Measuring the Effect of Hurricanes on US Real Estate Prices

MMSS Senior Thesis

Kevin He

Advising Professor: Mark Witte

Northwestern University
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1. Abstract

In this paper, I examine the impact of the rising frequency and intensity of hurricanes on real estate prices. In particular, I focus on the state of Florida, which, due to its geographic location, has historically had one of the greatest levels of exposure to hurricanes in the US. Using data on indexed residential real estate prices at the neighborhood level from 1996 to 2018, I first classify each neighborhood based on its proximity to the ocean, as those along the coast naturally experience greater devastation from flooding in the event of a hurricane. After separating the costal and non-costal neighborhoods, I run difference-in-difference models to test whether property prices in coastal regions have been valued at a discount relative to properties in non-coastal areas due to their higher risks of hurricane damage. To my surprise, I find that despite the growing devastation of hurricanes, costal residential real estate does not appear to have depreciated in market value relative to safer properties further inland. This result is also reflected from running fixed effects regression on panel data from 1996 to 2018, leading me to conclude that residential real estate market prices in Florida have not priced in the growing hurricane risks.
2. Acknowledgements

I would like to thank Prof. Mark Witte for guiding me along in this project since the very beginning. His insights and direction played a critical role in helping me frame my questions, execute my analysis, and interpret my results. I’d also like to thank the Northwestern MMSS program for this opportunity to pursue a topic of my own interest, as well as for equipping me with the skills and tools needed to conduct my study. I want to express my deep gratitude to my parents for guiding and supporting me through all four years of university, without which none of this would have happened. A special thank you, also, to my friends, who have accompanied me on this long and exciting journey. Your support and the memories we’ve shared have shaped who I am, and I will hold them dearly as I soon embark on the next chapter of my life.
3. Introduction

Climate change, or global warming, is one of the core issues facing our world today. Its effects on our ecosystem, particularly the rising sea levels, higher rainfalls during storms, and warmer temperatures, have been the main contributors to the rising intensity of hurricanes observed in the past few decades. In 2017, we witnessed three of the most catastrophic hurricanes in recent US history: Hurricane Harvey in Southern Texas, Hurricane Irma in Florida, and Hurricane Maria in Puerto Rico, incurring USD$125 billion, USD$65 billion, and USD$90 billion in damages respectively (Frohlich). Beyond the immediate economic impact of these disasters, it is rational to also find the threat of hurricanes reflected in long term real estate values, especially in regions like the coast of Florida that are highly susceptible to these occurrences. This study therefore aims to measure how residential real estate prices have responded to the growing frequency and magnitude of hurricanes.

To carry out the study, I first found data on indexed residential real estate prices at the neighborhood level across the US. Focusing only on Florida, which is geographically the most exposed to hurricane damage, I proceeded to manually separate neighborhoods based on their proximity to the ocean, as coastal real estate naturally has a higher risk of experiencing severe hurricane damage than properties further inland. This classification process leaves each neighborhood with two labels: ‘coastal’ or ‘noncoastal’, with the coastal regions acting as the treatment group in the steps to follow.

The main analysis takes the form of a difference-in-difference model, where real estate prices between the two categories are compared and tested to isolate the effects of having a higher exposure to severe hurricane risks. As the data spans across all months between April 1996 and November 2018, multiple difference-in-difference models that can be run for different start and end dates. There are three periods that I focus on: (1) April 1996 – November 2018, which spans the entire dataset, (2) January 2012 – November 2018, which captures only the period where the real estate market recovers
after the 2008 financial crisis, and (3) January 2016 – November 2018, which, from graphical analysis, seems to show coastal real estate prices appreciate significantly less than non-coastal real estate.

To further substantiate the difference-in-difference model results, I also implement a fixed-effects regression using panel data. This mainly allows for comparison with the estimated difference-in-difference coefficients. The results of both all models will then be analyzed and compared with my initial hypothesis. I also attempt to explain why the results ended up as they were.
4. Literature Review

The real estate market is an ideal asset class to help investigate the effects of climate change. A major reason for this is that the long-term nature of houses and buildings leave them exposed to the long-term risks that climate change imposes. At the same time, as we have seen in 2008, the importance of the real estate market to the overall economy is not be underestimated. Homes are not only the largest asset held by the majority of households in the US, but also an important source of household debt which fuels the economy. It is therefore no surprise that there have been several studies in recent years relating to real estate prices and the effects of global warming.

