is sufficient variation in elevation within neighborhoods and that there are a sufficient number of neighborhoods that contain both high and low elevation properties.

We adjust the transaction prices for inflation using the consumer price index (CPI), with 2018 as the base year. We remove observations with transaction prices below $25,000 or above $1,000,000 in order to remove outliers such as multi-million-dollar mansions and small un-inhabited lots. We drop transactions by corporations, businesses, universities, banks, condo associations, and other non-individual entities so that only single-family homes are represented. The full list of what is excluded is found in Appendix 2. We also drop observations if the property is below 0.05 acres or above 50 acres or if the home value is above $1,000,000. Our final property transaction dataset includes information on 173,809 single family home sales from 1980 to 2018. Each observation includes the date of sale, a unique PIN for each parcel, the buyers' names, a neighborhood identifier number, the acreage, 2018 assessed home value, and the property address.

4.3 Final Dataset

After merging, each transaction contains the unique PIN number of the parcel, the neighborhood number, the CPI-adjusted transaction price, the parcel centroid elevation in meters, the binary indicator variable for high or low elevation parcels, the acreage of the parcel, and the value of any standing structures on the property. A binary variable is also created that displays a 1 if the transaction occurred post-hurricane, i.e., after October 8th, 2016. In Table 2 we provide summary statistics for our key variables in our final dataset. We can see that in the Savannah real estate market most of the homes are in the low elevation areas. Only 14.4% of homes are high elevation. We can also see from Table 2 that the low elevation properties are slightly larger in acreage and vary more in size.

Table 2: Final Dataset Summary Statistics

All Observations	*mean*	*sd*	*min*	*max*	*N*
Transaction Price (2018 Dollars)	*$211,334.6*	*$170,492.7*	*$25,000*	*$1,000,000*	*155,071*
Elevation (Meters)	*3.551*	*3.101*	*-2*	*14*	*155,071*
Lot Size (Acres)	*1.143*	*2.016*	*.05*	*50*	*155,071*
2018 Home Value	*$161,872*	*$118,044*	*$0*	*$990,100*	*155,071*
High Elevation Observations (>7 Meters)					
Transaction Price (2018 Dollars)	*$201,631*	*$165,747.6*	*$25,000*	*$1,000,000*	*22,357*
Elevation (Meters)	*7.7*	*.815*	*7*	*14*	*22,357*
Lot Size (Acres)	*1.019*	*.661*	*.10*	*40*	*22,357*
2018 Home Value	*$163,848.7*	*$126,110.5*	*$0*	*$983,275*	*22,357*
Low Elevation Observations (<7 Meters)					
Transaction Price (2018 Dollars)	*$212,969.3*	*$171,225.7*	*$25,000*	*$1,000,000*	*132,714*
Elevation (Meters)	*2.851*	*2.898*	*-2*	*6.9*	*132,714*
Lot Size (Acres)	*1.164*	*2.161*	*.05*	*50*	*132,714*
2018 Home Value	*$161,539*	*$116,627*	*$0*	*$990,100*	*132,714*

Notes: Transaction price refers to the final selling price of properties, converted to 2018 dollars using the consumer price index. Elevation in meters comes from the USGS. Lot size is the square acreage of the property. 2018 home value is the value of the house, which is a proxy for a suite of home characteristics. Summary statistics are provided for three groupings: all parcels, solely high elevation parcels, and solely low elevation parcels.

CHAPTER 5: MODEL SPECIFICATION

In this section we introduce the empirical specifications that we use to estimate the effects of Hurricane Matthew on property prices. Our primary specification uses a difference-in-difference approach to estimate the storm event's effects on the relative values of high and low elevation homes. The second model is an event study specification which provides information about property price trends over time and seasonality of the market. We include this analysis to examine whether the estimated effects in our main specification are driven by changes in the value of high or low elevation homes. The third model replicates our main specification for the subset of properties that were transacted multiple times from 1980 to 2018, enabling us to include a property-specific fixed effect. We include this analysis to provide a different method of accounting for unobserved home characteristics in the model. This serves as a robustness check of our use of the home value variable in the main model, which is an imperfect proxy for home characteristics.

