**Storm Surges, Informational Shocks, and the Price of Urban Real Estate:**

**An Application to the Case of Hurricane Sandy[[1]](#footnote-1)\***

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**Abstract:** The impacts of a major hurricane on residential real estate can be devastating. Hurricanes in Houston (with Hurricane Harvey), Florida (with Hurricane Irma), and New York City (with Hurricane Sandy) are examples of how flooding can unexpectedly extend beyond the FEMA flood zones. Such surprises or shocks can provide property owners—especially those that are not flooded—with new information about future flood risks, based on the difference of the property distance from the flood zone and the distance to the actual locations of flooding. We use a difference-in-differences approach to quantify the effects of these shocks on residential property values for dry (non-flooded) properties in New York City for Hurricane Sandy. The average effect of a negative “surprise” was to increase house prices by about 9% per mile further away from the storm. The corresponding positive “surprise” effect is statistically insignificant.

*Key words*: Hurricane Sandy, Storm Surges, New York City, Real Estate Prices

JEL Classification: R3

1. **Introduction**

Over the past decade, hurricanes in the United States, including 2017 in Houston (Hurricane Harvey) and Florida (Irma), and 2012 in New York City (Hurricane Sandy), are examples of how flooding damage can unexpectedly extend beyond the Federal Emergency Management Agency (FEMA) designated flood zones.[[2]](#footnote-2) Such surprises or shocks can provide property owners—including those that were not flooded—with new information about future flood risks, based on the difference between the distance of their properties from the flood zone and the distance to the actual locations of flooding. We quantify the effects of these shocks on property values for non-flooded properties.

Hurricanes, of course, can impose costly damage. When Harvey struck the Houston, Texas area in late-August 2017, damage assessment was about $125 billion (Mooney, 2018). In early September 2017, Hurricane Irma hit Florida, with waist-deep flooding in downtown Miami (Sun-Sentinel, 2017). The total costs of Irma were estimated to be about $50 billion (National Hurricane Center, 2018).

On a somewhat smaller but nevertheless dramatic scale, on October 29, 2012, Hurricane Sandy made landfall in New York City. It was arguably the largest and most damaging storm to hit the New York metropolitan region. There were 65 deaths in New York, New Jersey and Connecticut related to the storm. The surge level at Battery Park in lower Manhattan topped out at 13.88 feet at 9:24 pm, surpassing the old record of 10.02 feet, set by Hurricane Donna in 1960 (CNN, 2013). Estimates of total losses for New York City alone were about $19 billion, and $33 billion for the entire state.[[3]](#footnote-3)

Studies to date have focused on estimating the cost of the damage—how much did the storm destroy in terms of market value or replacement costs (ESA, 2013). However, to our knowledge, relatively less work has explored the implicit costs of storm surges on the value of real estate in the city for properties *that were not damaged by the surge*. Understanding how the flooding affected the properties that remained dry is important because it can give clues to how the market perceives the future risks of storm surges that are likely to occur more frequently over time. Which neighborhoods reacted the most and why? This paper investigates real estate price volatility due to the shock from the storm surges, by focusing on changes in real estate prices for those properties not directly flooded.

Our focus is on the price (or treatment) effects of distance from the surge for non-flooded properties at least 1/8 mile from the surge but no more than 1 mile away from the surge. We also consider how these treatment effects are different for non-flooded properties closer versus further from Sandy storm surge locations as compared vis a vis the insurance flood zone delineations. The floodzome maps are assumed to be how residents form their expectations regarding flood risk. These flood zones are important because they are intimately tied to flood insurance rates.

In 1968, the U.S. Congress created the National Flood Insurance Program (NFIP) to help provide a means for property owners to financially protect themselves. The NFIP offers flood insurance to homeowners, renters, and business owners if their respective town or city participates in the NFIP. Participating communities agree to adopt and enforce ordinances that meet or exceed Federal Emergency Management Agency (FEMA) requirements to reduce the risk of flooding (FEMA, 2017b).[[4]](#footnote-4)

FEMA partners with states and communities through the Risk Mapping, Assessment, and Planning (Risk MAP) program to identify flood hazards and assess flood risks. These data are incorporated into flood maps, known as Flood Insurance Rate Maps (FIRMs), which support the NFIP and provide the basis for community floodplain management regulations and flood insurance requirements. Most commonly used for insurance purposes are the 100-year floodplain maps, which are regions designated to have a 1% chance of being inundated each year.

Real estate buyers, who seek a mortgage, are often required to purchase flood insurance if they are within a FEMA-designated floodplain (FEMA, 2017a). The FEMA floodplain maps thus serve as a publicly available assessment of the likelihood of a property being flooded. In addition, for those outside the floodplain, the distance to the plain can presumably be used to provide information about the relative flood safety of the neighborhood. Being 20 feet from a floodplain suggests that a property is potentially at more risk than one 2,000 feet away.

While it is relatively straightforward to estimate the effects of the storm on those properties that were flooded by a major storm, our main goal is to estimate the degree to which properties that remained dry were not directly impacted by a storm. If the Hurricane represents an informational shock about the likelihood of future damage then, presumably, this effect will be priced into properties, as people reassess the likelihood of future storm shocks and the potential damage they could cause.

This paper aims to isolate the changing expectations of the real estate market, via hedonic regressions, to look at housing prices after the storm surge. Our contributions not only include a better understanding of how storms affect real estate values, but also demonstration that these effects often can be different across various locations. We accomplish this by breaking up the estimation samples into two subsamples – properties experiencing “negative” shocks (i.e., properties that were closer to the storm surge than the FEMA flood map boundaries), and those with “positive” shocks (i.e., being further from the storm surge than expected based on the FEMA flood zone).