The most recent and relevant study to my topic is Bernstein, Gustafson and Lewis (2019), published only a couple months earlier, which focuses on measuring the price effect of rising sea levels on homes. Using data on individual homes across the US South-Eastern coastline, the study analyzes the evolution of prices for homes that are equidistant from the ocean but have different elevations. The underlying hypothesis is that homes with lower elevation would be in greater danger of flooding from the rise of the sea level due to global warming, and therefore would be priced at a discount compared to homes that have higher elevation. Using hedonic regression, the researchers found that homes exposed to the sea level rise are sold at an approximate 7% discount to comparable homes that are relatively less exposed to the sea level rise. This relates to my thesis because I am also attempting to find how the real estate market prices a long-term risk caused climate-change. However, there are several key differences between my study and theirs, the first being that I am not use geographic elevation as a primary factor. The second is that I will be using difference-in-difference and fixed effects regressions instead of hedonic regressions. Another is that Bernstein, Gustafson and Lewis are focused on individual properties, while my scope is at the neighborhood level.
Another example of such a study is Butsic, Hanak and Valleta (2011), where they assessed the impact of climate change on the value of real estate near ski resorts in Western US and Canada. The two main variables of focus were the home prices in areas where the local economy is strongly dependent on the ski resorts (dependent variable) and the amount of snowfall as a percentage of total precipitation (independent variable). In other words, the effect of climate change was captured using snowfall, as it is directly affected by rising temperatures. The relationship between these variables was estimated using a hedonic regression that controlled for a variety of other environmental and location attributes, as well as the time of sale for the property. The regression yielded a statistically significant positive relationship between snowfall and home prices near the ski resorts, indicating that the continuation of global warming would reduce home prices in those areas. This relates to my thesis because I also want to model how home prices have changed in reaction to incremental changes in the environment. However, I plan on using the exposure to hurricanes as opposed to snowfall as a proxy for the climate change effects.

A more recent study often cited by online media is Keenan, Hill and Gumber (2018), which was designed to test two hypotheses relating to housing prices in Miami-Dade County, Florida (MDC): 1. The rate of price appreciation for real estate in MDC is positively related to the elevation of the area. 2. The rate of price appreciation in low elevation areas is lower than that of higher elevation areas since 2000. The hypothesis testing was done in two steps. The first step was creating a price index based on elevation levels that allow for the comparison of property price appreciation. The second step was a linear mixed effects regression of each index against time. The results revealed significant statistical support for both hypotheses, meaning that the real estate markets are taking into account the risks of flooding from rising sea levels. The methods used in this study are important for my thesis as I also plan on using an index of housing prices to track changes for different areas. Aside from this, my analysis will
not depend on the properties’ geographic elevation levels. Also, instead of using a linear mixed model, I plan on using the difference-in-difference model.

Even more recently, a study published in August 2018 - Baldauf, Garlappi and Yannelis (2018) examined the impact of people’s beliefs in the severity of global warming as measured by real estate prices in US coastal regions. This study separates people into two categories based on surveys: those who believe that climate change is a serious threat to their lives (believers), and those who don’t (deniers). The model also relies on the assumption of homophily, where people derive better utility living in neighborhoods with like-minded people so that in equilibrium, there will be ‘believer districts’ and ‘denier districts’. Using elevation maps, the study also marked out certain areas that would be flooded if sea levels rise by six feet from the level in 2017. With these assumptions set up, a hedonic model for historical property transaction prices was ran, testing the hypothesis that believer districts valued the potential flood areas at a discount compared to denier districts. The results showed that the hypothesis was correct - the differences in property valuation averaged 7% between believers and deniers, indicating that heterogenous beliefs in the severity of climate change have a significant impact in home prices. I included this study as a reference because its results suggest the need for me to consider the beliefs held by locals in the areas that I’m examining. After all, the market price reflects how much people are willing to pay, which can even be independent from what is rational. Besides this, the assumptions in this study, particularly that of homophily, differ greatly from what I have planned.