For our primary model we utilize a difference-in-difference model on our full dataset of transactions from 1980-2018. It exploits variation in elevation as a proxy for risk exposure before and after the storm's impact. Stated directly, home transaction price is regressed on the acreage of the property, the total dollar value of the house, a dummy variable for post hurricane that activates October 8th, 2016, a dummy variable for high elevation (>7 Meters), and the interaction term between Post Hurricane and High Elevation. 7 meters is chosen for the elevation cutoff because it is the halfway point of elevations in the county. We include robustness checks around the elevation cutoff in Appendix 1. We also include fixed effects for each month of the sample (denoted λ_t) and for each unique neighborhood in the dataset (denoted N_i).

$$
\begin{aligned}
Price_{it} \; = \; & \beta_0 + \beta_1 Acreage_i + \beta_2 HomeValue_i \\
& + \beta_3 PostHurricane_t + \beta_4 High\,Elevation_i \\
& + \boldsymbol{\beta_5 (High\,Elevation_i} \times \boldsymbol{Post\,Hurricane_t}) + N_i + \lambda_t \\
& + e_{it}
\end{aligned} \qquad \textbf{(1)}
$$

Our coefficient of interest is β_5, associated with the interaction term high elevation x post-hurricane. A positive estimate of this coefficient would indicate an increase in value for high elevation homes relative to low elevation homes after the hurricane and would be consistent with shifting preferences towards safer properties. A negative estimate would not support our hypothesis. The home value variable is assumed to be a good proxy of home characteristics.

The second model we employ is an event study. The equation that is estimated evaluates changes in property prices for each month from January 2014 to December 2018 for high versus low elevation homes, which we define as above or below 7 meters above sea level as in Model 1. We narrow our window to this date range in order to get approximately the same amount of data before and after the hurricane for this model. The coefficients associated with high elevation are our coefficients of interest.

$$
Price_{it} \; = \; \boldsymbol{\Sigma\, \beta_t (High\,Elevation_i})\gamma_t + \Sigma \propto_t \gamma_t + e_{it} \qquad \textbf{(2)}
$$

The estimated coefficients for high and low elevation homes (β_t), respectively, are used to create a graphic of the study range with an indication of the hurricane's impact date. The idea is that this will shed light on the time trends underlying the market and will allow us to compare high elevation homes to low elevation homes before and after the hurricane to determine whether there is a structural break visible, with the assumption that homes with relatively higher elevation would be more naturally protected from storm damage. Essentially, this will allow us to see the driving factors behind the effect. This could be that low elevation homes lost value, high elevation homes gained value, or a mix of both.

Our third and final model, the repeat sales model, looks only at homes with multiple transactions during the period of observation from January 1980 to December 2018. Homes with multiple transactions are identified by their unique PIN in the dataset. This is done using parcel-specific fixed effects (fixed effects for each unique parcel), denoted as ψ_i. This allows for parcel characteristics to be controlled for explicitly, since parcels are being compared to themselves through time. Monthly fixed effects for each month of the sample are also included, denoted as λ_t. Stated directly, CPI adjusted transaction price is regressed on the interaction term high elevation x post hurricane and high elevation by itself, with parcel specific and monthly fixed effects.

$$\begin{aligned} Price_{it} = {} & \beta_0 + \beta_1(High\,Elevation_i \times PostHurricane_t) \\ & + \beta_2 High\,Elevation_i + \psi_i + \lambda_t + e_{it} \end{aligned} \quad \textbf{(3)}$$

Essentially, this is equivalent to our first specification but with control variables (acreage, home value) removed because the parcel fixed effects absorb these effects. This alternative difference-in-difference model is included to understand if a different method of controlling for home characteristics has a significant effect on the results, which will inform us about our assumptions made in using the home value in our primary model.

