Damage vs. Risk Perception: Why Do House Prices Recover After Hurricanes?*

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Abstract

I study house price dynamics following Hurricane Sandy to explain the common puzzling finding of a price drop followed by a complete price recovery. Applying a quasi-experimental difference-in-differences research design on Zillow parcel-level sales data combined with FEMA data on damaged structures, I show that the extent of direct damages drives the decline in house prices. The extent of remodeling expenditures, as estimated from building permits, is found to be responsible for causing the return of prices to pre-storm levels. Comparing flood insurance take-up rates in the affected and non-affected areas within the floodplains, I find no revision in perceived risk.

Keywords: Flood risk, House prices, Price recovery, Risk signal.

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1 INTRODUCTION

I study the house price dynamics following a major storm and provide an explanation of these dynamics over time. Virtually all studies of the housing market response to a major storm show that house prices immediately drop. There are two possibilities explaining the cause of the drop—a change in risk perception or the direct damages from a flood. Similarly, there has been a differentiation in the literature, as some papers have found a permanent house price decline after hurricanes (Ortega and Taspinar 2018; Gibson and Mullins 2020). Other work, however, has found only a temporary decline (Atreya, Ferreira, and Kriesel 2013; Atreya and Ferreira 2015; Zhang and Leonard 2018). Most of these papers, however, have not been able to identify the extent to which price movements are due to flood damage compared to changes in risk perception.[1] In addition, papers that find the temporary effects of hurricanes on house prices were not able to explain the recovery empirically. In this paper, I provide empirical evidence that house prices drop due to direct damage and the price recovery afterward is due to remodeling and rebuilding. I further provide empirical support that the house prices drop is not due to homeowners in floodplains reassessing their perceived risk.

Hurricanes can have permanent impacts on house prices if hurricanes convey new information, thus heightening homeowners' risk perception. If hurricanes, however, do not change risk perception, the impacts of hurricanes on house prices will reflect damage and the cost of repair. In the latter case, hurricanes only have transitory impacts on prices. Using Hurricane Sandy as a case study to examine housing markets in 16 New Jersey counties over 20 years, I analyze house price dynamics following this major storm. I use the Federal Emergency Management Agency (FEMA) parcel-level data on damaged structures combined with Zillow's housing transactions to show that the immediate price declines following a major storm reflect the extent

1. Ortega and Taspinar (2018) is an exception, in that they are concerned with identifying changes in risk perception. Because they do not compare the impact of damages within the floodplains, so do not fully hold constant potential changes in risk perception.

to which flooded houses suffer damage. I use the detailed-building information from FEMA, where each building affected by Sandy is assigned into one of the four categories of damage (affected, minor, major, and destroyed) to isolate the price effects of damage versus risk perception. I isolate the price effects due to direct damages using difference-in-differences estimation on the group of damaged properties and the group of non-damaged properties within the 100-year floodplain.

Further, I assemble novel parcel-level building permit data to assess the ultimate causes of house price recovery. I link each damaged property during Hurricane Sandy to the administrative building permit to examine the extent of spending on renovations and rebuilding of the homeowners on these properties. This allows me to show that price recovery reflects whether the damages are repaired and the house quality likely improves because of the remodeling.

Finally, I test for the change in risk perception using flood insurance take-up rates and percent of housing transactions. Risk perception is also a potentially important factor that can move house prices, and it is possible that an actual hurricane might alter perceived risk, even for homeowners within a floodplain. Moreover, flood insurance, on the other hand, and the floodplain designation, might mitigate any changes. Previous studies explain the decline followed by a recovery in house prices by the influence of the "availability heuristic" (Tversky and Kahneman 1973), in which individuals make decisions based on available knowledge. Floods may provide a new source of information and cause homeowners to update their beliefs, but the effect would vanish as the events fade (Atreya, Ferreira, and Kriesel 2013; Hennighausen and Suter 2020). To eliminate changes in risk perception as a cause, I study the change in risk perception by examining the flood insurance take-up rates and the percentage of properties sold in the affected areas versus non-affected areas within floodplains.

The paper's first major finding is that the declines in house prices after Sandy reflect the extent of damages. Properties with major damage immediately face a 31% sharp decline in prices, while properties with minor damage immediately face a 12% decline.

Other studies have only found average changes rather than being able to distinguish between the severity of the damage, such as Bin and Polasky (2004), Kousky (2010), and Zhang and Leonard (2018) find a 6%-22% decline in house prices of high-risk properties after large flood events.

The paper's second major finding is that renovations and rebuilding play a significant role in house price recovery after Hurricane Sandy. Spending on renovations and rebuilding is associated with damage levels. The most significant rebuilding occurs for those properties with major damage, as expected. Among damaged properties, 57.5% are renovated, and 6.2% of them are rebuilt cumulatively within seven years after Sandy. I find that the house price recovery after Hurricane Sandy is consistent with the extent of spending on remodeling and rebuilding.[2] Prices of non-damaged properties in floodplains decrease by 4.2%-5.0% relative to non-damaged properties out of floodplains.[3] Prices of damaged properties in floodplains, however, increase by 12% relative to non-damaged properties out of the floodplain. Pooling all properties in floodplains together, I find no difference in the prices of these properties relative to non-floodplain properties after Hurricane Sandy. My work is unique in that I link the level of price recovery to the level of damages, but others have also found that housing prices recover after flood events (Atreya and Ferreira 2015; Zhang 2016).

These empirical results suggest no persistent penalty on the prices of floodplain properties after Hurricane Sandy. Using the flood insurance take-up rates, I show that residents who purchase a house within a floodplain do not appear to change their perceived level of risk. Flood insurance take-up rates in census tracts affected by Hurricane Sandy do not increase relative to those not affected. Potential homeowners can decide if they want to buy properties in 100-year floodplains or out of the floodplains. Homeowners who buy properties in the floodplains would be expected to have higher risk tolerance. If homeowners anticipate their flood risk, experiencing floods may not

2. A quick recovery post flood events is supported by Kocornik-Mina et al. (2020) who find that economic activity, measured by nighttime lights, recovers fully within a year of a major flood.

3. Doing meta-analysis on 37 published studies, Beltrán, Maddison, and Elliott (2018) find a 4% decline in floodplain properties immediately after a flood, but there is a significant prices recovering following a flood.

impact their risk-taking behaviors. This explains my finding about the quick recovery in house prices in floodplains after Hurricane Sandy.[4] I also show that there is no sudden jump or drop in the percentage of damaged and non-damaged properties sold after Hurricane Sandy. These findings suggest the price effects are only transitory. My results are consistent with other studies that find the short-lived negative impact of earthquake on house prices. Bleich (2003) finds that the negative impacts of the Northridge Earthquake only last three years. Other studies on the impacts of disasters, such as oil spills, wildfires, hurricanes, and typhoons events also find the effects on property values tend to be temporary (Siegel, Caudill, and Mixon 2013; Winkler and Gordon 2013; McCoy and Walsh 2018; Coulson, McCoy, and McDonough 2020).

My work contributes to the literature in several ways. First, I am able to explain the recovery in house prices by determining the extent of planned rebuilding and remodeling using detailed parcel-level building permit data. I show that the house price changes reflect the extent of damage and the extent of spending on renovation. McCoy and Zhao (2018) use building permit data from seven quarters after Hurricane Sandy to estimate the probability that homeowners would invest in damaged buildings in floodplains in New York. The authors find that homeowners are more likely to invest in damaged properties in floodplains relative to those out of the floodplain. My paper analyzes a much more extended period of time compared to the McCoy and Zhao (2018) paper. My building permit data includes two years before and seven years after Sandy, a period that reflects a more complete picture of the recovery progress in New Jersey after Sandy.

Second, my study contributes to the literature on the price effects of actual flood risks in housing markets. Several papers, such as (Hallstrom and Smith 2005; Bin and Landry 2013; Atreya and Ferreira 2015), find a decline in the prices of high-risk properties after actual flood events. This effect is only temporary and completely vanishes after a few years. Those studies, however, do not have detailed information on

4. Boustan, Kahn, and Rhode (2012) find that people are attracted to areas with a high risk of flooding.

damaged buildings caused by floods and are not able to explain the price recovery empirically. My study has information on which buildings were damaged and to what extent. In addition, I am able to explain the observed price recovery in those studies determined by renovation and rebuilding.

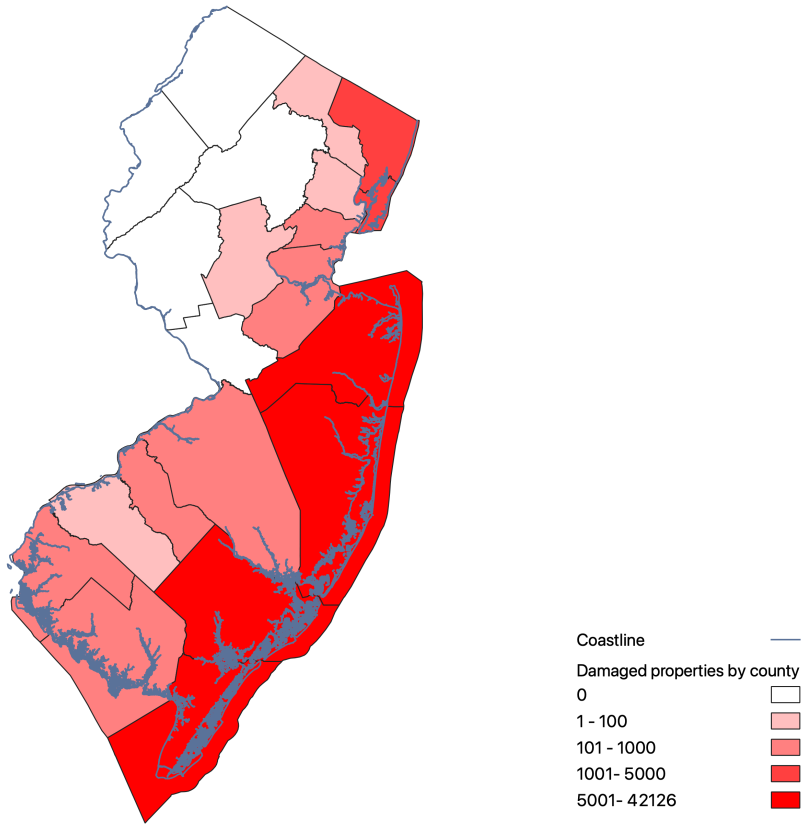
My study also adds to the literature on disasters and their effects on housing markets Studies find the negative effects of the largest oil spill in the Gulf of Mexico on coastal housing markets (Cano-Urbina, Clapp, and Willardsen 2019; Winkler and Gordon 2013). Similarly, studies on the impacts of wildfires on house prices find a decline in prices of properties located in high-risk areas (Mueller, Loomis, and González-Cabán 2009; Mueller and Loomis 2014; Stetler, Venn, and Calkin 2010).