We find that, on average, only the negative shocks have a statistically significant treatment effect of the proximity to the storm surge on property values. These results are robust to various regression specifications. Thus when investigating the geographic impacts of storms and/or other shocks to cities, it is vital to understand the variation in these two types of impacts; this is crucial not only for measurement reasons but for the policy implications about where to deploy resources before or after a storm. The finding of a statistically significant effect from negative shocks but not from positive shocks is consistent with the literature in behavioral economics, which finds that negative events can often unleash extreme reactions from people (Card and Dahl, 2011).

The remainder of this paper proceeds as follows. First, we review the literature on how storm risk information impacts real estate, and more generally, how storms impact real estate, to demonstrate that our approach has not been considered in other storm and real estate studies. Then we present our approach, followed by a discussion of the data we use for our analysis of New York City and information shocks resulting from hurricane Sandy. This sets the stage for the presentation of our empirical results. Finally, we offer some concluding remarks.

1. **Literature Review**

The events in the past few years of Hurricane Harvey in Texas and Irma in Florida demonstrate that the FEMA flood zones have left residential real estate owners an imperfect measure of flooding likelihoods (Fessenden, et al., 2017). This motivates the need to study how information shocks due to unanticipated flood risk information might impact house prices. There is little known research on this specific topic.

There is a growing literature on the specific topic of flood risk information. One recent paper is Yi and Choi (2020), who study the 2008 floods in Des Moines, Iowa. They use a difference-in-differences approach to track properties that sold over time and found that homeowners update their perceptions of flood risks in locations where the flood extended beyond pre-existing flood zones. Another paper in this literature is Bin and Landry (2013), who find that the effects of unexpected flood risk following a major storm disappear after several years. They examine Pitt County, North Carolina and find a discount of between 5% and 9% following Hurricanes Fran and Floyd. More recent data indicate a higher discount rate, although as noted above, these effects vanish as additional time elapses.

The findings of Bin and Landry (2013) are similar to those of Atreya et al. (2013), who examined a 100-year flood event that occurred in one county in Georgia. Immediately after the flood, house prices fell for properties within the flood plains, but these effects became smaller over time and eventually vanished. A related study is Atreya and Ferreira (2015), who found that prices of flooded properties after this same 100-year flood in Albany, Georgia fell by much more than properties that were in the flood zones but were also dry as a result of the storm.

Other relevant research on flood risk information includes Smith et al. (2006), who focus on damaged properties after Hurricane Katrina in the Miami area. They find that middle income individuals move away from risk. Wealthy individuals, on the other hand, prefer to stay in their homes but purchase insurance. Lower income individuals prefer to move into affordable housing. In a related paper, Carbone et al. (2006) studied two separate counties’ responses to risk information from Hurricane Andrew in Florida – one county that was damaged, and another county with no damage. They find that the storm provides significant information to residents of these two counties.

Zhang (2016) considers whether there was any impact on properties locating in the floodplain in Fargo, ND. They use a spatial quantile approach to address this. A key finding is that lower priced houses are affected more adversely by being in the floodplain.

In another recent study, McCoy and Zhao (2018) find that the likelihood of investment in damaged buildings is higher for properties in the flood zones than flooded properties outside the flood zones, and the latter effect is statistically insignificant while the former effect is significant.

Pommeranz and Steininger (2018) estimate various spatial hedonic models for housing prices in Dresden, Germany. In particular, they investigate the impacts of flood zone risk categorization (low risk, moderate risk, high risk, extremely high risk) on housing prices. They estimate both direct and indirect effects. Direct effects are the impacts of a house's flood zone risk on the price, while indirect effects are based on a weighted average of flood zone risks from surrounding properties. That is, the indirect effect aims to test for spillovers of risk from surrounding properties. They find negative indirect effects from surrounding properties (i.e., higher average neighborhood risk leads to lower prices), but no statistically significant direct effects. This suggests that buyers use the average risk of a neighborhood to estimate home values, likely because of the difficulty of ascertaining the specific risk of a particular property. Our paper, unlike theirs, looks at the impact of new information, and thus we aim to see how home buyers update their housing prices when they acquire this additional information about the risk of flooding.

More broadly, there are a variety of studies that investigate the impacts of storms or natural disaster on real estate and local economies without specifically focusing on the changes in flood risk. These include studies of specific hurricanes, as well as others on the proximity to the coast. We mention one in particular here, because of its focus on Hurricane Sandy in New York City. Specifically, Ortega and Taspinar (2018) examine Sandy and the New York City housing market, and they address the question of whether housing demand shifted towards less exposed areas. They divide the city into six Hurricane Evacuation Zones (HEZ’s). They allow for “treatments” of 0 (no damage), 1 (minor damage), and 2 (major damage), and compare prices post-Sandy for the treatment versus control groups. The control group is the property sales outside of the flood zone. Their difference-in-differences model includes a dependent variable of the log of house sales prices, and they include a dummy for post-Sandy sales for being in zones 1 or 2, and neighborhood and time fixed effects. They also estimate a second difference-in-differences model with all three treatment groups, each of which is interacted with a post-Sandy dummy variable. They find evidence that the treatment effects are significant. They also find that for damaged houses, the treatment effects appear to be permanent, with a drop in values between 17% and 22%.[[5]](#footnote-5), [[6]](#footnote-6)

With these studies in mind, our research examines treatment effects of proximity to the storm surge, and also considers both positive and negative surges that do not precisely overlap with the pre-determined flood zones. Given the data limitations in general for sales of flooded properties, we now turn to our methodology to estimate the impacts on dry properties.

1. **The Theory of Price Effects**

Our aim is to understand how a storm shock can affect those properties that were not damaged by the storm. The point is that for many property owners the storm represented new information on the potential damage due to storm surges. Our main identification strategy is to look at the shock that occurred based on proximity to the storm surge. In short, our variable of interest is the treatment effect for proximity to the storm for properties that sold after the storm, conditional on the distance to the closest FEMA boundary.