CHAPTER 6: RESULTS

6.1 Primary Model Results

Table 1 displays the results of the primary model (difference-in-difference) estimated with data from the full sample period of January 1980 to December 2018. We sequentially add fixed effects in the estimation results from left to right, and column 4 displays the preferred specification. Column 1 shows results without any fixed effects and finds a $17,928.98 average increase in high elevation homes relative to low elevation homes post hurricane. This is 8.48% of the average area home price of $211,344. Column 1 also displays a significant coefficient on high elevation by itself, which shows that overall in the market high elevation homes sell for $13,468.47 less than comparable low elevation homes. Column 2 adds month-year fixed effects to the regression. The addition of month-year fixed effects lowers the coefficient on the high elevation x post hurricane interaction to $14,620.38. The coefficient for high elevation by itself also decreases in magnitude to a $10,084.03 price discount for high elevation homes.

Columns 3 and 4 display results with controls for neighborhood characteristics using the neighborhood identifier fixed effects. Column 3 shows results with only the neighborhood controls and not time controls. The model does not estimate a statistically significant coefficient for high elevation by itself when neighborhood fixed effects are included. Column 4 is our overall preferred specification, and column 4's coefficient on the interaction term is this study's main coefficient of interest. The estimated coefficients in Column 4 come from a model that includes both month-year and neighborhood fixed effects. It displays that, all else equal, high elevation homes gained a $14,898, or 7% of the average area home price, premium relative to low elevation homes. Column 5 shows the model results with standard errors clustered at the neighborhood level. The coefficient of interest remains significant, but at the $P \leq .05$ level instead of P≤ .001 level. This both confirms our findings and shows that there is less variation within neighborhoods than in aggregate. In sum, these findings suggest that Hurricane Matthew increased the premium for high elevation homes in Chatham County relative to low elevation homes on average, and that high elevation homes in this market typically sell for a discount relative to low elevation homes. These results most likely reflect the higher willingness-to-pay for homes close to the beach in this market, and the increase in demand for relatively more protected properties following the storm. Furthermore, in order to ensure that it was sale value and not number of homes sold that was most affected by the storm, we look at monthly high and low elevation home sales in Appendix 4. It provides evidence that the number of homes sold was largely stable during the period 2014-2018.

Table 3: Primary Results With/Without Fixed Effects

	(1)	*(2)*	*(3)*	***(4)***	*(5)*
Acreage	4,459.567***	4,952.841***	2,853.736***	2,970.647***	2,970.647***
	(191,459)	(181.700)	(207.671)	(198.093)	(704.7)
2018 Home Value	0.648***	0.651***	0.326***	0.312***	0.312***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.0253)
Post Hurricane Matthew	4,818.739***	28,234.640	7,625.792***	25,148.140	25,148.140*
	(1,676.562)	(21,663.030)	(1,523.133)	(19,529.360)	(12,635.4)
High Elevation	-13,468.470***	-10,084.030***	1,822.170	1,534.298	1,534.298
	(1,138.420)	(1,081.942)	(1,293.216)	(1,233.880)	(2,235.4)
High Elevation x Post Hurricane	17,928.980***	14,620.380***	16,812.100***	**14,897.860*** **	14,897.860*
	(4,315.874)	(4,091.682)	(3,887.195)	(3,705.930)	(7,236.0)
Month-Year FE?	No	Yes	No	Yes	Yes
Neighborhood FE?	No	No	Yes	Yes	Yes
Observations	155,071	155,071	155,071	155,071	155,071
R^2	0.207	0.291	0.368	0.429	.429
Adjusted R^2	0.207	0.289	0.365	0.424	.398

Notes: Table shows the results of our primary difference-in-difference model with and without time and neighborhood fixed effects. Column 4 contains our preferred specification. Column 5 displays the results with standard errors clustered at the neighborhood level. * p < 0.05 ** p < 0.01 *** p < 0.001

6.2 Event Study Results

Figure 3 shows the coefficient estimates from the event study specification for the time period from January 2014 to December 2018. We run the model on the reduced dataset of 2014 to 2018 in order to have around the same amount of data on either side of the hurricane. Ultimately the results of our event study help illustrate the market dynamics and provide evidence related to our research hypothesis. Looking at Figure 5, it is possible that high elevation homes retained their value following the storm more than low elevation homes, but the volatility of the market and its subsequent rebound make conclusions from this model difficult to make. We can also see, however, that the average prices for both types of properties are volatile, and that the hurricane didn't have a hugely visible negative impact on the market. The relative changes in valuation of risk compared to coastal amenity value are fairly small relative to the overall prices of the homes and persistent factors in the market. Therefore, from these results alone we cannot identify a causal relationship between the hurricane and the relative prices of low and high elevation properties.

