Evaluating the Impact of Hurricane Intensity on Residential Property Prices: A Difference-in-Differences Analysis

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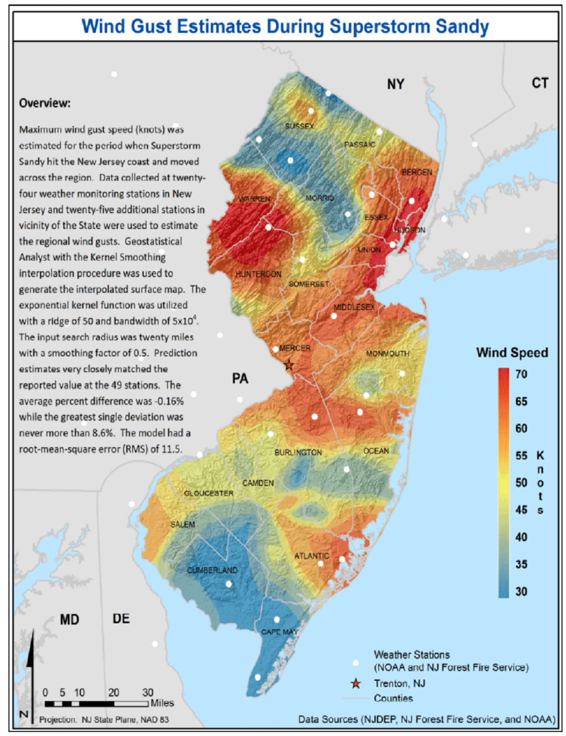
Abstract

This study investigates the impact of Hurricane Sandy on housing prices in Atlantic County, New Jersey, using a Difference-in-Differences (DiD) approach. Hurricane Sandy, which struck the northeastern U.S. in October 2012, caused significant damage to homes, particularly in New Jersey, leading to a sharp decline in tourism and local economic activity. Atlantic County, designated as a flood zone, faced substantial insurance recovery costs and long-term property value disruptions. This study uses housing price data from Atlantic County and Sussex County, which served as a control group due to its relatively low exposure to the hurricane's effects. The analysis spans eight quarters before and eight quarters after the event to capture both immediate and long-term effects. By comparing pre- and post-disaster price trends in the treatment (higher intensity) and control counties (lower intensity), the study tests the hypothesis that Hurricane Sandy increases housing prices in Atlantic County, reflecting limited supply and the inherent valuable location characteristics that would hold post-disaster. The findings of this research offer valuable insights for policymakers, real estate developers, and homeowners, providing a better understanding of how natural disasters influence housing markets and economic resilience.

Keywords: Hurricane Sandy, Housing Prices, Difference-in-Differences, Natural Disasters, Real Estate Markets, Economic Resilience, Property Value, Insurance Costs, Flood Zones

Introduction

The impact of natural disasters on home prices and value has been a topic of significance for quite some time, with many studies focusing on flooding and wind damage post hurricanes, and wildfires. This study focuses on the effect of Hurricane Sandy on sale assessment values in Atlantic County, New Jersey. Hurricane Sandy struck the northeastern coastline in October of 2012, with the most devastating damages occurring in New Jersey. The hurricane led to significant property damage, a decline in tourism, and a designation of Atlantic County as a flood zone, resulting in high insurance recovery costs. It caused an estimated $70 billion in damage across the northeastern U.S., with a significant portion of that occurring in New Jersey. According to data from the Federal Emergency Management Agency (FEMA), more than 340,000 homes in New Jersey were damaged, affecting property values and the local economy, making it one of the most costly natural disasters in American history. To assess the hurricane's impact on property value, we use a Difference-in-Differences (DiD) analysis, comparing sale assessment value in Atlantic County with those in Sussex County over eight quarters before and after the storm. DiD is a statistical technique used to estimate causal effects by comparing the differences in outcomes over time between a treatment group and a control group. Its validity is based on a parallel trend assumption, which essentially means that absent the hurricane, the two counties would have followed similar trends. To validate this assumption and the reliability of our findings, we conducted balance tests to compare pre-treatment characteristics across the treatment and control groups. Additionally, a falsification test was performed by selecting an alternative date for the intervention and assessing whether any significant effects were detected, ensuring the observed impact is specific to Hurricane Sandy. As previously mentioned, the treatment group for this study is Atlantic County, while the control group is Sussex County - an area less affected by the hurricane due to its higher altitude, geographical position, and distance from the coastline (~70 miles). Understanding the effect of natural disasters on housing prices is critical for policymakers, real estate developers, and homeowners. Housing prices reflect perceptions of risk and recovery, which are central to the economic health of affected areas. By studying Hurricane Sandy’s impact, we can better predict the resilience of housing markets in future disaster-prone regions and inform insurance and rebuilding policies. Housing assessment value data for Atlantic County and Sussex County is used, collected from tax assessor records spanning the years before and after Hurricane Sandy. This data allows for a robust comparison of trends to assess the hurricane's impact. After research was conducted, it is hypothesized that the average home value in Atlantic County will increase post disaster due to the limited supply and the inherent valuable location characteristics that would hold post disaster. Depending on the areas being studied as treatment and control groups for different studies, the effects of natural disasters on home value differ, while some view a decrease for areas further from coastal zones - where flooding and damage due to a natural disaster is unexpected, some other studies using areas in close proximity to the coastline saw an increase in housing value. Our study uniquely examines the impact of Hurricane Sandy within the same state by comparing two areas affected by the storm, one of which experienced limited intensity. This allows us to assess whether there is a significant difference in the effects of the hurricane between two counties within the same state, where the storm's severity varied across regions. Furthermore, to examine the effect of Hurricane Sandy on housing prices in Atlantic County, we conducted an event study using a Difference-in-Differences (DiD) model, focusing on sale assessment values before and after the hurricane and accounting for municipality-specific fixed effects within Atlantic County compared to Sussex County.



Literature Review

Natural disasters cause severe physical and economic damage, both globally and in the U.S. Over the past decade, 417 natural disasters on average have been recorded annually worldwide. In 2023 alone, the economic losses due to natural disasters globally amounted to about 380 billion U.S. dollars (USD) (Salas, 2024). Examples include the Northridge (U.S.) earthquake in 1994, the Kobe (Japan) earthquake in 1995, the 2004 Indian Ocean earthquake that caused the Asian tsunami, Hurricane Katrina (U.S.) in 2005, the 2011 earthquake and tsunami in Japan, and Hurricane Harvey (U.S.) in 2017 (Botzen, Deschenes, & Sanders, 2019). Natural disasters are an increasing concern globally but also in the U.S., for their devastating effect on human lives and their economic impact. In 2023 in the U.S., severe convective storms (including hurricanes, tropical storms, and cyclones), caused overall losses of 72 billion USD. These are localized, short-lived storms that can produce severe weather like heavy rain, strong winds, hail, lightning, and tornadoes. Meanwhile, wildfire, drought, and heatwaves resulted in economic losses of 20 billion USD, and tropical cyclone damage amounted to under 5 billion USD (Rudden, 2024).

Of these natural disasters that occur worldwide and in the U.S., convective storms and major floods (which are sometimes caused by these storms) are arguably some of those most damaging. About 15 tropical cyclones make landfall across the globe each year, including an average of 3 in the U.S. where they are concentrated along the Gulf and east coasts (Graff Zivin, Liao, and Panassié, 2023). Floods represent 40% of all natural disasters worldwide, with damages in the U.S. totalling over 260 billion (in 2009 USD) between 1955 to 2009. The increasing scale of economic flood damage is primarily caused by the increased risk from climate change and the increased value of property at risk in hazardous areas, as capital and people moving into floodplains drives up costs. As of 2000, FEMA identified over 6 million buildings located in a 100-year floodplain in the U.S., where there is a 1% chance of a flood occurring annually (Bin & Polasky, 2004).