Lastly, I was also inspired by Sah, Ziobrowski and Ziobrowski (2008), which focused on the performance of Real Estate Investment Trusts (REITs) during hurricanes. In particular, their study tracked the performance of multiple publicly traded REITs with heavy exposure to hurricane-affected regions and applied two models to test whether the REITs were price efficiently. Efficiency in this sense refers to whether or not the REITs experienced abnormal movement as a result of the hurricane since large
anomalies would indicate that the previous pricing did not accurately incorporate the risks of hurricanes. The two models that were used were the Fama-French factor model and a variation of the market model. From the results, no statistically significant abnormal returns were found during the event window of the hurricane, indicating that public information regarding hurricanes is efficiently factored into the pricing of the REITs. This differs from my thesis in that my thesis will be using housing prices as the primary data instead of REIT returns. However, the results from this study are important because the efficient pricing of REITs regarding hurricanes implies that the underlying assets of the REITs are also adequately priced to reflect hurricane risks. In other words, it provides confidence that once I separate out the hurricane effects, the difference in real estate valuation between high and low-risk areas would indeed be reflective of how the market values the additional risks from climate change.
5. Hypothesis

Due to the nature of this study, I believed it was highly likely to observe a significant discrepancy in residential real estate prices between regions of higher and lower risks of hurricane damage. It makes intuitive sense for people to prefer homes that are at a lower risk of suffering potential damages from hurricanes. The question then boils down to a matter of how much prices react to these chances.
6. Data

6.2 Raw data

My source of data is Zillow.com, a website focused on buying and selling residential real estate. The raw dataset that I used contains 7442 neighborhoods across all the different states in the US. For each neighborhood, the residential real estate price is in the form of an index created by Zillow called the Zillow Home Value Index (ZHVI). According to the source, the ZHVI is a dollar denominated, seasonally adjusted measure of the median estimated home value in the neighborhood. This index value is recorded in monthly increments, and for most neighborhoods, the data is available from April 1996 to November 2018. Figure 1 below shows a snapshot of the raw data.

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</table>

Figure 1: snapshot of raw data

6.3 Data processing

To process the data, I first extract only the neighborhoods that are in Florida and do not have missing data, which leaves me with 468 neighborhoods. For each neighborhood, I used Google Maps to find its exact location. If the neighborhood’s area covers land that is within 2 blocks from the ocean, I label that neighborhood as having ‘1’ in the new column ‘Coastal’. This classifies 139 neighborhoods as coastal, and 329 neighborhoods as non-coastal. For example, Angell City, located on Merrit Island, shown
in Figure 1 below, would be labeled as coastal. Meanwhile, Springtree, located far inland in Gainesville, would be labeled as non-coastal.

Figure 2: Angell City, FL (coastal) and Springtree, FL (non-coastal)

After processing the data, the dataset then looks like below in Figure 3.

<table>
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</tr>
</tbody>
</table>

Figure 3: snapshot of processed data
7. Methodology

7.1 Difference-in-difference model

Based on the data I have available, it seemed that the difference in difference model would be the most efficient and simple choice to measure the effects of differing hurricane risks on real estate prices while controlling for other factors. More specifically, the treatment group would be the neighborhoods labeled as coastal, the two time periods would be the start and end months, while the difference-in-difference estimator would be the interaction between ‘coastal’ and time. The formula for this difference-in-difference model is:

\[ Price_i = \alpha + \beta_1 \times Coastal_i + \beta_2 \times Time_i + \beta_3 \times DID_i \]

Where:

- \( Price_i \) is the indexed home value for the neighborhood \( i \)
- \( Coastal_i \) is the dummy variable for being near the coast, such that \( Coastal_i = 1 \) when the neighborhood is labeled as ‘coastal’, and 0 otherwise, as defined in the Data section
- \( Time_i \) is the dummy variable for time, such that \( Time_i = 0 \) for the starting month, and \( Time_i = 1 \) for the ending month
- \( DID_i \) is the difference-in-difference dummy variable created such that

\[ DID_i = Coastal_i \times Time_i \]