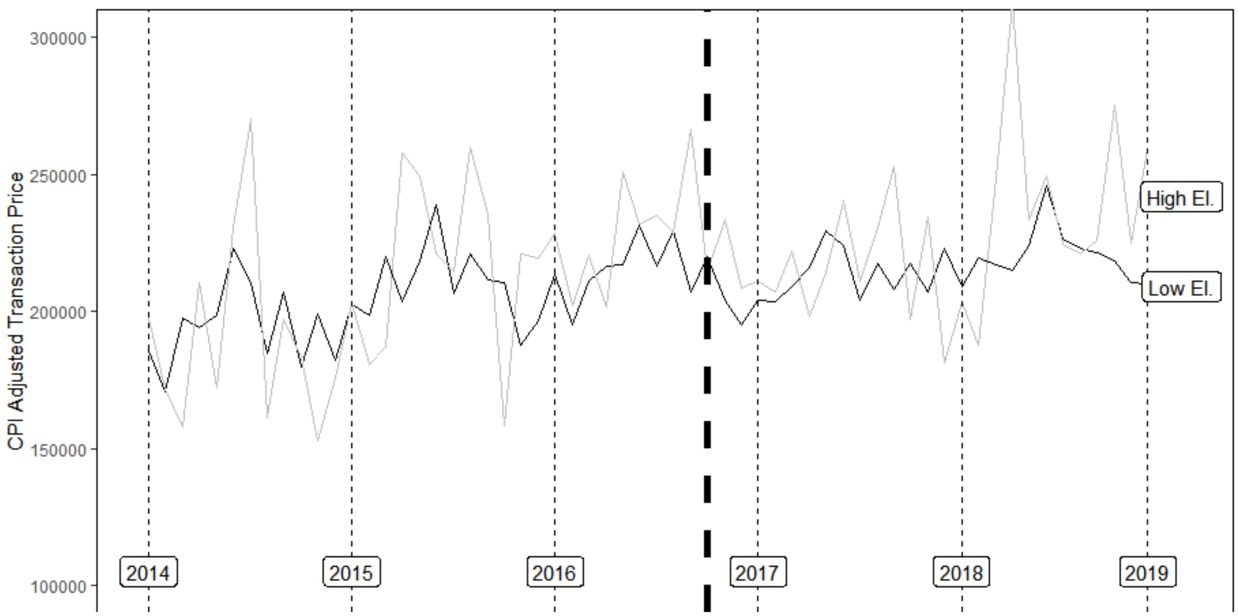

Figure 4: Chatham County Hurricane Matthew Event Study Coefficients 2014-2018. Figure shows the results of our event study model for high and low elevation homes. Coefficients are estimated for every month from January 2014 to December 2018. Immediately following the storm (denoted with bold, vertical, dashed line) high elevation homes appear to have retained value better than low elevation homes, however the effect is difficult to interpret from this model due to the volatility of the market. We know from model 1 that high elevation homes had gained an average of $14,897.86 relative to low elevation homes by December 2018, but visually that is unclear.

6.3 Repeat Sales Model Results

We display the results for the repeated sales model in Table 4. The coefficient for post hurricane by itself is not significantly different than zero. However, our coefficient of interest – the coefficient on the interaction term- is significant and very close to the estimates provided by the main model. Table 4 reports a $15,759.50 increase in the average price of high elevation homes relative to low elevation homes in the first column. This provides support for our assumptions in the primary model. Specifically, that our use of the entire home value instead of a suite of home characteristics was a reasonable choice. We can also say that different methods of including the home characteristics in the model produce overall similar results.