There is much literature available that empirically analyzes the effects of many natural disasters, but there is particularly much research done on convective storms and floods. Much of this literature studies the relational effect between property values (residential and commercial) and disasters, particularly understanding the extent to which these events influence property values and risk perception among homeowners, and whether these impacts are temporary or persistent over time. Housing prices in a given area can be influenced by various factors, not just natural disasters, including neighborhood characteristics, demographics, proximity to water or highways, and elevation as highlighted by Atreya, Ferreira, and Kriesel (2013). While the initial damage from convective storms and floods is physical, it has behavioral and thus economic consequences, including disinvestment from affected regions, diminished employment opportunities, and out-migration, among others. In well-functioning real estate markets, these impacts should be capitalized into housing values (Rosen, 1974).

The literature shows different perspectives and hypotheses on the relational effect of natural disasters on property values. Studies such as those by Graff Zivin, Liao, and Panassié (2023) and Fisher and Rutledge (2021) study hurricanes across the U.S., including Florida, to highlight the broader economic consequences of hurricanes and supply shocks in the mainly residential housing but also commercial property markets, which cause a decrease in property values after a hurricane. Studies like Atreya, Ferreira, and Kriesel (2013), Kousky (2010), Ortega and Taspinar (2017), and Bin and Polasky (2004), use housing prices as a proxy for flood risk awareness and perception in coastal and inland areas, demonstrating that properties located in a 100-year or 500-year (0.2% chance of a flood annually) floodplain affect homeowner behavior. Other papers such as that by Daepp, Bunten, and Hsu (2023) study this from a more sociological perspective, examining the effects of racial composition changes in Texas neighborhoods due to Hurricane Katrina-induced migration, focusing on housing prices and segregation preferences among incumbent residents.

The existing literature does consistently find that tropical storm disasters and floods influence housing prices, but the direction and magnitude of these effects vary depending on the study design, geographic context, and severity of the event. Atreya, Ferreira, and Kriesel (2013) analyzed the effects of the 1994 "flood of the century" due to Tropical Storm Alberto in Dougherty County, Georgia, using hedonic pricing, spatial, and DiD models. They found a 25 to 44% decrease in housing prices in the 100-year floodplain immediately after the flood, with the discount dissipating within 4 to 9 years. Similar results were found by Bin and Polasky (2004), an earlier study examining prices in the coastal plain of Pitt County, North Carolina as a result of Hurricane Floyd in 1999, though this study did not examine the persistence of these effects. Specifically, they found that a house located within a floodplain has a 5.7% lower market value than an equivalent house located outside the floodplain.

In contrast, Kousky (2010), examined the Great Mississippi and Missouri Rivers Flood of 1993 using similar models and found no significant change in 100-year floodplain prices but found a 2 to 5% decline in 500-year floodplain properties. While not empirically examined, this study noted that residents often suffer from probability heuristics, where dramatic events disproportionately influence perceived risk, regardless of their actual likelihood of recurrence. Kousky (2010) noted that residents also often have incorrect assumptions of the floodplain year definitions which are based on outdated FEMA maps, suggesting that outdated information and misunderstandings of floodplain terminology influence how disasters affect housing prices. Federal Reserve Bank of Dallas, Murphy, Strobl, and Ecole Polytechnique (2010) take a unique approach, focusing on hurricane intensity, rather than a binary treatment, offering a more nuanced understanding of how natural disasters shape housing markets. The authors found that hurricane destruction temporarily increases housing prices by 3 to 4% within 3 years, driven by supply shocks, while local incomes decline slightly. Ortega and Taspinar (2017) also conducted an intensive study, revealing a 9% long-term reduction in housing prices in flood-prone areas in New York City (NYC), driven by a persistent increase in perceived flood risk. Severely damaged properties experienced immediate and sharp price declines (17 to 22%) but showed partial recovery over time, while non-damaged properties saw a gradual but lasting decline of 8%.

Graff Zivin, Liao, and Panassié (2023) similarly observed a transitory price increase (up to 10%) and declining transaction probabilities in Florida post-hurricane, followed by a return to baseline within 3 years. Their study also highlighted demographic shifts, with higher-income buyers increasingly dominating post-disaster markets, suggesting gentrification effects. Daepp, Bunten, and Hsu (2023) found that neighborhoods receiving 100 additional Katrina survivors saw a 2.2% decline in house price growth after 5 years, primarily driven by movers from predominantly Black areas, though these price effects rebounded within a decade.

Data sources used across the literature include parcel-level sales data of residential homes (including characteristics like number of rooms, age, acres, etc.). GIS data was used to understand neighborhood variables like distance to important nearby features, elevation, and floodplain status. Census data was sometimes used to identify demographic data e.g., median household income and the percentage of nonwhite residents (Atreya, Ferreira, & Kriesel, 2013). Data on admission to the National Flood Insurance Program (NFIP) was used throughout these studies as flood insurance can potentially influence housing prices, however due to privacy regulations, insurance data at the property level is not available, which limits controlling for its effects, making its influence unclear (Kousky, 2010). Kousky (2010) also discusses how federal disaster aid can complicate interpretations of housing price shifts, but FEMA does not provide detailed data on disaster assistance at the county level, making it difficult to separate the effects of perceived risk versus expectations of government support.

The studies reviewed employ various econometric approaches to isolate the effects of natural disasters on housing markets. Common methods include:

- **Difference-in-Differences (DiD)**: Used to compare pre- and post-disaster outcomes between treated and control groups. Graff Zivin, Liao, and Panassié (2023) utilized a staggered DiD design to analyze multiple hurricane events over time, while Ortega and Taspinar (2017) used a DiD framework to assess Hurricane Sandy's long-term effects on NYC housing markets.
- **Hedonic Pricing Models:** Widely used to decompose property values into their constituent characteristics, such as location, flood risk, and neighborhood features. It’s also effective at testing marginal willingness to pay for changes in environmental quality (Bin & Polasky, 2004; Atreya, Ferreira, & Kriesel, 2013).

- **Spatial Autoregressive Econometric Models (SARAR):** These models account for spatial dependencies and are particularly useful in studying flood risk, as neighboring properties often influence one another's values (Atreya, Ferreira, & Kriesel, 2013).
- **Panel Event-Study Designs:** These incorporate controls for socioeconomic characteristics and analyze pre- and post-trends to capture dynamic impacts (Daepp, Bunten, & Hsu, 2023).
- **Dynamic Panel Models:** Federal Reserve Bank of Dallas, Murphy, Strobl, and Ecole Polytechnique (2010) used a dynamic equilibrium correction panel model with a hurricane destruction index, capturing how hurricane intensity influences housing prices over time. The hurricane destruction index, which accounts for wind speed and property exposure, improved explanatory power compared to simpler binary treatment variables.
- **Repeat Sales Model:** Used to track changes in property values over time by comparing prices of the same property in multiple transactions. Kousky (2010) employed this approach to assess how flood risk perception evolved post-flood in Missouri, focusing on within-property variations to eliminate bias from static property characteristics. This method is useful for isolating temporal price changes related to disasters, but it is limited by data availability for properties with multiple sales.
- **Fixed Effects Model:** These models control for unobserved heterogeneity at the property, neighborhood, or regional level. Ortega and Taspinar (2017) included fixed effects for neighborhoods and blocks in their analysis, allowing them to account for location-specific characteristics that do not vary over time. Similarly, Federal Reserve Bank of Dallas, Murphy, Strobl, and Ecole Polytechnique (2010) incorporated fixed effects into their dynamic panel model to control for regional differences across coastal cities.

Most literature used multiple approaches within a given study. Our study contributes to this literature by employing an intensive event study, following the DiD framework to analyze Hurricane Sandy's impact on New Jersey housing markets, focusing on Atlantic County (more affected) versus Sussex County (less affected). By focusing on property-level sales assessment values and incorporating FEMA damage estimates that capture varying degrees of hurricane intensity, we address gaps in the literature and provide insights into how varying damage levels influence property prices within a single state, offering a more nuanced understanding of natural disasters' localized effects, and exploring how coastal characteristics might mitigate price declines, as suggested by Kousky (2010) and Graff Zivin, Liao, and Panassié (2023).