That is, we aim to estimate:

$$lnP\_{i}=θtreatment\_{i}+X\_{i}ζ+ε\_{i}$$

where

$$treatment\_{i}=(Post Storm)\_{i}×(Surge Distance)\_{i}$$

for $i=1,…,N,$ non-flooded properties, and where $X\_{i}$are control variables (including property characteristics and the FEMA floodplain distance), and $ε\_{i}$ is the error term. Thus $θ$—the primary variable of interest—represents the change in price due to the change in the proximity to the storm.

We examine dry properties at least 0.03 miles from the surge and less than 1 mile from the surge in the non-flooded areas. In other words, we drop any observation for which the storm surge distance is less than 0.03 mile from that observation. We also only consider properties that are no further than one mile away from the storm surge, on the dry side of the surge, and also that sold within a short period of time before and after the storm. We also drop any properties that were flooded (i.e., for which the storm surge reached the property).

 We also consider whether properties with “positive” or “negative” shocks experience a different impact of proximity to Sandy on house prices. First, note that distance is measured from the centroid of the property. The positive and negative shock variables are measuring the distance in each subgroup. So, if the distance from a property to the Sandy flood, minus the distance between the same property and the FEMA floodplain, *Sandy-FEMA,* is positive, it means that the FEMA floodplain was closer to the property than the storm (a large positive shock). A negative value for *Sandy-FEMA* means the storm was closer to the property than the FEMA floodplain (a large negative shock). We return to this issue in the results section below.

1. **Hurricane Sandy**
	1. **The Data**

Here we provide some basic information about the data; Appendix A gives more details about the data collection, processing, and sources. **Table 1** provides descriptive statistics for the data set for 2011-2014, which is our main sample for the difference-in-difference regressions. Information about additional control variables are provided in the Appendix.

**{Table 1 about here: Desc stats.}**

Recall that the date Hurricane Sandy hit New York City was October 29, 2012. We provide statistics for residential properties that were within one mile (but outside of) the storm surge boundary, but at least 0.03 miles from the storm surge boundary, and sold between January 1, 2011 and December 31, 2013 (see **Figure 1**). Here residential properties are any kind of structure that has at least one residential unit. However, the vast majority (83%) of the properties in the sample are one- or two-family homes. But apartment buildings and at least one housing complex are included in the sample (dummy variables for building types are included in the regressions). The largest fraction of properties (33.9%) are in the borough of Queens. The next largest fraction is in Brooklyn (28.9%). Less than 4% of sales were in Manhattan. There are 31,982 residential property sales that satisfy the filters described above. The average property in this sample sold for slightly over $962,000, was 73.7 years old, had 2.4, floors and sold for a price per square foot of approximately $266 (median of $243) with slightly more than 4,200 square feet (median of 1,890 square feet).

We utilized GIS shapefiles related to the storm surge of Hurricane Sandy. These files have been generously provided by the Natural Resources Defense Council (NRDC). The maps indicate the location of the storm surge and the location of the FEMA floodplain. The maps show four areas: the area of FEMA floodplain that remained dry, the area in the FEMA floodplain that was hit by the storm surge, the area of the surge that was outside of the FEMA floodplain, and the area that was neither in the floodplain nor the storm surge. Thus, we categorize each property based on it being in one of those four areas. We restrict our analysis to the unaffected (“dry”) properties since we are interested in the impacts of an informational shock. Also, many flooded properties could not be easily sold after the storm, so it is not sensible to include the flooded properties in our analysis. As described in Section 3 above, we focus on properties that were at least 0.03 miles from the storm surge and no more than one mile from the dry side of the storm surge, which sold between the date of the storm (October 29, 2012) and the end of 2013.

* 1. **Hedonic Regression Results**

We hypothesize that the coefficient for the treatment effect would be positive—the greater the distance from Sandy, the greater the housing price. **Table 2**, Column (1) presents results for a regression of the log of sale price per square foot against a constant, the treatment effect, and *distance to FEMA*, including year-quarter dummies, and census tract fixed-effects. This sample includes residential properties that sold between the dates of January 1, 2011 and the end of 2013. The parameter estimate on the treatment effect is 0.0405 (with t-stat = 2.92), which suggests that with each mile away from the storm surge, prices rose by 4.05%, which appears to be a reasonable estimate.

Next, in Column (2), we add additional hedonic controls, including the log of number of units in the property, the log of land area, the log of building’s age, the log of building area, and the log of the number of floors in the building. The parameter estimate for the treatment effect is slightly higher in this specification, equal to 0.054 (with t-stat = 4.72). All of the hedonic controls (with the exception of the number of floors in the residence) are highly significant and have the expected signs.

**{Table 2 about here: Diff-in-diff Regs 1-mile 2011 to 2013}**

New York City has such a diverse range of residential dwellings, that it is reasonable to also include a more detailed set of control variables that distinguishes these characteristics. Therefore, in Column (3) of **Table 2** we add in a more comprehensive set of building characteristics, which are described in detail in the Appendix, but account for additional features of the property, such as lot shape and location within the block, building type dummies, and if it has a basement or not. For ease of presentation, the parameter estimates from these additional variables are suppressed in **Table 2**, but they are available upon request. We also include an additional regressor for distance to the shore, which has a positive and significant coefficient. The inclusion of this full set of hedonic controls has no impact on the signs and significance of the hedonic controls that are presented in Column (2) of **Table 2**, but the coefficient on thetreatment effect variable is also positive and significant, equal to approximately 0.042. This implies that for every mile further away from the storm surge, residential sale prices per square foot were approximately 4% higher.

In **Table 3**, we re-estimate the three models shown in **Table 2** but by extending the end-date of the sample through the end of 2014. While the coefficient estimates are all positive as would be expected for thetreatment effect variable, they are much larger by close to 50%, in the range of 0.05 to 0.07, and significant. This suggests that it took some time for the full effects of the storm to be manifested in the housing market. For the remainder of the paper, we proceed with retaining the end date of 2014 in the analysis.