Column 2 shows an alternative model that is run on a further narrowed-down dataset of only properties which sold at least twice and had at least one of the sales after the hurricane (in late 2016, 2017, or 2018). This alternate version also provides consistent and significant estimates of our variable of interest. This model, closely zoomed in on the experience of specific properties, provides similar and significant estimates for our variable of interest. This version of the model reports a $23,495.60 average increase in high elevation homes after the hurricane, which is a bit higher than the $14,693 average increase found in the main model, and the $15,759 average increase in the main version of Model 3.

Table 4: Repeat Sales Model Results

	(1)	*(2)*
Post Hurricane Matthew	-10,058.687	-19,980.8
	(16,708.884)	(11,971.9)
High Elevation x Post Hurricane	**15,759.497*****	**23,495.6*****
	(4,623.227)	(3,863.9)
Month-Year FE?	Yes	Yes
Parcel FE?	Yes	Yes
Observations	89,381	17,172
R^2	0.782	0.765

Notes: This table displays the results of model 3, the repeated sales model. The results in column 1 represent only homes which transacted multiple times during the time period 1980-2018. The results in column 2 show results for the same model refined further to only properties which sold at least twice during the time period 1980-2018 AND had at least one of those sales after the hurricane. Both versions of the model returned statistically significant evidence of a shift in value towards higher elevation homes.

CHAPTER 7: DISCUSSION

We can see from the results in Table 3 that the housing market of Savannah, GA proved robust to the major storm event in 2016, Hurricane Matthew, but approximately $14,897.86 in premium was transferred to higher elevation homes at a county-wide level. This likely reflects revised risk perceptions of residents in the area resulting from the unusually severe storm event. This is consistent with prior work indicating a learning mechanism following unusually severe storms that adjust people's perception of risk. This fits within the framework of previous research such as Filippova (2020), Bekkensen and Barrage (2017), Bernstein et al. (2019), and Garlappi and Yannelis (2018) which find that in some markets, amenity value will not totally mark reductions in value from increased storm risk and climate change, while in other markets it will. It is clear that housing markets are quite heterogeneous and specific research is required for storm impact analysis at the local level. In this case we provide evidence that in the Savannah market the amenity value shift from Hurricane Matthew is visible, and thus was not completely masked by the overall amenity values in the area. Our results are also consistent with our event study analysis of the event which shows that high elevation homes possibly retained value better than low elevation homes following the storm, but it is visually unclear from the event study. We are also able to confirm with the results of Model 3 that our assumptions in using home/structure value in place of a suite of physical home characteristics (due to data limitations) did not bias our results. Put simply, the results of our models show a statistically significant increase in mean price for high elevation homes in Savannah of around $14,898 following Hurricane Matthew in October 2016, which is in line with our hypothesis of risk perceptions being altered by significant natural disasters.

These results likely indicate the presence of climate change belief in at least a portion of Chatham County since these beliefs are a mechanism through which the storm changed people's views of future risk in the area. Those individuals that have higher levels of belief in climate change are potentially more likely to sell lower elevation properties after the storm and to buy higher elevation properties. Further research could look into the relative proportions of these heterogeneous individuals in Savannah compared to the broader U.S. population. Such an analysis would shed light on how our findings might extrapolate to other coastal areas.

In addition to changing risk preferences, the difference between low and high elevation home prices could stem from adjusted insurance rates following the storm. For homes with more damage or more risk of future damage, insurance rates likely increased following the storm. This increase in regular payments on these coastal homes may decrease their sale value and increase their likelihood of being sold, compared with high elevation homes where the premiums may have remained more constant. Future work might explicitly consider the role of insurance in mediating or enhancing the impacts of major weather events on housing markets.