Understanding how natural disasters affect property markets has significant implications for policymakers, urban planners, institutional investors and residents. The literature highlights the role of risk perception, supply shocks, and demographic shifts in shaping market outcomes, emphasizing the need for targeted policies to enhance disaster resilience. By examining both immediate and longer-term effects, our study contributes to broader discussions on climate adaptation, risk communication, and the economic consequences of increasing climate volatility in New Jersey.

Data

Residential Property Data

Data was collected from the New Jersey Property Tax System, known as MOD-IV, Historical Database (HDB). HDB is a comprehensive searchable database containing over 30 years of New Jersey real estate parcel data maintained by municipal assessors where users can download data for analysis and research purposes. The database contains over 105 million parcel records and serves as the state's official record of real estate parcel information, overseen by the NJ Division of Taxation, with data provided by assessors from all 564 municipalities. The variables that were extracted are the following:

- **county_name:** NJ county where the property is located
- **municipality_name:** Name of the NJ municipality
- **property_location:** Street address of the property
- **deed_date:** Date when the property deed was recorded (Year variable derived from this)
- **sale_assessment:** Assessed value of the property at the time of sale
- **residential:** Indicator of whether the property is a residential property

Demographics Data

The demographic data for Atlantic and Sussex County, New Jersey was taken from the United States Census Bureau. It uses the ACS (American Community Survey) data for 1 year estimates in both 2010 and 2011. These values will be used later on in the robustness evaluation of the study to determine if these counties are in fact similar before the treatment (Hurricane Sandy) occurs. The variables that were extracted are the following:

- **Population Density:** The total population
- **Male:** Percentage of population that is male
- **Female:** Percentage of population that is female
- **MedianAge:** Median age
- **CollegeDegree:** Percent of the total population that has earned a college degree
- **HouseholdIncome**: The median household income (dollars)
- **UnemploymentRate:** The unemployment rate (percentage)
- **HouseSize:** Average number of bedrooms in housing units
- **OwnedHomes:** Percentage of homes that are owned
- **MarriedFamilyOwners:** Percentage of households that are owned and occupied by families
- **AssessmentValue:** Median sale assessment value

Figure 1: Demographics by County - 2010 and 2011

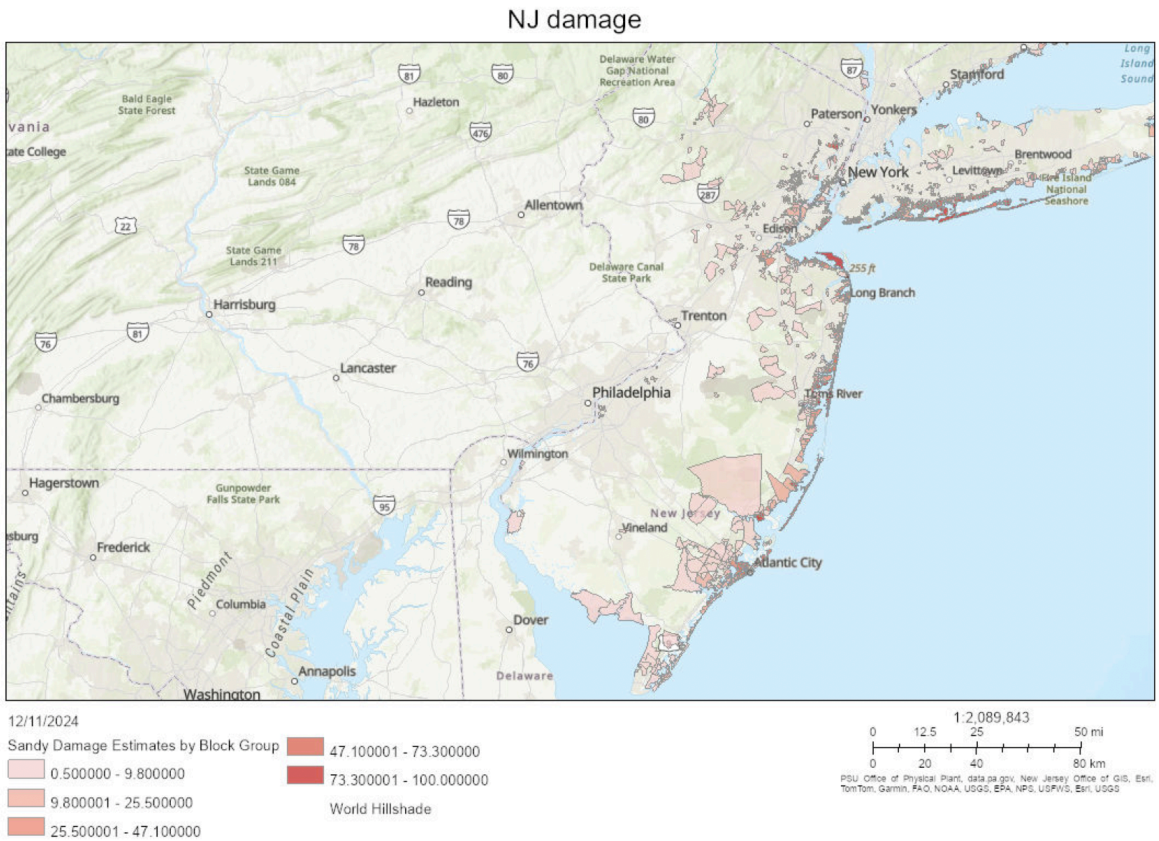
Demographics Across Groups - Pre Hurricane Sandy

	Atlantic - 2010	Sussex - 2010	Atlantic - 2011	Sussex - 2011
PopulationDensity	274685.000	149239.000	274338.000	148517.000
Male	0.483	0.493	0.485	0.501
Female	0.517	0.507	0.515	0.499
MedianAge	40.400	41.500	40.100	42.300
CollegeDegree	0.467	0.396	0.502	0.475
HouseholdIncome	52571.000	84115.000	50829.000	83839.000
UnemploymentRate	0.126	0.110	0.149	0.117
HouseSize	2.650	2.690	2.670	2.670
OwenedHomes	0.734	0.847	0.669	0.836
MarriedFamilyOwners	0.468	0.606	0.435	0.611
AssessmentValue	315000.000	283700.000	318800.000	271150.000

Hurricane Intensity of Treatment

To understand the specific amount of damage done to various areas of New Jersey from Hurricane Sandy for this intensive DiD event study, data was pulled from the Office of Policy Development and Research at the Department of Housing and Urban Development. The dataset contains a map of Sandy damage estimates by block group in New Jersey based on FEMA Individual Assistance (IA) Registrant Inspection Data. A FEMA housing inspection is used to assess home and personal property loss and to determine eligibility for FEMA IA, post hurricane. If the property has flood damage, the inspector measures the height of the flooding, indicating the highest floor of the flooding and the extent of the flooding in that room. For property without flooding, HUD has estimated minor/major/severe damage based on the damage inspection estimates. The map shows various percentage ranges of damage from the hurricane, ranging from 0.5% - 100%.

Figure 2: Map of Hurricane Sandy Damage



Data Exploration

Figure 3: Summary Statistics of Raw Assessment Value Data Extracted

Statistic	N	Mean	St. Dev.	Min	Max
Year	8,300	2,012.413	1.286	2,010	2,014
SaleAssessment	8,300	357,128.700	410,426.500	0	6,540,600
Residential	8,300	1.000	0.000	1	1

Some key takeaways from the raw data summary statistics would be the minimum and maximum values of the key variables ‘Year’ and ‘sale_assessment’. Based on the deed date, the year and quarter were extracted. The data contains quarterly sales assessment values from the years of 2010 to 2014. The sale assessment data (dependent variable) has a minimum value of $0 and a maximum of $6,540,000. Another thing to note from this table is that only residential homes within the counties Atlantic and Sussex will be studied. Among the residential properties, we noticed that some entries still had unusually low or zero sale assessments, these were likely cases of valued properties.