The remainder of the paper is structured as follows. Section 2 presents the study area. Section 3 describes the data. Section 4 outlines the empirical method. I present my main results in Section 5. I provide a discussion where I compare and contrast with the literature in Section 6 and conclude in Section 7.

2 Study Area

The state of New Jersey is home to 8.79 million people, with a population density of 1,195.5 per square mile in 2010 (Census). New Jersey Coast includes 127 miles of coastline along the Atlantic Ocean and 83 miles of shoreline along the Raritan and Delaware Bays. The coastline area of New Jersey is one of the most densely populated and heavily developed coastlines in the US.

Figure 1: New Jersey and Extent of Sandy Damage by County.



On October 29, 2012, Hurricane Sandy made landfall in the State of New Jersey and became the most destructive natural disaster ever in this state. With strong wind and heavy precipitation exacerbated by the full moon high tides, Sandy caused the most deaths and property damage along the New Jersey coastline. The average rainfall totals were 2.78 inches, with the 10.29 maximum rainfall totals recorded at Cape May station. The highest storm surge of 8.57 feet was measured by Nation Ocean Service (NOS) at Sandy Hook in the Gateway National Recreation Area (Blake et al. 2013). The total cost of damages is approximately $65 billion (2012 US $, ICAT Damage Estimator), and about $37 billion for New Jersey alone, including damages to residents, businesses, and infrastructures (Hoopes 2013). Hurricane Sandy led to extensive loss of residential properties and commercial buildings and disruption in transportation and business operations. When Sandy occurred, it was the second largest hurricane in US history, only behind Hurricane Katrina in 2005. The study area includes 16 among

21 counties in New Jersey affected by Hurricane Sandy, as in Figure 1. Coastal counties are impacted more severely compared to inland counties.

3 Data

3.1 Floodplain Maps

I obtain historical floodplain maps from FEMA Q3 Flood Data—the first digitized version of Flood Insurance Rate Maps (FIRMs), and FEMA National Flood Hazard Layer (NFHL) Inventory Table. Originally, FIRMs were issued by the community and were distributed under hard copies. Later, with the development of automated cartography and Geographic Information System (GIS), FEMA started converting to the Digital Flood Insurance Rate Map (DFIRM). To assist the disaster recovery operation and post-disaster mitigation activities after Hurricane Hugo in 1989, FEMA produced Q3 Flood Data, which are digitized from the existing hardcopy of the currently effective FIRMs as of September 1996.

To identify the effective floodplain map of communities when Hurricane Sandy occurred, I find if there are any map revisions between the effective date of Q3 Flood Data and Sandy. I use the Community Map History Tables in the latest Flood Insurance Study (FIS) to do so. If a community has Flood Insurance Rate Maps (FIRMs) revised at any time between September 1996 and October 2012, next, I check the FEMA NFHL Inventory Table to find if the revision map exists here; if not I exclude that community. This means that when Hurricane Sandy happens, the FEMA Q3 Flood Data are outdated, and no revised NFHL exists. On the other hand, if there is no map revision between those periods, the Q3 Data were in effect when Hurricane Sandy occurred.

An example is the City of Estell Manor, Atlantic County, which has its FIRM effective date on November 3rd, 1978. The FIRM is revised on July 2nd, 2003, according to the FIS Community History Map Table. This means Q3 Flood Data is not effective as of the time Hurricane Sandy occurs. Next, I check the NFHL Inventory Table and find the floodplain map is effective on July 2nd, 2003, for this community and use it as a floodplain map for this community when Hurricane Sandy occurs. Another example to illustrate this process is the Township of Monroe, Middlesex County. According to the Community History Map Table, this community has its FIRM effective date on April 17th, 1985, then the FIRM is revised on February 4th, 1998. There is no revised map for this community on the FEMA NFHL, so this Township is excluded from my analysis. About 17% of communities is excluded from my study.

After hurricane Sandy, FEMA issued the preliminary floodplain maps for New Jersey counties. The new floodplain maps after Hurricane Sandy are obtained from the National Flood Hazard Layer (NFHL) Data-County level on FEMA Map Service Center. Communities that are excluded in the old floodplain map are also excluded in the new floodplain map.

Using the historical floodplain maps allowed me to identify the floodplain status for each property when Hurricane Sandy occurred. The new floodplain maps allow me to identify the flood risk status of the property after Hurricane Sandy. Properties having floodplain status changes between the two maps would be eliminated from my sample.

3.2 HOUSE PRICE DATA

My primary variable of interest is house price which is obtained from Zillow Transaction and Assessment Database (ZTRAX).[5] I use the sale transaction of 16 New Jersey counties from 2000-2019 from this database. This data also includes tax account identifiers, geo-coordinates, and property characteristics such as year built, number of bedrooms, bathrooms, etc. One limitation of this database is that property characteristics are only captured at one point in time, the most recent tax assessment date. Thus, property characteristics do not reflect the property's condition when it is sold.

Transactions with missing sale price data are eliminated. I removed transactions if they are family transfers or foreclosures because these transactions do not reflect

5. Data is provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

the fair market values. I further restrict my sample of transactions to single-family residential properties only. I trim 1% top and bottom prices to remove outliers. I later trim 1% bottom year built to remove unreasonable year built (e.g.,1288) since I believe these are more likely the report errors. Each transaction is identified month and year sold using the document date. If the document date is missing, the recording date is used instead.

3.3 FEMA Historical Damage Assessment Database

Sandy damage assessment for the 16 New Jersey counties is obtained from FEMA Historical Damage Assessment Database, a repository of geospatial damage assessment from past national disaster events. This data includes the damage assessment point where the impact building was located. Each building affected by Sandy is assigned into 1 of the four categories (affected, minor, major, destroyed) by visual assessment using post-event imagery. Flood depth is also reported in this dataset.

This assessment dataset provides properties that suffered physical damage from Hurricane Sandy. While properties located in affected areas might not have directly suffered from Sandy and are not included in this data, those properties experienced indirect damage such as disruption in transportation, business operations, or blackouts.

The longitude and latitude of each affected building is mapped into each parcel. Similarly, the longitude and latitude from the ZTRAX database of each sale transaction are mapped into each parcel. If the geo-coordinates from the FEMA damage assessment and the geo-coordinates of the ZTRAX database correspond to the same parcel, these longitude and latitude of these two data set mention the same property. Multiple geo-coordinates line up in the same parcels are eliminated. Geo-coordinates that do not correspond to any parcels or lines upon roads are also eliminated from the sample.

3.4 New Jersey Building Permit Data

New Jersey construction permits raw data is obtained from the New Jersey Department of Community Affairs (NJ DCA) for the period 2010-2019. This data is the monthly building permit reports to NJ DCA by municipalities. Information on each construction permit includes the permit number, the status of the permit, whether the project is still in progress or if the project is done and gets the certificate, date the permit or certificate is issued. There are four types of permits: new, addition, alteration, and demolition. According to NJ DCA, renovation belongs to the alteration permit type. This data also includes construction costs associated with the permit, and this cost is reported by applicants.

I use treasury municipality code, tax block, and tax lot information from each permit to create a unique identifier following New Jersey parcel maps. Then I use this unique identifier to merge with the New Jersey statewide parcel map to identify which property is associated with which permit. More details about the merging process are presented in the Appendix.

3.5 Supplemental Data

Four supplemental sources of data also included in this study: New Jersey statewide parcel map, 2010 New Jersey TIGER/Line shapefile, New Jersey Coastline, and flood insurance data.

New Jersey statewide parcel geodatabase is obtained from New Jersey Geographic Information Network. Each parcel is provided with a unique parcel identification number which is calculated using four components: municipality code, tax block, tax lot, and qualifier code.

In addition, I use the 2010 TIGER/Line shapefile to identify which census tract and census block group each property belongs to. I obtain New Jersey Coastline version 20090116 from the New Jersey Department of Environmental Protection. I overlay this

Coastline map with the statewide parcel map in GIS and calculate the distance from each parcel to the coastline using the proximity function in ArcGIS.

The last dataset in this study is flood insurance data from Open FEMA. Flood insurance data are NFIP policies from 2009 to 2019 in the 16 New Jersey counties. Each observation is an individual contract with information on premium and coverage. I restrict my sample to only include policies written for one-to-four family properties. Finally, I exclude tracts (2% of observations) that have the total number of flood insurance policy written for floodplain (non-floodplain) properties larger than the total number of floodplain (non-floodplain) properties in those tracts.

3.6 Descriptive Statistics

Table 1 provides descriptive statistics of my sample of 16 New Jersey counties. Floodplain denotes areas with a 1% chance of flooding in any given year (100-year floodplain) designated by FEMA Flood Insurance Rate Maps. Areas that are not in this 100-year floodplain are denoted as non-floodplain. A parcel (property) is in the floodplain if any part of the parcel is on the floodplain map. Columns 1 and 2 in Table 1 present summary statistics for damaged and non-damaged properties in 100-year floodplains. Damaged properties in floodplains are closer to the coastline, around 281 yards from the coast, and sell at an average of $516,230. Non-damaged properties in floodplains are further from the coastline and sell at lower prices on average. Columns 3 and 4 of Table 1 present summary statistics for damaged and non-damaged properties out of the floodplains. Damaged properties out of floodplains are closer to the coastline and sell at higher prices on average than those not damaged. Table A.1 presents the average prices of damaged and non-damaged properties in and out of floodplains before and after Hurricane Sandy. On average, house prices of all four groups are increasing after Hurricane Sandy. The largest increase is damaged floodplain properties which is surprising, but this could be explained by the construction spending on remodeling and rebuilding.