As a difference-in-difference model, the key coefficient of interest is \( \beta_3 \), the difference-in-difference estimator. If \( \beta_3 \) is negative and significant, the model would indicate that the residential real estate values of neighborhoods that are close to the coast have been priced at a discount compared to neighborhoods that are further inland, as I hypothesized. This would offer evidence that people may be pricing in the risks posed by hurricane damage due to living close to the coast. On the other hand, if \( \beta_3 \) is
positive or insignificant, the model would indicate that there is insufficient or no evidence that people are valuing properties at a discount to the higher hurricane risks.

While $\alpha$, $\beta_1$, and $\beta_2$ are less relevant to the final conclusions of the model, they still serve an important purpose of making sure the model’s results are legitimate. In particular, $\alpha$ is expected to be positive, as it would represent the indexed value of non-coastal homes in time period 0. $\beta_1$ is expected to also be positive, since the average value of coastal homes is much higher than the average value of non-coastal homes. This may be due to people’s preferences of living along the coast, likely due to the better scenery. Depending on the start and end period, $\beta_2$ should also be positive. This is because the overall value of real estate has steadily appreciated since the financial crisis. According to Economic Research from the Federal Reserve Bank of St. Louis, the average sales price of houses sold in the US has also surpassed the peak level before the 2005 housing bubble burst (FRED). Therefore, we would any model that uses November 2018 as the end date to have positive $\beta_2$.

As previously mentioned, I will run multiple difference-in-difference models with different starting months, as summarized in Table 1 below:

<table>
<thead>
<tr>
<th>Model</th>
<th>Time Period</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Apr 1996 – Nov 2018</td>
<td>To capture the entire dataset, including a boom and bust cycle</td>
</tr>
<tr>
<td>2</td>
<td>Jan 2012 – Nov 2018</td>
<td>To capture only the recovery period after the financial crisis when almost all property values were appreciating</td>
</tr>
<tr>
<td>3</td>
<td>Jan 2016 – Nov 2018</td>
<td>To capture the final two years available in the data, which graphically seemed to show the non-coastal neighborhoods</td>
</tr>
</tbody>
</table>
appreciating at a significantly greater rate than coastal neighborhoods (see Results section for further details)

*Table 1: summary of difference in difference models*

The results from all three models can then be compared and contrasted, and may help reveal how the gap in property valuation between coastal and non-coastal neighborhoods might expand or contract. All three models are implemented using the statistical software R.

### 7.2 Fixed effects model

To complement the results of the difference-in-difference models, I decided to also implement a two-way fixed effects model, making greater use of the panel data available. After all, the long-term nature of hurricane risks, and the fact that hurricanes affect almost all neighborhoods in the state justifies the use of fixed effects models. The formula for this model is:

\[
Price_{it} = \beta_1 * Coastal_{it} + RegionEffects + TimeEffects + \epsilon_{it}
\]

Where:

- \(Price_{it}\) is the indexed home value for neighborhood \(i\) at time \(t\)
- \(Coastal_{it}\) is the dummy variable for being near the coast at time \(t\), such that \(Coastal_{it} = 1\) when the neighborhood is labeled as ‘coastal’, and 0 otherwise. Note that this variable for a given \(i\) is the same for all \(t\)
- \(\epsilon_{it}\) is the error term

Here, the main coefficient of interest is \(\beta_1\), which indicates the effect of being near the coast after accounting for neighborhood effects and time. As with the difference-in-difference models, a
negative and significant $\beta_1$ would show that property values closer to the coast are on average discounted relative to those that are further inland. Being a two-way fixed effects model, this regression would also consider the individual neighborhood effects, as well as the effect of each time increment.