Due to the large range of sale assessment values, it was decided that the outliers will be removed and the value of homes will be filtered for those above 100 thousand dollars and below 2 million dollars. This will reduce noise in the dataset for the DiD, ensure that the dataset accurately represents typical residential property transactions and it will also enhance the comparability of homes across the two counties. An upper threshold of 2 million dollars was chosen because residential properties below this value are reasonably common, and only 1% of the data exceeded this limit. Including properties above 2 million would skew the mean due to their significantly higher valuations, so removing them ensures a more accurate representation of typical residential property prices

Figure 4: Distribution of Assessment Values - Pre and Post Cleaning

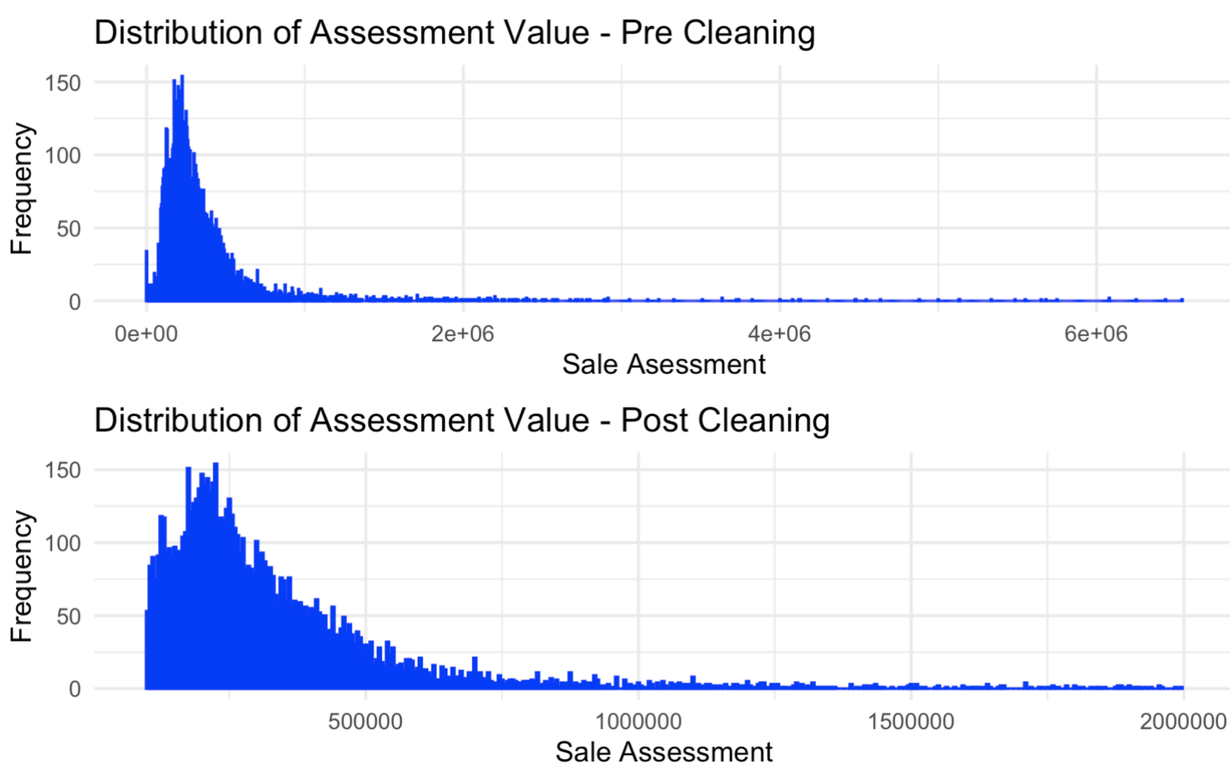


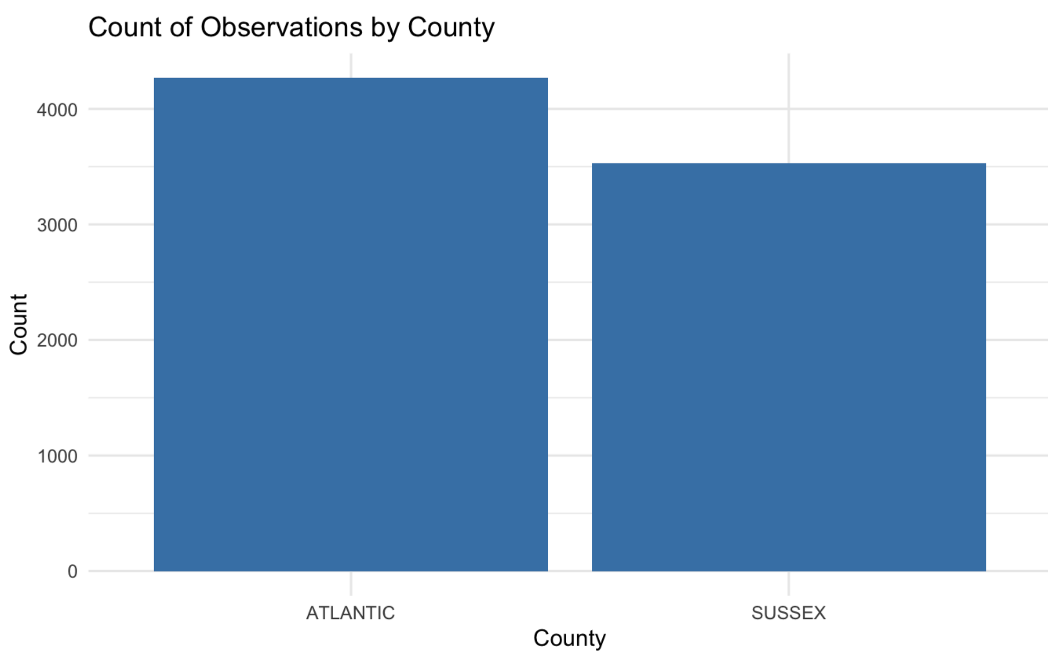
Figure 5: Summary Statistics for Sale Assessment Values Pre and Post Capping

Sale Assessment Summary Stats Before and After Capping

	Mean	Median	Minimum	Maximum	Skew	SD
SaleAssessmentPre	357,129	261,000	0	6,540,600	6.86	410,426
SaleAssessmentPost	340,298	269,550	100,000	1,996,800	2.85	247,503

As you can see from the table above, once the sale assessment value filter was placed on the data we now have values from $100,000 to roughly $2,000,000 homes. As shown, this significantly reduced the skew from a value of 6.86 to 2.85.

Figure 6: Bar Chart of Observations By County



While analyzing the data, a slight difference in the number of observations was noted between Atlantic County and Sussex County. When extracted, there were no missing values, suggesting this difference is due to the variation in housing units between the two counties. This is likely attributable to differences in population size, which will be highlighted in the demographics table.