Figure A.1 presents the average sale prices of properties in floodplains and out of

Table 1: Summary Statistics: Zillow Sales Transaction Dataset

	Floodplain		Non-Floodplain	
	Damaged	Non-Damaged	Damaged	Non-Damaged
House Price (thousands)	517.58	358.24	414.56	292.57
	(362.35)	(312.11)	(339.24)	(206.29)
log(Price)	6.00	5.54	5.73	5.45
	(0.76)	(0.88)	(0.81)	(0.73)
House Age	33.47	42.67	52.66	45.41
	(31.69)	(31.92)	(35.31)	(31.78)
Distance to Beach (yards)	283.13	3,602.97	752.98	7,635.55
	(273.76)	(6,699.33)	(1,419.16)	(7,212.39)
Lot Size	0.44	0.39	0.36	0.37
	(3.91)	(1.69)	(3.20)	(1.39)
Bedrooms	3.67	3.24	3.26	3.17
	(1.16)	(0.99)	(1.24)	(1.41)
Bathrooms	2.39	2.47	2.61	2.51
	(1.13)	(1.08)	(1.27)	(1.02)
Observations	33,360	72,524	2,454	1,026,423

Note: Mean variables; sd in parentheses. Distance to the beach is calculated using the proximity function in ArcGIS measured in feet and then converted into yards.

floodplains. In both floodplains and non-floodplains, house prices started declining in 2008 due to the crisis and then recovered. Properties located in floodplains are sold at higher prices compared to properties not in the floodplains. In addition, properties in floodplains experienced a slight decline in prices immediately following Hurricane Sandy in 2012, but it quickly captured the same trend as non-floodplain properties since 2014.

Table 2 provides descriptive statistics of flood insurance aggregated by census tract level. On average, 32% of properties in floodplains carry flood insurance, while only 3% of properties outside of the floodplains carry flood insurance. These findings are in line with Bradt, Kousky, and Wing (2021). The flood insurance price per $1000 coverage is about 3.7 times higher for floodplain properties compared to those not in the floodplain.

Table 2: Summary Statistics: Flood Insurance Policies In Force

	(1) Floodplain	(2) Non-Floodplain
Number of Policy	118.05	18.46
	(388.8)	(33.18)
Price per $1000 Coverage	7.73	2.03
	(3.588)	(1.056)
Number of Parcels	229.48	1172.05
	(582.4)	(663.8)
Year Built	1980.46	1983.18
	(13.07)	(12.69)
Share Insured	0.32	0.03
	(0.264)	(0.0746)
Share Adapted	0.08	0.01
	(0.132)	(0.0383)
Observations	9,474	14,828

Note: Mean variables at census tract level; sd in parentheses. Parcels are the number of one-to-four family residential properties.

4 Estimation Strategy

4.1 Effects of Hurricane Sandy on House Prices

Hurricanes only have transitory impact on house prices if the impact of hurricanes reflects damages and the cost of repair. Hurricanes, however, have permanent impacts on house prices if they convey new information, thus heightening homeowners' risk perception. Homeowners infer their flood risk based on their floodplain status from the FIRMs. FEMA flood designation conveys to homeowners the probability of being flooded. One would expect homeowners in the flood zone to be more informed about their flood risk and have higher risk tolerance. In addition, if the damages are insured market reaction following a catastrophic event such as Hurricane Sandy would not create a significant response in the flood zone.

To study the effect of Hurricane Sandy on the housing market in the floodplains, I examine the change in prices after Hurricane Sandy of the damaged properties versus non-damaged properties within floodplains, where homeowners are likely to anticipate their flood risk. Moreover, these properties also have the same underlying risk as inferred from FEMA floodplain maps. Potential homeowners can decide if they want to buy properties in 100-year floodplains or out of the floodplains. Their preferences toward flood risks differ between these two areas (e.g., they decided to buy properties with a high risk of flooding in the first place). Therefore, it is important to keep risk preferences, underlying flood risk, and flood insurance regulations constant when analyzing the effect of hurricanes and floods on house prices. An appropriate approach is to compare all 100-year floodplain properties, whether they are damaged or not.

I construct my treatment group to include all damaged properties located in the old floodplain when Hurricane Sandy occurred, and that were also located in the new floodplain as the new map was released. My comparison group includes all non-damaged properties that are also in the floodplains. The key identification is that in the absence of Hurricane Sandy, the damaged and non-damaged properties, which have the same flood risk in the floodplain, will have the same trend. I apply the difference-in-differences estimation as in Equation 1:

$$\log(P_{ibt}) = \alpha + \beta Damage_i \times PostS_t + \gamma Damage_i + \theta \mathbf{X}_{it} + \lambda_{gt} + \alpha_b + \epsilon_{ibt} \ . \quad (1)$$

The outcome variable is the price in the log form of property i, located in census block group b, which is sold in year t. The variable $Damage_i$ equals 1 for properties that suffered damages during Hurricane Sandy. The variable $PostS_t$ equals 1 for properties that are sold after Sandy. The variable $\mathbf{X}_{it}$ is the vector of controls for housing characteristics such as house age or lot size. λ_{gt} is the year fixed effects which I allow to vary by the distance to the coastline, with distance to coast categorized into four groups (g = {waterfront, walking distance, biking distance, driving distance}). α_b are census block group fixed effects, respectively. β is the parameter of interest, which measure the average effect of Hurricane Sandy on damaged properties relative to non-damaged properties in floodplains.

To assess the validity of the parallel trend assumption for this difference-in-differences research design, I estimate the event study coefficients β_t as in Equation 2:

$$\log(P_{ibt}) = \sum_{y=2000}^{2019} \beta_t 1[t = y] \times Damage_i + \theta \mathbf{X}_{it} + \lambda_{gt} + \alpha_b + \epsilon_{ibt} \ . \tag{2}$$

The omitted reference year is 2011, the year just before Hurricane Sandy occurred. The parameters of interest, β_t equals zero for the year before Sandy occurs, would support the parallel trend assumption. In addition, the equation above allows me to examine the effect of Hurricane Sandy varying by year.

4.2 Heterogeneous Effects by Damaged Levels

I next investigate the heterogeneous effects of Hurricane Sandy on house prices by damage levels. FEMA assigned damage levels into four categories: destroyed, major, minor, and affected, using post-event imagery.[6] Here, I group destroyed and major categories into one group called major damage. I rename the affected category as very minor damage group to avoid any confusion. Therefore, three treatment groups are major, minor, and very minor.

I begin with the treatment group is properties with major damage during Hurricane Sandy. The comparison group is properties with no damage during Hurricane Sandy. Both treatment and comparison groups are properties within floodplain areas. I estimate the event study coefficients ψ_t as in Equation 3:

$$\log(P_{ibt}) = \sum_{y=2007}^{2019} \psi_t 1[t = y] \times Major_i + \theta \mathbf{X}_{it} + \lambda_{gt} + \alpha_b + \epsilon_{ibt} \ . \tag{3}$$

The parameters of interest, ψ_t, measure the outcomes of severe damage properties during Hurricane Sandy relative to those non-damaged properties in the floodplains. Properties with major damages will take longer to repair and renovate. Among floodplain properties, properties with major damage during Hurricane Sandy are the riskiest compared to those in the other two groups. If Hurricane Sandy permanently

6. According to FEMA, destroyed structures are classified based on a visual post-event imagery review that the structure was collapsed. Affected structures were classified based on a visual post-event imagery review indicating there were missing roof segments, failure of structural elements, and visible damage.

increases the risk perception of homeowners associated with locations, the prices of severely damaged properties would face a persistent penalty relative to non-damaged property prices. Otherwise, the price of severely damaged properties would decline sharply immediately after Sandy and slowly recover to the pre-Sandy levels after homeowners renovate their damaged houses.

I next study the prices of properties with minor damage relative to non-damaged properties in floodplains. I estimate Equation 3 where my treatment group is properties with minor damage in floodplains, and my comparison group is properties with no damage also in floodplains. Prices of properties with minor damage are expected to decline immediately after Sandy, but not as sharp as properties with major damage. In addition, properties with minor damage are expected to recover faster than properties with major damage.

To study the prices of properties with very minor damage, I estimate Equation 3 where the treatment group includes all properties with very minor damage in floodplains, and the comparison group includes non-damaged properties in floodplains. Compared to the properties with major and minor damage, the properties with very minor damage are properties with the least damage. If Hurricane Sandy imposed a penalty on the prices of damaged properties, this group would face a smaller price penalty.

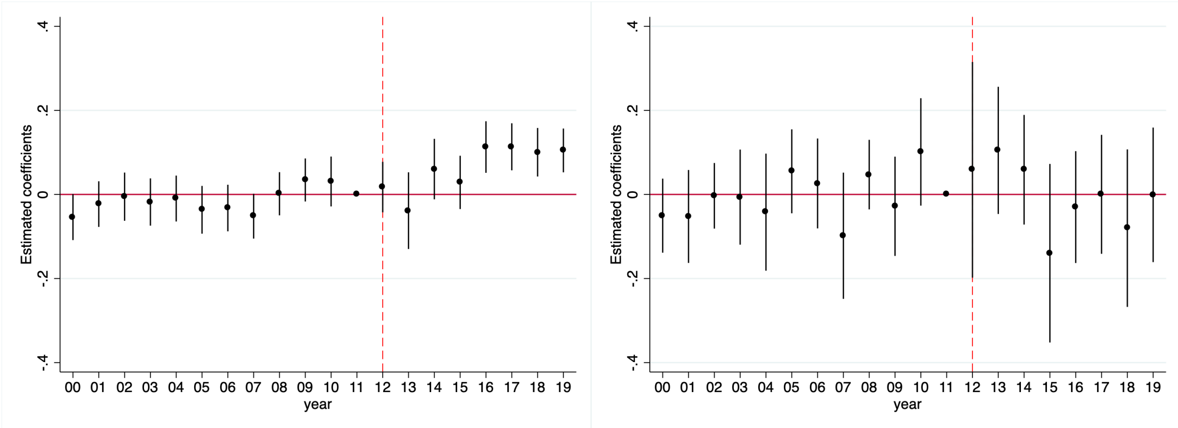
5 Results

5.1 House Price Dynamics

Table 3 presents the estimates of the coefficients corresponding to Equation 1 for properties in floodplains. After controlling for observable differences such as house ages and distance to coast between damaged and non-damaged properties, the coefficients capture the differences between the treatment and control group before Hurricane Sandy are not statistically different from 0. The main coefficient of interest is the coefficient of the interaction term of damage and post Sandy indicators. The coefficients

Figure 2: Event Study, Effects of Hurricane Sandy on Prices of Damaged Properties.

(a) Floodplain (b) Non-Floodplain



Note: These figures plot event study estimate for the effect of Hurricane on log of house prices. The coefficients are estimated from Equation 2. The circles plot the point estimates, and the bars plot the 95% confidence intervals.