Further research should look into future hurricanes and attempt to draw the lines between individual storms and between hurricane seasons as they increase in intensity and length- which was convincingly shown in a June 2020 PNAS study which shows that hurricanes and tropical storms in the Atlantic have been and are continuing to grow in magnitude and frequency due to warmer oceans and higher sea levels (Kossin and Knapp 2020). A similar framework could furthermore be applied to other types of natural disasters which are increasing with climate change such as wildfires and heat waves (IPPC 2021). It would be interesting to see how the effect changes with time, storm severity, storm type, location, etc. Additionally, a similar case study of Jacksonville, Florida would be particularly relevant to this study as both were severely impacted by Hurricane Matthew in 2016, but are quite different markets. Furthermore, as future storms hit coastal areas, repeat studies of the same location would be useful to capture the evolving attitudes of households in individual markets. Future data availability could also make replicating this study useful- in particular if data becomes available that outlines specific damages from a storm to each parcel. Much more work is left to do to understand and properly make policy decisions when faced with increased risk each year for much of the country's Atlantic and Gulf coasts.

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APPENDIX 1: ELEVATION CUTOFF ROBUSTNESS CHECK

Here we display results for model 1 with varying elevation cutoffs. Elevation in the county ranges from -2 to 14, and here we display the effects of choosing 5m, 6m, 7m, 8m, and 9m as the cutoff for high versus low elevation properties. 7m is used in the main study because it is roughly halfway in the elevation range of the county. We display these robustness checks in Table 5 without fixed effects, and in Table 6 with both month-year and neighborhood fixed effects. The 7m cutoff lies in the middle of the results range and appears to be a reasonable cutoff point. The gradual increase in the coefficient magnitude on the interaction term as we move from 5m to 9m is also indicative of a consistent effect between high and low elevation homes.

Table 5: Primary Results w/ Differing High Elevation Cutoffs (No Fixed Effects)

	5m	*6m*	*7m*	*8m*	*9m*
Acreage	4,403.738***	4,429.313***	4,459.567***	4,483.693***	4,498.293***
	(191.481)	(191.427)	(191.459)	(191.438)	(191.463)
2018 Home Value	0.647***	0.648***	0.648***	0.648***	0.648***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Post Hurricane Matthew	4,996.265***	4,108.788***	4,818.739***	5,354.532***	6,337.571***
	(1,895.702)	(1,761.658)	(1,676.562)	(1,602.762)	(1,570.207)
High Elevation	-12,740.100***	-14,664.220***	-13,468.470***	-16,669.400***	-16,074.810***
	(850.742)	(965.140)	(1,138.420)	(1,585.744)	(2,239.998)
High Elevation x Post Hurricane	**7,551.520****	**15,0132.010*****	**17,928.980*****	**29,916.920*****	**33,990.200*****
	(3,269.325)	(3,662.375)	(4,315.874)	(6,024.346)	(8,849.408)
Constant	105,319.500***	104,065.700***	102,712.200***	101,922.600***	101,279.300***
	(756.209)	(725.525)	(711.665)	(700.958)	(696.081)
Month-Year FE?	No	No	No	No	No
Neighborhood FE?	No	No	No	No	No
Observations	155,071	155,071	155,071	155,071	155,071
High Elevation Observations	51,028	34,113	22,357	10,578	5,080
R^2	.207	.207	.207	.207	.207
Adjusted R^2	.207	.207	.207	.207	.207

Notes: This table displays model 1 results with varying cutoffs for high elevation. No fixed effects are included. The cutoffs range from 5m to 9m, relative to 7m in the main study. Sign and significance remain the same for all coefficients except High Elevation x Post Hurricane at 5 meters, which goes from three stars to two. A direct increase in the magnitude and significance of the coefficient of interest in seen as the cutoff moves from 5m to 9m.