Figure 7: Summary Statistics By Treatment and Control Group

Summary of Sale Assessment Value By Group - Post Cleaning

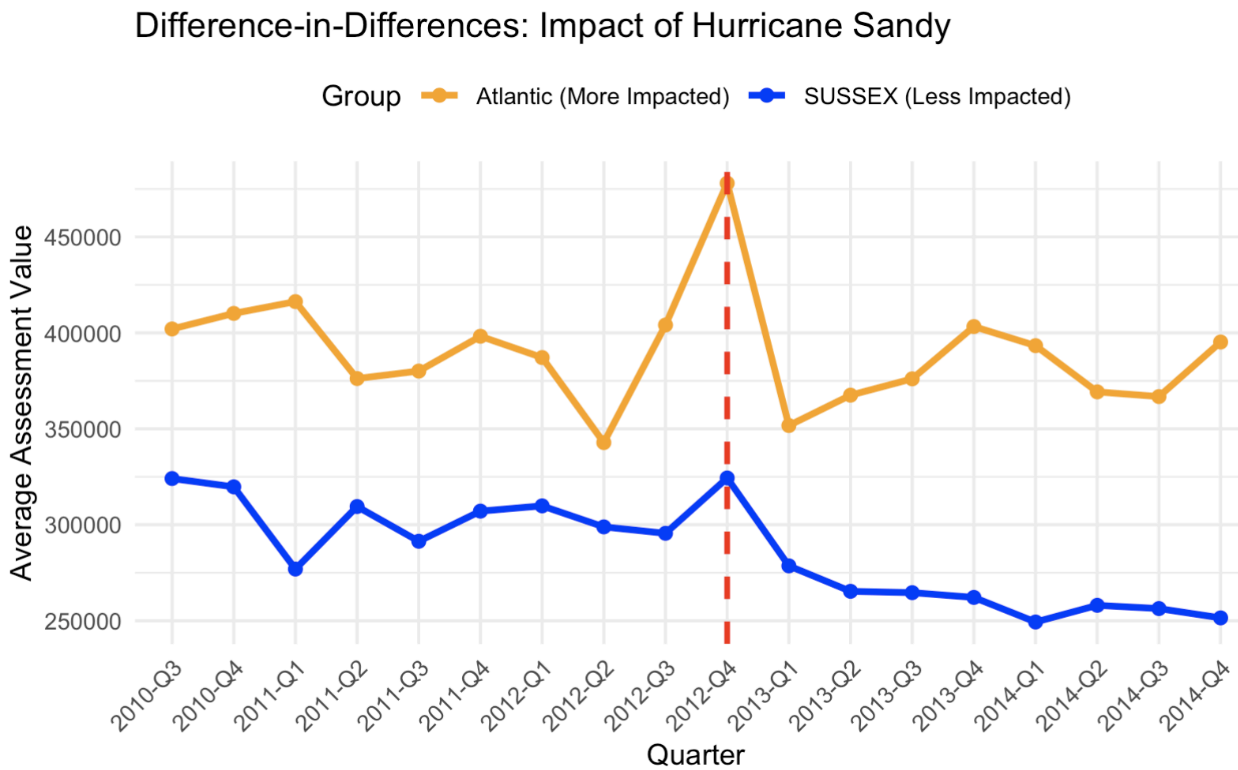
CountyName	Mean	Median	SD	Min	Max	Skew
ATLANTIC	388735.8	302800	299075.2	1e+05	1996800	2.337991
SUSSEX	281763.9	245700	144728.8	1e+05	1784000	2.551587

This table provides an overview of the sale assessment statistics for both counties, allowing for a comparison of housing values before the experiment. Notably, the skewness for Atlantic County decreased from 5.5 to 2.3 after capping the values, indicating a reduction of outliers in the county's data. The key takeaway is that, over the four years captured in the data, Atlantic County consistently exhibited higher housing values compared to Sussex County. This difference may be attributed to a range of factors, including the county's location and its socioeconomic characteristics. However, it is important to emphasize that these higher values should not be interpreted as indicative of extreme or disproportionate housing prices. Rather, they offer a glimpse into the general trend of higher housing values in Atlantic County throughout the study period.

When selecting two counties for model comparison, three key principles were applied to ensure a robust analysis:

1. **Sufficient Pre- and Post-Intervention Data**: At least 8 quarters of data before and after the natural disaster in October 2012 were required to establish reliable baseline trends and capture long-term effects.
2. **Parallel Trends Before the Disaster**: The counties needed to exhibit similar trends in property prices before the disaster, a critical assumption of the difference-in-differences (DiD) model. This ensures any divergence post-disaster can be attributed to the intervention. In the below graph, both counties show aligned trends up to when the hurricane occurs.
3. **Post-Intervention Divergence**: A clear change in property price trends post-disaster was necessary, with the treatment county (higher intensity) showing a noticeable impact while the control county (lower intensity) remained relatively unaffected. These criteria ensured the validity of the DiD model and provided meaningful insights into the disaster's impact on property prices. Post hurricane impact, there is a divergence in the parallel trends, Atlantic county's price valuation rises while Sussex remains steady / decreases slightly.

<u>Figure 8: Hurricane Sandy Impact on Residential Property Values</u>



Methodology

Overview of the Difference-in-Differences (DiD) Framework

The Difference-in-Differences (DiD) method is a quasi-experimental econometric approach used to estimate causal effects by comparing changes in outcomes over time between a treatment group and a control group. This method assumes that in the absence of treatment, the treatment group would have followed the same trend as the control group (parallel trends assumption). The DiD model is particularly suited for studying natural experiments, such as the impact of Hurricane Sandy on property sale values.

The underlying assumptions of the DiD approach are:

1. **Parallel Trends**: Prior to the intervention, the outcome variable trends for both groups must be similar. This ensures that observed differences post-treatment can be attributed to the intervention.
2. **No Spillover Effects**: The treatment should only affect the treated group, with no indirect effects on the control group.
3. **Consistency**: The treatment and control groups are consistently observed, with no unobserved heterogeneity that correlates with both the treatment and the outcome.

This study uses the DiD approach to evaluate the hypothesis that Hurricane Sandy had a significant impact on residential property sale assessments in Atlantic County compared to Sussex County.

Estimation Equation and Variables

The best model specification for this analysis is given by:

$$\text{Sale Assessment}_{it} = \beta_0 + \beta_1 \text{Impacted}_i + \beta_2 \text{Time}_t + \beta_3 (\text{Impacted}_i \cdot \text{Time}_t) + \epsilon_{it}$$

The DiD approach utilized a linear regression model, with post-cleaned residential property prices as the dependent variable and time, intensity of treatment, and interaction terms as the independent variables.

- **Sale Assessment:** Assessed value of the residential property at the time of sale in Sussex and Atlantic counties.
- **Time**: Indicates whether the event (hurricane) has occurred, where 0 = before the event and 1 = after the event. This variable helps the model distinguish between the periods before and after the hurricane.
- **Intensity of treatment**: Reflects the intensity of the hurricane's impact on each county. The intensity was calculated as the average impact percentages of cities within each county, as reported by FEMA.
- **Atlantic County**: Impact percentages ranged from 47.1% to 100%, with an average of approximately 73%.
- **Sussex County**: Impact percentages ranged from 0.5% to 9.8%, with an average of approximately 5%.
- **Interaction (Time x Intensity of treatment)**: Captures the change in the dependent variable (residential values) attributable to the intervention, measuring the difference in the outcome for the treated group compared to the control group, adjusted for the intensity of the hurricane's impact after the event.

Figure 9: Diff in Diff - Hurricane Sandy impact on Residential Property Values

```
==================================================
                          Dependent variable:
                      ----------------------------
                            sale_assessment
--------------------------------------------------
Intensity_of_teatment        125,868.900***
                              (12,321.010)

Time                         -39,944.720***
                               (8,867.074)

Interaction                   53,759.800***
                              (16,323.120)

Constant                     297,237.900***
                               (6,776.968)

--------------------------------------------------
Observations                       7,798
R2                                 0.049
Adjusted R2                        0.048
Residual Std. Error     241,437.000 (df = 7794)
F Statistic           133.240*** (df = 3; 7794)
==================================================
Note:                 *p<0.1; **p<0.05; ***p<0.01
```

Results

Coefficient & Data interpretation

- **Intensity of treatment (125,869)**: For every 1 unit increase in treatment intensity, the baseline sale assessment of properties in the treated group is expected to increase by $125,869 prior to the hurricane. Coefficient is statistically significant.
- **Time (-39,945)**: In the post-hurricane period, sale assessment decreased by an average of $39,945 for all properties, regardless of treatment intensity. Coefficient is statistically significant.
- **Interaction (53,760)**: For every 1 unit increase in treatment intensity, sale assessment increased by $53,760 more in the post-hurricane period compared to the pre-hurricane period. This is the key difference in difference effect, indicating that higher intensity hurricane impacts are associated with higher sale assessment post hurricane relative to less impacted properties. Coefficient is statistically significant.