**{Table 3 about here: After Sandy within 1 mile but up to 2014}**

Now we consider the issue of positive versus negative shocks. **Table 4** shows the coefficient estimates from when we divide the sample into two subsamples—those with positive shocks, *Sandy-FEMA≥0* (Column (1)), and those with negative shocks, *Sandy-FEMA<0* (Column (2)). **Figure 1** maps all the residential property sales between the date of Sandy and the end of 2014, where a blue dot is a negative shock, a red dot is a positive shock.

 **{Figure 1 about here: Map}**

The results from **Table 4** column (1) suggest that, on average, there was no significant relationship between the treatment effect and housing prices for positive shocks. The treatment effect coefficients for the negative shocks are positive and statistically significant (with value of 0.087). These estimates are on the high end of the treatment effect estimates of **Tables 2 and 3** which do not distinguish between positive, and negative shocks.

**{Table 4 about here : +, - shocks}**

This implies that if a property is further away from Sandy than expected, there is no significant impact of being further from the storm surge. But for properties that are closer to Sandy than expected, the treatment effect coefficient implies that moving further away from the storm surge would raise property values. Properties where the storm surge came a mile closer than expected (i.e., from the FEMA flood zones) would have experienced a 8.7% reduction in sale prices per square foot by moving a mile away from the storm surge, ceteris paribus.

**4.2.1 Additional Tests**

To confirm that the results are, in fact, picking up a true shock, we performed several additional tests. **Table 5** presents the results of a regression but only for 2011—a period before the storm. If Sandy were a true shock, we would expect that the distance to Sandy variable to be statistically insignificant prior to the storm. **Table 5** recreates the regressions for **Table 2** but only for the year 2011. In short, across specifications, the coefficient estimate for Sandy is statistically insignificant, thus providing evidence that storm was a true shock.

**{Table 5 about here: regression for 2011 only}**

We also conduct another test, this time by assuming a “fake” storm date that was before the actual storm. In this exercise, we create a fake “post storm” dummy for October 29, 2011 (one year before the actual storm). The data sample for this exercise is from January 1, 2011 to Oct. 28, 2012. The results are presented in **Table 6**. We find that the “fake” treatment effect is statistically insignificant across all 3 specifications.

**{Table 6 about here: “fake Sandy” diff-n-diff}**

We also present some graphical evidence of the benefits from being located away from the storm. **Figure 2** shows regression results quarter-by-quarter (using the same specification as **Table 2**, Column (3); results available upon request). In 2012Q3, before the storm, the estimate is negative.

**{Figure 2 about here: quarterly coeffs.}**

Then we see a large jump in 2012Q4 when the storm took place. After that the coefficients remain positive for the rest of the year. We provide the 95% confidence interval bands as well. The bands tend to be quite wide, likely due, in part, to the large number of census tract fixed effects we include in each regression. But overall, the graph provides evidence of a positive benefit from being further from the storm after the storm.

1. **Conclusion**

This paper estimates the effects that a major hurricane has on properties that are not flooded by the storm. Specifically, our difference-in-differences approach examines how prices of non-flooded properties are affected by the distance to the flood zone, following the storm. After the storm, the distance to the inundation zone provides new information about future flooding expectations from storm surges. We consider residential properties in New York City that sell before and after Hurricane Sandy, on the dry side, in a band within one mile of the storm surge but at least 0.03 miles (158 feet) from the surge. As part of our analysis, we also separate the sample into those that had positive or negative shocks to explore for the possibility that the effects of the surge are different. The parameter estimate for the negative shock is statistically significant and positive–implying a negative shock leads to lower prices—but the parameter estimate for the positive shock is insignificant.

Interestingly, our estimate of the effect of a negative shock on property values (about 8.7% decrease for a 1 mile shock) is lower than the effects that Ortega and Taspinar (2018) found for flooded properties (17% to 22% discount). This implies that perhaps the negative shock in flood risk leads property owners to immediately internalize the prospects of a greater likelihood of being flooded in the future, although since the timing and extent of future flood damage is uncertain, this shock effect is less than the flooding effect found by others. Given that the average property in our sample sold for approximately $962,000, the impacts of a 1-mile negative shock result in prices that are approximately $83,700 lower, on average. With the publicly available FEMA flood plain maps as the best data existing before the storm, the possibility of a property being closer to the flood plain after the storm than previously thought can be a valuable information source for potential home buyers in New York City.

In support of the above conjecture that perhaps property owners immediately internalize the shock effect of a greater future flood risk, we find evidence that people react to these shocks, even though there was no direct impact of the flood on their properties. Perhaps the recurrence of other storms in different parts of the U.S. serves as an ongoing reminder of the potential impacts of being closer to the storm and the effects of the “surprise” from Sandy being closer to properties than expected by the FEMA flood maps.

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**Tables**

**Table 1: Descriptive Statistics**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** | **Obs** |
| Sales price ($) | 962,466 | 4,585,683 | 33,000 | 395,000,000 | 31,982 |
| Price Per Square Foot | 266.37 | 126.36 | 29.96704 | 665 | 31,982 |
| Dist. to Sandy (miles) | 0.467 | 0.28 | 0.030039 | 1.0 | 31,982 |
| Dist. to FEMA (miles) | 0.580 | 0.37 | 9.12E-05 | 2.0 | 31,982 |
| Sandy Dist. - FEMA Dist. (Miles) | -0.113 | 0.28 | -1.08788 | 1.0 | 31,982 |
| Dist. to shoreline (miles) | 0.932 | 0.65 | 0.00324 | 7.2 | 30,002 |
| # Units | 4.25 | 15.33 | 1 | 698 | 31,982 |
| Bldg. Area (ft2) | 4,259.62 | 14,940.36 | 356 | 690,703 | 31,982 |
| Lot Area (ft2) | 3,331.72 | 4,146.67 | 353 | 273,600 | 31,982 |
| Building Age | 73.67 | 29.23 | 0 | 213.0 | 31,978 |
| # floors | 2.37 | 1.18 | 0 | 36.0 | 31,982 |
| Manhattan | 0.04 | 0.20 | 0 | 1.0 | 31,982 |
| Bronx | 0.16 | 0.36 | 0 | 1.0 | 31,982 |
| Brooklyn | 0.28 | 0.45 | 0 | 1.0 | 31,982 |
| Queens | 0.34 | 0.47 | 0 | 1.0 | 31,982 |
| Staten Island | 0.19 | 0.39 | 0 | 1.0 | 31,982 |