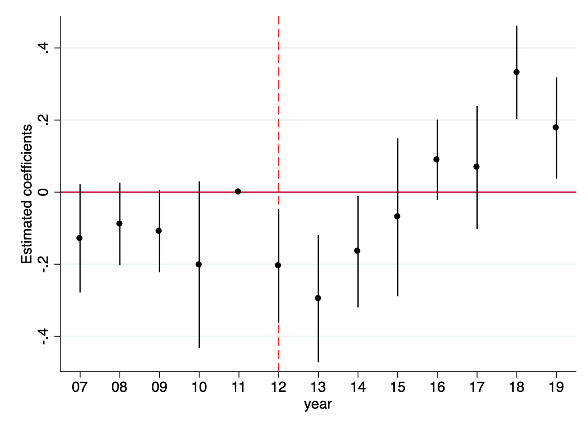
of the interaction term range between 0.087 and 0.092, suggesting that damaged properties sold at an 9.1% to 9.6%[7] higher relative to non-damaged properties sold in the floodplains. Figure 2a plots the estimated event study coefficients corresponding to

Equation 2 for prices of damaged properties relative to non-damaged properties in floodplains. Before Hurricane Sandy, damaged and non-damaged properties in floodplains are not statistically different in prices. A year after Hurricane Sandy, damaged properties decrease by 3.8% in prices, although the effect is statistically insignificant. Four years after Hurricane Sandy, prices of damaged properties in floodplain increase about 10% - 11% relative to non-damaged properties in floodplain. These results suggest that house prices fully recover seven years after Hurricane Sandy. In the next section, I will show that renovation and rebuilding play an important role in this recovery.

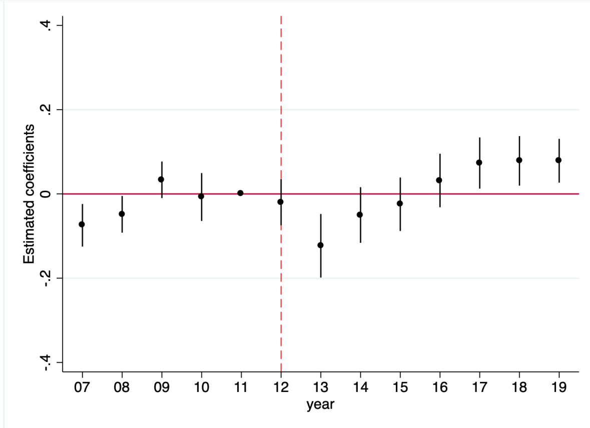
7. These numbers are calculated as e^{β} -1, β is the coefficients in Table 3

Figure 3: Event Study, Effects of Hurricane Sandy on Prices of Damaged Properties.

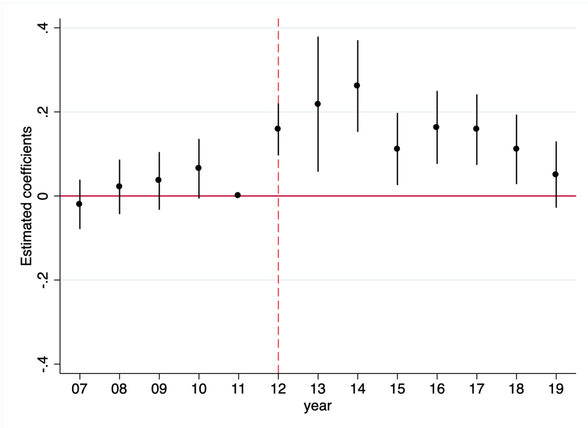
(a) Major vs. Non-Damaged



(b) Minor vs. Non-Damaged



(c) Very Minor vs. Non-Damaged



Note: These figures plot event study estimate for the effect of Hurricane by severity levels on log of house prices. The coefficients are estimated from Equation 3. The circles plot the point estimates, and the bars plot the 95% confidence intervals.

Prices of properties that are damaged out of the floodplains, however, do not have a similar experience. Table 4 presents the estimates of the coefficients corresponding to Equation 1 for properties out of the floodplains. The coefficients of the interaction terms are statistically insignificant for all four columns suggesting no change in damaged properties relative to non-damaged properties out of the floodplains following Hurricane Sandy. Figure 2b shows consistent result with Table 4. One possibility is that the extent of damage out of floodplains is less severe compared to floodplains. Hence, the spending associated with renovating and rebuilding is much smaller than floodplains.

Figure 3a plots the estimated event study coefficients corresponding to Equation 3

Table 3: Effect of Hurricane Sandy on House Prices in Floodplain

	(1)	(2)	(3)	(4)
	log(houseprice)	log(houseprice)	log(houseprice)	log(houseprice)
Damage x PostSandy	0.087***	0.087***	0.087***	0.092***
	(0.019)	(0.018)	(0.018)	(0.018)
Damage	-0.005	-0.007	0.004	-0.001
	(0.021)	(0.021)	(0.021)	(0.023)
House Age		-0.004***	-0.004***	-0.004***
		(0.000)	(0.000)	(0.000)
Lot Size			0.006*	0.002
			(0.003)	(0.003)
Constant	5.520***	5.622***	5.629***	5.531***
	(0.033)	(0.033)	(0.035)	(0.039)
Observations	105,639	104,455	95,766	95,766
FE	Block group	Block group	Block group	Tract
Year x Distance FE	Yes	Yes	Yes	Yes
R-squared	0.624	0.638	0.645	0.595

Note: Standard errors in parentheses. SE clustered at block group level. A block group includes 400 housing units on average, with a minimum of 250, and a maximum of 550 housing units (Census Bureau). Difference-in-Differences estimation corresponds to Equation 1. Outcome variable is the house prices in log form. The treatment group includes all damaged properties in floodplains, and the comparison group includes all non-damaged properties that are also in floodplains. The parameters of interest are the coefficients of the interaction terms (Damage x PostSandy).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

for prices of major-damaged properties relative to non-damaged properties in floodplains. Properties with major damage face an immediate 31% sharp decline in price and take longer to recover. Properties with minor damage face an 11% decline in price and recover faster, as shown in Figure 3b. Properties with very minor damage do not face any decline in prices, as shown in Figure 3c. Table A.2 shows the average price recovery by damage levels after Sandy. Properties in very minor damage group are sold at a premium price relative to non-damaged properties prior to Sandy as shown in this table. As I only observe prices when properties are sold, the points estimate suggest that may be only nicer properties are sold for this group of properties.

5.2 Remodeling and Rebuilding

I am going to use detailed parcel-level building permit data to explain the recovery in housing prices in New Jersey after Hurricane Sandy in this section. There are four types of building permits: new, addition, alteration, and demolition. Renovation is considered an alteration type of permit. I examine three types of building permits in

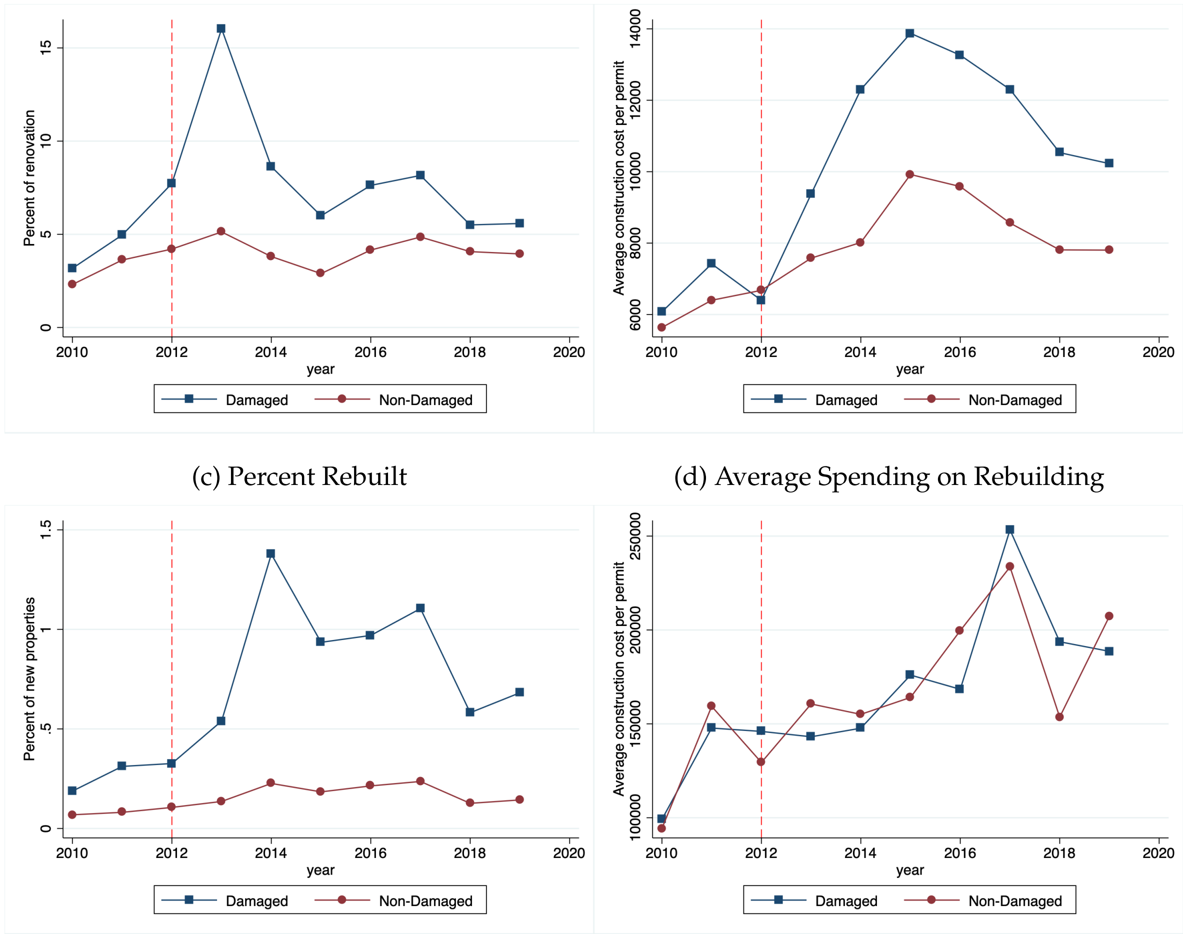
Table 4: Effect of Hurricane Sandy on House Prices out of Floodplain

	(1)	(2)	(3)	(4)
	log(houseprice)	log(houseprice)	log(houseprice)	log(houseprice)
Damage x PostSandy	0.014	0.023	0.021	0.017
	(0.031)	(0.032)	(0.034)	(0.034)
Damage	0.088	0.069	0.066	0.108*
	(0.052)	(0.049)	(0.051)	(0.043)
House Age		-0.005***	-0.005***	-0.005***
		(0.000)	(0.000)	(0.000)
Lot Size			0.010***	0.010***
			(0.001)	(0.002)
Constant	5.184***	5.343***	5.385***	5.362***
	(0.094)	(0.085)	(0.092)	(0.105)
Observations	1,028,674	992,099	939,932	939,932
FE	Block group	Block group	Block group	Tract
Year x Distance FE	Yes	Yes	Yes	Yes
R-squared	0.606	0.631	0.634	0.574

Note: Standard errors in parentheses. SE clustered at block group level. A block group includes 400 housing units on average, with a minimum of 250, and a maximum of 550 housing units (Census Bureau). Difference-in-Differences estimation corresponds to Equation 1. Outcome variable is the house prices in log form. The treatment group includes all damaged properties that are not in the floodplains, and the comparison group includes all non-damaged properties that are also not in the floodplains. The parameters of interest are the coefficients of the interaction terms (Damage x PostSandy).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

this section: alteration permits, demolition permits, and permits for new houses. I use information from each building permit, such as municipality code, tax lot, and tax block, to merge each building permit into damaged and non-damaged properties.