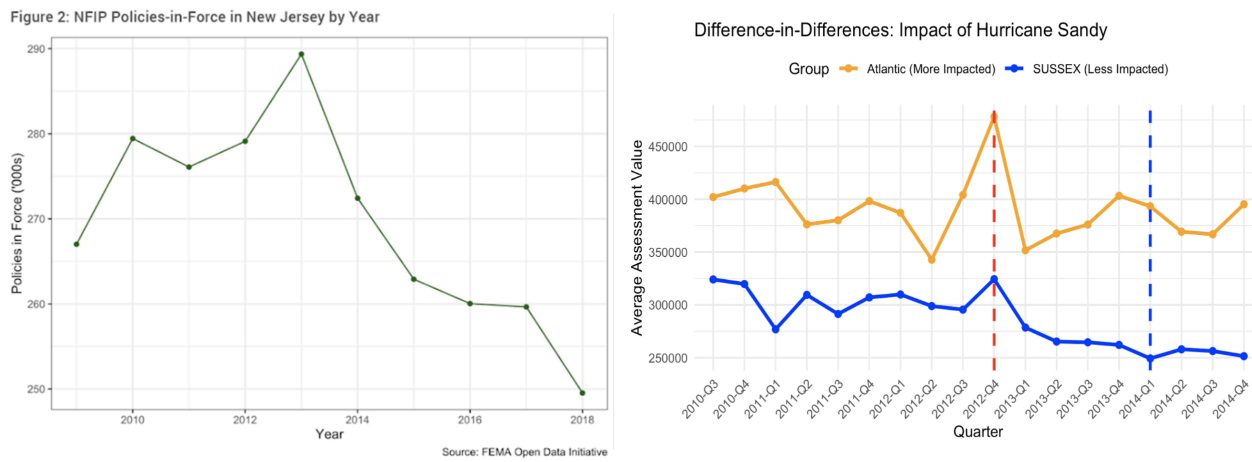
- **Adjusted R^2 (0.048)**: Suggests that only 4.8% of the variation in sale assessment is explained by the model. While low, this is not uncommon in social sciences or real estate studies where many unobserved factors influence sale assessment values.
- **Residual Std. Error (241,437)**: Represents the typical deviation of observed sale assessment from the predicted values, suggesting variation in sale assessment not captured by the model.
- **F-Statistic (133.2)**: The F-statistic indicates the overall model is statistically significant ($p < 0.01$), meaning that the predictors collectively explain variation in sale assessment better than a model with no predictors.

The interaction term confirms that properties exposed to higher hurricane intensity experienced a larger increase in sale assessment post-hurricane, compared to less impacted properties. This suggests the hurricane's intensity positively impacted property values, potentially due to recovery efforts, insurance payouts, or redevelopment activities. The general post-hurricane period effect (time) is significant, implying systemic price changes across all properties. The Intensity of treatment shows that properties in more-affected areas had higher baseline prices pre-hurricane, likely due initial differences in property values between impacted and non-impacted regions, driven by commercial development. Atlantic county is on the coastline and as a result surrounded by casinos, shopping areas, and other businesses which added to the initial valuation prices. What was not expected is post hurricane, the prices recovered after 3 quarters, followed by higher lows in price fluctuations.

As a reference point, other studies show that hurricanes significantly affect housing markets, with price dynamics shaped by damage intensity and risk perception. For instance, Federal Reserve Bank of Dallas, Murphy, Strobl, and Ecole Polytechnique (2010) observed a temporary 3-4% rise in housing prices within three years due to supply shocks, despite slight income declines. Conversely, Ortega and Taspinar (2017) found a 9% long-term price drop in flood-prone NYC areas, driven by heightened flood risk, with severely damaged properties initially losing 17-22% in value before partially recovering. Similarly, Graff Zivin, Liao, and Panassié (2023) documented short-term price increases (up to 10%) in Florida, followed by a return to baseline within three years.

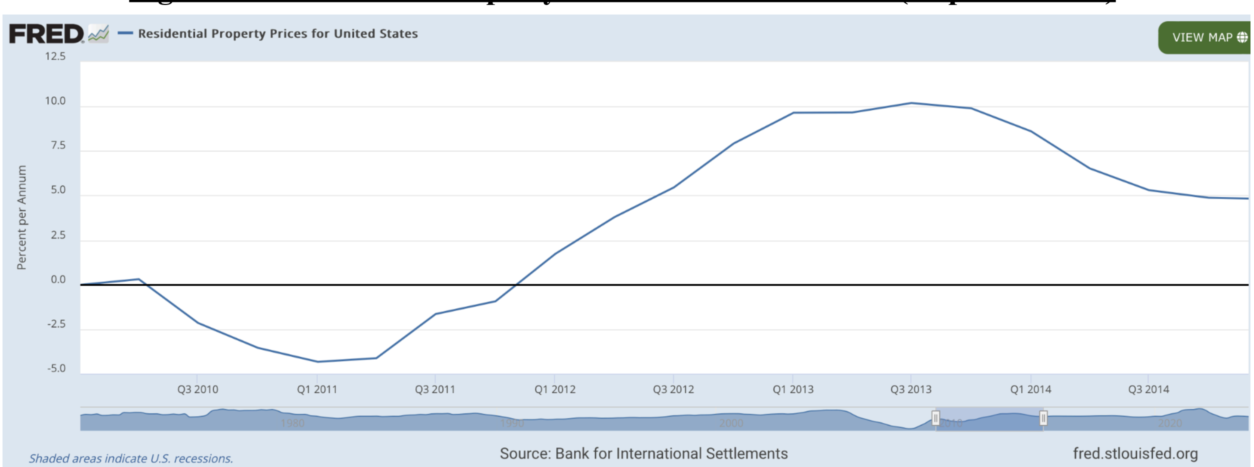
After Hurricane Sandy, residential property valuations initially dropped due to immediate disaster impacts such as damaged infrastructure and reduced demand. However, valuations rebounded over 3 quarters, reflecting recovery efforts, federal aid, and NFIP insurance payouts. The NFIP, despite its outdated maps of flood areas and subsidized premiums, likely played a role in stabilizing the market during recovery. This highlights the importance of accessible insurance in supporting property values post-disaster. However, NFIP reforms, such as increasing premiums from the spike in NJ claims from 2012-2013 highlighted in the below left graph, could affect future recovery dynamics, highlighted in the right graph in blue where house prices dipped once again. As these premiums normalized, it seems valuations recovered.

Figure 10: NFIP insurance claims vs Residential Property Values



When comparing the trends of the two counties to the U.S residential property prices from the FRED database, Atlantic County deviates from the overall market. As shown below in figure 11, U.S residential property prices in the comparable period decreased, opposite of the price value increase seen by Atlantic County post natural disaster, suggesting Hurricane Sandy indeed had a material impact on housing values.

Figure 11: Residential Property Prices for United States (% per Annum)



Limitations

The primary limitation of this experiment lies in data availability. Public property pricing data can be difficult to access, as not all counties maintain or provide publicly available datasets. While many counties have searchable databases, the lack of accessible compiled public datasets limited the scope of the experiment. This constraint prevented a more ideal comparison, such as analyzing a county with no hurricane impact (control) versus one that was only lightly impacted (treatment). Additionally, reliance on publicly available data restricted the comprehensiveness of the analysis. Access to commercial or paid databases, such as those offered by Zillow, would have allowed for a more detailed examination, including more granular pricing trends. Given the limited availability of data outside New Jersey, it would allow counties with no hurricane exposure beyond the current state to serve as a control group for the experiment. Lastly, the dataset from the state was limited as it lacked key variables such as information on the owner, inhabitants, number of floors, income, tax rates, or foreclosure status. Including these variables in the difference-in-differences analysis could provide additional detail and enhance the robustness of the results. All these factors would help enhance measures of fit, such as the adjusted R^2, leading to stronger and more precise conclusions about the effects of the disaster on property prices.