Table 6: Primary Results w/ Differing High Elevation Cutoffs (Fixed Effects)

	5m	*6m*	*7m*	*8m*	*9m*
Acreage	2,973.452***	2,970.169***	2,970.647***	2,968.168***	2,967.603***
	(198.121)	(198.101)	(198.093)	(198.088)	(198.092)
2018 Home Value	0.313***	0.313***	0.312***	0.312***	0.312***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Post Hurricane Matthew	24,804.530	24,629.030	25,148.140	24,784.130	25,351.130
	(19,544.990)	(19,535.170)	(19,529.360)	(19,526.570)	(19,525.930)
High Elevation	1,412.353	887.018	1,534.298	-781.274	12.978
	(961.911)	(1,062.219)	(1,233.880)	(1,673.907)	(2,323.171)
High Elevation x Post Hurricane	**6,561.152****	**10,863.270*****	**14,897.860*****	**25,643.150*****	**31,695.090*****
	(2,813.402)	(3,147.074)	(3,705.930)	(5,174.489)	(7,575.527)
Constant	134,906.200***	134,983.600***	134,899.300***	134,945.000***	134,907.100***
	(33,714.450)	(33,713.870)	(33,713.140)	(33,712.540)	(33,713.210)
Month-Year FE?	Yes	Yes	Yes	Yes	Yes
Neighborhood FE?	Yes	Yes	Yes	Yes	Yes
Observations	155,071	155,071	155,071	155,071	155,071
High Elevation Observations	51,028	34,113	22,357	10,578	5,080
R^2	.429	.429	.429	.429	.429
Adjusted R^2	.424	.424	.424	.424	.424

Notes: This table displays model 1 results with varying cutoffs for high elevation. Both fixed effects are included. The cutoffs range from 5m to 9m, relative to 7m in the main study. Again, sign and significance remain the same for all coefficients except High Elevation x Post Hurricane at 5 meters, and the effect increases as the elevation cutoff is raised.

APPENDIX 2: DATA CLEANING TO GET SINGLE FAMILY HOMES

In order to be left with single-family homes, observations are dropped from the final dataset if the buyer or seller variable contains any of the following:

"LLC, INC, CORP, CORPORATION, TRUST, UNIVERSITY, ORGANIZATION, LLP, BANK, DEVELOPMENT, DEVELOPERS, COMPANY, PARTNERS, PLANTATION, FARMS, CONTRACT, SERVICES, AFFAIRS, LIMITED, EVANGELISTIC, CHURCH, PROPERTY, MANAGEMENT, CONSTRUCTION, HOMES, POWER, TEMPLE, CITY, HOLDINGS, HOLDING, SOLUTIONS, DEPT, DEPARTMENT, PROPERTIES, BUILDERS, ENTERPRISES, COASTAL, CONDO, APTS, APARTMENTS, RENTAL, MISSIONARY, MISSIONARIES, HOTEL, SAVANNAH, CHRISTIAN, HOSPITAL, COMMERCIAL, RESIDENCE, SPA".

APPENDIX 3: RESTRICTED TIME FRAME MAIN MODEL

Here we display the results of model 1 with the sample restricted to only observations between January 2014 to December 2018. Compared to the full model 1, the coefficient of interest on the interaction term is less in magnitude but of the same sign and interpretation as the main model. Since we get very similar results using both the time frame 1980-2018 as with 2014-2018, we can be confident that our results are indeed from an effect during the 2014-2018 date range.

Table 7: Restricted Sample Results

	(1)
Acreage	2,756.363***
	(318.644)
2018 Home Value	0.643***
	(0.007)
Post Hurricane Matthew	2,632.454
	(11,609.880)
High Elevation	-5,156.616**
	(2,340.742)
High Elevation x Post Hurricane	5,171.234*
	(2,921.629)
Constant	251,755.700***
	(53,511.740)
Month-Year FE?	Yes
Neighborhood FE?	Yes
Observations	21,088
R^2	0.758
Adjusted R^2	0.749

Notes: This table displays the results of model 1 run on only data from 2014-2018, instead of from 1980-2018. The significance on terms is slightly less than in the main model, but our coefficients of interest are significant and the interpretation the same. We can see from these results that the effect driving our results was present during the 2014-2018 timeframe.