Notes: Statistics given for residential properties sold between January 1, 2011 and December 31, 2014, within one mile of Sandy flood zone (on dry side), but more than 0.03 miles from the flood and outside the FEMA floodplain. Information about additional variables used in regressions is given in the Appendix.

**Table 2: Difference-In-Difference Regression for Sandy within 1 mile. Dep. Var.: Ln(Price per square foot), 2011-2013**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **(1)** | **(2)** | **(3)** |
| Dist Sandy (miles) x PostSandy | 0.0405\*\* | 0.0537\*\*\* | 0.0424\*\*\* |
|  | (2.92) | (4.72) | (4.88) |
| Dist. to FEMA (miles) | -0.0358\* | -0.028 | -0.0728\*\*  |
|  | (2.22) | (1.58) | (2.78) |
| ln(# units) |  | 0.128\*\*\* | 0.376\*\*\* |
|  |  | (5.61) | (15.65) |
| ln(land area) |  | 0.250\*\*\* | 0.188\*\*\* |
|  |  | (16.84) | (32.18) |
| ln(age) |  | -0.0654\*\*\* | -0.0843\*\*\* |
|  |  | (8.10) | (7.57) |
| ln(building area) |  | -0.543\*\*\* | -0.609\*\*\* |
|  |  | (23.29) | (-37.63)  |
| ln(# floors) |  | 0.0764 | 0.0244 |
|  |  | (1.88) | (0.81) |
| Dist. to shore (miles) |  |  | 0.0699\*\*  |
|  |  |  | (4.02) |
| Constant | 5.417\*\*\* | 7.727\*\*\* | 9.038\*\*\* |
|   | (318.31) | (27.49) | (67.42) |
| N | 23223 | 23135 | 23135 |
| R-sq | 0.457 | 0.546 | 0.568 |
| adj. R-sq | 0.423 | 0.518 | 0.54 |
| AIC | 22350.7 | 18141.6 | 17027.7 |
| BIC | 22382.9 | 18173.8 | 17076 |

Notes: Column (3) has additional building-level controls not shown. t statistics in parentheses.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough. All regressions contain year-quarter dummies and census tract fixed effects.

**Table 3: Diff-In-Diff Regression for Sandy within 1 mile. Dep. Var.: Ln(Price per square foot), 2011-2014**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **(1)** | **(2)** | **(3)** |
| Dist. Sandy (miles) x PostSandy | 0.0638\* | 0.0696\*\* | 0.0527\* |
|  | (2.30) | (3.02) | (2.67) |
| Dist. to FEMA (miles) | -0.0283 | -0.0143 | -0.0520\* |
|  | (1.32) | (0.78) | (2.23) |
| ln(# units) |  | 0.130\*\*\* | 0.375\*\*\* |
|  |  | (5.23) | (9.35) |
| ln(land area) |  | 0.252\*\*\* | 0.184\*\*\* |
|  |  | (18.13) | (40.91) |
| ln(age) |  | -0.0639\*\*\* | -0.0834\*\*\* |
|  |  | (7.37) | (8.24) |
| ln(building area) |  | -0.530\*\*\* | -0.600\*\*\* |
|  |  | (22.17) | (32.89) |
| ln(# floors) |  | 0.0783 | 0.0202 |
|  |  | (2.03) | (0.89) |
| Dist. to shore (miles) |  |  | 0.0646\*\*  |
|  |  |  | (3.90) |
| Constant | 5.406\*\*\* | 7.587\*\*\* | 9.043\*\*\* |
|   | -208.72 | -25.63 | -44.18 |
| N | 31982 | 31833 | 29883 |
| R-sq | 0.445 | 0.532 | 0.556 |
| adj. R-sq | 0.42 | 0.511 | 0.534 |
| AIC | 31241.2 | 25713.6 | 22619.6 |
| BIC | 31274.7 | 25747.1 | 22661.1 |

Notes: Column (3) has additional building-level controls not shown. t statistics in parentheses.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough. All regressions contain year-quarter dummies and census tract fixed effects.

**Table 4: Diff-In-Diff Regression for Sandy within 1 mile. Dep. Var.: Ln(Price per square foot), 2011-2014, Positive vs. Negative Shocks**

|  |  |  |
| --- | --- | --- |
|  | **Pos. Shock** | **Neg. Shock** |
| **Variable** | (1) | (2) |
| Dist. Sandy (miles) x PostSandy | -0.011 | 0.0874\*  |
|  | (0.29) | (2.66) |
| Dist. to FEMA (miles) | -0.115\*\* | -0.012 |
|  | (3.21) | (0.41) |
| ln(# units) | 0.335\*\*\* | 0.373\*\*\* |
|  | (13.23) | (5.92) |
| ln(land area) | 0.169\*\*\* | 0.192\*\*\* |
|  | (16.82) | (13.16) |
| ln(age) | -0.0845\*\*\* | -0.0808\*\*\* |
|  | (17.24) | (4.90) |
| ln(building area) | -0.605\*\*\* | -0.601\*\*\* |
|  | (64.14) | (23.24) |
| ln(# floors) | -0.00524 | 0.0297 |
|  | (0.19) | (1.32) |
| Dist. to shore (miles) | 0.127\*\*\* | 0.0273\*  |
|  | (17.34) | (2.21) |
| Constant | 7.086\*\*\* | 8.851\*\*\* |
|   | (76.42) | (47.60) |
| N | 9967 | 19916 |
| R-sq | 0.614 | 0.541 |
| adj. R-sq | 0.59 | 0.512 |
| AIC | 5186.6 | 16547.5 |
| BIC | 5215.4 | 16587 |

Notes: additional building-level controls not shown. t statistics in parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough. All regressions contain year-quarter dummies and census tract fixed effects.