Event Study

This section presents the results of an event study conducted to examine the impact of the hurricane on housing prices in Atlantic County, NJ, using a difference-in-differences (DiD) framework. The model includes both the "Treated" and "Control" groups, which allows us to assess how the shock influenced the sale assessments over time, especially when considering municipality-specific fixed effects. The focus of this analysis is on the estimated effects of the event relative to the shock period (defined as relative_time = 0), which allows for the identification of significant changes in housing prices before, during, and after the event.

Model Specification

The regression model used to estimate the effects of the event on housing prices is as follows:

$$\text{sale\_assessment} = \beta_0 + \beta_1 \text{Treated} + \sum \beta_t \text{as.factor(relative\_time)} + \sum \beta_m \text{municipality\_name} + \epsilon$$

Where:

- `Treated` indicates whether a municipality was affected by the hurricane.
- `as.factor(relative_time)` captures the time-varying effects relative to the event period.
- `municipality_name` accounts for municipality-specific fixed effects to control for local factors that might affect housing prices over time.

<u>**Figure 12: Results from event study**</u>

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	175339.5	56827.3	3.085	0.002039	**
Treated	264745.7	81738.8	3.239	0.001205	**
as.factor(relative_time)-8	-2783.7	25729.8	-0.108	0.913849	
as.factor(relative_time)-7	-42003.7	27380.9	-1.534	0.125058	
as.factor(relative_time)-6	-13845.8	26794.9	-0.517	0.605357	
as.factor(relative_time)-5	-27474.9	25449.8	-1.080	0.280367	
as.factor(relative_time)-4	-16242.5	27073.3	-0.600	0.548559	
as.factor(relative_time)-3	-5662.8	25468.2	-0.222	0.824048	
as.factor(relative_time)-2	-24254.7	25259.1	-0.960	0.336966	
as.factor(relative_time)-1	-28092.5	24206.4	-1.161	0.245864	
as.factor(relative_time)0	-660.8	25159.6	-0.026	0.979048	
as.factor(relative_time)1	-41062.0	24744.7	-1.659	0.097070	.
as.factor(relative_time)2	-56477.7	23848.2	-2.368	0.017899	*
as.factor(relative_time)3	-63691.3	23479.2	-2.713	0.006689	**
as.factor(relative_time)4	-62854.9	24178.7	-2.600	0.009351	**
as.factor(relative_time)5	-65457.1	25491.3	-2.568	0.010253	*
as.factor(relative_time)6	-70760.6	23827.6	-2.970	0.002990	**
as.factor(relative_time)7	-67613.5	22805.5	-2.965	0.003038	**
as.factor(relative_time)8	-71519.9	23732.9	-3.014	0.002591	**
municipality_nameAndover Township	90753.9	51485.0	1.763	0.077986	.
municipality_nameAtlantic City	-46217.3	19475.6	-2.373	0.017664	*
municipality_nameBranchville Borough	138110.8	58994.5	2.341	0.019253	*
municipality_nameByram Township	123956.5	50971.0	2.432	0.015042	*
municipality_nameCorbin City	-204014.5	42717.8	-4.776	1.82e-06	***
municipality_nameFranklin Borough	41477.3	52252.8	0.794	0.427347	
municipality_nameFredon Township	217040.1	53035.2	4.092	4.31e-05	***
municipality_nameGreen Township	202097.0	52256.0	3.867	0.000111	***
municipality_nameHamburg Borough	28363.7	57658.6	0.492	0.622786	
municipality_nameHopatcong Borough	121999.2	50375.0	2.422	0.015466	*
municipality_nameLinwood	-119831.7	12225.6	-9.802	< 2e-16	***
municipality_nameLongport Borough	381239.9	13801.7	27.623	< 2e-16	***
municipality_nameMargate City	112529.2	8554.2	13.155	< 2e-16	***
municipality_nameNorthfield	-142996.0	12074.1	-11.843	< 2e-16	***
municipality_nameOgdensburg Borough	103839.7	54074.9	1.920	0.054857	.
municipality_nameSomers Point	-211794.7	11381.0	-18.609	< 2e-16	***
municipality_nameSparta Township	164088.1	50248.6	3.266	0.001097	**
municipality_nameStanhope Borough	56779.2	51990.2	1.092	0.274817	
municipality_nameVentnor City	NA	NA	NA	NA	
Treated:as.factor(relative_time)-8	54261.7	47746.1	1.136	0.255798	
Treated:as.factor(relative_time)-7	119903.8	50043.6	2.396	0.016599	*
Treated:as.factor(relative_time)-6	-11044.9	48098.4	-0.230	0.818384	
Treated:as.factor(relative_time)-5	30899.6	47249.1	0.654	0.513149	
Treated:as.factor(relative_time)-4	54894.4	49022.4	1.120	0.262842	
Treated:as.factor(relative_time)-3	-10780.7	46706.9	-0.231	0.817465	
Treated:as.factor(relative_time)-2	-13880.4	46321.6	-0.300	0.764450	
Treated:as.factor(relative_time)-1	58686.5	45336.7	1.294	0.195546	
Treated:as.factor(relative_time)0	84044.3	46215.6	1.819	0.069022	.
Treated:as.factor(relative_time)1	45949.3	46617.0	0.986	0.324323	
Treated:as.factor(relative_time)2	78940.0	44450.7	1.776	0.075789	.
Treated:as.factor(relative_time)3	89878.0	43981.5	2.044	0.041032	*
Treated:as.factor(relative_time)4	132797.8	45043.0	2.948	0.003205	**
Treated:as.factor(relative_time)5	124812.5	47598.9	2.622	0.008754	**
Treated:as.factor(relative_time)6	96154.9	44410.2	2.165	0.030406	*
Treated:as.factor(relative_time)7	115870.0	42837.4	2.705	0.006848	**
Treated:as.factor(relative_time)8	130794.4	43805.9	2.986	0.002837	**

The **municipality fixed effects** capture the baseline price levels and trends for each municipality, controlling for time-invariant factors that affect property prices (e.g., local economic conditions, long-term trends). The **interaction term (Treated × Relative Time)**, on the other hand, represents the **differential effect** of the hurricane on the treated municipalities (i.e., municipalities affected by the storm) relative to the control municipalities over different time periods.

From the interaction term, we can observe that the **Treated** group starts to show significant increases in sale assessments starting at **relative time 3** (post-treatment), with the effects becoming more pronounced through **relative time 8**. In particular:

- **Relative Time 3**: The coefficient is **$89,878.0**, and the p-value is **0.0410**, which indicates a significant increase in sale assessments compared to the pre-treatment period.
- **Relative Time 4-8**: The coefficients are consistently positive and significant, with values ranging from **$132,797.8** at relative time 4 to **$130,794.4** at relative time 8. These results suggest that the treated group experienced a significant increase in sale assessments after the treatment.

Figure 13: Detailed impact of Hurricane

The results from the **municipality fixed effects** suggest several interesting findings in relation to the event study.