Due to limitations on the available computational power, I am unable to run this regression using monthly data for all 468 neighborhoods across all the years (22 years total). Instead, I extract from each neighborhood only the indexed price during April as the representative price for each respective year, thus significantly reducing the size of the dataset and the computational time needed. This also means that in the model, time would increment by 1 year per period. Again, this process is done using the statistical software R.
8. Results and discussion

8.1 Data trends and expectations

Before analyzing the results of the model, it is useful to first understand the shape of the data. As seen in Figure 4, there is a wide gap in the average indexed price of homes between coastal and non-coastal neighborhoods. In fact, homes in coastal neighborhoods were on average approximately 50% more expensive than homes in non-coastal neighborhoods. This discrepancy has also increased over the years with the exception of the five years following the burst of the 2005 housing bubble. At the latest available date, November 2018, the average for coastal neighborhoods was almost double of the average for non-coastal neighborhoods. Based on this, we would expect a positive and significant $\beta_1$ (the coefficient for Coastal$_i$) in the difference-in-difference model.

![Florida Residential Real Estate - Costal vs Non-coastal, 1996-2018, raw average indexed price](image)

*Figure 4: comparison of the average indexed price between coastal and non-coastal neighborhoods*

To see in greater detail how the indexed prices have evolved, Figure 5 below illustrates the average indexed prices of coastal and non-coastal neighborhoods rebased to 100, using April 1996 as
the base month. From this graph, we see that coastal neighborhoods have in fact appreciated more than non-coastal neighborhoods over the 22 year period. Another insight from this graph is that the indexed price of the average neighborhood has appreciated since 1996 regardless of its location. In other words, it is reasonable to expect $\beta_2$ (the coefficient for $Time_t$) to be positive and significant in the difference-in-difference model for 1996-2018, as well as for 2012-2018, and 2016-2018.

![Florida Residential Real Estate - Costal vs Non-coastal, 1996-2018, rebased to 100](image)

*Figure 5: average indexed price of coastal and non-coastal neighborhoods rebased to 100*

A closer examination of the average indexed price movements from 2012 to 2018 provides justification for why a separate difference-in-difference model is needed for the period 2016-2018. As in the Figure 6 below, 2012-2018 encapsulates a period where the average indexed price for all locations steadily appreciated as the housing market recovered following the global financial crisis. The interesting aspect of this graph occurs around the second quarter of 2016, where the average for non-coastal neighborhoods begins to appreciate at a greater rate than coastal neighborhoods. This gap appears to persist till the end of the time period and seems to be in favor of my initial hypothesis. After
all, 2016 was known to have the most intense Atlantic hurricane season since 2012, while 2017 had three of the most devastating hurricanes in recent American history: Hurricane Harvey – Texas – US$125 billion in damages, Hurricane Irma – Florida – US$65 billion in damages, and Hurricane Maria – Puerto Rico – US$92 billion in damages. Therefore, it was important that I investigate this particular period in greater detail through running its own difference-in-difference model.

8.2 Difference-in-difference model results

The first difference-in-difference model uses the period April 1996 to November 2018. Its results are pictured in Figure 7 below:
In model 1, the DID coefficient is highly significant, but also very positive. This goes directly against my hypothesis, as it indicates that home prices of coastal neighborhoods have appreciated far more than home prices of non-coastal neighborhoods during the time span.

The other parts of the model seem to match my expectations. The intercept reflects the average price of homes in non-coastal neighborhoods in April 1996, and its magnitude roughly matches that seen in the graphs of section 8.1. While the coefficient for Coastal is only significant at the 8% level, its direction and magnitude also match how much coastal neighborhoods were priced more than non-coastal ones in 1996. The coefficient of Time again appears legitimate, based on the high degree of price appreciation over the 22-year period. While the adjusted R-squared value appears to be quite low, it is not troubling given the broad range of neighborhoods captured in the data.

The second difference-in-difference model’s results are shown in Figure 8 below. This model spans from January 2012 to November 2018, the recovery period after the financial crisis.
In this model, the DID coefficient is almost significant at the 5% level. However, like with model 1, it is highly positive, which again appears to contrast with my initial hypothesis that homes in coastal neighborhoods would be valued less over time as hurricane intensity rises.