Figure 4: Average Renovation Spending, Percent of Properties Renovated and Rebuilt in Floodplain.



(a) Percent Renovated (b) Average Spending on Renovation

(c) Percent Rebuilt (d) Average Spending on Rebuilding

Note: $AverageConstructionSpending_{ijt} = TotalSpending_{ijt}/TotalPermit_{ijt}$. $TotalSpending_{ijt}$ is calculated by taking the sum of spending on all permits issued for damaged (non-damaged) properties in floodplain (non-floodplain) in year t. $TotalPermit_{ijt}$ is calculated by taking the sum of all permits issued for damaged (non-damaged) properties in floodplain (non-floodplain) in year t.

If Sandy heightened homeowners' risk perceptions, damaged properties would likely face permanent penalties on prices. In addition, homeowners in these high-risk areas will be more likely to buy flood insurance. On the other hand, Sandy will not impose any permanent impacts on prices if Sandy does not convey new information to homeowners in these high-risk areas due to their expectations when they decide to buy properties in floodplains. Moreover, if these damages are insured, I expect an increase in the number of renovated properties after Sandy and a quick price recovery after renovations.

I calculate the $\mathsf{PercentRenovated}$ as in Equation 4:

$$\mathsf{PercentRenovated}_{ijt} = 100\% \times \frac{\mathsf{TotalAlterationPermit}_{ijt}}{\mathsf{TotalParcel}_{ij}}, \tag{4}$$

and $\mathsf{PercentRebuilt}$ as in Equation 5:

$$\mathsf{PercentRebuilt}_{ijt} = 100\% \times \frac{\mathsf{TotalNewPermit}_{ijt}}{\mathsf{TotalParcels}_{ij}}, \tag{5}$$

where $i = \{damaged, non-damaged\}$ and $j = \{floodplain, non-floodplain\}$. I restrict the building permits that are issued for one and two families only.[8] I calculate the $\mathsf{TotalAlterationPermit}_{ijt}$ by summing up all permits of alteration type issued for damaged (non-damaged) properties in floodplains (non-floodplain) at year t. Similarly, I calculate $\mathsf{TotalNewPermit}_{ijt}$ by summing up all permits of new type issued for damaged (non-damaged) properties in floodplain (non-floodplain) at year t. $\mathsf{PercentRebuilt}_{ijt}$ and $\mathsf{PercentRenovated}_{ijt}$ are the outcome variables of group i at location j in year t.

Figure 4a plots the percent of damaged and non-damaged properties are renovated, and Figure 4c plots the percent of damaged and non-damaged properties that are rebuilt before and after Sandy in floodplains. On average, the percentage of damaged properties renovated increases compared to before Hurricane Sandy, especially a significant jump in 2013, a year after Sandy. Similarly, the percentage of damaged properties rebuilt increase significantly after Hurricane Sandy with a year lagged compare to modeling. Nevertheless, the percent renovation of non-damaged properties does not increase after Sandy. Figure 4b plots the average construction cost per permit of damaged and non-damaged properties in floodplains from 2010 to 2019. Figure 4d plots the average construction cost of new property per building permit. After Sandy, owners of damaged properties spent a larger amount of money to renovate their houses compared to before Sandy and compared to non-damaged properties. On the other hand, average construction costs to build a new property are similar between dam-

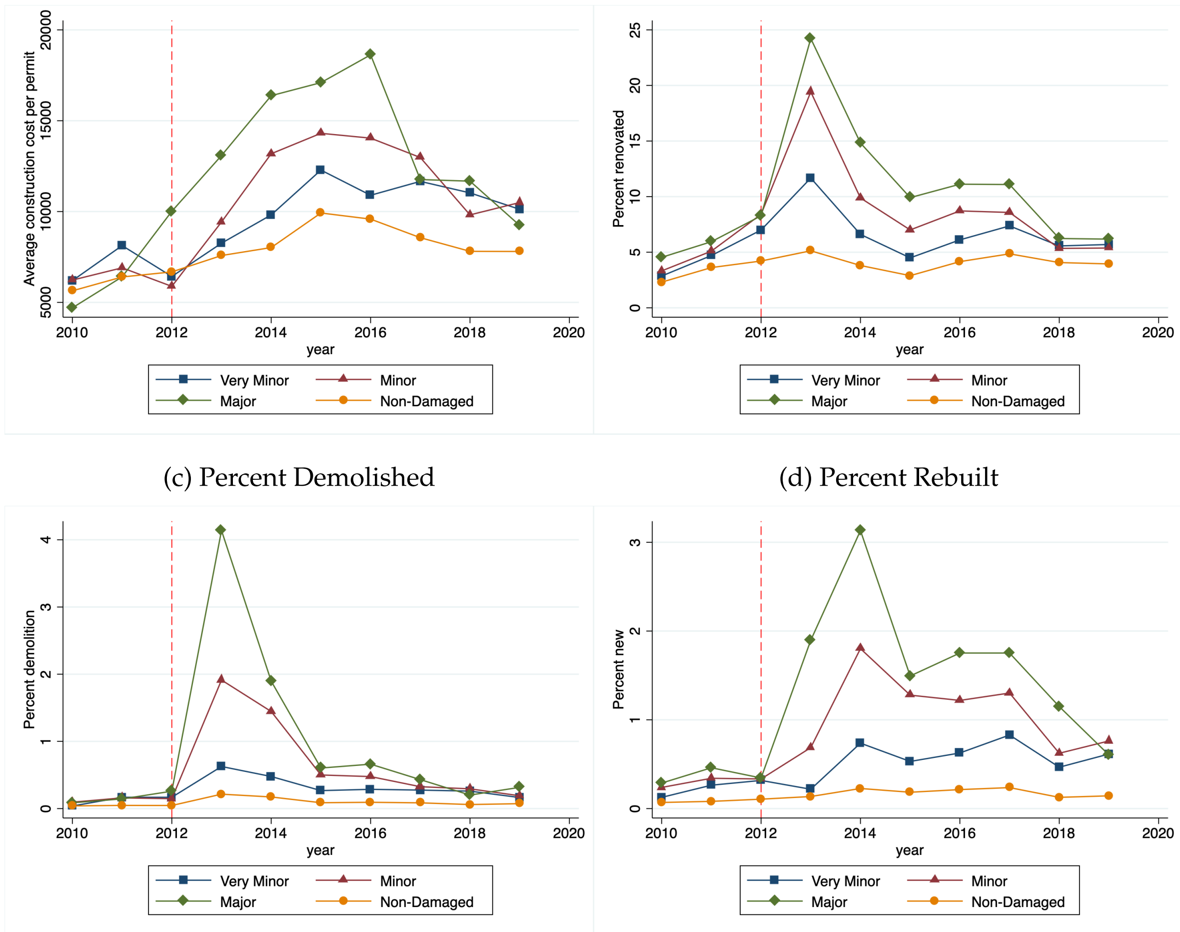
8. The numerators in Equations 4 and 5 are building permits issued for 1 and 2 families, while the numerators are the number of one-to-four family residential properties, the $\mathsf{percent\_renovated}$ and $\mathsf{percent\_new}$ are in the lower bounds.

aged and non-damaged properties, which is expected.

Figure 5: Average Renovation Spending, Percent of Properties Renovated, Demolished, and Rebuilt in Floodplain.

(a) Average Spending on Renovation (b) Percent Renovated

(c) Percent Demolished (d) Percent Rebuilt



Note: The data in Figures 5b, 5c, 5d are the percent renovated, percent demolished, and percent rebuilt, respectively, over time of properties reported damage extents as very minor, minor, major, and destroyed. The data in Figure 5a is the average spending per permit of properties reported damage extents as very minor, minor, and major.

Figure 5 plots the renovation, rebuilding, and demolition by damage levels. As expected, the highest renovation costs go into the properties with major and minor damages, as in Figure 5a. Most of the homeowners decided to renovate their damaged houses immediately after Hurricane Sandy, as shown in Figure 5b. In addition, most demolition permits were issued a year after Sandy for the properties with major and minor damages, as in Figure 5c. The largest rebuilt properties are two years after Sandy for those with major damage, as in Figure 5d. Around 24% of properties with major damage, 20% of properties with minor damage, and 12% of properties with very minor damage were renovated a year after Sandy, as in Figure 5b.

I further estimate the construction spending on damaged properties relative to non-damaged properties within floodplains as in Equation 6:

$$\mathrm{spending}_{izt} = \alpha + \beta \mathrm{Damage}_i \times \mathrm{PostS}_t + \gamma \mathrm{Damage}_i + \theta \mathrm{Age}_{it} + \alpha_z + \alpha_t + \epsilon_{izt} \ . \quad (6)$$

and I estimate the construction spending on properties based on their extent of damage as in Equation 7:

$$\begin{aligned} \mathrm{spending}_{izt} &= \alpha + \eta_1 \mathrm{VeryMinor}_i \times \mathrm{PostS}_t + \eta_2 \mathrm{Minor}_i \times \mathrm{PostS}_t \\ &+ \eta_3 \mathrm{Major}_i \times \mathrm{PostS}_t + \kappa_1 \mathrm{VeryMinor}_i + \kappa_2 \mathrm{Minor}_i + \kappa_3 \mathrm{Major}_i \\ &+ \theta \mathrm{Age}_{it} + \alpha_z + \alpha_t + \epsilon_{izt} \ , \end{aligned} \quad (7)$$

where $\mathrm{spending}_{izt}$ is the spending on renovation or rebuilding of property i in zip code z at year t. The variables $\mathrm{VeryMinor}_i, \mathrm{Minor}_i, \mathrm{Major}_i$ equal 1 for properties reported as every minor damage, minor damage, and major damage respectively. α_z and α_t are zip code and year fixed effects.