Figure 14: Table displaying the municipality fixed effects

municipality_name <chr>	estimate <dbl>	std_error <dbl>	t_value <dbl>	p_value <dbl>	Group <chr>
Atlantic City	-46217.3	19475.6	-2.373	1.7664e-02	Treated
Branchville Borough	138110.8	58994.5	2.341	1.9253e-02	Control
Byram Township	123956.5	50971.0	2.432	1.5042e-02	Control
Corbin City	-204014.5	42717.8	-4.776	1.8200e-06	Treated
Fredon Township	217040.1	53035.2	4.092	4.3100e-05	Control
Green Township	202097.0	52256.0	3.867	1.1100e-04	Control
Hopatcong Borough	121999.2	50375.0	2.422	1.5466e-02	Control
Linwood	-119831.7	12225.6	-9.802	2.0000e-16	Treated
Longport Borough	381239.9	13801.7	27.623	2.0000e-16	Treated
Margate City	112529.2	8554.2	13.155	2.0000e-16	Treated
Northfield	-142996.0	12074.1	-11.843	2.0000e-16	Treated
Somers Point	-211794.7	11381.0	-18.609	2.0000e-16	Treated
Sparta Township	164088.1	50248.6	3.266	1.0970e-03	Control

Significant Differences:

- The negative coefficients for treated municipalities such as **Atlantic City** (-46,217.3), **Corbin City** (-204,014.5), **Linwood** (-119,831.7), and **Northfield** (-142,996.0) suggest that these municipalities experienced a **relative decrease** in property values compared to **Ventnor City**, the baseline before the hurricane
- On the other hand, municipalities like **Longport Borough** (381,239.9), **Margate City** (112,529.2), and **Somers Point** (-211,794.7) exhibit large **positive coefficients**, indicating that these areas saw a **relative increase** in property values compared to **Ventnor City** before the hurricane.
- Given that major cities like Atlantic City already had lower property values before the storm, it's possible that these areas took longer to recover, which could explain the initial negative effects in the first two post-hurricane terms. However, the mitigation measures implemented in the county likely helped facilitate recovery starting from the third term, leading to longer-term growth in property values.

Balance Test

Figure 15: Balance Table - Assessing Robustness

Balance Table

Variable	Mean (Sussex)	Mean (Atlantic)	SD (Sussex)	SD (Atlantic)	Difference in Means	P-Value
PopulationDensity	148878.00	274511.50	510.53	245.37	-125633.50	0.00
Male	0.50	0.48	0.01	0.00	0.01	0.17
Female	0.50	0.52	0.01	0.00	-0.01	0.17
MedianAge	41.90	40.25	0.57	0.21	1.65	0.12
CollegeDegree	0.44	0.48	0.06	0.02	-0.05	0.42
HouseholdIncome	83977.00	51700.00	195.16	1231.78	32277.00	0.01
UnemploymentRate	0.11	0.14	0.00	0.02	-0.02	0.26
HouseSize	2.68	2.66	0.01	0.01	0.02	0.29
OwenedHomes	0.84	0.70	0.01	0.05	0.14	0.14
MarriedFamilyOwners	0.61	0.45	0.00	0.02	0.16	0.06
AssessmentValue	277425.00	316900.00	8874.19	2687.01	-39475.00	0.08

This balance table provides a comparison of socio-economic and demographic variables between Sussex and Atlantic County. The analysis aims to determine the robustness of the DiD findings by confirming the demographics pre hurricane are in fact similar and that there is no significant difference in the median assessment value. The findings from the above figure 11 show the following:

Variables without Significant Differences

Population Density: P-Value of 0.00

The mean population density is significantly higher in Atlantic County compared to Sussex County, with a significant difference in means (p-value = 0.00 < 0.05). This indicates a denser population in Atlantic County which would explain the higher observation numbers in the dataset for housing units.

Household Income: P-Value of 0.01

The mean household income is significantly higher in Sussex compared to Atlantic, with a significant difference in means (p-value = 0.01 < 0.05). We would expect this could potentially lead to higher housing assessment values although that is not shown in the data from 2010-2011. After looking into this more to try to explain why this could be, the monthly housing cost for Atlantic county is $1,875 compared to Sussex which is $2,224. This suggests that Sussex has a higher living cost which would result in higher wages.

Variables without Significant Differences
Male: P-Value of 0.17
Female: P-Value of 0.17
Median Age: P-Value of 0.12
College Degree: P-Value of 0.42
Unemployment Rate: P-Value of 0.26
House Size: P-Value of 0.29
Owned Homes: P-Value of 0.14
Married Family Owners: P-Value of 0.06

For these variables, there are no statistically significant differences between Sussex and Atlantic, indicating a balanced comparison group for the difference-in-differences analysis. These variables are relatively well-matched across both Counties.

Key Significance Test: Median Assessment Values

Assessment Value:
Mean (Sussex): 277,425.00
Mean (Atlantic): 316,900.00
Difference in Means: -39,475.00
P-Value: 0.08

The mean assessment value is higher in Atlantic compared to Sussex, and this difference is shown to not be statistically significant (p-value = 0.08). The higher assessment values in Atlantic County could reflect some characteristics such as regional factors like population density and household income.

This balance table analysis reveals significant differences in population density and household income between Sussex County and Atlantic County. However, the absence of significant differences in other socio-economic and demographic variables indicates that the regions are otherwise well-matched. This comparability supports the robustness of the difference-in-differences approach for assessing the impact of Hurricane Sandy on housing assessment values. Overall, the balanced nature of the data enhances the reliability of the analysis.

As another way to ensure the robustness of the DiD study examining Hurricane Sandy's impact on residential property values, a falsification test was incorporated. This test evaluates whether the model produces spurious results in periods or groups where low intensity of treatment occurred. Specifically, the DiD model was applied to pre-hurricane data, selecting 2011-Q4—a quarter one year before the hurricane—as a placebo period. The goal was to confirm the lower intensity of treatment effects during this period without intervention. As anticipated, the interaction term (time × intensity of treatment) in the placebo analysis exhibited a no statistical significance level, reinforcing the validity of the primary findings. This result supports the argument that observed post-hurricane effects are attributable to the hurricane rather than pre-existing trends. Moreover, the study maintained the parallel trends assumption by both visually and statistically confirming that trends between the higher intensity treated and the control group (lower intensity) aligned prior to the hurricane. Collectively, these steps ensure that the findings are robust and not artifacts of methodological or design choices.

Figure 16: Placebo DiD - Hurricane Sandy Impact on Residential Property Values

	Dependent variable:
	sale_assessment
Intensity_of_teatment	133,378.200***
	(17,141.380)
Time_Placebo	-30,904.900***
	(10,644.870)
Interaction_Placebo	30,203.470
	(19,439.330)
Constant	298,171.300***
	(9,431.286)
Observations	7,798
R2	0.047
Adjusted R2	0.047
Residual Std. Error	241,600.700 (df = 7794)
F Statistic	129.538*** (df = 3; 7794)
Note:	*p<0.1; **p<0.05; ***p<0.01

Conclusion

This study aimed to assess the impact of Hurricane Sandy on housing prices in Atlantic County, New Jersey, by comparing it with Sussex County, which was less affected by the hurricane. The results indicate a significant increase in housing prices in the post-hurricane period, particularly in areas with higher intensity impacts from the storm. The analysis suggests that, contrary to what might be expected from the immediate aftermath of a disaster, property values in more impacted regions increased over time due to recovery efforts, federal aid, and insurance payouts. These findings provide valuable insights into the resilience of housing markets following natural disasters. The study's implications extend beyond just the real estate market. It highlights the importance of timely recovery efforts, particularly through insurance programs such as the NFIP, which played a crucial role in stabilizing housing prices in the aftermath of the hurricane. While the study's methodology was robust, limitations in data availability, such as the lack of more granular commercial property data, affected the precision of the results.

Ultimately, the findings emphasize the need for stronger disaster preparedness, especially in disaster-prone regions, to help mitigate the long-term economic consequences of such events. Policymakers and real estate developers should focus on enhancing disaster resilience and improving insurance mechanisms to better support property values during recovery. As natural disasters continue to challenge communities, understanding their effects on property markets is critical for informed decision-making and future preparedness.

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