This time, $\alpha$ (intercept), $\beta_1$ (coefficient for Coastal), and $\beta_2$ (coefficient for Time) are all positive and significant at the 1% level. These numbers make sense, since $\alpha$ represents the average price for non-coastal neighborhoods in Jan 2012, while $\beta_1$ highlights how homes in coastal neighborhoods are on average valued much higher than those in non-coastal neighborhoods, and the positive $\beta_2$ shows how almost all home prices have appreciated over the time period. The adjusted R-squared value, however, is even lower than that in model 1, indicating a poor fit. However, again as mentioned previously, this value is not as important given the span of the dataset, and how spread out the home prices are.

The results of the third and final DID model, which focuses on the period January 2016-November 2018, is shown below in Figure 9.
In model 3, the DID coefficient is positive but insignificant, indicating that homes in coastal neighborhoods have not been valued at a discount relative to homes in neighborhoods further inland over the time span. In fact, no conclusive statement can be made regarding shifts in the relative valuation of the two neighborhoods since the result is insignificant even at the 50% level. Hence, this model also provides evidence against my initial hypothesis.

Looking at the other parts of the model, $\alpha$ (intercept), $\beta_1$ (coefficient for Coastal), and $\beta_2$ (coefficient for Time) are all positive and significant at the 1% level, with the exception of $\beta_2$, which is almost significant at the 5% level. For the same reasons as in for model 2, the direction of the other coefficients as well as the low adjusted R-squared value make sense. To my surprise, although the graph of the average price comparison (Figure 6) showed a notable difference between home prices in coastal and non-coastal neighborhoods, the model does not indicate such a phenomenon.
8.3 Fixed effects model results

A condensed summary of the fixed effects model results is shown below in Figure 10.

As you can see, $\beta_1$ (the estimated coefficient for Coastal$_{it}$) is again positive. However, this is not significant at any level less than 18%. This model therefore indicates that home prices in coastal neighborhoods have not notably depreciated relative to home prices in non-coastal neighborhoods over the span of 23 years, which is in line with the results from the previous difference-in-difference models. Unlike the difference-in-difference models, however, the adjusted R-squared value for the fixed effects regression is quite high, indicating a reasonable fit.

8.4 Summary of results

Overall, the results of all four models can be summarized in Table 2 below. Since all four models, both difference-in-difference and fixed effects yielded results where the coefficient for ‘Coastal’ is either positive or insignificant at the 5% level, it is reasonable to state that I find no evidence of homes in coastal neighborhoods valued at a discount relative to homes in non-coastal neighborhoods throughout
the time span of the dataset. I therefore reject my initial hypothesis, according to which the coefficient for ‘Coastal’ should be negative.

<table>
<thead>
<tr>
<th>Model</th>
<th>Time Period</th>
<th>Coefficient of ‘Coastal’</th>
<th>Significance level</th>
</tr>
</thead>
<tbody>
<tr>
<td>DID 1</td>
<td>Apr 1996 – Nov 2018</td>
<td>202,106</td>
<td>&lt;0.01%</td>
</tr>
<tr>
<td>DID 2</td>
<td>Jan 2012 – Nov 2018</td>
<td>99,689</td>
<td>5.03%</td>
</tr>
<tr>
<td>DID 3</td>
<td>Jan 2016 – Nov 2018</td>
<td>31,137</td>
<td>58.56%</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Apr 1996 – Apr 2018</td>
<td>29,005</td>
<td>18.80%</td>
</tr>
</tbody>
</table>

*Table 2: model results summary*
9. Conclusion

Based on the results of the three difference-in-difference models and the fixed effects model, I find no evidence that the home prices of neighborhoods in coastal regions have been valued at a discount from 1996 to 2018 compared to home prices in neighborhoods further in-land. This indicates that despite the increasing frequency and intensity of hurricanes, and the fact that coastal real estate in Florida are most at risk of potential hurricane damage, the real estate market in Florida does not appear to have priced these factors into the market value of residential properties.

While this conclusion may seem surprising, it is important to keep in mind that the market for residential real estate may not be the only place that reflects and quantifies the long-term risks of hurricane damage. More specifically, these potential risks may be priced into the insurance premiums for these homes, rather than the raw market value itself. I therefore invite anyone hoping to continue researching this topic to focus on the evolution of insurance premiums for these high-risk regions in order to effectively measure the hurricane risks.
10. Sources

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