Columns 1 and 2 in Table 5 presents the estimated coefficients of outcome variable within floodplains corresponding to Equations 6 and 7, respectively. On average, owners of damaged properties spend $10,380 more relative to non-damaged properties to renovate or rebuild their houses after Hurricane Sandy. This result is consistent with Figure 4b. As expected, the largest amount of spending is incurred for properties with major damage. Owners of major damaged properties spend three times more to remodel than those only affected, while they spend two times more to remodel than those with minor damage.

Column 3 in Table 5 presents the estimated coefficients of the outcome variable out of floodplain corresponding to Equation 6. Coefficients of $\mathrm{Damage} \times \mathrm{PostS}$ and Damage are statistically insignificant, indicating renovation spending of damaged properties is not different from non-damaged properties before and after Hurricane

Table 5: Construction Spending on Damaged Properties

	Floodplain		Non-Floodplain
	(1) spending	(2) spending	(3) spending
damage x postS	10380.834***		-2498.503
	(1274.524)		(3638.508)
damage	-2013.736*		5795.447
	(922.394)		(3617.723)
house age	15.132**	15.208**	-1.488
	(4.872)	(4.877)	(0.939)
very_minor		-1862.852	
		(1363.404)	
minor		-2717.929*	
		(1098.884)	
major		1035.320	
		(2660.378)	
very_minor x postS		6226.105**	
		(1937.208)	
minor x postS		11440.101***	
		(1403.750)	
major x postS		22191.717***	
		(4726.311)	
cons	9642.222***	9658.880***	8576.347***
	(885.148)	(877.956)	(336.320)
Observations	112,491	112,491	871,858
FE	zip code	zip code	zip code
Year FE	Yes	Yes	Yes
R-squared	0.060	0.061	0.036

Note: Standard errors in parentheses. SE clustered at zip code level. Difference-in-Differences estimation corresponds to Equations 6 and 7. Outcome variable is the construction spending. The treatment group includes all damaged properties in floodplains, and the control group includes all non-damaged properties that are also in floodplains. The parameters of interest are the coefficients of the interaction terms (damage x postS, very_minor x postS, minor x postS, and major x postS).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Sandy. This explains the house price pattern out of floodplains. There is no price drop followed by price recovery out of floodplains. A possible explanation is due to the extent of the damage. Properties out of floodplains experience very minor damage, which these properties could be inhabited without remodeling. My findings of house price pattern and renovation out of floodplain support for the price pattern in floodplain.

5.3 NUMBER OF HOUSING TRANSACTIONS

In this section, I use the number of sale transactions to examine the selection in the housing market after Hurricane Sandy. A concern is that homeowners of damaged properties might worry about future floods because they directly experience floods. These homeowners might be willing to sell their properties at discount prices and move to safer areas. In this case, you might expect to observe more damaged properties sold relative to non-damaged properties in the high-risk areas after Hurricane Sandy. If the supply of houses in the safe areas is fixed, house prices in those safe areas will increase. House prices in high-risk areas would experience a persistent penalty.

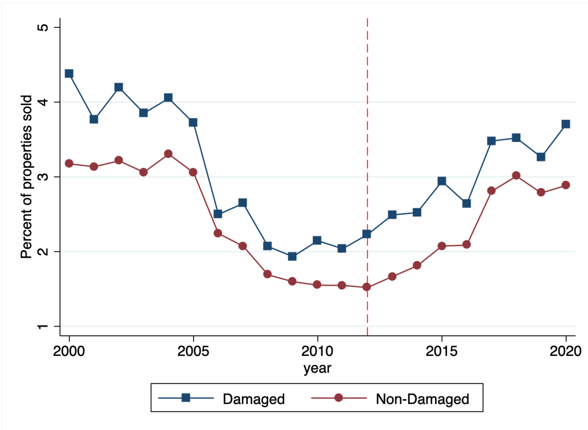
Another concern is that it might be selection into sales between damaged and non-damaged properties that will impact the estimation results. Damaged properties might be more difficult to sell without price concessions compared to non-damaged properties. I examine these concerns by calculating the percent of damaged and non-damaged properties sold over years in floodplains and percent of damaged and non-damaged properties sold over years out of floodplains as in Equation 8:

$$\mathit{PercentSold}_{ijt} = 100\% \times \frac{\mathit{TotalTransaction}_{ijt}}{\mathit{TotalParcels}_{ij}} \ . \tag{8}$$

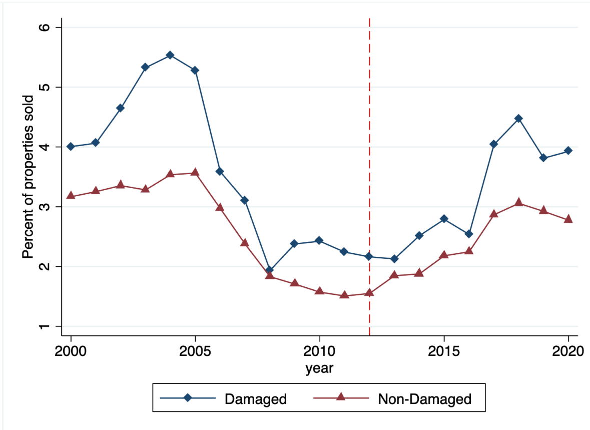
where $i = \{damaged, non-damaged\}$, and $j = \{floodplain, non-floodplain\}$.

Figure 6: Percent of Single Family Houses Sold by Year

(a) Floodplain



(b) Non-Floodplain



(c) Floodplain by Damage Levels

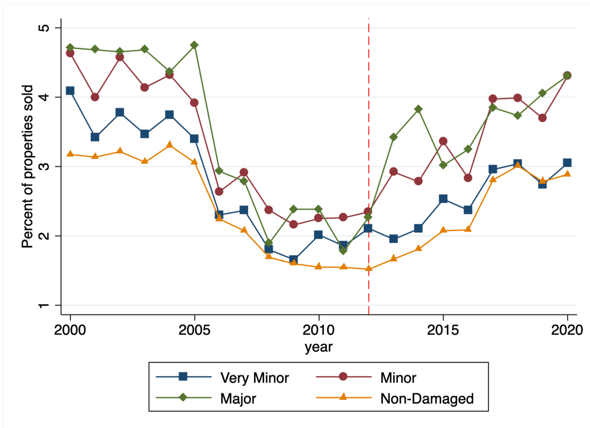


Figure 6 plots the percent of single family houses sold annually from Equation 8. Similar to the house price trends in Figure A.1, the percent of properties sold drop, matching the financial crisis and recover around year 2012. Figure 6 shows that the concerns above are not valid. Figure 6a plots the percent of properties sold for damaged and non-damaged groups in floodplain areas from 2000-2019. Damaged and non-damaged properties in floodplains do not have a sudden jump or a sharp decline after Hurricane Sandy. Figure 6b plots the percent of properties sold in damaged and non-damaged groups out of floodplain areas during the same periods. There was a slight jump in the sales of the non-damaged properties out of floodplains immediately after Sandy. However, later the sale of this group followed a similar trend to damaged properties out of floodplains. Figure 6c plots the percent of properties sold by the extent of damage. Properties with major and minor damage experienced a larger increase in transactions relative to non-damaged properties two years after Sandy. The trends of transactions for these two groups, however, were similar to the trend of non-damaged properties since 2015. These graphs suggest that there is no adverse selection on the transactions of damaged properties.

5.4 Flood Insurance Take-up Rates

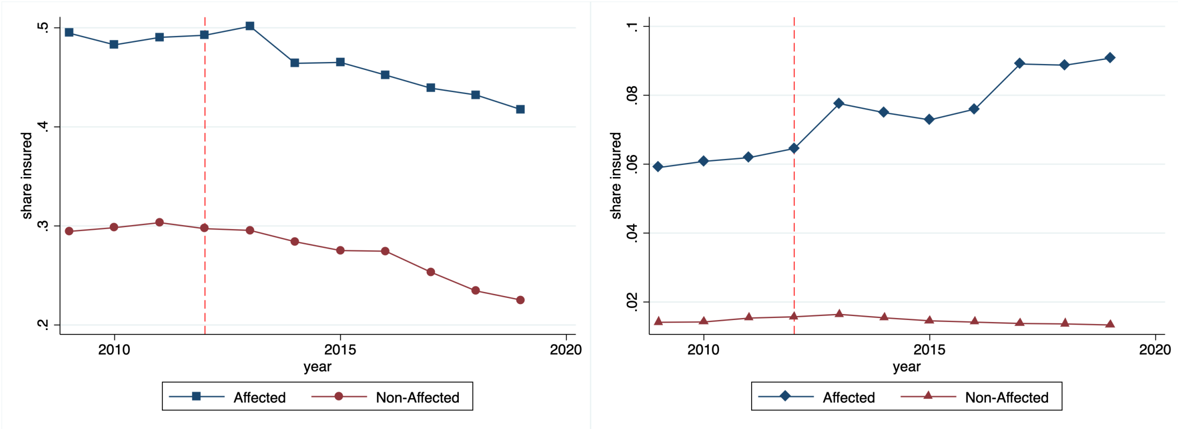
Next, I use flood insurance take-up rates to examine whether experiencing a flood during Hurricane Sandy will increase homeowner risk perception. To study if hurricane Sandy has heightened the perceived risk of flooding on homeowners in the floodplains where people anticipate their flood risks, I compare the share of properties in floodplains that has flood insurance between affected census tracts and non-afffected census tracts over time.

Although properties that carry federally backed mortgages in floodplains are required to buy flood insurance, this requirement is not strictly enforced. The take-up rate of flood insurance in the 100-year floodplain is remarkably low at 48.3% nationwide in 2019. Only 2.2% of properties outside of floodplains carries flood insurance in the same year (Bradt, Kousky, and Wing 2021). If Hurricane Sandy increases risk perception to homeowners in the high-risk areas, I would expect the take-up of flood insurance to increase more in the affected areas relative to unaffected areas after Sandy. We might argue that hurricane Sandy heightens risk perception for all homeowners in the 100-year floodplains, both impact and non-impact areas, so we might not see the difference in take-up rate between these two groups. If that is the case, we would see an increase in take-up rates for both groups after 2012 compared to before 2012.

Figure 7a plots the share of floodplain properties that have flood insurance over time in the affected and non-affected census tracts. Affected tracts mean those tracts have at least one property damaged by Sandy. On average, the flood insurance take-up rate is higher for affected tracts relative to non-affected tracts within floodplains. However, the take-up rate trends are similar in those areas before Hurricane Sandy. Immediately after Sandy, the take-up rate slightly increased in the affected tracts, but this increase was temporary. The flood insurance take-up rate in affected and non-affected tracts has followed the same trend since 2013.