**Table 5: Before Sandy (2011) within 1 mile. Dep. Var.: Ln(Price per square foot)**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **(1)** | **(2)** | **(3)** |
| Dist. Sandy (miles) | -0.036 | 0.000531 | -0.0444 |
|  | (0.31) | (0.01) | (0.32) |
| Dist. to FEMA (miles) | -0.0412 | -0.0388 | -0.0854\* |
|  | (0.57) | (0.53) | (2.65) |
| ln(# units) |  | 0.0965\*\* | 0.431\*\*\* |
|  |  | (3.72) | (8.46) |
| ln(land area) |  | 0.250\*\*\* | 0.183\*\*\* |
|  |  | (11.59) | (9.85) |
| ln(age) |  | -0.0672\*\*\* | -0.0856\*\*\* |
|  |  | (5.50) | (6.15) |
| ln(building area) |  | -0.555\*\*\* | -0.600\*\*\* |
|  |  | (17.81) | (44.98) |
| ln(# floors) |  | 0.0733 | 0.0339 |
|  |  | (1.48) | (1.69) |
| Dist. to shore (miles) |  |  | 0.121 |
|  |  |  | (1.23) |
| Constant | 5.445\*\*\* | 7.855\*\*\* | 7.595\*\*\* |
|   | (176.18) | (22.05) | (45.23) |
| N | 6831 | 6801 | 6801 |
| R-sq | 0.526 | 0.609 | 0.629 |
| adj. R-sq | 0.431 | 0.53 | 0.551 |
| AIC | 5618.2 | 4305.8 | 3945.6 |
| BIC | 5645.5 | 4333.1 | 3972.9 |

Notes: additional building-level controls not shown. t statistics in parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough. All regressions contain year-quarter dummies and census tract fixed effects.

**Table 6: Falsification Diff-n-Diff.**

A fake “post storm” dummy was created that was on Oct. 29, 2011 one year before the actual storm. Sample is from January 1, 2011 to Oct. 28, 2012. The “fake” treatment effect is statistically insignificant.

**Dep. Var.: Ln(Price per square foot)**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **(1)** | **(2)** | **(3)** |
| Dist. Sandy (miles) x Post29Oct2011 | 0.0174 | 0.00257 | 0.000599 |
|  | (1.31) | (0.16) | (0.04) |
| Dist. to FEMA (miles | -0.0346 | -0.019 | -0.0717\*\*  |
|  | (1.40) | (0.83) | (2.86) |
| ln(# units) |  | 0.111\*\*\* | 0.345\*\*\* |
|  |  | (4.79) | (14.00) |
| ln(land area) |  | 0.243\*\*\* | 0.181\*\*\* |
|  |  | (14.18) | (19.19) |
| ln(age) |  | -0.0641\*\*\* | -0.0826\*\*\* |
|  |  | (8.48) | (7.66) |
| ln(building area)  | -0.547\*\*\* | -0.596\*\*\* |
|  |  | (20.07) | (35.56) |
| ln(# floors) |  | 0.0649 | 0.0113 |
|  |  | (1.34) | (0.60) |
| Dist. to shore (miles) |  | 0.0777\*\*\* |
|  |  |  | (11.08) |
| Constant | 5.426\*\*\* | 7.833\*\*\* | 9.273\*\*\* |
|   | (247.75) | (22.28) | (46.45) |
| N | 13028 | 12983 | 12983 |
| R-sq | 0.482 | 0.569 | 0.588 |
| adj. R-sq | 0.426 | 0.522 | 0.541 |
| AIC | 11961 | 9566.3 | 8980.5 |
| BIC | 11990.9 | 9596.2 | 9017.8 |

Notes: additional building-level controls not shown. t statistics in parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough. All regressions contain year-quarter dummies and census tract fixed effects.

**Figures**

Figure : Shock values across NYC for dry properties within 1 mile of the storm surge Red dot are housing sales where storm came closer to the property than the closest FEMA map boundary. Blue dots are where the closest FEMA boundary was closer to the storm. Sales shown here were after Hurricane Sandy and through 2014.

Figure : Estimated distance to Sandy coefficients for dry properties from individual quarter-by-quarter regressions (within one mile of Sandy flood zone). The storm occurred in 2012Q4. The blue vertical line is the approximate date of the storm.

**Appendix 1: The Data**

1. Data Sources and Preparation
* *Real Estate Sales*: Source: New York City Department of Finance. Data about individual sales, which includes prices, sales, date, building type at sale, building type at date of download (this allows to check if the building type has changed since the sale), gross square footage, land area of lot, and year built. The sales data contains all transfers of title. We removed all transactions that were less than $10,000 on the assumption that they were not bona fide, open market sales. Further in the regressions we excluded observations that were in the lower first or upper 99th percentile or price per square foot of building area to further eliminate observations that were outliers (both due to possibility of being non-market transaction or were genuine outliners).
* *Additional Building Information*: Source: New York City Department of City Planning (DCP). The DCP annually produces the Primary Land Use Tax Lot Output (PLUTO) file which contains information about each tax lot in the city, including the building type, the number of units, the number of residential units, building area, age, lot size and shape, and other variables about the structure and location (see Table A.1). The PLUTO file also contains census tracts and latitude and longitude coordinates, which we used to find the distance to the Sandy flood zone and the FEMA floodplains.