APPENDIX 4: NUMBER OF MONTHLY HOME SALES

Figure 6 displays the number of single-family home transactions per month for low and high elevation homes. In Figure 6 we can see the seasonality of the coastal market reflected in the peaks and troughs, particularly among the low elevation properties. We can also see that the hurricane did not have a noticeable effect on the numbers of homes sold in the market, either for low or high elevation properties.

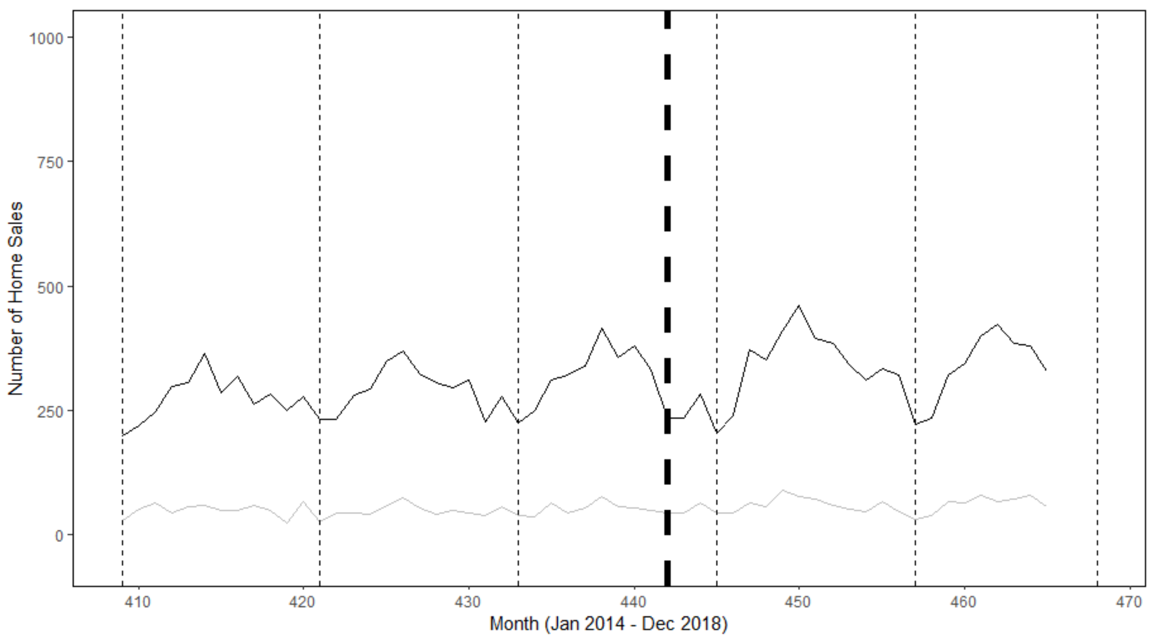

Figure 5: Number of Monthly Home Sales 2014-2018 (Savannah, Georgia). This figure shows the number of monthly home sales split between high and low elevation properties, with the thicker dashed vertical line representing Hurricane Matthew's landfall.

APPENDIX 5: NEIGHBORHOOD VARIATION IN ELEVATION

In Table 8 we explore the variation in elevation within neighborhoods in our data, splitting them into bins based on each neighborhood's variance of the elevation variable. The table shows that a sizeable amount of the neighborhoods have a moderate or high level of variation in elevation. It is good news for our analysis that the majority of the neighborhoods have varying elevations. Only 189 out of the total 755 had a constant elevation within the neighborhood. We additionally calculated that 218 neighborhoods out of the total 755 contained both high and low elevation properties (above and below 7 meters). This is approximately 29% of the neighborhoods. 526 neighborhoods contained only low elevation properties, and 11 contained only high elevation properties.

Table 8: Neighborhood Elevation Variance

Intra-Neighborhood Variance in Elevation	# Of Neighborhoods
0	189
0≤10	510
10+	58
All Neighborhoods	755

Notes: This table displays the number of neighborhoods in the final dataset who fall into each of three bins based on their variance of the elevation variable. 189 neighborhoods have little to no variation in elevation, 510 neighborhoods have a moderate amount of variation, and 58 neighborhoods have a high level of variation.