Figure 7: Share of Properties with Flood Insurance Aggregated by Census Tract

(a) Floodplain (b) Non-Floodplain



Note: FEMA Flood insurance data. Share insured is calculated by taking the total numbers of flood insurance written for one-to-four families residence in a year divided by the total one-to-four families parcel in the census tract. Affected tract means that census tract has at least one property damaged by Hurricane Sandy.

Homeowners in the affected areas out of floodplains, however, may worry about their future flood risk. After Hurricane Sandy, there is a permanent increase in the flood insurance take-up rate in affected areas. Given that they may be more risk-averse when deciding to buy their house out of floodplains, being affected by Sandy may cause them to update their flood risk. In contrast, homeowners in floodplains may have higher expectations about their flood risk; experiencing floods does not cause them to revise their perceived risk.

5.5 Repeat Sales

In this section, I estimate the effect of Hurricane Sandy on house prices using a repeat sales sample. I keep the properties that are sold at least twice during my study period; among these transactions, one transaction must occur before hurricane Sandy in 2012, and one transaction must occur after the hurricane in 2012. Instead of including block group fixed effects as in Section 5.1, I apply difference-in-differences estimation, including property fixed effect, as in Equations 9 and 10 below. The property fixed effects would remove the heterogeneity in the time-invariant characteristics across properties.

My repeat sales analysis estimates the following equations:

$$\log(P_{it}) = \alpha_i + \delta Damage_i \times PostS_t + \theta HouseAge_{it} + \alpha_t + \epsilon_{it}, \tag{9}$$

and

$$\log(P_{it}) = \alpha_i + \delta_1 VeryMinor_i \times PostS_t + \delta_2 Minor_i \times PostS_t + \delta_3 Major_i \times PostS_t$$
$$+ \theta HouseAge_{it} + \alpha_t + \epsilon_{it}. \tag{10}$$

Table 6: Effect of Hurricane Sandy on House Prices using Repeat Sales Sample

	Floodplain		Non-Floodplain
	(1)	(2)	(3)
	log(House Price)	log(House Price)	log(House Price)
Damage x PostSandy	0.151***		-0.001
	(0.025)		(0.057)
VeryMinor x PostSandy		0.161***	
		(0.032)	
Minor x PostSandy		0.139***	
		(0.026)	
Major x PostSandy		0.180*	
		(0.071)	
Constant	5.228***	5.228***	4.954***
	(0.038)	(0.038)	(0.006)
Observations	38,389	38,389	382,458
FE	Property	Property	Property
Year FE	Yes	Yes	Yes
R-squared	0.816	0.816	0.798

Note: Standard errors in parentheses. SE clustered at block group level. A block group includes 400 housing units on average, with a minimum of 250, and a maximum of 550 housing units (Census Bureau). Difference-in-Differences estimation corresponds to Equations 9 and 10 using a repeat sales sample. A house must be sold at least twice, one transaction occurs before hurricane Sandy, one transaction occurs after Hurricane Sandy in order to be included in the sample. Outcome variable is the house prices in log form. The treatment group includes all damaged properties in floodplains, and the comparison group includes all non-damaged properties that are also in floodplains. The parameters of interest are the coefficients of the interaction terms (Damage x PostSandy, VeryMinor x PostSandy, Minor x PostSandy, and Major x PostSandy).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 reports the estimation results on a repeat sales sample that properties are sold at least twice during my study period. On average, damaged properties located in the floodplain are sold at a 15.1% higher price relative to non-damaged properties in the floodplain after Hurricane Sandy, as shown in column 1, Table 6. With a repeat sales sample, the same house is sold before and after Hurricane Sandy; therefore, the damaged properties sold at a premium relative to non-damaged properties would indicate the house quality improvement after renovation or rebuilding. Column 2, Table 6 reports the estimation results corresponding to Equation 10. Properties in the floodplain with very minor, minor, and major damage are sold at 16.1%, 13.9%, and 18.0% higher relative to non-damaged properties after Hurricane Sandy. On the other hand, there is no difference in prices of damaged and non-damaged properties out of the floodplain after Hurricane Sandy, as shown in column 3. The results in Table 6 are consistent which what I found in Sections 5.1 and 5.2, which provide supportive evidence for the higher prices of damaged properties after the hurricane due to the renovation and rebuilding that improved the quality of houses in the floodplains.

6 DISCUSSION

In this section, I provide the link between the decline in house prices due to Sandy, the average renovation and rebuilding spending, and the price recovery after Hurricane Sandy. Comparing and contrasting with the literature that studies the impacts of hurricanes on house prices in general, or the impacts of Hurricane Sandy on the New York housing market in particular, I show that rebuilding and renovating play a significant role in price recovery in the New Jersey housing markets.

In Section 5.1, I provide evidence of the effects of Hurricane Sandy on house prices due to direct damage. In Table 3, all properties of treatment and comparison groups are located within floodplains. The difference between these two groups is whether properties suffer damages during Sandy. In Section 5.4, I show that homeowners in affected areas within floodplains do not change their risk perception. Therefore the house price decline after Sandy is likely due to direct damage impacts. The house prices dropped immediately after Sandy, including the expected repair costs due to damage and the non-money costs such as time to monitor the renovation or the stress during the renovation process. The construction spending in column (3) is reported by applicants applying for building permits, which shows the extent of spending on renovation and rebuilding is associated with the extent of damage.

My paper is closely related to Ortega and Taspinar (2018), in which the authors study the effects of Hurricane Sandy on New York housing markets. The authors find a 5% - 8% permanent decline in prices of non-damaged properties in floodplains relative to non-damaged properties that are not in the floodplains. Using a similar approach, I find the penalty for non-damaged properties located in floodplains is 4.2% - 5%, as shown in Table A.4, which is consistent with their finding. I also find a consistent result with Ortega and Taspinar (2018) that there is no persistent difference in prices of damaged properties and non-damaged properties.[9]

My findings, however, differ from that paper when looking at the damaged properties in floodplains relative to non-damaged properties in and out of the floodplain. I show that damaged properties are sold at a 9.1% premium relative to non-damaged properties within floodplains, as shown in Table 3. Similarly, I find that damaged properties in floodplain are sold at a 12% - 13% premium relative to non-damaged properties out of the floodplain. Pooling all properties in the floodplain together, I find that there is no persistent penalty on prices of floodplain properties, as shown in Figure A.2. My explanation for why there is no permanent price effect of Hurrican Sandy is the extent of repair and remodeling. Prices increase in the damaged properties group (due to rebuilding and renovating) exceed the decrease in prices of non-damaged properties. My findings are consistent with the common findings in the literature of the temporary impacts of hurricanes on house prices.

9. Ortega and Taspinar (2018) find an initially 17% - 22% decline in prices of damaged properties in floodplain relative to non-damaged properties out of floodplain, however, these discount decrease to 8% that is similar to the discount of non-damaged properties in floodplains.

7 CONCLUSION

This paper aims to study the house price dynamics due to a major storm and provide an interpretation of these patterns over time. By isolating the price effects of hurricanes due to direct damage and using Hurricane Sandy as a case study, I find that Sandy only imposed a transitory impact on house prices in New Jersey's 16 affected counties. I find that, base on flood insurance data, Hurricanes do not change risk perception of individuals that experience floods. I find that house price declines immediately after the storm reflect the cost of repairs and remodeling. I use administrative building permit data to explain the recovery in house prices by determining the extent of planned remodeling and rebuilding. There is evidence of a significant increase in renovation immediately after Sandy. The most extensive renovation spending is on the properties with the most damage. I also show evidence of the increase in demolition permits for the properties with major damage a year after Sandy, and the increase in rebuilding permits for those properties two years after Sandy.

My research has shown the dynamic price path of housing prices after a major storm is fully explained by rebuilding, and that the risk perceptions of consumers seem unchanged by a major storm event. The interesting implication of this work is that floodplain designations by FEMA appear to provide significant information to consumers. To the extent that floodplain designations are valid, then it is perfectly rational that house prices fall immediately after a major storm damages property. And, it is perfectly rational that house prices recover as repairs and accompanying remodeling restore houses to at least their prior condition.

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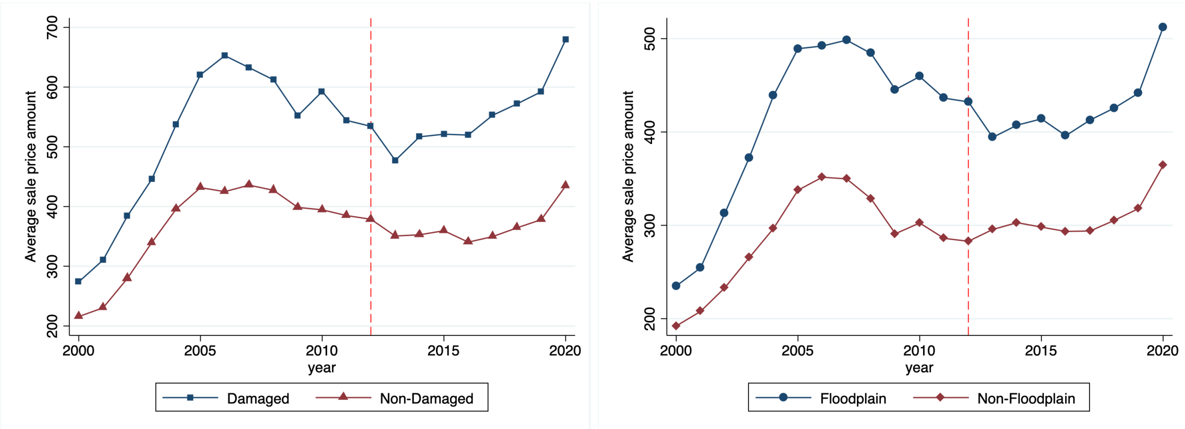
A Complementary Tables and Figures

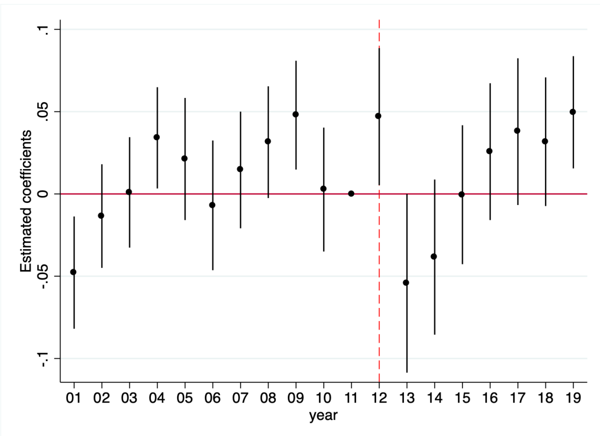
Figure A.1: Average House Price.