The PLUTO data was merged with the sales data by the unique borough-block-lot (BBL) id number. In the data set we retained observations where the building types remained constant within the sales file and with the data in the PLUTO file. Furthermore, we dropped observation where the age, log size, building area were different across files to remove buildings that might have been torn down or substantially changed over time.

* *Sandy Flood Zone and FEMA Floodplain*: GIS shapefiles were generously provided by the National Resources Defense Council (NRDC). They provided us with GIS shape files that indicated the locations in the city of the surge flood, and the locations of FEMA floodplain. We used the same files as shown in Figure 1 of their report on Sandy, at <https://www.nrdc.org/sites/default/files/hurricane-sandy-coastal-flooding-report.pdf>.

Using this information, we then created our Sandy-related variables, which include the distance to the flood zone boundary for all properties, the distance to the shoreline, and the distance to the FEMA floodplain boundary. For flooded properties, we ascertained whether the building was in the FEMA floodplain map that was in effect in 2012. We also used the NRDC shape file to ascertain the distance of each property to the closest shoreline.

1. **Additional Variables Not Shown in Regression Table**

In several specifications, we included additional building and lot controls not shown in the table. These include building type-style dummies (e.g., a dummy variable for one-family, cape-code style, one for one-family, two-story-detached, etc.), dummies for proximity to other structures, dummies for basement types, and dummies for lot shape. Descriptive statistics are available upon request.

|  |
| --- |
| **Building Type** |
| **Type** | **Style** |
| One family dwelling | Cape code |
| One family dwelling | Two stories, detached |
| One family dwelling | One story |
| One family dwelling | Large suburban residence |
| One family dwelling | City residence |
| One family dwelling | Attached or semi-detached |
| One family dwelling | Summer cottage |
| One family dwelling | Mansion or town house |
| One family dwelling | Bungalow |
| Two family dwelling | Brick |
| Two family dwelling | Frame |
| Two family dwelling | Converted from one family |
| Two family dwelling | Misc. |
| Walk up apartment | Three families |
| Walk up apartment | Over six families |
| Walk up apartment | Five to six families |
| Walk up apartment | Four families |
| Walk up apartment | Old law tenement |
| Walk up apartment | Converted dwelling |
| Walk up apartment | Cooperative |
| Walk up apartment | Over six families with stories |
| Walk up apartment | Co-op conversion from Loft |
| Walk up apartment | Garden Apartments |
| Elevator apartment | Semi-fireproof |
| Elevator apartment | Artists in residence |
| Elevator apartment | Fireproof |
| Elevator apartment | Converted |
| Elevator apartment | Fireproof with stores |
| Elevator apartment | Semi-fireproof with stores |
| Elevator apartment | Misc. |
| Residence - multiple use | Primary one family with two stores or offices |
| Residence - multiple use | Primary one family with one store or office |
| Residence - multiple use | Primary two family with one store or office |
| Residence - multiple use | Single or multiple dwelling with stores or offices |
| **Building Proximity to Other Buildings** |
| Detached |   |
| Semi-attached |   |
| Attached |   |
| **Basement Code** |
| Above grade full basement |   |
| Below grade full basement |   |
| Above grade partial basement |   |
| Below grade partial basement |   |
| Unknown |   |
| **Lot Shape** |
| Regular shaped |   |
| Irregular shaped |   |
| Unknown |   |

Table A.1: Additional Control Variables Used in Some Specifications.

**Appendix 2: Additional Results**

For the sake of conciseness, the following regression tables only present the coefficient estimates for the key independent variable, *Distance to Sandy x PostSandy Dummy.* The full regression results are available upon request.

**Table A.1: *Distance to Sandy x PostSandy Dummy* within 1 mile, positive shock values of different sizes. Eq. (1) is any positive shock. (2) is greater than 0.05 miles, etc. Dep. Var.: Ln(Price per square foot), 2011-2013**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
|   | **>0** | **>0.05** | **>0.1** | **>0.125** | **>0.15** |
| Dist. Sandy x PostSandy | -0.011 | 0.0137 | -0.00238 | -0.0431 | -0.0477 |
|   | (0.29) | (0.36) | (0.06) | (1.08) | (1.19) |
| N | 9967 | 3668 | 2641 | 2253 | 2060 |
| R-sq | 0.614 | 0.56 | 0.583 | 0.584 | 0.581 |
| adj. R-sq | 0.59 | 0.527 | 0.551 | 0.551 | 0.547 |
| AIC | 5186.6 | 1620.6 | 955.3 | 787.4 | 733.7 |
| BIC | 5215.4 | 1645.5 | 973 | 804.5 | 750.6 |

Notes: Other control variables not shown. The specification is the same as Table 2, Column (3). t statistics in parentheses.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough.

**Table A.2: *Distance to Sandy x PostSandy Dummy* within 1 mile, negative shock values of different sizes. Eq. (1) is any negative shock. (2) is less than -0.05 miles, etc. Dep. Var.: Ln(Price per square foot), 2011-2013**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
|   | **<0** | **<-0.05** | **<-0.1** | **<-0.125** | **<-0.15** |
| Dist. Sandy x PostSandy | 0.0664\*\* | 0.0421 | 0.0408\*\*\* | 0.0437\*\*\* | 0.0530\*\*\* |
|   | (2.92) | (1.90) | (8.97) | (5.35) | (5.44) |
| N | 15396 | 9552 | 7347 | 6881 | 6566 |
| R-sq | 0.563 | 0.552 | 0.549 | 0.557 | 0.554 |
| adj. R-sq | 0.528 | 0.514 | 0.511 | 0.521 | 0.519 |
| AIC | 12085.4 | 7089.7 | 5082.4 | 4571 | 4401.3 |
| BIC | 12116 | 7118.3 | 5110 | 4598.3 | 4428.4 |

Notes: Other control variables not shown. The specification is the same as Table 2, Column (3). t statistics in parentheses.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough.