(a) Floodplain Properties (b) All Properties



Note: Average prices (in thousands) of single residential properties. House prices are obtained from Zillow data.

Figure A.2: Effects of Hurricane Sandy on House Prices.



Note: These figures plot event study estimate for the effect of Hurricane on log of house prices. The coefficients are estimated from Equation 2. The treatment group includes all properties in floodplain (both damaged and non-damaged properties), and the comparison group includes all non-damaged properties that are out of the floodplain. The circles plot the point estimates, and the bars plot the 95% confidence intervals.

Table A.1: Summary Statistics Before and After Hurricane Sandy

Panel A:	Damaged			Non-Damaged		
Floodplain	Before	After	Difference	Before	After	Difference
house price	489.78	561.13	**71.35**	351.20	369.16	**17.97**
	(344.64)	(384.03)	(4.17)	(305.27)	(322.43)	(2.42)
log(houseprice)	5.95	6.07	**0.12**	5.53	5.55	**0.02**
	(0.74)	(0.79)	(0.008)	(0.85)	(0.92)	(0.007)
Observations	20,383	12,768		44,387	27,620	

Panel B:	Damaged			Non-Damaged		
Non-Floodplain	Before	After	Difference	Before	After	Difference
house price	405.30	425.51	**20.21**	282.26	310.25	**28.00**
	(333.39)	(342.80)	(14.07)	(195.15)	(222.65)	(0.43)
log(houseprice)	5.71	5.75	**0.05**	5.42	5.48	**0.06**
	(0.80)	(0.82)	(0.03)	(0.71)	(0.78)	(0.001)
Observations	1,492	951		639,061	379,797	

Note: Average prices of damaged properties and non-damaged properties in floodplains (top) and out of floodplains (bottom) before and after Hurricane Sandy

Table A.2: Effect of Hurricane Sandy on House Prices by Damage Levels

	(1) log(houseprice)	(2) log(houseprice)	(3) log(houseprice)	(4) log(houseprice)
very_minor	0.067**	0.069**	0.078**	0.097***
	(0.025)	(0.024)	(0.024)	(0.028)
minor	-0.062**	-0.066**	-0.055*	-0.074**
	(0.023)	(0.023)	(0.022)	(0.025)
major	-0.135***	-0.137***	-0.119**	-0.157***
	(0.036)	(0.036)	(0.038)	(0.035)
very_minor x postS	0.109***	0.112***	0.116***	0.124***
	(0.025)	(0.024)	(0.023)	(0.022)
minor x postS	0.068***	0.067***	0.067***	0.073***
	(0.018)	(0.018)	(0.018)	(0.018)
major x postS	0.142**	0.131**	0.106*	0.106*
	(0.046)	(0.048)	(0.051)	(0.051)
house age		-0.004***	-0.004***	-0.004***
		(0.000)	(0.000)	(0.000)
lotsize			0.006*	0.002
			(0.003)	(0.003)
cons	5.520***	5.622***	5.628***	5.531***
	(0.033)	(0.033)	(0.035)	(0.039)
Observations	105,639	104,455	95,766	95,766
FE	Block group	Block group	Block group	Tract
Year x Distance FE	Yes	Yes	Yes	Yes
R-squared	0.643	0.649	0.584	0.56

Note: Standard errors in parentheses. SE clustered at block group level. A block group includes 400 housing units on average, with a minimum of 250, and a maximum of 550 housing units (Census Bureau). Difference-in-Differences estimation corresponds to Equation 1. Outcome variable is the house prices in log form. The treatment group includes all damaged properties in floodplains, and the comparison group includes all non-damaged properties are also in floodplains. The parameters of interest are the coefficients of the interaction terms (very_minor x postS, minor x postS, major x postS).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Effects of Being in Floodplain on Prices of Non-damaged Properties

	(1) log(houseprice)	(2) log(houseprice)	(3) log(houseprice)	(4) log(houseprice)
floodplain x postS	-0.043**	-0.046***	-0.041**	-0.049***
	(0.014)	(0.013)	(0.013)	(0.013)
floodplain	0.028*	0.024	0.020	0.035
	(0.014)	(0.013)	(0.013)	(0.019)
house age		-0.005***	-0.005***	-0.005***
		(0.000)	(0.000)	(0.000)
lotsize			0.010***	0.009***
			(0.001)	(0.002)
cons	5.276***	5.439***	5.434***	5.343***
	(0.044)	(0.043)	(0.046)	(0.050)
Observations	1,041,190	1,005,462	950,446	950,446
FE	Block group	Block group	Block group	Tract
Year x Distance FE	Yes	Yes	Yes	Yes
R-squared	0.602	0.627	0.630	0.565

Note: Standard errors in parentheses. SE clustered at block group level. A block group includes 400 housing units on average, with a minimum of 250, and a maximum of 550 housing units (Census Bureau). Difference-in-Differences estimation corresponds to Equation 1. Outcome variable is the house prices in log form. The treatment group includes all non-damaged properties in floodplains, and the comparison group includes all non-damaged properties are out of the floodplains. The parameters of interest are the coefficients of the interaction terms (floodplain x postS).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

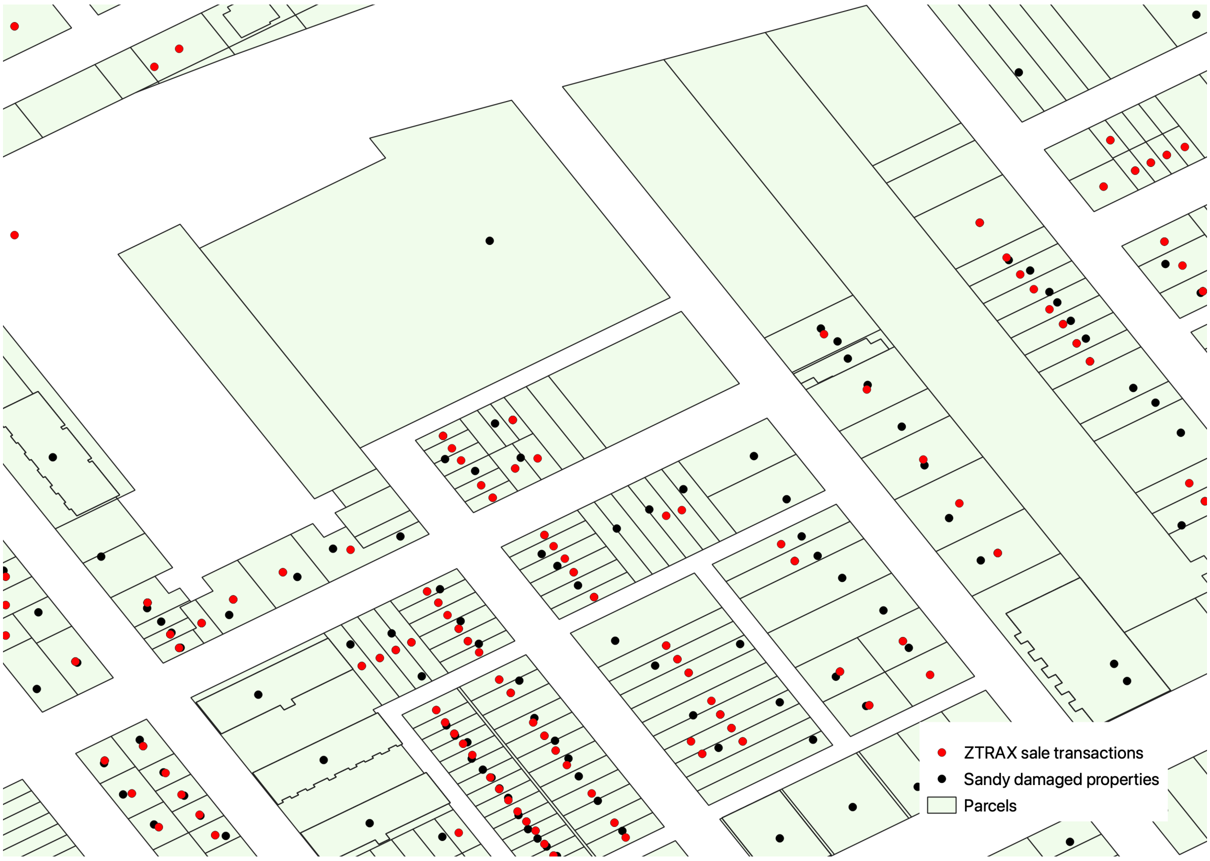
Table A.4: Effect of Hurricane Sandy on House Prices

	(1) log(houseprice)	(2) log(houseprice)	(3) log(houseprice)	(4) log(houseprice)
damage_floodplain x postS	0.123***	0.113***	0.124***	0.115***
	(0.023)	(0.022)	(0.021)	(0.021)
damage_floodplain	0.107*	0.087	0.097*	0.212***
	(0.050)	(0.047)	(0.044)	(0.043)
house age		-0.005***	-0.005***	-0.005***
		(0.000)	(0.000)	(0.000)
lotsize			0.009***	0.008***
			(0.001)	(0.002)
cons	5.237***	5.417***	5.445***	5.267***
	(0.040)	(0.038)	(0.039)	(0.045)
Observations	1,036,914	1,001,244	947,194	947,194
FE	Block group	Block group	Block group	Tract
Year x Distance FE	Yes	Yes	Yes	Yes
R-squared	0.605	0.629	0.632	0.567

Note: Standard errors in parentheses. SE clustered at block group level. A block group includes 400 housing units on average, with a minimum of 250, and a maximum of 550 housing units (Census Bureau). Difference-in-Differences estimation corresponds to Equation 1. Outcome variable is the house prices in log form. The treatment group includes all damaged properties in floodplains, and the comparison group includes all non-damaged properties are out of the floodplains. The parameters of interest are the coefficients of the interaction terms (damage_floodplain x postS).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Extended Data

Figure B.1: Merging ZTRAX and Damage Assessment Databases.



Note: This map shows how ZTRAX and FEMA damage assessment data are merged. Transactions in the ZTRAX data include the longitude and latitude of the transacted properties. The longitude and latitude of the properties are assigned into parcels using ArcGIS. Each damaged building from FEMA includes longitude and latitude, which are assigned to parcels using the New Jersey statewide parcel map. If the observations from ZTRAX and FEMA data belong to the same parcel, the two observations mention the same house.