**Table A.3: *Distance to Sandy x PostSandy Dummy* within 0.5 miles. Dep. Var.: Ln(Price per square foot), Columns (1)-(3) are 2011-2013; Columns (4)-(6) are 2011-2014**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Dist. Sandy x PostSandy | 0.0407 | 0.0259 | 0.0289 | 0.108 | 0.0877 | 0.089 |
|   | (0.49) | (0.31) | (0.34) | (1.65) | (1.67) | (1.64) |
| N | 13086 | 13034 | 13034 | 18013 | 17941 | 16844 |
| R-sq | 0.451 | 0.541 | 0.564 | 0.439 | 0.528 | 0.553 |
| adj. R-sq | 0.41 | 0.507 | 0.53 | 0.408 | 0.502 | 0.526 |
| AIC | 12859.9 | 10498.9 | 9835.6 | 17934.9 | 14773.6 | 12980.6 |
| BIC | 12889.8 | 10528.8 | 9865.5 | 17966.1 | 14804.8 | 13011.5 |

Notes: Other control variables not shown. The specification are the same as Table 2. t statistics in parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough.

**Table A.4 *Distance to Sandy x PostSandy Dummy* within 1 mile, *Sandy, FEMA and dist. to shore* variable in logs. Dep. Var.: Ln(Price per square foot), Columns (1)-(3) are 2011-2013; Columns (4)-(6) are 2011-2014**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| ln(Dist. Sandy) x PostSandy | 0.00925 | 0.00895 | 0.00534 | 0.0205\* | 0.0188\*\* | 0.0125\* |
|   | (1.89) | (1.79) | (1.37) | (2.66) | (3.06) | (2.77) |
| N | 23223 | 23135 | 23135 | 31982 | 31833 | 29883 |
| R-sq | 0.457 | 0.546 | 0.568 | 0.445 | 0.532 | 0.556 |
| adj. R-sq | 0.423 | 0.518 | 0.54 | 0.42 | 0.511 | 0.534 |
| AIC | 22351.7 | 18149.9 | 17032.3 | 31242.6 | 25724.3 | 22624.4 |
| BIC | 22383.9 | 18182.1 | 17088.7 | 31276.1 | 25757.8 | 22665.9 |

Notes: Other control variables not shown. The specifications are the same as Table 2. t statistics in parentheses.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough

**Table A.5: *Distance to Sandy x PostSandy Dummy* within 1 mile, by shock type, *Sandy and FEMA* variable in logs. Dep. Var.: Ln(Price per square foot), 2011-2014**

|  |  |  |
| --- | --- | --- |
|  | **(1)** | **(2)** |
|  | >0 | <0 |
| ln(Dist. Sandy) x PostSandy | -0.00392 | 0.0210\* |
|  | (0.35) | (2.40) |
| N | 9967 | 19916 |
| R-sq | 0.614 | 0.541 |
| adj. R-sq | 0.59 | 0.512 |
| AIC | 5199.5 | 16557.8 |
| BIC | 5228.3 | 16589.4 |

Notes: Other control variables not shown. The specifications are the same as Table 4. t statistics in parentheses.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01. Standard errors clustered by borough.

1. \*We thank the National Resources Defense Council for providing GIS maps related to Hurricane Sandy. Earlier versions of the paper were presented at the 2017 AREUEA National Conference and the 2017 and 2020 Eastern Economics Association meetings. We thank the associate editor of this journal and the anonymous referees, as well as Steve Malpezzi and Suleyman Taspinar, for their comments. Any errors belong to the authors. [↑](#footnote-ref-1)
2. For Harvey see: <https://www.nytimes.com/interactive/2017/09/01/us/houston-damaged-buildings-in-fema-flood-zones.html?mcubz=1&_r=1>. [↑](#footnote-ref-2)
3. For New York City see: <http://www.nyc.gov/html/sirr/downloads/pdf/final_report/Ch_1_SandyImpacts_FINAL_singles.pdf>. [↑](#footnote-ref-3)
4. Note that as of October 2020, the FIRMS for New York City have not officially changed from what they were before Sandy. Evidently, the process of changing the maps has proven too politically contentious (New York City, 2020). [↑](#footnote-ref-4)
5. Other more general studies, that do not explicitly focus on risk perceptions, include Bin et al. (2011), who focus on a similar geographic area in North Carolina as Bin and Landry (2013), to estimate an approximate value of lost property due to potential flooding in these areas. For a 20 to 70 year period into the future, they forecast between a $179 million and $576 million loss for properties in four counties near the shore in North Carolina. Atreya and Czajkowski (2019) use a spatial hedonic model to study the price effects of proximity to the coast in Galveston, Texas. They find that with ¼ mile from the coast, properties sell for higher prices than those that are further away. An earlier study in this literature is MacDonald, Murdoch and White (1987), who estimate a hedonic house price function to study Monroe, Louisiana, an area prone to flooding. Given the nonlinear functional form for the dependent variable (i.e., the sales price), it is not straightforward in general to indicate one magnitude and direction for the marginal effects, but these effects depend on the fitted values of each of the sales prices. They provide a few examples of the effects for a small sample of homes, and they find that for these houses a higher flood risk leads to a decrease in sales prices in the range of $2000 to $8000. But none of these studies explicitly consider how changes in expectations of flood risks impact house prices. [↑](#footnote-ref-5)
6. Examining the impacts of a hurricane as a natural experiment extends beyond the literature on real estate impacts. Meltzer et al. (2019) investigate the impact of Hurricane Sandy on small businesses vulnerability in New York City by looking at firms and employment before and after the storm. Their regression results show significant post-Sandy job declines, of about 4.5 to 6 per census block, for the retail sector only. But, across all job types, the impacts from Sandy are noisy and largely insignificant. [↑](#footnote-ref-6)